The Neo4j Graph Data Science Library Manual v2.0

[[graph-data-science]]

Table of Contents

This is the manual for Neo4j Graph Data Science library version 2.0.

The manual covers the following areas:

- Introduction — An introduction to the Neo4j Graph Data Science library.
- Installation — Instructions for how to install and use the Neo4j Graph Data Science library.
- Common usage — General usage patterns and recommendations for getting the most out of the Neo4j Graph Data Science library.
- Graph management — A detailed guide to the graph catalog and utility procedures included in the Neo4j Graph Data Science library.
- Graph Algorithms — A detailed guide to each of the algorithms in their respective categories, including use-cases and examples.
- Machine learning — A detailed guide to the machine learning procedures included in the Neo4j Graph Data Science library.
- Production deployment — This chapter explains advanced details with regards to common Neo4j components.
- Python client — Documentation of the Graph Data Science client for Python users.
- Operations reference — Reference of all procedures contained in the Neo4j Graph Data Science library.
- Migration from Graph Data Science library Version 1.x — Additional resources - migration guide, books, etc - to help using the Neo4j Graph Data Science library.

The source code of the library is available at GitHub. If you have a suggestion on how we can improve the library or want to report a problem, you can create a new issue.

Chapter 1. Introduction

This chapter provides a brief introduction of the main concepts in the Neo4j Graph Data Science library.

This library provides efficiently implemented, parallel versions of common graph algorithms for Neo4j, exposed as Cypher procedures.

1.1. Algorithms

Graph algorithms are used to compute metrics for graphs, nodes, or relationships.

They can provide insights on relevant entities in the graph (centralities, ranking), or inherent structures like communities (community-detection, graph-partitioning, clustering).

Many graph algorithms are iterative approaches that frequently traverse the graph for the computation using random walks, breadth-first or depth-first searches, or pattern matching.

Due to the exponential growth of possible paths with increasing distance, many of the approaches also have high algorithmic complexity.

Fortunately, optimized algorithms exist that utilize certain structures of the graph, memoize already explored parts, and parallelize operations. Whenever possible, we've applied these optimizations.

The Neo4j Graph Data Science library contains a large number of algorithms, which are detailed in the Algorithms chapter.

1.1.1. Algorithm traits

Algorithms in GDS have specific ways to make use of various aspects of its input graph(s). We call these *algorithm traits*. When an algorithm supports an algorithm trait this indicates that the algorithm has been implemented to produce well-defined results in accordance with the trait. The following algorithm traits exist:

Directed

The algorithm is well-defined on a directed graph.

Undirected

The algorithm is well-defined on an undirected graph.

Homogeneous

The algorithm will treat all nodes and relationships in its input graph(s) similarly, as if they were all of the same type. If multiple types of nodes or relationships exist in the graph, this must be taken into account when analysing the results of the algorithm.

Heterogeneous

The algorithm has the ability to distinguish between nodes and/or relationships of different types.

Weighted

The algorithm supports configuration to set node and/or relationship properties to use as weights. These values can represent *cost*, *time*, *capacity* or some other domain-specific properties, specified via the nodeWeightProperty, nodeProperties and relationshipWeightProperty configuration parameters. The algorithm will by default consider each node and/or relationship as equally important.

1.2. Graph Catalog

In order to run the algorithms as efficiently as possible, the Neo4j Graph Data Science library uses a specialized graph format to represent the graph data. It is therefore necessary to load the graph data from the Neo4j database into an in memory graph catalog. The amount of data loaded can be controlled by so called graph projections, which also allow, for example, filtering on node labels and relationship types, among other options.

For more information see Graph Management.

1.3. Editions

The Neo4j Graph Data Science library is available in two editions.

- The open source Community Edition includes all algorithms and features, but is limited to four CPU cores.
- The Neo4j Graph Data Science library Enterprise Edition:
  - Can run on an unlimited amount of CPU cores.
  - Supports the role-based access control system (RBAC) from Neo4j Enterprise Edition.
  - Supports various additional model catalog features
    - Storing unlimited amounts of models in the model catalog
    - Publishing a stored model
    - Persisting a stored model to disk
  - Supports an optimized graph implementation

For more information see System Requirements - CPU.

Chapter 2. Installation

> *This chapter provides instructions for installation and basic usage of the Neo4j Graph Data Science library.*

The Neo4j Graph Data Science (GDS) library is delivered as a plugin to the Neo4j Graph Database. The plugin needs to be installed into the database and added to the allowlist in the Neo4j configuration. There are two main ways of achieving this, which we will detail in this chapter.

This chapter is divided into the following sections:

1. Supported Neo4j versions
2. Neo4j Desktop
3. Neo4j Server
4. Enterprise Edition Configuration
5. Neo4j Docker
6. Neo4j Causal Cluster
7. Additional configuration options
8. System Requirements

2.1. Supported Neo4j versions

Below is the compatibility matrix for the GDS library vs Neo4j. In general, you can count on the latest version of GDS supporting the latest version of Neo4j and vice versa, and we recommend you always upgrade to that combination.

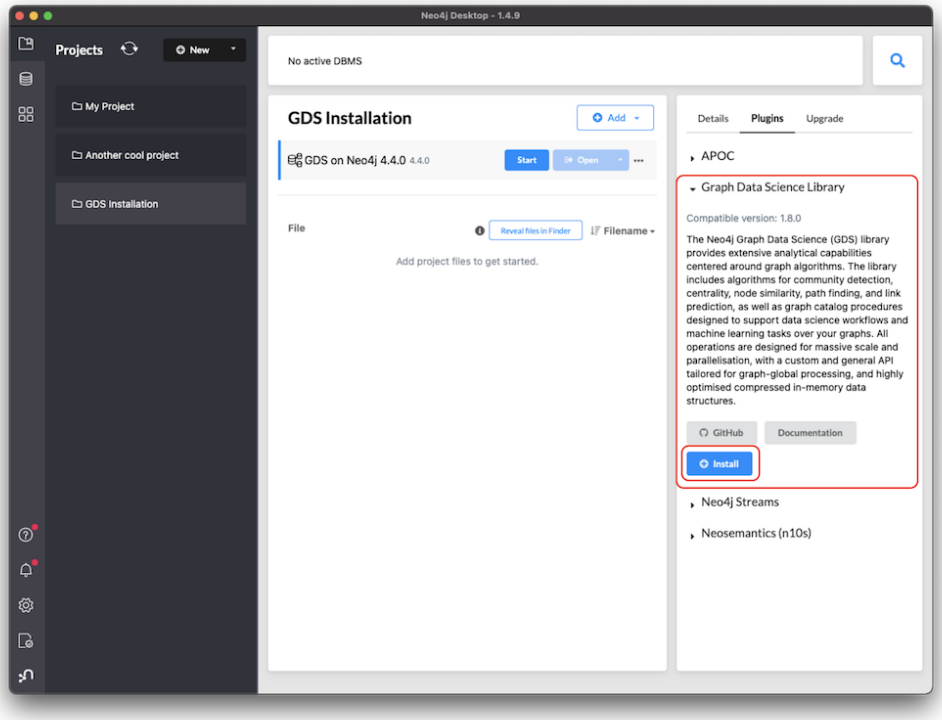
We list software with major and minor version only, e.g. GDS library 1.8. You should read that as any patch version of that major+minor version, but again, do upgrade to the latest patch always, to ensure you get all bug fixes included.

Not finding your version of GDS or Neo4j listed? Time to upgrade!

Neo4j Graph Data Science	Neo4j version
`2.0.5` [1]	`4.4`
	`4.3`
`1.8` [2]	`4.4`
	`4.3`
	`4.2`
	`4.1` [3]
`1.1` [1]	`3.5`

2.2. Neo4j Desktop

The most convenient way of installing the GDS library is through the Neo4j Desktop plugin called Neo4j Graph Data Science. The plugin can be found in the 'Plugins' tab of a database.



The installer will download the GDS library and install it in the 'plugins' directory of the database. It will also add the following entry to the settings file:

```
dbms.security.procedures.unrestricted=gds.*
```

This configuration entry is necessary because the GDS library accesses low-level components of Neo4j to maximise performance.

If the procedure allowlist is configured, make sure to also include procedures from the GDS library:

```
dbms.security.procedures.allowlist=gds.*
```

Before `Neo4j 4.2`, the configuration setting is called `dbms.security.procedures.whitelist`

2.3. Neo4j Server

The GDS library is intended to be used on a standalone Neo4j server.

Running the GDS library on a core member of a Neo4j Causal Cluster is not supported. Read more about how to use GDS in conjunction with Neo4j Causal Cluster deployment below.

On a standalone Neo4j Server, the library will need to be installed and configured manually.

1. Download `neo4j-graph-data-science-[version].jar` from the Neo4j Download Center and copy it into the `$NEO4J_HOME/plugins` directory.
2. Add the following to your `$NEO4J_HOME/conf/neo4j.conf` file:

   ```
   dbms.security.procedures.unrestricted=gds.*
   ```

   This configuration entry is necessary because the GDS library accesses low-level components of Neo4j to maximise performance.

3. Check if the procedure allowlist is enabled in the `$NEO4J_HOME/conf/neo4j.conf` file and add the GDS library if necessary:

   ```
   dbms.security.procedures.allowlist=gds.*
   ```

   Before `Neo4j 4.2`, the configuration setting is called `dbms.security.procedures.whitelist`

4. Restart Neo4j

2.3.1. Verifying installation

To verify your installation, the library version can be printed by entering into the browser in Neo4j Desktop and calling the `gds.version()` function:

```
RETURN gds.version()
```

To list all installed algorithms, run the `gds.list()` procedure:

```
CALL gds.list()
```

2.4. Enterprise Edition Configuration

Unlocking the Enterprise Edition of the Neo4j Graph Data Science library requires a valid license key. To register for a license, please contact Neo4j at https://neo4j.com/contact-us/?ref=graph-analytics.

The license is issued in the form of a license key file, which needs to be placed in a directory accessible by the Neo4j server. You can configure the location of the license key file by setting the `gds.enterprise.license_file` option in the `neo4j.conf` configuration file of your Neo4j installation. The location must be specified using an absolute path. It is necessary to restart the database when configuring the license key for the first time and every time the license key is changed, e.g., when a new license key is added or the location of the key file changes.

Example configuration for the license key file:

```
gds.enterprise.license_file=/path/to/my/license/keyfile
```

If the `gds.enterprise.license_file` setting is set to a non-empty value, the Neo4j Graph Data Science library will verify that the license key file is accessible and contains a valid license key. When a valid license key is configured, all Enterprise Edition features are unlocked. In case of a problem, e.g, when the license key file is inaccessible, the license has expired or is invalid for any other reason, all calls to the Neo4j Graph Data Science Library will result in an error, stating the problem with the license key.

2.5. Neo4j Docker

The Neo4j Graph Data Science library is available as a plugin for Neo4j on Docker. The plugins guide for Docker is found at the operations manual.

To run a Neo4j Container with GDS available, you can run

```
docker run -it --rm \
  --publish=7474:7474 --publish=7687:7687 \
  --user="$(id -u):$(id -g)" \
  -e NEO4J_AUTH=none \
  --env NEO4JLABS_PLUGINS='["graph-data-science"]' \
  neo4j:4.4
```

2.6. Neo4j Causal Cluster

This feature is not available in AuraDS

In a Neo4j Causal Cluster, GDS should only be installed on a *Read Replica* instance.

In order to install the GDS library on a *Read Replica* you can follow the steps from Neo4j Server. Additionally, the Neo4j Causal Cluster must be configured to use server-side routing.

For more details, see GDS with Neo4j Causal Cluster.

2.7. Additional configuration options

In order to make use of certain features of the GDS library, additional configuration is necessary. Configuration is done in the *neo4j.conf* configuration file before starting the DBMS. The following features require such additional configuration:

2.7.1. Graph export

Exporting graphs to CSV files requires the configuration parameter `gds.export.location` to be set to the absolute path to the folder in which exported graphs will be stored. This directory has to be writable by the Neo4j process.

2.7.2. Model persistence

The model persistence feature requires the configuration parameter `gds.model.store_location` to be set to the absolute path to the folder in which the models will be stored. This directory has to be writable by the Neo4j process.

2.8. System Requirements

2.8.1. Main Memory

The GDS library runs within a Neo4j instance and is therefore subject to the general Neo4j memory configuration.

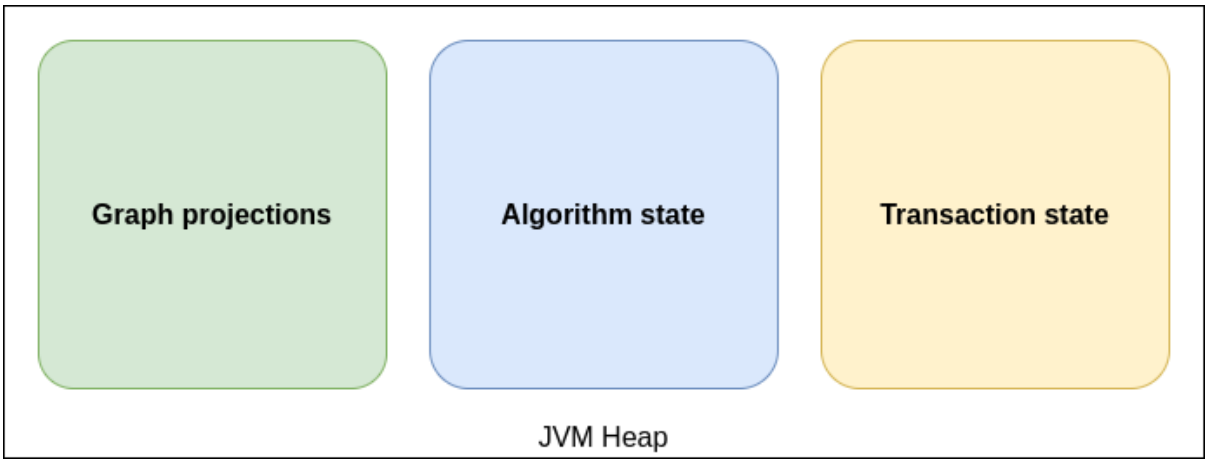


Figure 1. GDS heap memory usage

Heap size

The heap space is used for storing graph projections in the graph catalog and algorithm state. When writing algorithm results back to Neo4j, heap space is also used for handling transaction state (see dbms.tx_state.memory_allocation). For purely analytical workloads, a general recommendation is to set the heap space to about 90% of the available main memory. This can be done via dbms.memory.heap.initial_size and dbms.memory.heap.max_size.

To better estimate the heap space required to project graphs and run algorithms, consider the Memory Estimation feature. The feature estimates the memory consumption of all involved data structures using information about number of nodes and relationships from the Neo4j count store.

Page cache

The page cache is used to cache the Neo4j data and will help to avoid costly disk access.

For purely analytical workloads including native projections, it is recommended to decrease dbms.memory.pagecache.size in favor of an increased heap size. However, setting a minimum page cache size is still important when projecting graphs:

- For native projections, the minimum page cache size for projecting a graph can be roughly estimated by `8KB * 100 * readConcurrency`.

- For Cypher projections, a higher page cache is required depending on the query complexity.

However, if it is required to write algorithm results back to Neo4j, the write performance is highly depended on store fragmentation as well as the number of properties and relationships to write. We recommend starting with a page cache size of roughly `250MB * writeConcurrency` and evaluate write performance and adapt accordingly. Ideally, if the memory estimation feature has been used to find a good heap size, the remaining memory can be used for page cache and OS.

Decreasing the page cache size in favor of heap size is **not** recommended if the Neo4j instance runs both, operational and analytical workloads at the same time. See Neo4j memory configuration for general information about page cache sizing.

2.8.2. CPU

The library uses multiple CPU cores for graph projections, algorithm computation, and results writing. Configuring the workloads to make best use of the available CPU cores in your system is important to achieve maximum performance. The concurrency used for the stages of projection, computation and writing is configured per algorithm execution, see Common Configuration parameters

The default concurrency used for most operations in the Graph Data Science library is 4.

The maximum concurrency that can be used is limited depending on the license under which the library is being used:

- Neo4j Graph Data Science Library - Community Edition (GDS CE)
  - The maximum concurrency in the library is limited to 4.
- Neo4j Graph Data Science Library - Enterprise Edition (GDS EE)
  - The maximum concurrency in the library is unlimited. To register for a license, please contact Neo4j at https://neo4j.com/contact-us/?ref=graph-data-science.

Concurrency limits are determined based on whether you have a GDS EE license, or if you are using GDS CE. The maximum concurrency limit in the graph data science library is not set based on your edition of the Neo4j database.

[1] This version series is end-of-life and will not receive further patches. Please use a later version.
[2] This version series will go out of support on 29 September 2022
[3] There is a bug in Neo4j 4.1.1 that can lead to an exception when using Cypher projection. If possible, use the latest patch version.

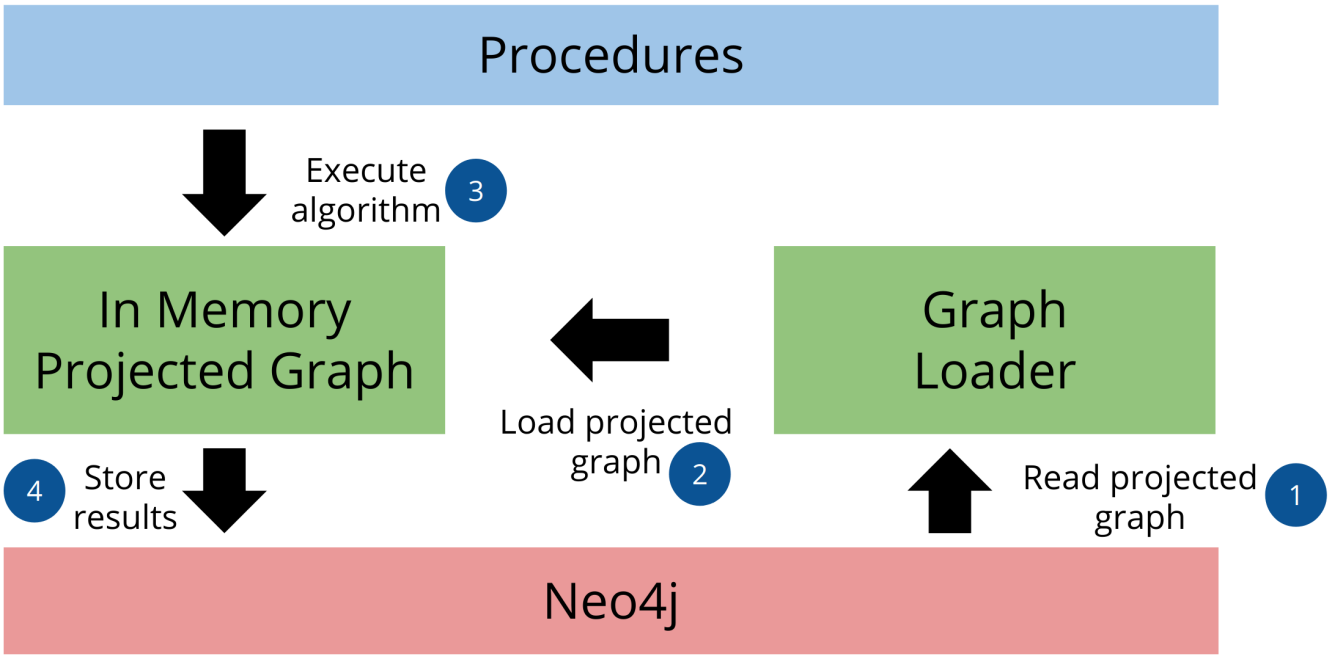
Chapter 3. Common usage

This chapter explains the common usage patterns and operations that constitute the core of the Neo4j Graph Data Science library.

The GDS library usage pattern is typically split in two phases: development and production. In the development phase the goal is to establish a workflow of useful algorithms. In order to do this, the system must be configured, graph projections must be defined, and algorithms must be selected. It is typical to make use of the memory estimation features of the library. This enables you to successfully configure your system to handle the amount of data to be processed. There are two kinds of resources to keep in mind: the projected graph and the algorithm data structures.

In the production phase, the system would be configured appropriately to successfully run the desired algorithms. The sequence of operations would normally be to project a graph, run one or more algorithms on it, and consume results.

The below image illustrates an overview of standard operation of the GDS library:



The GDS library runs its procedures greedily in terms of system resources. That means that each procedure will try to use:

- as much memory as it needs (see Memory estimation)
- as many CPU cores as it needs (not exceeding the limits of the `concurrency` it's configured to run with)

Concurrently running procedures share the resources of the system hosting the DBMS and as such may affect each other's performance. To get an overview of the status of the system you can use the System monitor procedure.

The more detail on each individual operation, see the corresponding section:

1. Graph Catalog
2. Projecting graphs
3. Running algorithms

In this chapter, we will go through these aspects and guide you towards the most useful operations.

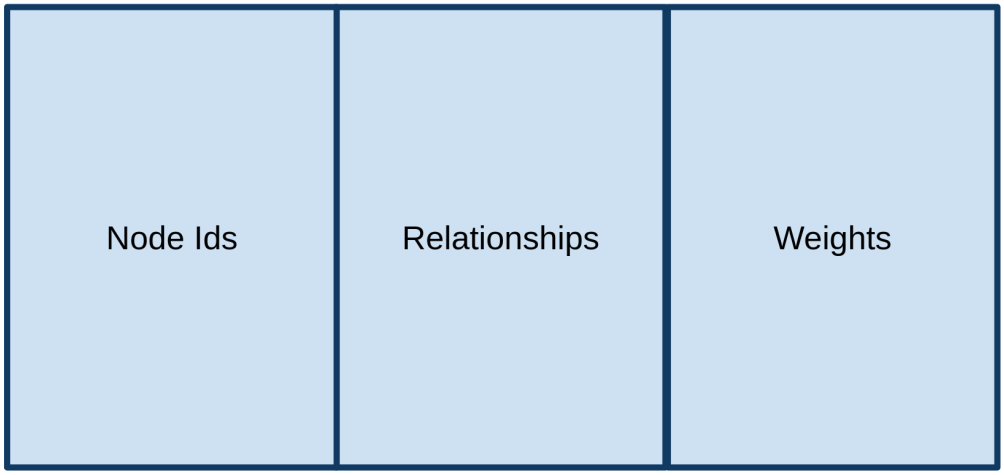
This chapter is divided into the following sections:

- Memory Estimation
- Projecting graphs
- Running algorithms
- Logging
- Monitoring system
- System Information

3.1. Memory Estimation

> *This section describes how to estimate memory requirements for the projected graph model used by the Neo4j Graph Data Science library.*

The graph algorithms library operates completely on the heap, which means we'll need to configure our Neo4j Server with a much larger heap size than we would for transactional workloads. The diagram belows shows how memory is used by the projected graph model:



In Memory Graph Model

The model contains three types of data:

- Node ids - up to 2^{45} ("35 trillion")
- Relationships - pairs of node ids. Relationships are stored twice if `orientation: "UNDIRECTED"` is used.
- Weights - stored as doubles (8 bytes per node) in an array-like data structure next to the relationships

Memory configuration depends on the graph projection that we're using.

3.1.1. Estimating memory requirements for algorithms

In many use cases it will be useful to estimate the required memory of projecting a graph and running an algorithm *before* running it in order to make sure that the workload can run on the available free memory. To do this the `.estimate` mode can be used, which returns an estimate of the amount of memory required to run graph algorithms. Note that only algorithms in the production-ready tier are guaranteed to have an `.estimate` mode. For more details please refer to Syntax overview.

Syntax outline:

```
CALL gds[.<tier>].<algorithm>.<execution-mode>.estimate(
  graphNameOrConfig: String or Map,
  configuration: Map
) YIELD
  nodeCount: Integer,
  relationshipCount: Integer,
  requiredMemory: String,
  treeView: String,
  mapView: Map,
  bytesMin: Integer,
  bytesMax: Integer,
  heapPercentageMin: Float,
  heapPercentageMax: Float
```

Table 1. Parameters

Name	Type	Default	Optional	Description
graphNameOrConfig	String or Map	-	no	The name of the projected graph or a configuration to project a graph.
configuration	Map	-	no	The configuration of the algorithm.

The configuration map accepts the same configuration parameters as the estimated algorithm. See the specific algorithm documentation for more information.

In contrast to procedures that execute algorithms, for memory estimation it is possible to define a graph projection config. With this it is possible to measure the memory consumption of projecting a graph and executing the algorithm at the same time.

Table 2. Results

Name	Type	Description
`nodeCount`	Integer	The number of nodes in the graph.
`relationshipCount`	Integer	The number of relationships in the graph.
`requiredMemory`	String	An estimation of the required memory in a human readable format.
`treeView`	String	A more detailed representation of the required memory, including estimates of the different components in human readable format.
`mapView`	Map	A more detailed representation of the required memory, including estimates of the different components in structured format.

Name	Type	Description
bytesMin	Integer	The minimum number of bytes required.
bytesMax	Integer	The maximum number of bytes required.
heapPercentageMin	Float	The minimum percentage of the configured maximum heap required.
heapPercentageMax	Float	The maximum percentage of the configured maximum heap required.

Graph creation configuration

Table 3. Parameters

Name	Type	Default	Optional	Description
node projection	String, List of String or Map	null	yes	The node projection used for anonymous graph creation via a Native projection.
relationship projection	String, List of String or Map	null	yes	The relationship projection used for anonymous graph creation a Native projection.
nodeQuery	String	null	yes	The Cypher query used to select the nodes for anonymous graph creation via a Cypher projection.
relationshipQuery	String	null	yes	The Cypher query used to select the relationships for anonymous graph creation via a Cypher projection.
nodeProperties	String, List of String or Map	null	yes	The node properties to project during anonymous graph creation.
relationshipProperties	String, List of String or Map	null	yes	The relationship properties to project during anonymous graph creation.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'.
readConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for creating the graph.

3.1.2. Estimating memory requirements for graphs

The `gds.graph.project` procedures also support `.estimate` to estimate memory usage for just the graph. Those procedures don't accept the graph name as the first argument, as they don't actually project the graph.

Syntax

```
CALL gds.graph.project.estimate(nodeProjection: String|List|Map, relationshipProjection: String|List|Map,
configuration: Map)
YIELD requiredMemory, treeView, mapView, bytesMin, bytesMax, heapPercentageMin, heapPercentageMax,
nodeCount, relationshipCount
```

The `nodeProjection` and `relationshipProjection` parameters follow the same syntax as in `gds.graph.project`.

Table 4. Parameters

Name	Type	Default	Optional	Description
nodeProjection	String or List or Map	-	no	The node projection to estimate for.
relationshipProjection	String or List or Map	-	no	The relationship projection to estimate for.
configuration	Map	{}	yes	Additional configuration, such as concurrency.

The result of running `gds.graph.project.estimate` has the same form as the algorithm memory estimation results above.

It is also possible to estimate the memory of a fictive graph, by explicitly specifying its node and relationship count. Using this feature, one can estimate the memory consumption of an arbitrarily sized graph.

To achieve this, use the following configuration options:

Table 5. Configuration

Name	Type	Default	Optional	Description
nodeCount	Integer	0	yes	The number of nodes in a fictive graph.
relationshipCount	Integer	0	yes	The number of relationships in a fictive graph.

When estimating a fictive graph, syntactically valid `nodeProjection` and `relationshipProjection` must be specified. However, it is recommended to specify `'*'` for both in the fictive graph case as this does not interfere with the specified values above.

The query below is an example of estimating a fictive graph with 100 nodes and 1000 relationships.

Example

```
CALL gds.graph.project.estimate('*', '*', {
  nodeCount: 100,
  relationshipCount: 1000,
  nodeProperties: 'foo',
  relationshipProperties: 'bar'
})
YIELD requiredMemory, treeView, mapView, bytesMin, bytesMax, nodeCount, relationshipCount
```

Table 6. Results

requiredMemory	bytesMin	bytesMax	nodeCount	relationshipCount
"593 KiB"	607576	607576	100	1000

The `gds.graph.project.cypher` procedure has to execute both, the `nodeQuery` and `relationshipQuery`, in order to count the number of nodes and relationships of the graph.

Syntax

```
CALL gds.graph.project.cypher.estimate(nodeQuery: String, relationshipQuery: String, configuration: Map)
YIELD requiredMemory, treeView, mapView, bytesMin, bytesMax, heapPercentageMin, heapPercentageMax,
nodeCount, relationshipCount
```

Table 7. Parameters

Name	Type	Default	Optional	Description
nodeQuery	String	-	no	The node query to estimate for.
relationshipQuery	String	-	no	The relationship query to estimate for.
configuration	Map	{}	yes	Additional configuration, such as concurrency.

3.1.3. Automatic estimation and execution blocking

All procedures in the GDS library that support estimation, including graph creation, will do an estimation check at the beginning of their execution. This includes all execution modes, but not the `estimate` procedures themselves.

If the estimation check can determine that the current amount of free memory is insufficient to carry through the operation, the operation will be aborted and an error will be reported. The error will contain details of the estimation and the free memory at the time of estimation.

This heap control logic is restrictive in the sense that it only blocks executions that are certain to not fit into memory. It does not guarantee that an execution that passed the heap control will succeed without depleting memory. Thus, it is still useful to first run the estimation mode before running an algorithm or graph creation on a large data set, in order to view all details of the estimation.

The free memory taken into consideration is based on the Java runtime system information. The amount of free memory can be increased by either dropping unused graphs from the catalog, or by increasing the maximum heap size prior to starting the Neo4j instance.

Bypassing heap control

Occasionally you will want the ability to bypass heap control if it is too restrictive. You might have insights into how your particular procedure call will behave, memory-wise; or you might just want to take a chance e.g. because the memory estimate you received is very close to system limits.

For that use case we have *sudo mode* which allows you to manually skip heap control and run your procedure regardless. Sudo mode is off by default to protect users - we fail fast if we can see your potentially long-running procedure would not be able to complete successfully.

To enable sudo mode, add the sudo parameter when calling a procedure. Here is an example of calling the popular Louvain community detection algorithm in sudo mode:

Run Louvain in sudo mode:

```
CALL gds.louvain.write('myGraph', { writeProperty: 'community', sudo: true })
YIELD communityCount, modularity, modularities
```

Accidentally enabling sudo mode when calling a procedure, causing it to run out of memory, will not significantly damage your installation, but it will waste your time.

3.2. Projecting graphs

> *This section discusses creating named graphs to be used for algorithm computation in the Neo4j Graph Data Science library.*

In order for any algorithm in the GDS library to run, we must first project a graph to run on. The graph is projected as a *named graph*. A named graph is given a name and stored in the graph catalog. For a detailed guide on all graph catalog operations, see Graph Catalog.

3.3. Running algorithms

> *This section describes the common execution modes for algorithms:* `stream`, `stats`, `mutate` *and* `write`.

All algorithms are exposed as Neo4j procedures. They can be called directly from Cypher using Neo4j Browser, `cypher-shell`, or from your client code using a Neo4j Driver in the language of your choice.

For a detailed guide on the syntax to run algorithms, please see the Syntax overview section. In short, algorithms are run using one of the execution modes `stream`, `stats`, `mutate` or `write`, which we cover in this chapter.

The execution of any algorithm can be canceled by terminating the Cypher transaction that is executing the procedure call. For more on how transactions are used, see Transaction Handling.

3.3.1. Stream

The `stream` mode will return the results of the algorithm computation as Cypher result rows. This is similar to how standard Cypher reading queries operate.

The returned data can be a node ID and a computed value for the node (such as a Page Rank score, or WCC componentId), or two node IDs and a computed value for the node pair (such as a Node Similarity similarity score).

If the graph is very large, the result of a `stream` mode computation will also be very large. Using the `ORDER BY` and `LIMIT` subclauses in the Cypher query could be useful to support 'top N'-style use cases.

3.3.2. Stats

The `stats` mode returns statistical results for the algorithm computation like counts or percentile distributions. A statistical summary of the computation is returned as a single Cypher result row. The direct results of the algorithm are not available when using the `stats` mode. This mode forms the basis of the `mutate` and `write` execution modes but does not attempt to make any modifications or updates anywhere.

3.3.3. Mutate

The `mutate` mode will write the results of the algorithm computation back to the projected graph. Note that the specified `mutateProperty` value must not exist in the projected graph beforehand. This enables running multiple algorithms on the same projected graph without writing results to Neo4j in-between algorithm executions.

This execution mode is especially useful in three scenarios:

- Algorithms can depend on the results of previous algorithms without the need to write to Neo4j.
- Algorithm results can be written altogether (see write node properties and write relationships).
- Algorithm results can be queried via Cypher without the need to write to Neo4j at all (see `gds.util.nodeProperty`).

A statistical summary of the computation is returned similar to the `stats` mode. Mutated data can be node properties (such as Page Rank scores), new relationships (such as Node Similarity similarities), or relationship properties.

3.3.4. Write

The `write` mode will write the results of the algorithm computation back to the Neo4j database. This is similar to how standard Cypher writing queries operate. A statistical summary of the computation is returned similar to the `stats` mode. This is the only execution mode that will attempt to make modifications to the Neo4j database.

The written data can be node properties (such as Page Rank scores), new relationships (such as Node Similarity similarities), or relationship properties. The `write` mode can be very useful for use cases where the algorithm results would be inspected multiple times by separate queries since the computational results are handled entirely by the library.

In order for the results from a `write` mode computation to be used by another algorithm, a new graph must be projected from the Neo4j database with the updated graph.

3.3.5. Common Configuration parameters

All algorithms allow adjustment of their runtime characteristics through a set of configuration parameters. Although some parameters are algorithm-specific, many are shared between algorithms and execution modes.

To learn more about algorithm specific parameters and to find out if an algorithm supports a certain parameter, please consult the algorithm-specific documentation page.

List of the most commonly accepted configuration parameters

concurrency - Integer

Controls the parallelism with which the algorithm is executed. By default this value is set to 4. For more details on the concurrency settings and limitations please see the CPU section of the System Requirements.

nodeLabels - List of String

If the graph, on which the algorithm is run, was projected with multiple node label projections, this parameter can be used to select only a subset of the projected labels. The algorithm will only consider nodes with the selected labels.

relationshipTypes - List of String

If the graph, on which the algorithm is run, was projected with multiple relationship type projections, this parameter can be used to select only a subset of the projected types. The algorithm will only consider relationships with the selected types.

nodeWeightProperty - String

In algorithms that support node weights this parameter defines the node property that contains the weights.

relationshipWeightProperty - String

In algorithms that support relationship weights this parameter defines the relationship property that contains the weights. The specified property is required to exist in the specified graph on all specified relationship types. The values must be numeric, and some algorithms may have additional value restrictions, such as requiring only positive weights.

maxIterations - Integer

For iterative algorithms this parameter controls the maximum number of iterations.

tolerance - Float

Many iterative algorithms accept the tolerance parameter. It controls the minimum delta between two iterations. If the delta is less than the tolerance value, the algorithm is considered converged and stops.

seedProperty - String

Some algorithms can be calculated incrementally. This means that results from a previous execution can be taken into account, even though the graph has changed. The `seedProperty` parameter defines the node property that contains the seed value. Seeding can speed up computation and write times.

writeProperty - String

In `write` mode this parameter sets the name of the node or relationship property to which results are written. If the property already exists, existing values will be overwritten.

writeConcurrency - Integer

In `write` mode this parameter controls the parallelism of write operations. The Default is `concurrency`

3.4. Logging

This section describes logging features in the Neo4j Graph Data Science library.

In the GDS library there are three types of logging: debug logging, progress logging and hints or warnings logging.

Debug logging provides information about events in the system. For example, when an algorithm computation completes, the amount of memory used and the total runtime may be logged. Exceptional events, when an operation fails to complete normally, are also logged. The debug log information is useful for understanding events in the system, especially when troubleshooting a problem.

Progress logging is performed to track the progress of operations that are expected to take a long time. This includes graph projections, algorithm computation, and result writing.

Hints or warnings logging provides the user with useful hints or warnings related to their queries.

All log entries are written to the log files configured for the Neo4j database. For more information on configuring Neo4j logs, please refer to the Neo4j Operations Manual.

3.4.1. Progress-logging procedure Beta

Progress is also tracked by the GDS library itself. This makes it possible to inspect progress via Cypher, in addition to looking in the log files. To access progress information for currently running tasks (also referred to as jobs), we can make use of the list progress procedure: `gds.beta.listProgress`. A task in the GDS library is defined as a running procedure, such as an algorithm or a graph load procedure.

The list progress procedure has two modes, depending on whether a `jobId` parameter was set: First, if `jobId` is not set, the procedure will produce a single row for each task currently running. This can be seen as the summary of those tasks, displaying the overall progress of a particular task for example. Second, if the `jobId` parameter is set it will show a detailed view for the given running job. The detailed view will produce a row for each step or task that job will perform during execution. It will also show how tasks are structured as a tree and print progress for each individual task.

Syntax

Getting the progress of tasks:

```
CALL gds.beta.listProgress(jobId: String)
YIELD
  jobId,
  taskName,
  progress,
  progressBar,
  status,
  timeStarted,
  elapsedTime
```

Table 8. Parameters

Name	Type	Default	Optional	Description
jobId	String	""	yes	The jobId of a running task. This will trigger a detailed overview for that particular task.

Table 9. Results

Name	Type	Description
`jobId`	String	A generated identifier of the running task.
`taskName`	String	The name of the running task, i.e. `Node2Vec`.
`progress`	String	The progress of the job shown as a percentage value.
`progressBar`	String	The progress of the job shown as an ASCII progress bar.
`status`	String	The current status of the job, i.e. `RUNNING` or `CANCELED`.
`timeStarted`	LocalTime	The local wall clock time when the task has been started.
`elapsedTime`	Duration	The duration from `timeStarted` to now.

Examples

Assuming we just started `gds.beta.node2vec.stream` procedure.

```
CALL gds.beta.listProgress()
YIELD
  jobId,
  taskName,
  progress
```

Table 10. Results

jobId	taskName	progress
"d21bb4ca-e1e9-4a31-a487-42ac8c9c1a0d"	"Node2Vec"	"42%"

3.4.2. User Log Alpha

Hints and warnings can also be tracked through the GDS library and be accessed via Cypher queries. The GDS library keeps track for each user their 100 most recent tasks that have generated hints or warnings and stores them in memory. When a user calls procedure `gds.alpha.userLog`, their respective list of generated hints and warnings is returned.

Syntax

Getting the hints and warnings for a user:

```
CALL gds.alpha.userLog()
YIELD
  taskName,
  timeStarted,
  message
```

Table 11. Results

Name	Type	Description
`taskName`	String	The name of the task that generated a warning or hint, i.e. `WCC`.
`timeStarted`	LocalTime	The local wall clock time when the task has been started.
`message`	String	A hint or warning associated with the task.

Examples

Suppose that we have called the `gds.wcc.stream` procedure and set a `relationshipWeightProperty` without specifying a `threshold` value. This generates a warning which can be accessed via the user log as seen below.

```
CALL gds.alpha.userLog()
YIELD
  taskName,
  message
```

Table 12. Results

taskName	message
"WCC"	"Specifying a `relationshipWeightProperty` has no effect unless `threshold` is also set"

3.5. Monitoring system

> *This section describes features for monitoring a system's capacity and analytics workload using the Neo4j Graph Data Science library.*

GDS supports multiple users concurrently working on the same system. Typically, GDS procedures are resource heavy in the sense that they may use a lot of memory and/or many CPU cores to do their computation. To know whether it is a reasonable time for a user to run a GDS procedure it is useful to know the current capacity of the system hosting Neo4j and GDS, as well as the current GDS workload on the system. Graphs and models are not shared between non-admin users by default, however GDS users on the same system will share its capacity.

3.5.1. System monitor procedure Alpha

To be able to get an overview of the system's current capacity and its analytics workload one can use the procedure `gds.alpha.systemMonitor`. It will give you information on the capacity of the DBMS's JVM instance in terms of memory and CPU cores, and an overview of the resources consumed by the GDS procedures currently being run on the system.

Syntax

Monitor the system capacity and analytics workload:

```
CALL gds.alpha.systemMonitor()
YIELD
  freeHeap,
  totalHeap,
  maxHeap,
  jvmAvailableCpuCores,
  availableCpuCoresNotRequested,
  jvmHeapStatus,
  ongoingGdsProcedures
```

Table 13. Results

Name	Type	Description
freeHeap	Integer	The amount of currently free memory in bytes in the Java Virtual Machine hosting the Neo4j instance.
totalHeap	Integer	The total amount of memory in bytes in the Java virtual machine hosting the Neo4j instance. This value may vary over time, depending on the host environment.
maxHeap	Integer	The maximum amount of memory in bytes that the Java virtual machine hosting the Neo4j instance will attempt to use.
jvmAvailableCpuCores	Integer	The number of logical CPU cores currently available to the Java virtual machine. This value may change vary over the lifetime of the DBMS.
availableCpuCoresNotRequested	Integer	The number of logical CPU cores currently available to the Java virtual machine that are not requested for use by currently running GDS procedures. Note that this number may be negative in case there are fewer available cores to the JVM than there are cores being requested by ongoing GDS procedures.
jvmHeapStatus	Map	The above-mentioned heap metrics in human-readable form.
ongoingGdsProcedures	List of Map	A list of maps containing resource usage and progress information for all GDS procedures (of all users) currently running on the Neo4j instance. Each map contains the name of the procedure, how far it has progressed, its estimated memory usage as well as how many CPU cores it will try to use at most.

`freeHeap` is influenced by ongoing GDS procedures, graphs stored the Graph catalog and the underlying Neo4j DBMS. Stored graphs can take up a significant amount of heap memory. To inspect the graphs in the graph catalog you can use the Graph list procedure.

Example

First let us assume that we just started `gds.beta.node2vec.stream` procedure with some arbitrary parameters.

We can have a look at the status of the JVM heap.

Monitor JVM heap status:

```
CALL gds.alpha.systemMonitor()
YIELD
  freeHeap,
  totalHeap,
  maxHeap
```

Table 14. Results

freeHeap	totalHeap	maxHeap
1234567	2345678	3456789

We can see that there currently is around `1.23 MB` free heap memory in the JVM instance running our Neo4j DBMS. This may increase independently of any procedures finishing their execution as `totalHeap` is currently smaller than `maxHeap`. We can also inspect CPU core usage as well as the status of currently running GDS procedures on the system.

Monitor CPU core usage and ongoing GDS procedures:

```
CALL gds.alpha.systemMonitor()
YIELD
  availableCpuCoresNotRequested,
  jvmAvailableCpuCores,
  ongoingGdsProcedures
```

Table 15. Results

jvmAvailableCpuCores	availableCpuCoresNotRequested	ongoingGdsProcedures
100	84	[{ procedure: "Node2Vec", progress: "33.33%", estimatedMemoryRange: "[123 kB ... 234 kB]", requestedNumberOfCpuCores: "16" }]

Here we can note that there is only one GDS procedure currently running, namely the `Node2Vec` procedure we just started. It has finished around `33.33%` of its execution already. We also see that it may use up to an estimated `234 kB` of memory. Note that it may not currently be using that much memory and so it may require more memory later in its execution, thus possible lowering our current `freeHeap`. Apparently it wants to use up to `16` CPU cores, leaving us with a total of `84` currently available cores in the system not requested by any GDS procedures.

3.6. System Information

> *This section describes features for obtaining information about the Neo4j Graph Data Science library installation.*

This feature is not available in AuraDS

3.6.1. System info procedure

To be able to get an overview of the system's current details one can use the procedure

`gds.debug.sysInfo`. It will give information on the installed GDS version, GDS edition, Neo4j version, configured memory and so on.

Syntax

Monitor the system capacity and analytics workload:

```
CALL gds.debug.sysInfo()
YIELD
  key,
  value
```

Table 16. Results

Name	Type	Description
key	String	Specific system property, i.e. `gdsVersion`.
value	AnyValue	The value for the property, i.e. `2.0.0`.

Example

Full view of the system configuration:

```
CALL gds.debug.sysInfo()
```

Table 17. Results

key	value
gdsVersion	2.0.0
gdsEdition	Unlicensed
neo4jVersion	4.4.4
minimumRequiredJavaVersion	11
featureSkipOrphanNodes	false
featureMaxArrayLengthShift	28
featurePropertyValueIndex	false
featureParallelPropertyValueIndex	false
featureBitIdMap	true
featureUncompressedAdjacencyList	false
featureReorderedAdjacencyList	false
buildDate	2022-03-24_11:47:27
buildJdk	11.0.13+8 (Eclipse Adoptium)
buildJavaVersion	11.0.13
buildHash	e7651e1fb90a486717a3fc74775c6d8d913bf410

key	value
availableCPUs	16
physicalCPUs	16
availableHeapInBytes	1073741824
availableHeap	1024 MiB
heapFreeInBytes	407734880
heapFree	388 MiB
heapTotalInBytes	536870912
heapTotal	512 MiB
heapMaxInBytes	1073741824
heapMax	1024 MiB
offHeapUsedInBytes	358530312
offHeapUsed	341 MiB
offHeapTotalInBytes	373211136
offHeapTotal	355 MiB
poolCodeheapNonNmethodsUsedInBytes	2702080
poolCodeheapNonNmethodsUsed	2638 KiB
poolCodeheapNonNmethodsTotalInBytes	4128768
poolCodeheapNonNmethodsTotal	4032 KiB
poolMetaspaceUsedInBytes	272810928
poolMetaspaceUsed	260 MiB
poolMetaspaceTotalInBytes	281907200
poolMetaspaceTotal	268 MiB
poolCodeheapProfiledNmethodsUsedInBytes	32784512
poolCodeheapProfiledNmethodsUsed	31 MiB
poolCodeheapProfiledNmethodsTotalInBytes	32833536
poolCodeheapProfiledNmethodsTotal	31 MiB
poolCompressedClassSpaceUsedInBytes	39226680
poolCompressedClassSpaceUsed	37 MiB
poolCompressedClassSpaceTotalInBytes	43331584
poolCompressedClassSpaceTotal	41 MiB
poolG1EdenSpaceFreeInBytes	315621376
poolG1EdenSpaceFree	301 MiB

key	value
poolG1EdenSpaceTotalInBytes	317718528
poolG1EdenSpaceTotal	303 MiB
poolG1EdenSpaceMaxInBytes	-1
poolG1EdenSpaceMax	N/A
poolG1OldGenFreeInBytes	92113504
poolG1OldGenFree	87 MiB
poolG1OldGenTotalInBytes	198180864
poolG1OldGenTotal	189 MiB
poolG1OldGenMaxInBytes	1073741824
poolG1OldGenMax	1024 MiB
poolG1SurvivorSpaceFreeInBytes	0
poolG1SurvivorSpaceFree	0 Bytes
poolG1SurvivorSpaceTotalInBytes	20971520
poolG1SurvivorSpaceTotal	20 MiB
poolG1SurvivorSpaceMaxInBytes	-1
poolG1SurvivorSpaceMax	N/A
poolCodeheapNonProfiledNmethodsUsedInBytes	11006592
poolCodeheapNonProfiledNmethodsUsed	10748 KiB
poolCodeheapNonProfiledNmethodsTotalInBytes	11010048
poolCodeheapNonProfiledNmethodsTotal	10752 KiB
freePhysicalMemoryInBytes	221818880
freePhysicalMemory	211 MiB
committedVirtualMemoryInBytes	40532049920
committedVirtualMemory	37 GiB
totalPhysicalMemoryInBytes	34359738368
totalPhysicalMemory	32 GiB
freeSwapSpaceInBytes	524550144
freeSwapSpace	500 MiB
totalSwapSpaceInBytes	1073741824
totalSwapSpace	1024 MiB
openFileDescriptors	587
maxFileDescriptors	10240

key	value
vmName	OpenJDK 64-Bit Server VM
vmVersion	11.0.8+10-LTS
vmCompiler	HotSpot 64-Bit Tiered Compilers
containerized	false
dbms.security.procedures.unrestricted	"jwt.security.**,gds.**"
dbms.memory.pagecache.size	512m
dbms.tx_state.memory_allocation	ON_HEAP
dbms.memory.off_heap.max_size	2147483648
dbms.memory.transaction.global_max_size	0
dbms.memory.transaction.max_size	0

Chapter 4. Graph management

This chapter explains the graph catalog, the different graph projection variants and utility functions in the Neo4j Graph Data Science library.

A central concept in the GDS library is the management of projected graphs.

This chapter is divided into the following sections:

- Graph Catalog
- Node Properties
- Utility functions
- Cypher on GDS graph
- Administration
- Backup and Restore

4.1. Graph Catalog

This section details the graph catalog operations available to manage named graph projections within the Neo4j Graph Data Science library.

Graph algorithms run on a graph data model which is a *projection* of the Neo4j property graph data model. A graph projection can be seen as a materialized view over the stored graph, containing only analytically relevant, potentially aggregated, topological and property information. Graph projections are stored entirely in-memory using compressed data structures optimized for topology and property lookup operations.

The graph catalog is a concept within the GDS library that allows managing multiple graph projections by name. Using its name, a graph projection can be used many times in the analytical workflow. Named graphs can be projected using either a Native projection or a Cypher projection. After usage, named graphs can be removed from the catalog to free up main memory.

The graph catalog exists as long as the Neo4j instance is running. When Neo4j is restarted, graphs stored in the catalog are lost.

This chapter explains the available graph catalog operations.

Name	Description
`gds.graph.project`	Adds a graph to the catalog using Native projection.
`gds.graph.project.cypher`	Adds a graph to the catalog using Cypher projection.
`gds.alpha.graph.project`	Adds a graph to the catalog using Cypher Aggregation.

Name	Description
gds.beta.graph.project.subgraph	Adds a graph to the catalog by filtering an existing graph using node and relationship predicates.
gds.graph.list	Prints information about graphs that are currently stored in the catalog.
gds.graph.exists	Checks if a named graph is stored in the catalog.
gds.graph.removeNodeProperties	Removes node properties from a named graph.
gds.graph.deleteRelationships	Deletes relationships of a given relationship type from a named graph.
gds.graph.drop	Drops a named graph from the catalog.
gds.graph.streamNodeProperty	Streams a single node property stored in a named graph.
gds.graph.streamNodeProperties	Streams node properties stored in a named graph.
gds.graph.streamRelationshipProperty	Streams a single relationship property stored in a named graph.
gds.graph.streamRelationshipProperties	Streams relationship properties stored in a named graph.
gds.graph.writeNodeProperties	Writes node properties stored in a named graph to Neo4j.
gds.graph.writeRelationship	Writes relationships stored in a named graph to Neo4j.
gds.graph.export	Exports a named graph into a new offline Neo4j database.
gds.beta.graph.export.csv	Exports a named graph into CSV files.

Projecting, using, listing, and dropping named graphs are management operations bound to a Neo4j user. Graphs projected by a different Neo4j user are not accessible at any time.

4.1.1. Projecting graphs using native projections

This section details projecting GDS graphs using `native` projections.

A projected graph can be stored in the catalog under a user-defined name. Using that name, the graph can be referred to by any algorithm in the library. This allows multiple algorithms to use the same graph without having to project it on each algorithm run.

Native projections provide the best performance by reading from the Neo4j store files. Recommended for both the development, and the production phase.

There is also a way to generate a random graph, see Graph Generation documentation for more details.

The projected graphs will reside in the catalog until:

- the graph is dropped using gds.graph.drop
- the Neo4j database from which to graph was projected is stopped or dropped
- the Neo4j database management system is stopped.

Syntax

A native projection takes three mandatory arguments: `graphName`, `nodeProjection` and `relationshipProjection`. In addition, the optional `configuration` parameter allows us to further configure the graph creation.

```
CALL gds.graph.project(
    graphName: String,
    nodeProjection: String or List or Map,
    relationshipProjection: String or List or Map,
    configuration: Map
)
YIELD
  graphName: String,
  nodeProjection: Map,
  nodeCount: Integer,
  relationshipProjection: Map,
  relationshipCount: Integer,
  projectMillis: Integer
```

To get information about a stored graph, such as its schema, one can use gds.graph.list.

Table 18. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
nodeProjection	String, List or Map	no	One or more node projections.
relationshipProjection	String, List or Map	no	One or more relationship projections.
configuration	Map	yes	Additional parameters to configure the native projection.

Table 19. Configuration

Name	Type	Default	Description
readConcurrency	Integer	4	The number of concurrent threads used for creating the graph.
nodeProperties	String, List or Map	{}	The node properties to load for *all* node projections.
relationshipProperties	String, List or Map	{}	The relationship properties to load for *all* relationship projections.
validateRelationships	Boolean	false	Whether to throw an error if the `relationshipProjection` includes relationships between nodes not part of the `nodeProjection`.

Table 20. Results

Name	Type	Description
graphName	String	The name under which the graph is stored in the catalog.
nodeProjection	Map	The node projections used to project the graph.
nodeCount	Integer	The number of nodes stored in the projected graph.
relationshipProjection	Map	The relationship projections used to project the graph.
relationshipCount	Integer	The number of relationships stored in the projected graph.
projectMillis	Integer	Milliseconds for projecting the graph.

Node Projection

Short-hand String-syntax for `nodeProjection`. The projected graph will contain the given `neo4j-label`.

```
<neo4j-label>
```

Short-hand List-syntax for `nodeProjection`. The projected graph will contain the given `neo4j-label`s.

```
[<neo4j-label>, ..., <neo4j-label>]
```

Extended Map-syntax for `nodeProjection`.

```
{
    <projected-label>: {
        label: <neo4j-label>,
        properties: <neo4j-property-key>
    },
    <projected-label>: {
        label: <neo4j-label>,
        properties: [<neo4j-property-key>, <neo4j-property-key>, ...]
    },
    ...
    <projected-label>: {
        label: <neo4j-label>,
        properties: {
            <projected-property-key>: {
                property: <neo4j-property-key>,
                defaultValue: <fallback-value>
            },
            ...
            <projected-property-key>: {
                property: <neo4j-property-key>,
                defaultValue: <fallback-value>
            }
        }
    }
}
```

Table 21. Node Projection fields

Name	Type	Optional	Default	Description
<projected-label>	String	no	n/a	The node label in the projected graph.

Name	Type	Optional	Default	Description
label	String	yes	`projected-label`	The node label in the Neo4j graph. If not set, uses the `projected-label`.
properties	Map, List or String	yes	{}	The projected node properties for the specified `projected-label`.
<projected-property-key>	String	no	n/a	The key for the node property in the projected graph.
property	String	yes	`projected-property-key`	The node property key in the Neo4j graph. If not set, uses the `projected-property-key`.
defaultValue	Float	yes	`Double.NaN`	The default value if the property is not defined for a node.
	Float[]		null	
	Integer		`Integer.MIN_VALUE`	
	Integer[]		null	

Relationship Projection

Short-hand String-syntax for `relationshipProjection`. The projected graph will contain the given `neo4j-type`.

```
<neo4j-type>
```

Short-hand List-syntax for `relationshipProjection`. The projected graph will contain the given `neo4j-type`s.

```
[<neo4j-type>, ..., <neo4j-type>]
```

Extended Map-syntax for `relationshipProjection`.

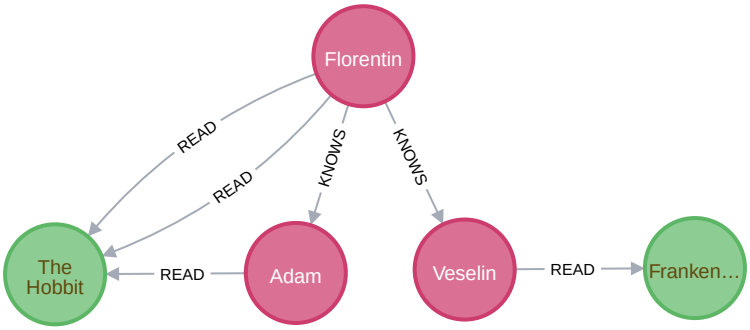
```
{
    <projected-type>: {
        type: <neo4j-type>,
        orientation: <orientation>,
        aggregation: <aggregation-type>,
        properties: <neo4j-property-key>
    },
    <projected-type>: {
        type: <neo4j-type>,
        orientation: <orientation>,
        aggregation: <aggregation-type>,
        properties: [<neo4j-property-key>, <neo4j-property-key>]
    },
    ...
    <projected-type>: {
        type: <neo4j-type>,
        orientation: <orientation>,
        aggregation: <aggregation-type>,
        properties: {
            <projected-property-key>: {
                property: <neo4j-property-key>,
                defaultValue: <fallback-value>,
                aggregation: <aggregation-type>
            },
            ...
            <projected-property-key>: {
                property: <neo4j-property-key>,
                defaultValue: <fallback-value>,
                aggregation: <aggregation-type>
            }
        }
    }
}
```

Table 22. Relationship Projection fields

Name	Type	Optional	Default	Description
<projected-type>	String	no	n/a	The name of the relationship type in the projected graph.
type	String	yes	`projected-type`	The relationship type in the Neo4j graph.
orientation	String	yes	`NATURAL`	Denotes how Neo4j relationships are represented in the projected graph. Allowed values are `NATURAL`, `UNDIRECTED`, `REVERSE`.
aggregation	String	no	`NONE`	Handling of parallel relationships. Allowed values are `NONE`, `MIN`, `MAX`, `SUM`, `SINGLE`, `COUNT`.
properties	Map, List or String	yes	{}	The projected relationship properties for the specified `projected-type`.
<projected-property-key>	String	no	n/a	The key for the relationship property in the projected graph.
property	String	yes	`projected-property-key`	The node property key in the Neo4j graph. If not set, uses the `projected-property-key`.
defaultValue	Float or Integer	yes	`Double.NaN`	The default value if the property is not defined for a node.

Examples

In order to demonstrate the GDS Graph Projection capabilities we are going to create a small social network graph in Neo4j. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (florentin:Person { name: 'Florentin', age: 16 }),
  (adam:Person { name: 'Adam', age: 18 }),
  (veselin:Person { name: 'Veselin', age: 20, ratings: [5.0] }),
  (hobbit:Book { name: 'The Hobbit', isbn: 1234, numberOfPages: 310, ratings: [1.0, 2.0, 3.0, 4.5] }),
  (frankenstein:Book { name: 'Frankenstein', isbn: 4242, price: 19.99 }),

  (florentin)-[:KNOWS { since: 2010 }]->(adam),
  (florentin)-[:KNOWS { since: 2018 }]->(veselin),
  (florentin)-[:READ { numberOfPages: 4 }]->(hobbit),
  (florentin)-[:READ { numberOfPages: 42 }]->(hobbit),
  (adam)-[:READ { numberOfPages: 30 }]->(hobbit),
  (veselin)-[:READ]->(frankenstein)
```

Simple graph

A simple graph is a graph with only one node label and relationship type, i.e., a monopartite graph. We are going to start with demonstrating how to load a simple graph by projecting only the `Person` node label and `KNOWS` relationship type.

Project `Person` nodes and `KNOWS` relationships:

```
CALL gds.graph.project(
  'persons',            ①
  'Person',             ②
  'KNOWS'               ③
)
YIELD
  graphName AS graph, nodeProjection, nodeCount AS nodes, relationshipProjection, relationshipCount AS
rels
```

① The name of the graph. Afterwards, `persons` can be used to run algorithms or manage the graph.

② The nodes to be projected. In this example, the nodes with the `Person` label.

③ The relationships to be projected. In this example, the relationships of type `KNOWS`.

Table 23. Results

graph	nodeProjection	nodes	relationshipProjection	rels
"persons"	{Person={label=Person, properties={}}}	3	{KNOWS={orientation=NATURAL, aggregation=DEFAULT, type=KNOWS, properties={}}}	2

In the example above, we used a short-hand syntax for the node and relationship projection. The used projections are internally expanded to the full `Map` syntax as shown in the `Results` table. In addition, we can see the projected in-memory graph contains three `Person` nodes, and the two `KNOWS` relationships.

Multi-graph

A multi-graph is a graph with multiple node labels and relationship types.

To project multiple node labels and relationship types, we can adjust the projections as follows:

Project `Person` and `Book` nodes and `KNOWS` and `READ` relationships:

```
CALL gds.graph.project(
  'personsAndBooks',    ①
  ['Person', 'Book'],   ②
  ['KNOWS', 'READ']     ③
)
YIELD
  graphName AS graph, nodeProjection, nodeCount AS nodes, relationshipCount AS rels
```

① Projects a graph under the name `personsAndBooks`.

② The nodes to be projected. In this example, the nodes with a `Person` or `Book` label.

③ The relationships to be projected. In this example, the relationships of type `KNOWS` or `READ`.

Table 24. Results

graph	nodeProjection	nodes	rels
"personsAndBooks"	{Book={label=Book, properties={}}, Person={label=Person, properties={}}}	5	6

In the example above, we used a short-hand syntax for the node and relationship projection. The used projections are internally expanded to the full `Map` syntax as shown for the `nodeProjection` in the Results table. In addition, we can see the projected in-memory graph contains five nodes, and the two relationships.

Relationship orientation

By default, relationships are loaded in the same orientation as stored in the Neo4j db. In GDS, we call this the `NATURAL` orientation. Additionally, we provide the functionality to load the relationships in the `REVERSE` or even `UNDIRECTED` orientation.

Project `Person` nodes and undirected `KNOWS` relationships:

```
CALL gds.graph.project(
  'undirectedKnows',                    ①
  'Person',                             ②
  {KNOWS: {orientation: 'UNDIRECTED'}}  ③
)
YIELD
  graphName AS graph,
  relationshipProjection AS knowsProjection,
  nodeCount AS nodes,
  relationshipCount AS rels
```

① Projects a graph under the name `undirectedKnows`.

② The nodes to be projected. In this example, the nodes with the Person label.

③ Projects relationships with type `KNOWS` and specifies that they should be `UNDIRECTED` by using the `orientation` parameter.

Table 25. Results

graph	knowsProjection	nodes	rels
"undirectedKnows"	{KNOWS={orientation=UNDIRECTED, aggregation=DEFAULT, type=KNOWS, properties={}}}	3	4

To specify the orientation, we need to write the `relationshipProjection` with the extended Map-syntax. Projecting the `KNOWS` relationships `UNDIRECTED`, loads each relationship in both directions. Thus, the `undirectedKnows` graph contains four relationships, twice as many as the `persons` graph in Simple graph.

Node properties

To project node properties, we can either use the `nodeProperties` configuration parameter for shared properties, or extend an individual `nodeProjection` for a specific label.

Project `Person` and `Book` nodes and `KNOWS` and `READ` relationships:

```
CALL gds.graph.project(
  'graphWithProperties',                                  ①
  {                                                       ②
    Person: {properties: 'age'},                          ③
    Book: {properties: {price: {defaultValue: 5.0}}}      ④
  },
  ['KNOWS', 'READ'],                                      ⑤
  {nodeProperties: 'ratings'}                             ⑥
)
YIELD
  graphName, nodeProjection, nodeCount AS nodes, relationshipCount AS rels
RETURN graphName, nodeProjection.Book AS bookProjection, nodes, rels
```

① Projects a graph under the name `graphWithProperties`.

② Use the expanded node projection syntax.

③ Projects nodes with the `Person` label and their `age` property.

④ Projects nodes with the `Book` label and their `price` property. Each `Book` that doesn't have the `price` property will get the `defaultValue` of `5.0`.

⑤ The relationships to be projected. In this example, the relationships of type `KNOWS` or `READ`.

⑥ The global configuration, projects node property `rating` on each of the specified labels.

Table 26. Results

graphName	bookProjection	nodes	rels
"graphWithProperties"	`{label=Book, properties={price={defaultValue=5.0, property=price}, ratings={defaultValue=null, property=ratings}}}`	5	6

The projected `graphWithProperties` graph contains five nodes and six relationships. In the returned `bookProjection` we can observe, the node properties `price` and `ratings` are loaded for `Books`.

GDS currently only supports loading numeric properties.

Further, the `price` property has a default value of `5.0`. Not every book has a price specified in the example graph. In the following we check if the price was correctly projected:

Verify the ratings property of Adam in the projected graph:

```
MATCH (n:Book)
RETURN n.name AS name, gds.util.nodeProperty('graphWithProperties', id(n), 'price') as price
ORDER BY price
```

Table 27. Results

name	price
"The Hobbit"	5.0
"Frankenstein"	19.99

We can see, that the price was projected with the Hobbit having the default price of 5.0.

Relationship properties

Analogous to node properties, we can either use the `relationshipProperties` configuration parameter or extend an individual `relationshipProjection` for a specific type.

Project `Person` and `Book` nodes and `READ` relationships with `numberOfPages` property:

```
CALL gds.graph.project(
  'readWithProperties',                    ①
  ['Person', 'Book'],                      ②
  {                                        ③
    READ: { properties: "numberOfPages" }  ④
  }
)
YIELD
  graphName AS graph,
  relationshipProjection AS readProjection,
  nodeCount AS nodes,
  relationshipCount AS rels
```

① Projects a graph under the name `readWithProperties`.

② The nodes to be projected. In this example, the nodes with a `Person` or `Book` label.

③ Use the expanded relationship projection syntax.

④ Project relationships of type `READ` and their `numberOfPages` property.

Table 28. Results

graph	readProjection	nodes	rels
"readWithProperties"	`{READ={orientation=NATURAL, aggregation=DEFAULT, type=READ, properties={numberOfPages={defaultValue=null, property=numberOfPages, aggregation=DEFAULT}}}}`	5	4

Next, we will verify that the relationship property `numberOfPages` were correctly loaded.

Stream the relationship property `numberOfPages` of the projected graph:

```
CALL gds.graph.streamRelationshipProperty('readWithProperties', 'numberOfPages')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfPages
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfPages
ORDER BY person ASC, numberOfPages DESC
```

Table 29. Results

person	book	numberOfPages
"Adam"	"The Hobbit"	30.0
"Florentin"	"The Hobbit"	42.0
"Florentin"	"The Hobbit"	4.0
"Veselin"	"Frankenstein"	NaN

We can see, that the `numberOfPages` property is loaded. The default property value is `Double.NaN` and could be changed using the Map-Syntax the same as for node properties in Node properties.

Parallel relationships

Neo4j supports parallel relationships, i.e., multiple relationships between two nodes. By default, GDS preserves parallel relationships. For some algorithms, we want the projected graph to contain at most one relationship between two nodes.

We can specify how parallel relationships should be aggregated into a single relationship via the `aggregation` parameter in a relationship projection.

For graphs without relationship properties, we can use the `COUNT` aggregation. If we do not need the count, we could use the `SINGLE` aggregation.

Project `Person` and `Book` nodes and `COUNT` aggregated `READ` relationships:

```
CALL gds.graph.project(
  'readCount',                          ①
  ['Person', 'Book'],                   ②
  {
    READ: {                             ③
      properties: {
        numberOfReads: {                ④
          property: '*',                ⑤
          aggregation: 'COUNT'          ⑥
        }
      }
    }
  }
)
YIELD
  graphName AS graph,
  relationshipProjection AS readProjection,
  nodeCount AS nodes,
  relationshipCount AS rels
```

① Projects a graph under the name `readCount`.

② The nodes to be projected. In this example, the nodes with a `Person` or `Book` label.

③ Project relationships of type `READ`.

④ Project relationship property `numberOfReads`.

⑤ A placeholder, signaling that the value of the relationship property is derived and not based on Neo4j property.

⑥ The aggregation type. In this example, `COUNT` results in the value of the property being the number of parallel relationships.

Table 30. Results

graph	readProjection	nodes	rels
"readCount"	{READ={orientation=NATURAL, aggregation=DEFAULT, type=READ, properties={numberOfReads={defaultValue=null, property=*, aggregation=COUNT}}}}	5	3

Next, we will verify that the `READ` relationships were correctly aggregated.

Stream the relationship property `numberOfReads` of the projected graph:

```
CALL gds.graph.streamRelationshipProperty('readCount', 'numberOfReads')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfReads
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfReads
ORDER BY numberOfReads DESC, person
```

Table 31. Results

person	book	numberOfReads
"Florentin"	"The Hobbit"	2.0
"Adam"	"The Hobbit"	1.0

person	book	numberOfReads
"Veselin"	"Frankenstein"	1.0

We can see, that the two READ relationships between Florentin, and the Hobbit result in 2 numberOfReads.

Parallel relationships with properties

For graphs with relationship properties we can also use other aggregations.

Project `Person` *and* `Book` *nodes and aggregated* `READ` *relationships by summing the* `numberOfPages`*:*

```
CALL gds.graph.project(
  'readSums',                                                    ①
  ['Person', 'Book'],                                            ②
  {READ: {properties: {numberOfPages: {aggregation: 'SUM'}}}}    ③
)
YIELD
  graphName AS graph,
  relationshipProjection AS readProjection,
  nodeCount AS nodes,
  relationshipCount AS rels
```

① Projects a graph under the name `readSums`.

② The nodes to be projected. In this example, the nodes with a `Person` or `Book` label.

③ Project relationships of type `READ`. Aggregation type `SUM` results in a projected `numberOfPages` property with its value being the sum of the `numberOfPages` properties of the parallel relationships.

Table 32. Results

graph	readProjection	nodes	rels
"readSums"	{READ={orientation=NATURAL, aggregation=DEFAULT, type=READ, properties={numberOfPages={defaultValue=null, property=numberOfPages, aggregation=SUM}}}}	5	3

Next, we will verify that the relationship property `numberOfPages` was correctly aggregated.

Stream the relationship property `numberOfPages` *of the projected graph:*

```
CALL gds.graph.streamRelationshipProperty('readSums', 'numberOfPages')
YIELD
  sourceNodeId, targetNodeId, propertyValue AS numberOfPages
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfPages
ORDER BY numberOfPages DESC, person
```

Table 33. Results

person	book	numberOfPages
"Florentin"	"The Hobbit"	46.0
"Adam"	"The Hobbit"	30.0

person	book	numberOfPages
"Veselin"	"Frankenstein"	0.0

We can see, that the two READ relationships between Florentin and the Hobbit sum up to 46 numberOfReads.

Validate relationships flag

As mentioned in the syntax section, the `validateRelationships` flag controls whether an error will be raised when attempting to project a relationship where either the source or target node is not present in the node projection. Note that even if the flag is set to `false` such a relationship will still not be projected but the loading process will not be aborted.

We can simulate such a case with the graph present in the Neo4j database:

Project `READ` and `KNOWS` relationships but only `Person` nodes, with `validateRelationships` set to true:

```
CALL gds.graph.project(
  'danglingRelationships',
  'Person',
  ['READ', 'KNOWS'],
  {
    validateRelationships: true
  }
)
YIELD
  graphName AS graph,
  relationshipProjection AS readProjection,
  nodeCount AS nodes,
  relationshipCount AS rels
```

Results

```
org.neo4j.graphdb.QueryExecutionException: Failed to invoke procedure `gds.graph.project`: Caused by:
java.lang.IllegalArgumentException: Failed to load a relationship because its target-node with id 3 is not
part of the node query or projection. To ignore the relationship, set the configuration parameter
`validateRelationships` to false.
```

We can see that the above query resulted in an exception being thrown. The exception message will provide information about the specific node id that was missing, which will help debugging underlying problems.

4.1.2. Projecting graphs using Cypher

This section details projecting GDS graphs using `Cypher` projections.

A projected graph can be stored in the catalog under a user-defined name. Using that name, the graph can be referred to by any algorithm in the library. This allows multiple algorithms to use the same graph without having to project it on each algorithm run.

Using Cypher projections is a more flexible and expressive approach with diminished focus on performance compared to the native projections. Cypher projections are primarily recommended for the

development phase (see Common usage).

There is also a way to generate a random graph, see Graph Generation documentation for more details.

The projected graph will reside in the catalog until:

- the graph is dropped using gds.graph.drop
- the Neo4j database from which the graph was projected is stopped or dropped
- the Neo4j database management system is stopped.

Syntax

A Cypher projection takes three mandatory arguments: `graphName`, `nodeQuery` and `relationshipQuery`. In addition, the optional `configuration` parameter allows us to further configure graph creation.

```
CALL gds.graph.project.cypher(
    graphName: String,
    nodeQuery: String,
    relationshipQuery: String,
    configuration: Map
) YIELD
    graphName: String,
    nodeQuery: String,
    nodeCount: Integer,
    relationshipQuery: String,
    relationshipCount: Integer,
    projectMillis: Integer
```

Table 34. Parameters

Name	Optional	Description
graphName	no	The name under which the graph is stored in the catalog.
nodeQuery	no	Cypher query to project nodes. The query result must contain an `id` column. Optionally, a `labels` column can be specified to represent node labels. Additional columns are interpreted as properties.
relationshipQuery	no	Cypher query to project relationships. The query result must contain `source` and `target` columns. Optionally, a `type` column can be specified to represent relationship type. Additional columns are interpreted as properties.
configuration	yes	Additional parameters to configure the Cypher projection.

Table 35. Configuration

Name	Type	Default	Description
readConcurrency	Integer	4	The number of concurrent threads used for creating the graph.
validateRelationships	Boolean	true	Whether to throw an error if the `relationshipQuery` returns relationships between nodes not returned by the `nodeQuery`.

Name	Type	Default	Description
parameters	Map	{}	A map of user-defined query parameters that are passed into the node and relationship queries.

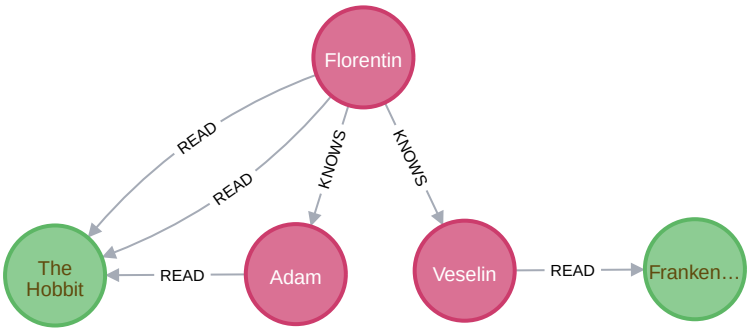
Table 36. Results

Name	Type	Description
graphName	String	The name under which the graph is stored in the catalog.
nodeQuery	String	The Cypher query used to project the nodes in the graph.
nodeCount	Integer	The number of nodes stored in the projected graph.
relationshipQuery	String	The Cypher query used to project the relationships in the graph.
relationshipCount	Integer	The number of relationships stored in the projected graph.
projectMillis	Integer	Milliseconds for projecting the graph.

To get information about a stored graph, such as its schema, one can use gds.graph.list.

Examples

In order to demonstrate the GDS Graph Project capabilities we are going to create a small social network graph in Neo4j. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (florentin:Person { name: 'Florentin', age: 16 }),
  (adam:Person { name: 'Adam', age: 18 }),
  (veselin:Person { name: 'Veselin', age: 20, ratings: [5.0] }),
  (hobbit:Book { name: 'The Hobbit', isbn: 1234, numberOfPages: 310, ratings: [1.0, 2.0, 3.0, 4.5] }),
  (frankenstein:Book { name: 'Frankenstein', isbn: 4242, price: 19.99 }),

  (florentin)-[:KNOWS { since: 2010 }]->(adam),
  (florentin)-[:KNOWS { since: 2018 }]->(veselin),
  (florentin)-[:READ { numberOfPages: 4 }]->(hobbit),
  (florentin)-[:READ { numberOfPages: 42 }]->(hobbit),
  (adam)-[:READ { numberOfPages: 30 }]->(hobbit),
  (veselin)-[:READ]->(frankenstein)
```

Simple graph

A simple graph is a graph with only one node label and relationship type, i.e., a monopartite graph. We are

going to start with demonstrating how to load a simple graph by projecting only the `Person` node label and `KNOWS` relationship type.

Project `Person` nodes and `KNOWS` relationships:

```
CALL gds.graph.project.cypher(
  'persons',
  'MATCH (n:Person) RETURN id(n) AS id',
  'MATCH (n:Person)-[r:KNOWS]->(m:Person) RETURN id(n) AS source, id(m) AS target')
YIELD
  graphName AS graph, nodeQuery, nodeCount AS nodes, relationshipQuery, relationshipCount AS rels
```

Table 37. Results

graph	nodeQuery	nodes	relationshipQuery	rels
"persons"	`"MATCH (n:Person) RETURN id(n) AS id"`	3	"MATCH (n:Person)-[r:KNOWS]->(m:Person) RETURN id(n) AS source, id(m) AS target"	2

Multi-graph

A multi-graph is a graph with multiple node labels and relationship types.

To retain the label and type information when we load multiple node labels and relationship types, we can add a `labels` column to the node query and a `type` column to the relationship query.

Project `Person` and `Book` nodes and `KNOWS` and `READ` relationships:

```
CALL gds.graph.project.cypher(
  'personsAndBooks',
  'MATCH (n) WHERE n:Person OR n:Book RETURN id(n) AS id, labels(n) AS labels',
  'MATCH (n)-[r:KNOWS|READ]->(m) RETURN id(n) AS source, id(m) AS target, type(r) AS type')
YIELD
  graphName AS graph, nodeQuery, nodeCount AS nodes, relationshipCount AS rels
```

Table 38. Results

graph	nodeQuery	nodes	rels
"personsAndBooks"	`"MATCH (n) WHERE n:Person OR n:Book RETURN id(n) AS id, labels(n) AS labels"`	5	6

Relationship orientation

The native projection supports specifying an orientation per relationship type. The Cypher projection will treat every relationship returned by the relationship query as if it was in `NATURAL` orientation. It is thus not possible to project graphs in `UNDIRECTED` or `REVERSE` orientation when Cypher projections are used.

Some algorithms require that the graph was loaded with `UNDIRECTED` orientation. These algorithms can not be used with a graph projected by a Cypher projection.

Node properties

To load node properties, we add a column to the result of the node query for each property. Thereby, we use the Cypher function coalesce() function to specify the default value, if the node does not have the property.

Project `Person` and `Book` nodes and `KNOWS` and `READ` relationships:

```
CALL gds.graph.project.cypher(
  'graphWithProperties',
  'MATCH (n)
   WHERE n:Book OR n:Person
   RETURN
    id(n) AS id,
    labels(n) AS labels,
    coalesce(n.age, 18) AS age,
    coalesce(n.price, 5.0) AS price,
    n.ratings AS ratings',
  'MATCH (n)-[r:KNOWS|READ]->(m) RETURN id(n) AS source, id(m) AS target, type(r) AS type'
)
YIELD
  graphName, nodeCount AS nodes, relationshipCount AS rels
RETURN graphName, nodes, rels
```

Table 39. Results

graphName	nodes	rels
"graphWithProperties"	5	6

The projected `graphWithProperties` graph contains five nodes and six relationships. In a Cypher projection every node from the `nodeQuery` gets the same node properties, which means you can't have label-specific properties. For instance in the example above the `Person` nodes will also get `ratings` and `price` properties, while `Book` nodes get the `age` property.

Further, the `price` property has a default value of `5.0`. Not every book has a price specified in the example graph. In the following we check if the price was correctly projected:

Verify the ratings property of Adam in the projected graph:

```
MATCH (n:Book)
RETURN n.name AS name, gds.util.nodeProperty('graphWithProperties', id(n), 'price') AS price
ORDER BY price
```

Table 40. Results

name	price
"The Hobbit"	5.0
"Frankenstein"	19.99

We can see, that the price was projected with the Hobbit having the default price of 5.0.

Relationship properties

Analogous to node properties, we can project relationship properties using the `relationshipQuery`.

Project `Person` and `Book` nodes and `READ` relationships with `numberOfPages` property:

```
CALL gds.graph.project.cypher(
  'readWithProperties',
  'MATCH (n) RETURN id(n) AS id, labels(n) AS labels',
  'MATCH (n)-[r:READ]->(m)
    RETURN id(n) AS source, id(m) AS target, type(r) AS type, r.numberOfPages AS numberOfPages'
)
YIELD
  graphName AS graph, nodeCount AS nodes, relationshipCount AS rels
```

Table 41. Results

graph	nodes	rels
"readWithProperties"	5	4

Next, we will verify that the relationship property `numberOfPages` was correctly loaded.

Stream the relationship property `numberOfPages` from the projected graph:

```
CALL gds.graph.streamRelationshipProperty('readWithProperties', 'numberOfPages')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfPages
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfPages
ORDER BY person ASC, numberOfPages DESC
```

Table 42. Results

person	book	numberOfPages
"Adam"	"The Hobbit"	30.0
"Florentin"	"The Hobbit"	42.0
"Florentin"	"The Hobbit"	4.0
"Veselin"	"Frankenstein"	NaN

We can see, that the `numberOfPages` are loaded. The default property value is `Double.Nan` and can be changed as in the previous example Node properties by using the Cypher function *coalesce()*.

Parallel relationships

The Property Graph Model in Neo4j supports parallel relationships, i.e., multiple relationships between two nodes. By default, GDS preserves the parallel relationships. For some algorithms, we want the projected graph to contain at most one relationship between two nodes.

The simplest way to achieve relationship deduplication is to use the `DISTINCT` operator in the relationship query. Alternatively, we can aggregate the parallel relationship by using the *count()* function and store the count as a relationship property.

Project `Person` and `Book` nodes and `COUNT` aggregated `READ` relationships:

```
CALL gds.graph.project.cypher(
  'readCount',
  'MATCH (n) RETURN id(n) AS id, labels(n) AS labels',
  'MATCH (n)-[r:READ]->(m)
    RETURN id(n) AS source, id(m) AS target, type(r) AS type, count(r) AS numberOfReads'
)
YIELD
  graphName AS graph, nodeCount AS nodes, relationshipCount AS rels
```

Table 43. Results

graph	nodes	rels
"readCount"	5	3

Next, we will verify that the `READ` relationships were correctly aggregated.

Stream the relationship property `numberOfReads` of the projected graph:

```
CALL gds.graph.streamRelationshipProperty('readCount', 'numberOfReads')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfReads
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfReads
ORDER BY numberOfReads DESC, person
```

Table 44. Results

person	book	numberOfReads
"Florentin"	"The Hobbit"	2.0
"Adam"	"The Hobbit"	1.0
"Veselin"	"Frankenstein"	1.0

We can see, that the two READ relationships between Florentin and the Hobbit result in `2` numberOfReads.

Parallel relationships with properties

For graphs with relationship properties we can also use other aggregations documented in the Cypher Manual.

Project `Person` and `Book` nodes and aggregated `READ` relationships by summing the `numberOfPages`:

```
CALL gds.graph.project.cypher(
  'readSums',
  'MATCH (n) RETURN id(n) AS id, labels(n) AS labels',
  'MATCH (n)-[r:READ]->(m)
    RETURN id(n) AS source, id(m) AS target, type(r) AS type, sum(r.numberOfPages) AS numberOfPages'
)
YIELD
  graphName AS graph, nodeCount AS nodes, relationshipCount AS rels
```

Table 45. Results

graph	nodes	rels
"readSums"	5	3

Next, we will verify that the relationship property `numberOfPages` were correctly aggregated.

Stream the relationship property `numberOfPages` of the projected graph:

```
CALL gds.graph.streamRelationshipProperty('readSums', 'numberOfPages')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfPages
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfPages
ORDER BY numberOfPages DESC, person
```

Table 46. Results

person	book	numberOfPages
"Florentin"	"The Hobbit"	46.0
"Adam"	"The Hobbit"	30.0
"Veselin"	"Frankenstein"	0.0

We can see, that the two `READ` relationships between Florentin and the Hobbit sum up to `46` numberOfPages.

Projecting filtered Neo4j graphs

Cypher-projections allow us to specify the graph to project in a more fine-grained way. The following examples will demonstrate how we to filter out `READ` relationship if they do not have a `numberOfPages` property.

Project `Person` and `Book` nodes and `READ` relationships where `numberOfPages` is present:

```
CALL gds.graph.project.cypher(
  'existingNumberOfPages',
  'MATCH (n) RETURN id(n) AS id, labels(n) AS labels',
  'MATCH (n)-[r:READ]->(m)
    WHERE r.numberOfPages IS NOT NULL
    RETURN id(n) AS source, id(m) AS target, type(r) AS type, r.numberOfPages AS numberOfPages'
)
YIELD
  graphName AS graph, nodeCount AS nodes, relationshipCount AS rels
```

Table 47. Results

graph	nodes	rels
"existingNumberOfPages"	5	3

Next, we will verify that the relationship property `numberOfPages` was correctly loaded.

Stream the relationship property `numberOfPages` from the projected graph:

```
CALL gds.graph.streamRelationshipProperty('existingNumberOfPages', 'numberOfPages')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfPages
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfPages
ORDER BY person ASC, numberOfPages DESC
```

Table 48. Results

person	book	numberOfPages
"Adam"	"The Hobbit"	30.0
"Florentin"	"The Hobbit"	42.0
"Florentin"	"The Hobbit"	4.0

If we compare the results to the ones from Relationship properties, we can see that using `IS NOT NULL` is filtering out the relationship from Veselin to the book Frankenstein. This functionality is only expressible with native projections by projecting a subgraph.

Using query parameters

Similar to Cypher, it is also possible to set query parameters. In the following example we supply a list of strings to limit the cities we want to project.

Project `Person` and `Book` nodes and `READ` relationships where `numberOfPages` is greater than 9:

```
CALL gds.graph.project.cypher(
  'existingNumberOfPages',
  'MATCH (n) RETURN id(n) AS id, labels(n) AS labels',
  'MATCH (n)-[r:READ]->(m)
    WHERE r.numberOfPages > $minNumberOfPages
    RETURN id(n) AS source, id(m) AS target, type(r) AS type, r.numberOfPages AS numberOfPages',
  { parameters: { minNumberOfPages: 9} }
)
YIELD
  graphName AS graph, nodeCount AS nodes, relationshipCount AS rels
```

Table 49. Results

graph	nodes	rels
"existingNumberOfPages"	5	2

Further usage of parameters

The parameters can also be used to directly pass in a list of nodes or a list of relationships. For example, pre-computing the list of nodes can be useful if the node filter is expensive.

Project `Person` nodes younger than 17 and their name not beginning with V, and `KNOWS` relationships:

```
CALL gds.graph.project.cypher(
  'personSubset',
  'MATCH (n)
    WHERE n.age < 20 AND NOT n.name STARTS WITH "V"
    RETURN id(n) AS id, labels(n) AS labels',
  'MATCH (n)-[r:KNOWS]->(m)
    WHERE (n.age < 20 AND NOT n.name STARTS WITH "V") AND
          (m.age < 20 AND NOT m.name STARTS WITH "V")
    RETURN id(n) AS source, id(m) AS target, type(r) AS type, r.numberOfPages AS numberOfPages'
)
YIELD
  graphName, nodeCount AS nodes, relationshipCount AS rels
```

Table 50. Results

graphName	nodes	rels
"personSubset"	2	1

By passing the relevant Persons as a parameter, the above query can be transformed into the following:

Project `Person` nodes younger than 20 and their name not beginning with V, and `KNOWS` relationships by using parameters:

```
MATCH (n)
WHERE n.age < 20 AND NOT n.name STARTS WITH "V"
WITH collect(n) AS olderPersons
CALL gds.graph.project.cypher(
  'personSubsetViaParameters',
  'UNWIND $nodes AS n RETURN id(n) AS id, labels(n) AS labels',
  'MATCH (n)-[r:KNOWS]->(m)
    WHERE (n IN $nodes) AND (m IN $nodes)
    RETURN id(n) AS source, id(m) AS target, type(r) AS type, r.numberOfPages AS numberOfPages',
  { parameters: { nodes: olderPersons} }
)
 YIELD
  graphName, nodeCount AS nodes, relationshipCount AS rels
 RETURN graphName, nodes, rels
```

Table 51. Results

graphName	nodes	rels
"personSubsetViaParameters"	2	1

4.1.3. Projecting graphs using Cypher Aggregation

This section details projecting GDS graphs using `Cypher` aggregations.

A projected graph can be stored in the catalog under a user-defined name. Using that name, the graph can be referred to by any algorithm in the library. This allows multiple algorithms to use the same graph without having to project it on each algorithm run.

Using Cypher aggregations is a more flexible and expressive approach with diminished focus on performance compared to the native projections. Cypher projections are primarily recommended for the development phase (see Common usage).

There is also a way to generate a random graph, see Graph Generation documentation for more details.

The projected graph will reside in the catalog until:

- the graph is dropped using gds.graph.drop
- the Neo4j database from which the graph was projected is stopped or dropped
- the Neo4j database management system is stopped.

Syntax

A Cypher aggregation is used in a query as an aggregation over the relationships that are being projected. It takes three mandatory arguments: `graphName`, `sourceNode` and `targetNode`. In addition, the optional `sourceNodeProperties`, `targetNodeProperties`, and `relationshipProperties` parameters allows us to project properties.

```
RETURN gds.alpha.graph.project(
    graphName: String,
    sourceNode: Node or Integer,
    targetNode: Node or Integer,
    nodesConfig: Map,
    relationshipConfig: Map
) YIELD
    graphName: String,
    nodeCount: Integer,
    relationshipCount: Integer,
    projectMillis: Integer
```

Table 52. Parameters

Name	Optional	Description
graphName	no	The name under which the graph is stored in the catalog.
sourceNode	no	The source node of the relationship. Must not be null.
targetNode	yes	The target node of the relationship. The targetNode can be null (for example due to an `OPTIONAL MATCH`), in which case the source node is projected as an unconnected node.
nodesConfig	yes	Properties and Labels configuration for the source and target nodes.
relationshipConfig	yes	Properties and Type configuration for the relationship.

Table 53. Results

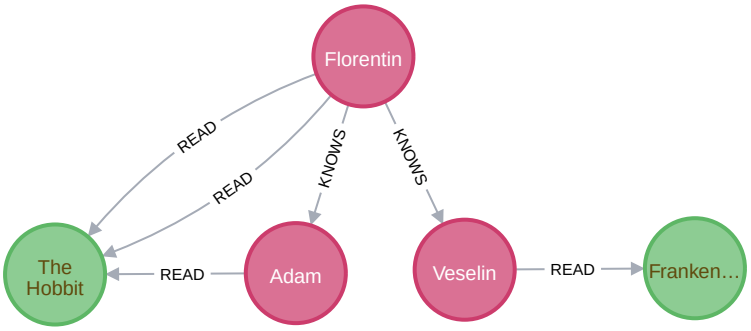
Name	Type	Description
graphName	String	The name under which the graph is stored in the catalog.
nodeCount	Integer	The number of nodes stored in the projected graph.
relationshipCount	Integer	The number of relationships stored in the projected graph.

Name	Type	Description
projectMillis	Integer	Milliseconds for projecting the graph.

To get information about a stored graph, such as its schema, one can use gds.graph.list.

Examples

In order to demonstrate the GDS Cypher Aggregation we are going to create a small social network graph in Neo4j. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (florentin:Person { name: 'Florentin', age: 16 }),
  (adam:Person { name: 'Adam', age: 18 }),
  (veselin:Person { name: 'Veselin', age: 20, ratings: [5.0] }),
  (hobbit:Book { name: 'The Hobbit', isbn: 1234, numberOfPages: 310, ratings: [1.0, 2.0, 3.0, 4.5] }),
  (frankenstein:Book { name: 'Frankenstein', isbn: 4242, price: 19.99 }),

  (florentin)-[:KNOWS { since: 2010 }]->(adam),
  (florentin)-[:KNOWS { since: 2018 }]->(veselin),
  (florentin)-[:READ { numberOfPages: 4 }]->(hobbit),
  (florentin)-[:READ { numberOfPages: 42 }]->(hobbit),
  (adam)-[:READ { numberOfPages: 30 }]->(hobbit),
  (veselin)-[:READ]->(frankenstein)
```

Simple graph

A simple graph is a graph with only one node label and relationship type, i.e., a monopartite graph. We are going to start with demonstrating how to load a simple graph by projecting only the `Person` node label and `KNOWS` relationship type.

Project `Person` nodes and `KNOWS` relationships:

```
MATCH (source:Person)-[r:KNOWS]->(target:Person)
WITH gds.alpha.graph.project('persons', source, target) AS g
RETURN
  g.graphName AS graph, g.nodeCount AS nodes, g.relationshipCount AS rels
```

Table 54. Results

graph	nodes	rels
"persons"	3	2

Graph with unconnected nodes

In order to project nodes that are not connected, we can use an `OPTIONAL MATCH`. To demonstrate we are projecting all nodes, where some might be connected with the `KNOWS` relationship type.

Project all nodes and `KNOWS` relationships:

```
MATCH (source) OPTIONAL MATCH (source)-[r:KNOWS]->(target)
WITH gds.alpha.graph.project('persons', source, target) AS g
RETURN
  g.graphName AS graph, g.nodeCount AS nodes, g.relationshipCount AS rels
```

Table 55. Results

graph	nodes	rels
"persons"	5	2

Arbitrary source and target ID values

So far, the examples showed how to project a graph based on existing nodes. It is also possible to pass INTEGER values directly.

Project arbitrary id values:

```
UNWIND [ [42, 84], [13, 37], [19, 84] ] AS sourceAndTarget
WITH sourceAndTarget[0] AS source, sourceAndTarget[1] AS target
WITH gds.alpha.graph.project('arbitrary', source, target) AS g
RETURN
  g.graphName AS graph, g.nodeCount AS nodes, g.relationshipCount AS rels
```

Table 56. Results

graph	nodes	rels
"arbitrary"	5	3

The projected graph does not know that the IDs did not originate from an existing node. Any procedure that interacts with the underlying db (such as the `.write` procedures) will likely produce wrong results or trigger exceptions.

Multi-graph

A multi-graph is a graph with multiple node labels and relationship types.

To retain the label when we load multiple node labels, we can add a `sourceNodeLabels` key and a `targetNodeLabels` key to the fourth `nodesConfig` parameter. — To retain the type information when we load multiple relationship types, we can add a `relationshipType` key to the fifth `relationshipConfig` parameter.

Project `Person` and `Book` nodes and `KNOWS` and `READ` relationships:

```
MATCH (source)
WHERE source:Person OR source:Book
OPTIONAL MATCH (source)-[r:KNOWS|READ]->(target)
WHERE target:Person OR target:Book
WITH gds.alpha.graph.project(
  'personsAndBooks',
  source,
  target,
  {
    sourceNodeLabels: labels(source),
    targetNodeLabels: labels(target)
  },
  {
    relationshipType: type(r)
  }
) AS g
RETURN g.graphName AS graph , g.nodeCount AS nodes, g.relationshipCount AS rels
```

Table 57. Results

graph	nodes	rels
"personsAndBooks"	5	6

The value for `sourceNodeLabels` or `targetNodeLabels` can be one of the following:

*Table 58. *NodeLabels key*

type	example	description
List of String	`labels(s)` or `['A', 'B']`	`Associate all labels in that list with the source or target node`
String	`'A'`	`Associate that label with the source or target node`
Boolean	`true`	`Associate all labels of the source or target node; same as labels(s)`
Boolean	`false`	`Don't load any label information for the source or target node; same as if nodeLabels was missing`

The value for `relationshipType` must be a `String`:

Table 59. relationshipType key

type	example	description
String	`type(r)` or `'A'`	`Associate that type with the relationship`

Relationship orientation

The native projection supports specifying an orientation per relationship type. The Cypher Aggregation will treat every relationship returned by the relationship query as if it was in `NATURAL` orientation. It is thus not possible to project graphs in `UNDIRECTED` or `REVERSE` orientation when Cypher projections are used.

Some algorithms require that the graph was loaded with `UNDIRECTED` orientation. These algorithms can not be used with a graph projected by a Cypher Aggregation.

Node properties

To load node properties, we add a map of all properties for the source and target nodes. Thereby, we use the Cypher function coalesce() function to specify the default value, if the node does not have the property.

The properties for the source node are specified as `sourceNodeProperties` key in the fourth `nodesConfig` parameter. The properties for the target node are specified as `targetNodeProperties` key in the fourth `nodesConfig` parameter.

Project `Person` and `Book` nodes and `KNOWS` and `READ` relationships:

```
MATCH (source)-[r:KNOWS|READ]->(target)
WHERE source:Book OR source:Person
WITH gds.alpha.graph.project(
  'graphWithProperties',
  source,
  target,
  {
    sourceNodeProperties: source { age: coalesce(source.age, 18), price: coalesce(source.price, 5.0),
.ratings },
    targetNodeProperties: target { age: coalesce(target.age, 18), price: coalesce(target.price, 5.0),
.ratings }
  }
) as g
RETURN g.graphName AS graph , g.nodeCount AS nodes, g.relationshipCount AS rels
```

Table 60. Results

graph	nodes	rels
"graphWithProperties"	5	6

The projected `graphWithProperties` graph contains five nodes and six relationships. In a Cypher Aggregation every node will get the same properties, which means you can't have node-specific properties. For instance in the example above the `Person` nodes will also get `ratings` and `price` properties, while `Book` nodes get the `age` property.

Further, the `price` property has a default value of `5.0`. Not every book has a price specified in the example graph. In the following we check if the price was correctly projected:

Verify the ratings property of Adam in the projected graph:

```
MATCH (n:Book)
RETURN n.name AS name, gds.util.nodeProperty('graphWithProperties', id(n), 'price') AS price
ORDER BY price
```

Table 61. Results

name	price
"The Hobbit"	5.0
"Frankenstein"	19.99

We can see, that the price was projected with the Hobbit having the default price of 5.0.

Relationship properties

Analogous to node properties, we can project relationship properties using the fifth parameter. If we only want to project relationship properties and not any node properties or labels, we must provide a `{}` value for the nodesConfig parameter.

Project `Person` and `Book` nodes and `READ` relationships with `numberOfPages` property:

```
MATCH (source)-[r:READ]->(target)
WITH gds.alpha.graph.project(
  'readWithProperties',
  source,
  target,
  {},
  { properties: r { .numberOfPages } }
) AS g
RETURN
  g.graphName AS graph, g.nodeCount AS nodes, g.relationshipCount AS rels
```

Table 62. Results

graph	nodes	rels
"readWithProperties"	5	4

Next, we will verify that the relationship property `numberOfPages` was correctly loaded.

Stream the relationship property `numberOfPages` from the projected graph:

```
CALL gds.graph.streamRelationshipProperty('readWithProperties', 'numberOfPages')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfPages
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfPages
ORDER BY person ASC, numberOfPages DESC
```

Table 63. Results

person	book	numberOfPages
"Adam"	"The Hobbit"	30.0
"Florentin"	"The Hobbit"	42.0
"Florentin"	"The Hobbit"	4.0
"Veselin"	"Frankenstein"	NaN

We can see, that the `numberOfPages` are loaded. The default property value is `Double.Nan` and can be changed as in the previous example Node properties by using the Cypher function coalesce().

Parallel relationships

The Property Graph Model in Neo4j supports parallel relationships, i.e., multiple relationships between two nodes. By default, GDS preserves the parallel relationships. For some algorithms, we want the projected graph to contain at most one relationship between two nodes.

The simplest way to achieve relationship deduplication is to use the `DISTINCT` operator in the relationship query. Alternatively, we can aggregate the parallel relationship by using the count() function and store the count as a relationship property.

Project `Person` and `Book` nodes and `COUNT` aggregated `READ` relationships:

```
MATCH (source)-[r:READ]->(target)
WITH source, target, count(r) AS numberOfReads
WITH gds.alpha.graph.project('readCount', source, target, {}, { properties: { numberOfReads: numberOfReads
} }) AS g
RETURN
  g.graphName AS graph, g.nodeCount AS nodes, g.relationshipCount AS rels
```

Table 64. Results

graph	nodes	rels
"readCount"	5	3

Next, we will verify that the `READ` relationships were correctly aggregated.

Stream the relationship property `numberOfReads` of the projected graph:

```
CALL gds.graph.streamRelationshipProperty('readCount', 'numberOfReads')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfReads
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfReads
ORDER BY numberOfReads DESC, person
```

Table 65. Results

person	book	numberOfReads
"Florentin"	"The Hobbit"	2.0
"Adam"	"The Hobbit"	1.0
"Veselin"	"Frankenstein"	1.0

We can see, that the two READ relationships between Florentin and the Hobbit result in 2 numberOfReads.

Parallel relationships with properties

For graphs with relationship properties we can also use other aggregations documented in the Cypher Manual.

Project Person and Book nodes and aggregated READ relationships by summing the numberOfPages:

```
MATCH (source)-[r:READ]->(target)
WITH source, target, sum(r.numberOfPages) AS numberOfPages
WITH gds.alpha.graph.project('readSums', source, target, {}, { properties: { numberOfPages: numberOfPages
} }) AS g
RETURN
  g.graphName AS graph, g.nodeCount AS nodes, g.relationshipCount AS rels
```

Table 66. Results

graph	nodes	rels
"readSums"	5	3

Next, we will verify that the relationship property numberOfPages were correctly aggregated.

Stream the relationship property numberOfPages of the projected graph:

```
CALL gds.graph.streamRelationshipProperty('readSums', 'numberOfPages')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfPages
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfPages
ORDER BY numberOfPages DESC, person
```

Table 67. Results

person	book	numberOfPages
"Florentin"	"The Hobbit"	46.0
"Adam"	"The Hobbit"	30.0
"Veselin"	"Frankenstein"	0.0

We can see, that the two READ relationships between Florentin and the Hobbit sum up to 46 numberOfPages.

Projecting filtered Neo4j graphs

Cypher-projections allow us to specify the graph to project in a more fine-grained way. The following examples will demonstrate how to filter out READ relationships if they do not have a numberOfPages property.

Project Person and Book nodes and READ relationships where numberOfPages is present:

```
MATCH (source) OPTIONAL MATCH (source)-[r:READ]->(target)
WHERE r.numberOfPages IS NOT NULL
WITH gds.alpha.graph.project('existingNumberOfPages', source, target, {}, { properties: r { .numberOfPages
} }) AS g
RETURN
  g.graphName AS graph, g.nodeCount AS nodes, g.relationshipCount AS rels
```

Table 68. Results

graph	nodes	rels
"existingNumberOfPages"	5	3

Next, we will verify that the relationship property `numberOfPages` was correctly loaded.

Stream the relationship property `numberOfPages` from the projected graph:

```
CALL gds.graph.streamRelationshipProperty('existingNumberOfPages', 'numberOfPages')
YIELD sourceNodeId, targetNodeId, propertyValue AS numberOfPages
RETURN
  gds.util.asNode(sourceNodeId).name AS person,
  gds.util.asNode(targetNodeId).name AS book,
  numberOfPages
ORDER BY person ASC, numberOfPages DESC
```

Table 69. Results

person	book	numberOfPages
"Adam"	"The Hobbit"	30.0
"Florentin"	"The Hobbit"	42.0
"Florentin"	"The Hobbit"	4.0

If we compare the results to the ones from Relationship properties, we can see that using `IS NOT NULL` is filtering out the relationship from Veselin to the book Frankenstein. This functionality is only expressible with native projections by projecting a subgraph.

4.1.4. Listing graphs

> *This section details how to list graphs stored in the graph catalog of the Neo4j Graph Data Science library.*

Information about graphs in the catalog can be retrieved using the `gds.graph.list()` procedure.

Syntax

List information about graphs in the catalog:

```
CALL gds.graph.list(
  graphName: String
) YIELD
  graphName: String,
  database: String,
  configuration: Map,
  nodeCount: Integer,
  relationshipCount: Integer,
  schema: Map,
  degreeDistribution: Map,
  density: Float,
  creationTime: Datetime,
  modificationTime: Datetime,
  sizeInBytes: Integer,
  memoryUsage: String
```

Table 70. Parameters

Name	Type	Optional	Description
graphName	String	yes	The name under which the graph is stored in the catalog. If no graph name is given, information about all graphs will be listed. If a graph name is given but not found in the catalog, an empty list will be returned.

Table 71. Results

Name	Type	Description
`graphName`	String	Name of the graph.
`database`	String	Name of the database in which the graph has been projected.
`configuration`	Map	The configuration used to project the graph in memory.
`nodeCount`	Integer	Number of nodes in the graph.
`relationshipCount`	Integer	Number of relationships in the graph.
`schema`	Map	Node labels, relationship types and properties contained in the projected graph.
`degreeDistribution`	Map	Histogram of degrees in the graph.
`density`	Float	Density of the graph.
`creationTime`	Datetime	Time when the graph was projected.
`modificationTime`	Datetime	Time when the graph was last modified.
`sizeInBytes`	Integer	Number of bytes used in the Java heap to store the graph.
`memoryUsage`	String	Human readable description of `sizeInBytes`.

The information contains basic statistics about the graph, e.g., the node and relationship count. The result field `creationTime` indicates when the graph was projected in memory. The result field `modificationTime` indicates when the graph was updated by an algorithm running in `mutate` mode.

The `database` column refers to the name of the database the corresponding graph has been projected on. Referring to a named graph in a procedure is only allowed on the database it has been projected on.

The `schema` consists of information about the nodes and relationships stored in the graph. For each node label, the schema maps the label to its property keys and their corresponding property types. Similarly, the schema maps the relationship types to their property keys and property types. The property type is either `Integer`, `Float`, `List of Integer` or `List of Float`.

The `degreeDistribution` field can be fairly time-consuming to compute for larger graphs. Its computation is cached per graph, so subsequent listing for the same graph will be fast. To avoid computing the degree distribution, specify a `YIELD` clause that omits it. Note that not specifying a `YIELD` clause is the same as requesting all possible return fields to be returned.

The `density` is the result of `relationshipCount` divided by the maximal number of relationships for a simple graph with the given `nodeCount`.

Examples

In order to demonstrate the GDS Graph List capabilities we are going to create a small social network graph in Neo4j.

The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (florentin:Person { name: 'Florentin', age: 16 }),
  (adam:Person { name: 'Adam', age: 18 }),
  (veselin:Person { name: 'Veselin', age: 20 }),
  (florentin)-[:KNOWS { since: 2010 }]->(adam),
  (florentin)-[:KNOWS { since: 2018 }]->(veselin)
```

Additionally, we will project a few graphs to the graph catalog, for more details see native projections and Cypher projections.

Project `Person` nodes and `KNOWS` relationships using native projections:

```
CALL gds.graph.project('personsNative', 'Person', 'KNOWS')
```

Project `Person` nodes and `KNOWS` relationships using Cypher projections:

```
CALL gds.graph.project.cypher(
  'personsCypher',
  'MATCH (n:Person) RETURN id(n) AS id, labels(n) as labels',
  'MATCH (n:Person)-[r:KNOWS]->(m:Person) RETURN id(n) AS source, id(m) AS target, type(r) as type')
```

Project `Person` nodes with property `age` and `KNOWS` relationships using Native projections:

```
CALL gds.graph.project(
  'personsWithAgeNative',
  {
    Person: {properties: 'age'}
  },
  'KNOWS'
)
```

List basic information about all graphs in the catalog

List basic information about all graphs in the catalog:

```
CALL gds.graph.list()
YIELD graphName, nodeCount, relationshipCount
RETURN graphName, nodeCount, relationshipCount
ORDER BY graphName ASC
```

Table 72. Results

graphName	nodeCount	relationshipCount
"personsCypher"	3	2
"personsNative"	3	2
"personsWithAgeNative"	3	2

List extended information about a specific named graph in the catalog

List extended information about a specific Cypher named graph in the catalog:

```
CALL gds.graph.list('personsCypher')
YIELD graphName, configuration
RETURN graphName, configuration.nodeQuery AS nodeQuery
```

Table 73. Results

graphName	nodeQuery
"personsCypher"	"MATCH (n:Person) RETURN id(n) AS id, labels(n) as labels"

List extended information about a specific native named graph in the catalog:

```
CALL gds.graph.list('personsNative')
YIELD graphName, configuration
RETURN graphName, configuration.nodeProjection AS nodeProjection
```

Table 74. Results

graphName	nodeProjection
"personsNative"	{Person={label=Person, properties={}}}

The above examples demonstrate that `nodeQuery` only has value when the graph is projected using Cypher projection while `nodeProjection` is present when we have a native graph. This is also true for `relationshipQuery` and relationshipProjection` respectively.

Despite different result columns being present for the different projections that we can use the Graph Schemas are the same, which is demonstrated in the example below.

Cypher graph schema:

```
CALL gds.graph.list('personsCypher')
YIELD graphName, schema
```

Table 75. Results

graphName	schema
"personsCypher"	{relationships={KNOWS={}}, nodes={Person={}}}

Native graph schema:

```
CALL gds.graph.list('personsNative')
YIELD graphName, schema
```

Table 76. Results

graphName	schema
"personsNative"	{relationships={KNOWS={}}, nodes={Person={}}}

Degree distribution of a specific graph

List information about the degree distribution of a specific graph:

```
CALL gds.graph.list('personsNative')
YIELD graphName, degreeDistribution;
```

Table 77. Results

graphName	degreeDistribution
"personsNative"	{p99=2, min=0, max=2, mean=0.6666666666666666, p90=2, p50=0, p999=2, p95=2, p75=0}

4.1.5. Check if a graph exists

We can check if a graph is stored in the catalog by looking up its name.

Syntax

Check if a graph exists in the catalog:

```
CALL gds.graph.exists(graphName: String) YIELD
  graphName: String,
  exists: Boolean
```

Table 78. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.

Table 79. Results

Name	Type	Description
graphName	String	Name of the removed graph.
exists	Boolean	If the graph exists in the graph catalog.

Additionally, to the procedure, we provide a function which directly returns the exists field from the procedure.

Check if a graph exists in the catalog:

```
RETURN gds.graph.exists(graphName: String)::Boolean
```

Examples

In order to demonstrate the GDS Graph Exists capabilities we are going to create a small social network graph in Neo4j and project it into our graph catalog.

The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (florentin:Person { name: 'Florentin', age: 16 }),
  (adam:Person { name: 'Adam', age: 18 }),
  (veselin:Person { name: 'Veselin', age: 20 }),
  (florentin)-[:KNOWS { since: 2010 }]->(adam),
  (florentin)-[:KNOWS { since: 2018 }]->(veselin)
```

Project `Person` nodes and `KNOWS` relationships:

```
CALL gds.graph.project('persons', 'Person', 'KNOWS')
```

Procedure

Check if graphs exist in the catalog:

```
UNWIND ['persons', 'books'] AS graph
CALL gds.graph.exists(graph)
  YIELD graphName, exists
RETURN graphName, exists
```

Table 80. Results

graphName	exists
"persons"	true
"books"	false

We can verify the projected `persons` graph exists while a `books` graph does not.

Function

As an alternative to the procedure, we can also use the corresponding function. Unlike procedures, functions can be inlined in other cypher-statements such as `RETURN` or `WHERE`.

Check if graphs exists in the catalog:

```
RETURN gds.graph.exists('persons') AS personsExists, gds.graph.exists('books') AS booksExists
```

Table 81. Results

personsExists	booksExists
true	false

As before, we can verify the projected `persons` graph exists while a `books` graph does not.

4.1.6. Removing graphs

This section details how to remove graphs stored in the graph catalog of the Neo4j Graph Data Science library.

To free up memory, we can remove unused graphs. In order to do so, the `gds.graph.drop` procedure comes in handy.

Syntax

Remove a graph from the catalog:

```
CALL gds.graph.drop(
  graphName: String,
  failIfMissing: Boolean,
  dbName: String,
  username: String
) YIELD
  graphName: String,
  database: String,
  configuration: Map,
  nodeCount: Integer,
  relationshipCount: Integer,
  schema: Map,
  density: Float,
  creationTime: Datetime,
  modificationTime: Datetime,
  sizeInBytes: Integer,
  memoryUsage: String
```

Table 82. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
failIfMissing	Boolean	true	By default, the library will raise an error when trying to remove a non-existing graph. When set to `false`, the procedure returns an empty result.
dbName	String	active database name	Then name of the database that was used to project the graph. When empty, the current database is used.
username	String	active user	The name of the user who projected the graph. Can only be used by GDS administrator.

Table 83. Results

Name	Type	Description
`graphName`	String	Name of the removed graph.
`database`	String	Name of the database in which the graph has been projected.
`configuration`	Map	The configuration used to project the graph in memory.
`nodeCount`	Integer	Number of nodes in the graph.
`relationshipCount`	Integer	Number of relationships in the graph.
`schema`	Map	Node labels, Relationship types and properties contained in the in-memory graph.
`density`	Float	Density of the graph.
`creationTime`	Datetime	Time when the graph was projected.
`modificationTime`	Datetime	Time when the graph was last modified.

Name	Type	Description
`sizeInBytes`	Integer	Number of bytes used in the Java heap to store the graph.
`memoryUsage`	String	Human readable description of `sizeInBytes`.

Examples

In this section we are going to demonstrate the usage of `gds.graph.drop`. All the graph names used in these examples are fictive and should be replaced with real values.

Basic usage

Remove a graph from the catalog:

```
CALL gds.graph.drop('my-store-graph') YIELD graphName;
```

If we run the example above twice, the second time it will raise an error. If we want the procedure to fail silently on non-existing graphs, we can set a boolean flag as the second parameter to false. This will yield an empty result for non-existing graphs.

Try removing a graph from the catalog:

```
CALL gds.graph.drop('my-fictive-graph', false) YIELD graphName;
```

Multi-database support Enterprise edition

If we want to drop a graph projected on another database, we can set the database name as the third parameter.

Try removing a graph from the catalog:

```
CALL gds.graph.drop('my-fictive-graph', true, 'my-other-db') YIELD graphName;
```

Multi-user support

If we are a GDS administrator and want to drop a graph that belongs to another user we can set the username as the fourth parameter to the procedure. This is useful if there are multiple users with graphs of the same name.

Remove a graph from a specific user's graph catalog:

```
CALL gds.graph.drop('my-fictive-graph', true, '', 'another-user') YIELD graphName;
```

See Administration for more details on this.

4.1.7. Projecting a subgraph Beta

This section details how to project subgraphs from existing graphs stored in the graph catalog of the Neo4j Graph Data Science library.

In GDS, algorithms can be executed on a named graph that has been filtered based on its node labels and relationship types. However, that filtered graph only exists during the execution of the algorithm, and it is not possible to filter on property values. If a filtered graph needs to be used multiple times, one can use the subgraph catalog procedure to project a new graph in the graph catalog.

The filter predicates in the subgraph procedure can take labels, relationship types as well as node and relationship properties into account. The new graph can be used in the same way as any other in-memory graph in the catalog. Projecting subgraphs of subgraphs is also possible.

Syntax

A new graph can be projected by using the `gds.beta.graph.project.subgraph()` *procedure:*

```
CALL gds.beta.graph.project.subgraph(
  graphName: String,
  fromGraphName: String,
  nodeFilter: String,
  relationshipFilter: String,
  configuration: Map
) YIELD
  graphName: String,
  fromGraphName: String,
  nodeFilter: String,
  relationshipFilter: String,
  nodeCount: Integer,
  relationshipCount: Integer,
  projectMillis: Integer
```

Table 84. Parameters

Name	Type	Description
graphName	String	The name of the new graph that is stored in the graph catalog.
fromGraphName	String	The name of the original graph in the graph catalog.
nodeFilter	String	A Cypher predicate for filtering nodes in the input graph. `*` can be used to allow all nodes.
relationshipFilter	String	A Cypher predicate for filtering relationships in the input graph. `*` can be used to allow all relationships.
configuration	Map	Additional parameters to configure subgraph creation.

Table 85. Subgraph specific configuration

Name	Type	Default	Optional	Description
concurrency	Integer	4	yes	The number of concurrent threads used for filtering the graph.

Table 86. Results

Name	Type	Description
graphName	String	The name of the new graph that is stored in the graph catalog.
fromGraphName	String	The name of the original graph in the graph catalog.
nodeFilter	String	Filter predicate for nodes.
relationshipFilter	String	Filter predicate for relationships.
nodeCount	Integer	Number of nodes in the subgraph.
relationshipCount	Integer	Number of relationships in the subgraph.
projectMillis	Integer	Milliseconds for projecting the subgraph.

The `nodeFilter` and `relationshipFilter` configuration keys can be used to express filter predicates. Filter predicates are Cypher predicates bound to a single entity. An entity is either a node or a relationship. The filter predicate always needs to evaluate to `true` or `false`. A node is contained in the subgraph if the node filter evaluates to `true`. A relationship is contained in the subgraph if the relationship filter evaluates to `true` and its source and target nodes are contained in the subgraph.

A predicate is a combination of expressions. The simplest form of expression is a literal. GDS currently supports the following literals:

- float literals, e.g., `13.37`
- integer literals, e.g., `42`
- boolean literals, i.e., `TRUE` and `FALSE`

Property, label and relationship type expressions are bound to an entity. The node entity is always identified by the variable `n`, the relationship entity is identified by `r`. Using the variable, we can refer to:

- node label expression, e.g., `n:Person`
- relationship type expression, e.g., `r:KNOWS`
- node property expression, e.g., `n.age`
- relationship property expression, e.g., `r.since`

Boolean predicates combine two expressions and return either `true` or `false`. GDS supports the following boolean predicates:

- greater/lower than, such as `n.age > 42` or `r.since < 1984`
- greater/lower than or equal, such as `n.age > 42` or `r.since < 1984`
- equality, such as `n.age = 23` or `r.since = 2020`
- logical operators, such as
- `n.age > 23 AND n.age < 42`
- `n.age = 23 OR n.age = 42`
- `n.age = 23 XOR n.age = 42`
- `n.age IS NOT 23`

Variable names that can be used within predicates are not arbitrary. A node predicate must refer to variable `n`. A relationship predicate must refer to variable `r`.

Examples

In order to demonstrate the GDS project subgraph capabilities we are going to create a small social graph in Neo4j.

The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (p0:Person { age: 16 }),
  (p1:Person { age: 18 }),
  (p2:Person { age: 20 }),
  (b0:Book   { isbn: 1234 }),
  (b1:Book   { isbn: 4242 }),
  (p0)-[:KNOWS { since: 2010 }]->(p1),
  (p0)-[:KNOWS { since: 2018 }]->(p2),
  (p0)-[:READS]->(b0),
  (p1)-[:READS]->(b0),
  (p2)-[:READS]->(b1)
```

Project the social network graph:

```
CALL gds.graph.project(
  'social-graph',
  {
    Person: { properties: 'age' },    ①
    Book: {}                          ②
  },
  {
    KNOWS: { properties: 'since' },   ③
    READS: {}                         ④
  }
)
YIELD graphName, nodeCount, relationshipCount, projectMillis
```

① Project `Person` nodes with their `age` property.

② Project `Book` nodes without any of their properties.

③ Project `KNOWS` relationships with their `since` property.

④ Project `READS` relationships without any of their properties.

Node filtering

Create a new graph containing only users of a certain age group:

```
CALL gds.beta.graph.project.subgraph(
  'teenagers',
  'social-graph',
  'n.age > 13 AND n.age <= 18',
  '*'
)
YIELD graphName, fromGraphName, nodeCount, relationshipCount
```

Table 87. Results

graphName	fromGraphName	nodeCount	relationshipCount
"teenagers"	"social-graph"	2	1

Node and relationship filtering

Create a new graph containing only users of a certain age group that know each other since a given point a time:

```
CALL gds.beta.graph.project.subgraph(
  'teenagers',
  'social-graph',
  'n.age > 13 AND n.age <= 18',
  'r.since >= 2012.0'
)
YIELD graphName, fromGraphName, nodeCount, relationshipCount
```

Table 88. Results

graphName	fromGraphName	nodeCount	relationshipCount
"teenagers"	"social-graph"	2	0

Bipartite subgraph

Create a new bipartite graph between books and users connected by the `READS` *relationship type:*

```
CALL gds.beta.graph.project.subgraph(
  'teenagers-books',
  'social-graph',
  'n:Book OR n:Person',
  'r:READS'
)
YIELD graphName, fromGraphName, nodeCount, relationshipCount
```

Table 89. Results

graphName	fromGraphName	nodeCount	relationshipCount
"teenagers-books"	"social-graph"	5	3

Bipartite graph node filtering

The previous example can be extended with an additional filter applied only to persons:

```
CALL gds.beta.graph.project.subgraph(
  'teenagers-books',
  'social-graph',
  'n:Book OR (n:Person AND n.age > 18)',
  'r:READS'
)
YIELD graphName, fromGraphName, nodeCount, relationshipCount
```

Table 90. Results

graphName	fromGraphName	nodeCount	relationshipCount
"teenagers-books"	"social-graph"	3	1

4.1.8. Node operations

> *This section details the operations available over node-properties stored in projected graphs within the Neo4j Graph Data Science library.*

The graphs in the Neo4j Graph Data Science Library support properties for nodes. We provide multiple operations to work with the stored node-properties in projected graphs. Node properties are either added during the graph projection or when using the `mutate` mode of our graph algorithms.

To inspect stored values, the `gds.graph.streamNodeProperties` procedure can be used. This is useful if we ran multiple algorithms in `mutate` mode and want to retrieve some or all of the results.

To persist the values in a Neo4j database, we can use `gds.graph.writeNodeProperties`. Similar to streaming node properties, it is also possible to write those back to Neo4j. This is similar to what an algorithm `write` execution mode does, but allows more fine-grained control over the operations.

We can also remove node properties from a named graph in the catalog. This is useful to free up main memory or to remove accidentally added node properties.

Syntax

Syntax descriptions of the different operations over node properties

```
CALL gds.graph.streamNodeProperty(
    graphName: String,
    nodeProperties: String,
    nodeLabels: String or List of Strings,
    configuration: Map
)
YIELD
    nodeId: Integer,
    propertyValue: Integer or Float or List of Integer or List of Float
```

Table 91. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
nodeProperties	String	no	The node property in the graph to stream.
nodeLabels	String or List of Strings	yes	The node labels to stream the node properties for graph.
configuration	Map	yes	Additional parameters to configure streamNodeProperties.

Table 92. Configuration

Name	Type	Default	Description
concurrency	Integer	4	The number of concurrent threads. Note, this procedure is always running single-threaded.

Table 93. Results

Name	Type	Description
nodeId	Integer	The id of the node.
propertyValue	• Integer • Float • List of Integer • List of Float	The stored property value.

```
CALL gds.graph.streamNodeProperties(
    graphName: String,
    nodeProperties: String or List of Strings,
    nodeLabels: String or List of Strings,
    configuration: Map
)
YIELD
    nodeId: Integer,
    nodeProperty: String,
    propertyValue: Integer or Float or List of Integer or List of Float
```

Table 94. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
nodeProperties	String or List of Strings	no	The node properties in the graph to stream.
nodeLabels	String or List of Strings	yes	The node labels to stream the node properties for graph.
configuration	Map	yes	Additional parameters to configure streamNodeProperties.

Table 95. Configuration

Name	Type	Default	Description
concurrency	Integer	4	The number of concurrent threads. Note, this procedure is always running single-threaded.

Table 96. Results

Name	Type	Description
nodeId	Integer	The id of the node.
nodeProperty	String	The name of the node property.
propertyValue	• Integer • Float • List of Integer • List of Float	The stored property value.

```
CALL gds.graph.writeNodeProperties(
    graphName: String,
    nodeProperties: String or List of Strings,
    nodeLabels: String or List of Strings,
    configuration: Map
)
YIELD
    writeMillis: Integer,
    propertiesWritten: Integer,
    graphName: String,
    nodeProperties: String or List of String
```

Table 97. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
nodeProperties	String or List of Strings	no	The node properties in the graph to write back.
nodeLabels	String or List of Strings	yes	The node labels to write back their node properties.
configuration	Map	yes	Additional parameters to configure writeNodeProperties.

Table 98. Configuration

Name	Type	Default	Description
concurrency	Integer	4	The number of concurrent threads used for running the procedure. Also provides the default value for `writeConcurrency`
writeConcurrency	Integer	'concurrency'	The number of concurrent threads used for writing the node properties.

Table 99. Results

Name	Type	Description
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
propertiesWritten	Integer	Number of properties written.
graphName	String	The name of a graph stored in the catalog.
nodeProperties	String or List of String	The written node properties.

```
CALL gds.graph.removeNodeProperties(
    graphName: String,
    nodeProperties: String or List of Strings,
    nodeLabels: String or List of Strings,
    configuration: Map
)
YIELD
    propertiesRemoved: Integer,
    graphName: String,
    nodeProperties: String or List of String
```

Table 100. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
nodeProperties	String or List of Strings	no	The node properties in the graph to remove.
nodeLabels	String or List of Strings	yes	The node labels to remove the node properties from.
configuration	Map	yes	Additional parameters to configure removeNodeProperties.

Table 101. Configuration

Name	Type	Default	Description
concurrency	Integer	4	The number of concurrent threads. Note, this procedure is always running single-threaded.

Table 102. Results

Name	Type	Description
propertiesRemoved	Integer	Number of properties removed.
graphName	String	The name of a graph stored in the catalog.
nodeProperties	String or List of String	The removed node properties.

Examples

In order to demonstrate the GDS capabilities over node properties, we are going to create a small social network graph in Neo4j and project it into our graph catalog.

The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (florentin:Person { name: 'Florentin', age: 16 }),
  (adam:Person { name: 'Adam', age: 18 }),
  (veselin:Person { name: 'Veselin', age: 20 }),
  (hobbit:Book { name: 'The Hobbit', numberOfPages: 310 }),
  (florentin)-[:KNOWS { since: 2010 }]->(adam),
  (florentin)-[:KNOWS { since: 2018 }]->(veselin),
  (adam)-[:READ]->(hobbit)
```

Project the small social network graph:

```
CALL gds.graph.project(
  'socialGraph',
  {
    Person: {properties: "age"},
    Book: {}
  },
  ['KNOWS', 'READ']
)
```

Compute the Degree Centrality in our social graph:

```
CALL gds.degree.mutate('socialGraph', {mutateProperty: 'score'})
```

Stream

We can stream node properties stored in a named in-memory graph back to the user. This is useful if we ran multiple algorithms in `mutate` mode and want to retrieve some or all of the results. This is similar to what an algorithm `stream` execution mode does, but allows more fine-grained control over the operations.

Single property

In the following, we stream the previously computed scores `score`.

Stream the `score` node property:

```
CALL gds.graph.streamNodeProperty('socialGraph', 'score')
YIELD nodeId, propertyValue
RETURN gds.util.asNode(nodeId).name AS name, propertyValue AS score
ORDER BY score DESC
```

Table 103. Results

name	score
"Florentin"	2.0
"Adam"	1.0
"Veselin"	0.0
"The Hobbit"	0.0

The above example requires all given properties to be present on at least one node projection, and the properties will be streamed for all such projections.

NodeLabels

The procedure can be configured to stream just the properties for specific node labels.

Stream the `score` property for `Person` nodes:

```
CALL gds.graph.streamNodeProperty('socialGraph', 'score', ['Person'])
YIELD nodeId, propertyValue
RETURN gds.util.asNode(nodeId).name AS name, propertyValue AS score
ORDER BY score DESC
```

Table 104. Results

name	score
"Florentin"	2.0
"Adam"	1.0
"Veselin"	0.0

It is required, that all specified node labels have the node property.

Multiple Properties

We can also stream several properties at once.

Stream multiple node properties:

```
CALL gds.graph.streamNodeProperties('socialGraph', ['score', 'age'])
YIELD nodeId, nodeProperty, propertyValue
RETURN gds.util.asNode(nodeId).name AS name, nodeProperty, propertyValue
ORDER BY name, nodeProperty
```

Table 105. Results

name	nodeProperty	propertyValue
"Adam"	"age"	18
"Adam"	"score"	1.0
"Florentin"	"age"	16
"Florentin"	"score"	2.0
"Veselin"	"age"	20
"Veselin"	"score"	0.0

When streaming multiple node properties, the name of each property is included in the result. This adds with some overhead, as each property name must be repeated for each node in the result, but is necessary in order to distinguish properties.

Write

To write the 'score' property for all node labels in the social graph, we use the following query:

Write the `score` property back to Neo4j:

```
CALL gds.graph.writeNodeProperties('socialGraph', ['score'])
YIELD propertiesWritten
```

Table 106. Results

propertiesWritten
4

The above example requires the `score` property to be present on *at least one* projected node label, and the properties will be written for all such labels.

NodeLabels

The procedure can be configured to write just the properties for some specific node labels. In the following example, we will only write back the scores of the `Person` nodes.

Write node properties of a specific projected node label to Neo4j:

```
CALL gds.graph.writeNodeProperties('socialGraph', ['score'], ['Person'])
YIELD propertiesWritten
```

Table 107. Results

propertiesWritten
3

If the `nodeLabels` parameter is specified, it is required that *all* given node labels have *all* of the given properties.

Remove

Remove the `score` property from all projected nodes in the `socialGraph`:

```
CALL gds.graph.removeNodeProperties('socialGraph', ['score'])
YIELD propertiesRemoved
```

Table 108. Results

propertiesRemoved
4

The above example requires all given properties to be present on *at least one* projected node label.

NodeLabels

Consider we compute the Degree Centrality only for a subset of the graph.

Compute the Degree Centrality for only the Book *nodes in our social graph:*

```
CALL gds.degree.mutate('socialGraph', {nodeLabels: ['Book'], mutateProperty: 'degree'})
```

The procedure can be configured to remove just the properties for s. In the following example, we will only remove the scores from the Book nodes.

Remove the degree *property from the projected* Book *nodes:*

```
CALL gds.graph.removeNodeProperties('socialGraph', ['degree'], ['Book'])
YIELD propertiesRemoved
```

Table 109. Results

propertiesRemoved
1

If the nodeLabels parameter is specified, it is required that *all* given node labels have *all* of the given properties.

Utility functions

Utility functions allow accessing specific nodes of in-memory graphs directly from a Cypher query.

Table 110. Catalog Functions

Name	Description
gds.util.nodeProperty	Allows accessing a node property stored in a named graph.

Syntax

Name	Description
gds.util.nodeProperty(graphName: STRING, nodeId: INTEGER, propertyKey: STRING, nodeLabel: STRING?)	Named graph in the catalog, Neo4j node id, node property key and optional node label present in the named-graph.

If a node label is given, the property value for the corresponding projection and the given node is returned.

If no label or `'*'` is given, the property value is retrieved and returned from an arbitrary projection that contains the given propertyKey. If the property value is missing for the given node, `null` is returned.

Examples

We use the `socialGraph` with the property `score` introduced above.

Access a property node property for Florentin:

```
MATCH (florentin:Person {name: 'Florentin'})
RETURN
  florentin.name AS name,
  gds.util.nodeProperty('socialGraph', id(florentin), 'score') AS score
```

Table 111. Results

name	score
"Florentin"	2.0

We can also specifically return the `score` property from the `Person` projection in case other projections also have a `score` property as follows.

Access a property node property from Person for Florentin:

```
MATCH (florentin:Person {name: 'Florentin'})
RETURN
  florentin.name AS name,
  gds.util.nodeProperty('socialGraph', id(florentin), 'score', 'Person') AS score
```

Table 112. Results

name	score
"Florentin"	2.0

4.1.9. Relationship operations

> *This section details the operations available over relationships and relationship properties stored in projected graphs within the Neo4j Graph Data Science library.*

The graphs in the Neo4j Graph Data Science Library support properties for relationships. We provide multiple operations to work with the stored relationship-properties in projected graphs. Relationship properties are either added during the graph projection or when using the `mutate` mode of our graph algorithms.

To inspect stored relationship property values, the `streamRelationshipProperties` procedure can be used. This is useful if we ran multiple algorithms in `mutate` mode and want to retrieve some or all of the results.

To persist relationship types in a Neo4j database, we can use `gds.graph.writeRelationship`. Similar to streaming relationship properties, it is also possible to write back to Neo4j. This is similar to what an

algorithm `write` execution mode does, but allows more fine-grained control over the operations. By default, no relationship properties will be written. To write relationship properties, these have to be explicitly specified.

We can also remove relationships from a named graph in the catalog. This is useful to free up main memory or to remove accidentally added relationship types.

Syntax

Syntax descriptions of the different operations over relationship types

```
CALL gds.graph.streamRelationshipProperty(
    graphName: String,
    relationshipProperties: List of String,
    relationshipTypes: List of Strings,
    configuration: Map
)
YIELD
    sourceNodeId: Integer,
    targetNodeId: Integer,
    relationshipType: String,
    propertyValue: Integer or Float
```

Table 113. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
relationshipProperties	List of String	no	The relationship properties in the graph to stream.
relationshipTypes	List of Strings	yes	The relationship types to stream the relationship properties for graph.
configuration	Map	yes	Additional parameters to configure streamNodeProperties.

Table 114. Configuration

Name	Type	Default	Description
concurrency	Integer	4	The number of concurrent threads. Note, this procedure is always running single-threaded.

Table 115. Results

Name	Type	Description
sourceNodeId	Integer	The id of the source node for the relationship.
targetNodeId	Integer	The id of the target node for the relationship.
relationshipType	Integer	The type of the relationship.
propertyValue	• Integer • Float	The stored property value.

```
CALL gds.graph.streamRelationshipProperties(
    graphName: String,
    relationshipProperties: List of String,
    relationshipTypes: List of Strings,
    configuration: Map
)
YIELD
    sourceNodeId: Integer,
    targetNodeId: Integer,
    relationshipType: String,
    relationshipProperty: String,
    propertyValue: Integer or Float
```

Table 116. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
relationshipProperties	List of String	no	The relationship properties in the graph to stream.
relationshipTypes	List of Strings	yes	The relationship types to stream the relationship properties for graph.
configuration	Map	yes	Additional parameters to configure streamNodeProperties.

Table 117. Configuration

Name	Type	Default	Description
concurrency	Integer	4	The number of concurrent threads. Note, this procedure is always running single-threaded.

Table 118. Results

Name	Type	Description
sourceNodeId	Integer	The id of the source node for the relationship.
targetNodeId	Integer	The id of the target node for the relationship.
relationshipType	Integer	The type of the relationship.
relationshipProperty	Integer	The name of the relationship property.
propertyValue	• Integer • Float	The stored property value.

```
CALL gds.graph.writeRelationship(
    graphName: String,
    relationshipType: String,
    relationshipProperty: String,
    configuration: Map
)
YIELD
  writeMillis: Integer,
  graphName: String,
  relationshipType: String,
  relationshipsWritten: Integer,
  relationshipProperty: String,
  propertiesWritten: Integer
```

Table 119. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
relationshipType	String	no	The relationship type in the graph to write back.
relationshipProperty	String	yes	The relationship property to write back.
configuration	Map	yes	Additional parameters to configure writeRelationship.

Table 120. Configuration

Name	Type	Default	Description
concurrency	Integer	4	The number of concurrent threads used for running the procedure. Also provides the default value for `writeConcurrency`. Note, this procedure is always running single-threaded.
writeConcurrency	Integer	'concurrency'	The number of concurrent threads used for writing the relationship properties. Note, this procedure is always running single-threaded.

Table 121. Results

Name	Type	Description
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
graphName	String	The name of a graph stored in the catalog.
relationshipType	String	The type of the relationship that was written.
relationshipsWritten	Integer	Number relationships written.
relationshipProperty	String	The name of the relationship property that was written.
propertiesWritten	Integer	Number relationships properties written.

```
CALL gds.graph.deleteRelationships(
    graphName: String,
    relationshipType: String
)
YIELD
  graphName: String,
  relationshipType: String,
  deletedRelationships: Integer,
  deletedProperties: Map
```

Table 122. Parameters

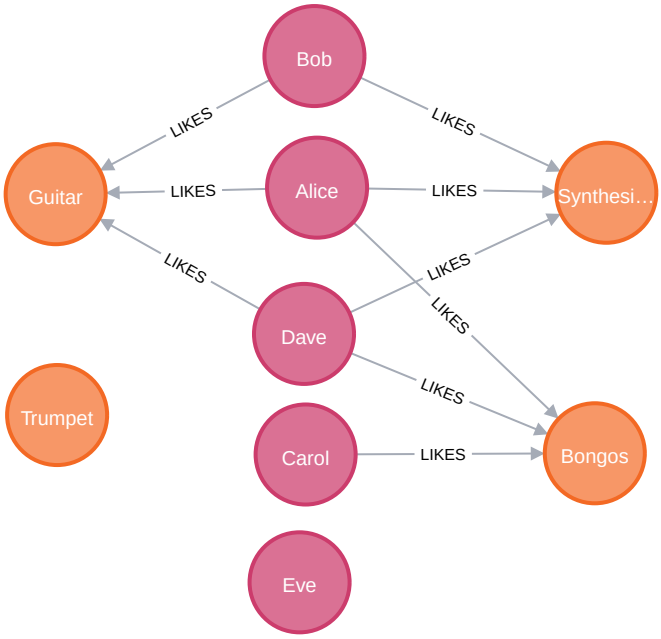
Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
relationshipType	String	no	The relationship type in the graph to remove.

Table 123. Results

Name	Type	Description
graphName	String	The name of a graph stored in the catalog.
relationshipType	String	The type of the removed relationships.
deletedRelationships	Integer	Number of removed relationships from the in-memory graph.
deletedProperties	Integer	Map where the key is the name of the relationship property, and the value is the number of removed properties under that name.

Examples

In order to demonstrate the GDS capabilities over node properties, we are going to create a small graph in Neo4j and project it into our graph catalog.



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:Person {name: 'Alice'}),
  (bob:Person {name: 'Bob'}),
  (carol:Person {name: 'Carol'}),
  (dave:Person {name: 'Dave'}),
  (eve:Person {name: 'Eve'}),
  (guitar:Instrument {name: 'Guitar'}),
  (synth:Instrument {name: 'Synthesizer'}),
  (bongos:Instrument {name: 'Bongos'}),
  (trumpet:Instrument {name: 'Trumpet'}),

  (alice)-[:LIKES { score: 5 }]->(guitar),
  (alice)-[:LIKES { score: 4 }]->(synth),
  (alice)-[:LIKES { score: 3, strength: 0.5}]->(bongos),
  (bob)-[:LIKES { score: 4 }]->(guitar),
  (bob)-[:LIKES { score: 5 }]->(synth),
  (carol)-[:LIKES { score: 2 }]->(bongos),
  (dave)-[:LIKES { score: 3 }]->(guitar),
  (dave)-[:LIKES { score: 1 }]->(synth),
  (dave)-[:LIKES { score: 5 }]->(bongos)
```

Project the graph:

```
CALL gds.graph.project(
  'personsAndInstruments',
  ['Person', 'Instrument'],          ①
  {
    LIKES: {
      type: 'LIKES',                 ②
      properties: {
        strength: {                  ③
          property: 'strength',
          defaultValue: 1.0
        },
        score: {
          property: 'score'          ④
        }
      }
    }
  }
)
```

① Project node labels `Person` and `Instrument`.

② Project relationship type `LIKES`.

③ Project property `strength` of relationship type `LIKES` setting a default value of `1.0` because not all relationships have that property.

④ Project property `score` of relationship type `LIKES`.

Compute the Node Similarity in our graph:

```
CALL gds.nodeSimilarity.mutate('personsAndInstruments', {   ①
  mutateRelationshipType: 'SIMILAR',                        ②
  mutateProperty: 'score'                                   ③
})
```

① Run NodeSimilarity in `mutate` mode on `personsAndInstruments` projected graph.

② The algorithm will add relationships of type `SIMILAR` to the projected graph.

③ The algorithm will add relationship property `score` for each added relationship.

Stream

Single property

The most basic case for streaming relationship information from a named graph is a single property. In the example below we stream the relationship property `score`.

Stream a single relationship property:

```
CALL gds.graph.streamRelationshipProperty(
  'personsAndInstruments',                  ①
  'score'                                   ②
)
YIELD
  sourceNodeId, targetNodeId, relationshipType, propertyValue
RETURN
  gds.util.asNode(sourceNodeId).name as source, gds.util.asNode(targetNodeId).name as target,
relationshipType, propertyValue
ORDER BY source ASC, target ASC
```

① The name of the projected graph.

② The property we want to stream out.

Table 124. Results

source	target	relationshipType	propertyValue
"Alice"	"Bob"	"SIMILAR"	0.6666666666666666
"Alice"	"Bongos"	"LIKES"	3.0
"Alice"	"Carol"	"SIMILAR"	0.3333333333333333
"Alice"	"Dave"	"SIMILAR"	1.0
"Alice"	"Guitar"	"LIKES"	5.0
"Alice"	"Synthesizer"	"LIKES"	4.0
"Bob"	"Alice"	"SIMILAR"	0.6666666666666666

source	target	relationshipType	propertyValue
"Bob"	"Dave"	"SIMILAR"	0.6666666666666666
"Bob"	"Guitar"	"LIKES"	4.0
"Bob"	"Synthesizer"	"LIKES"	5.0
"Carol"	"Alice"	"SIMILAR"	0.3333333333333333
"Carol"	"Bongos"	"LIKES"	2.0
"Carol"	"Dave"	"SIMILAR"	0.3333333333333333
"Dave"	"Alice"	"SIMILAR"	1.0
"Dave"	"Bob"	"SIMILAR"	0.6666666666666666
"Dave"	"Bongos"	"LIKES"	5.0
"Dave"	"Carol"	"SIMILAR"	0.3333333333333333
"Dave"	"Guitar"	"LIKES"	3.0
"Dave"	"Synthesizer"	"LIKES"	1.0

As we can see from the results, we get two relationship types (`SIMILAR` and `LIKES`) that have the `score` relationship property. We can further on filter the relationship types we want to stream, this is demonstrated in the next example.

Stream a single relationship property for specific relationship type:

```
CALL gds.graph.streamRelationshipProperty(
  'personsAndInstruments',                  ①
  'score',                                  ②
  ['SIMILAR']                               ③
)
YIELD
  sourceNodeId, targetNodeId, relationshipType, propertyValue
RETURN
  gds.util.asNode(sourceNodeId).name as source, gds.util.asNode(targetNodeId).name as target,
relationshipType, propertyValue
ORDER BY source ASC, target ASC
```

① The name of the projected graph.

② The property we want to stream out.

③ List of relationship types we want to stream the property from, only use the ones we need.

Table 125. Results

source	target	relationshipType	propertyValue
"Alice"	"Bob"	"SIMILAR"	0.6666666666666666
"Alice"	"Carol"	"SIMILAR"	0.3333333333333333
"Alice"	"Dave"	"SIMILAR"	1.0
"Bob"	"Alice"	"SIMILAR"	0.6666666666666666
"Bob"	"Dave"	"SIMILAR"	0.6666666666666666

source	target	relationshipType	propertyValue
"Carol"	"Alice"	"SIMILAR"	0.3333333333333333
"Carol"	"Dave"	"SIMILAR"	0.3333333333333333
"Dave"	"Alice"	"SIMILAR"	1.0
"Dave"	"Bob"	"SIMILAR"	0.6666666666666666
"Dave"	"Carol"	"SIMILAR"	0.3333333333333333

Multiple properties

It is also possible to stream multiple relationship properties.

Stream multiple relationship properties:

```
CALL gds.graph.streamRelationshipProperties(
  'personsAndInstruments',                    ①
  ['score', 'strength'],                      ②
  ['LIKES']                                   ③
)
YIELD
  sourceNodeId, targetNodeId, relationshipType, relationshipProperty, propertyValue
RETURN
  gds.util.asNode(sourceNodeId).name as source, gds.util.asNode(targetNodeId).name as target,
relationshipType, relationshipProperty, propertyValue
ORDER BY source ASC, target ASC
```

① The name of the projected graph.

② List of properties we want to stream out, allows us to stream more than one property.

③ List of relationship types we want to stream the property from, only use the ones we need.

Table 126. Results

source	target	relationshipType	relationshipProperty	propertyValue
"Alice"	"Bongos"	"LIKES"	"score"	3.0
"Alice"	"Bongos"	"LIKES"	"strength"	0.5
"Alice"	"Guitar"	"LIKES"	"score"	5.0
"Alice"	"Guitar"	"LIKES"	"strength"	1.0
"Alice"	"Synthesizer"	"LIKES"	"score"	4.0
"Alice"	"Synthesizer"	"LIKES"	"strength"	1.0
"Bob"	"Guitar"	"LIKES"	"score"	4.0
"Bob"	"Guitar"	"LIKES"	"strength"	1.0
"Bob"	"Synthesizer"	"LIKES"	"score"	5.0
"Bob"	"Synthesizer"	"LIKES"	"strength"	1.0
"Carol"	"Bongos"	"LIKES"	"score"	2.0
"Carol"	"Bongos"	"LIKES"	"strength"	1.0

source	target	relationshipType	relationshipProperty	propertyValue
"Dave"	"Bongos"	"LIKES"	"score"	5.0
"Dave"	"Bongos"	"LIKES"	"strength"	1.0
"Dave"	"Guitar"	"LIKES"	"score"	3.0
"Dave"	"Guitar"	"LIKES"	"strength"	1.0
"Dave"	"Synthesizer"	"LIKES"	"score"	1.0
"Dave"	"Synthesizer"	"LIKES"	"strength"	1.0

Multiple relationship types

Similar to the multiple relationship properties we can stream properties for multiple relationship types.

Stream relationship properties of a multiple relationship projections:

```
CALL gds.graph.streamRelationshipProperties(
  'personsAndInstruments',                          ①
  ['score'],                                        ②
  ['LIKES', 'SIMILAR']                              ③
)
YIELD
  sourceNodeId, targetNodeId, relationshipType, relationshipProperty, propertyValue
RETURN
  gds.util.asNode(sourceNodeId).name as source,     ④
  gds.util.asNode(targetNodeId).name as target,     ⑤
  relationshipType,
  relationshipProperty,
  propertyValue
ORDER BY source ASC, target ASC
```

① The name of the projected graph.

② List of properties we want to stream out, allows us to stream more than one property.

③ List of relationship types we want to stream the property from, only use the ones we need.

④ Return the `name` of the source node.

⑤ Return the `name` of the target node.

Table 127. Results

source	target	relationshipType	relationshipProperty	propertyValue
"Alice"	"Bob"	"SIMILAR"	"score"	0.6666666666666666
"Alice"	"Bongos"	"LIKES"	"score"	3.0
"Alice"	"Carol"	"SIMILAR"	"score"	0.3333333333333333
"Alice"	"Dave"	"SIMILAR"	"score"	1.0
"Alice"	"Guitar"	"LIKES"	"score"	5.0
"Alice"	"Synthesizer"	"LIKES"	"score"	4.0
"Bob"	"Alice"	"SIMILAR"	"score"	0.6666666666666666

source	target	relationshipType	relationshipProperty	propertyValue
"Bob"	"Dave"	"SIMILAR"	"score"	0.6666666666666666
"Bob"	"Guitar"	"LIKES"	"score"	4.0
"Bob"	"Synthesizer"	"LIKES"	"score"	5.0
"Carol"	"Alice"	"SIMILAR"	"score"	0.3333333333333333
"Carol"	"Bongos"	"LIKES"	"score"	2.0
"Carol"	"Dave"	"SIMILAR"	"score"	0.3333333333333333
"Dave"	"Alice"	"SIMILAR"	"score"	1.0
"Dave"	"Bob"	"SIMILAR"	"score"	0.6666666666666666
"Dave"	"Bongos"	"LIKES"	"score"	5.0
"Dave"	"Carol"	"SIMILAR"	"score"	0.3333333333333333
"Dave"	"Guitar"	"LIKES"	"score"	3.0
"Dave"	"Synthesizer"	"LIKES"	"score"	1.0

The properties we want to stream must exist for each specified relationship type.

Write

We can write relationships stored in a named in-memory graph back to Neo4j. This can be used to write algorithm results (for example from Node Similarity) or relationships that have been aggregated during graph creation.

The relationships to write are specified by a relationship type.

Relationships are always written using a single thread.

Relationship type

Write relationships to Neo4j:

```
CALL gds.graph.writeRelationship(
  'personsAndInstruments',        ①
  'SIMILAR'                       ②
)
YIELD
  graphName, relationshipType, relationshipProperty, relationshipsWritten, propertiesWritten
```

① The name of the projected graph.

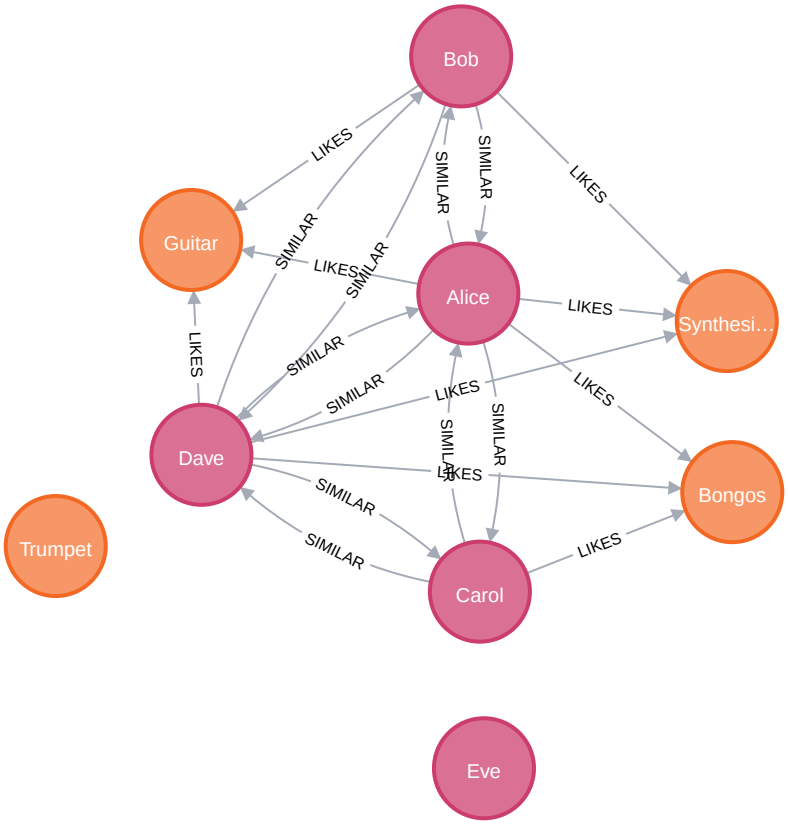
② The relationship type we want to write back to the Neo4j database.

Table 128. Results

graphName	relationshipType	relationshipProperty	relationshipsWritten	propertiesWritten
"personsAndInstruments"	"SIMILAR"	null	10	0

By default, no relationship properties will be written, as it can be seen from the results, the `relationshipProperty` value is `null` and `propertiesWritten` are `0`.

Here is an illustration of how the example graph looks in Neo4j after executing the example above.



The `SIMILAR` relationships have been added to the underlying database and can be used in Cypher queries or for projecting to in-memory graph for running algorithms. The relationships in this example are undirected because we used Node Similarity to mutate the in-memory graph and this algorithm creates undirected relationships, this may not be the case if we use different algorithms.

Relationship type with property

To write relationship properties, these have to be explicitly specified.

Write relationships and their properties to Neo4j:

```
CALL gds.graph.writeRelationship(
  'personsAndInstruments',          ①
  'SIMILAR',                        ②
  'score'                           ③
)
YIELD
  graphName, relationshipType, relationshipProperty, relationshipsWritten, propertiesWritten
```

① The name of the projected graph.

② The relationship type we want to write back to the Neo4j database.

③ The property name of the relationship we want to write back to the Neo4j database.

Table 129. Results

graphName	relationshipType	relationshipProperty	relationshipsWritten	propertiesWritten
"personsAndInstruments"	"SIMILAR"	"score"	10	10

Delete

We can delete all relationships of a given type from a named graph in the catalog. This is useful to free up main memory or to remove accidentally added relationship types.

Deleting relationships of a given type is only possible if it is not the last relationship type present in the graph. If we still want to delete these relationships we need to drop the graph instead.

Delete all relationships of type `SIMILAR` from a named graph:

```
CALL gds.graph.deleteRelationships(
  'personsAndInstruments',            ①
  'SIMILAR'                           ②
)
YIELD
  graphName, relationshipType, deletedRelationships, deletedProperties
```

① The name of the projected graph.

② The relationship type we want to delete from the projected graph.

Table 130. Results

graphName	relationshipType	deletedRelationships	deletedProperties
"personsAndInstruments"	"SIMILAR"	10	{score=10}

4.1.10. Export operations

This feature is not available in AuraDS

Create Neo4j databases from projected graphs

We can create new Neo4j databases from projected graphs stored in the graph catalog. All nodes, relationships and properties present in the projected graph are written to a new Neo4j database. This includes data that has been projected in `gds.graph.project` and data that has been added by running algorithms in `mutate` mode. The newly created database will be stored in the Neo4j `databases` directory using a given database name.

The feature is useful in the following, exemplary scenarios:

- Avoid heavy write load on the operational system by exporting the data instead of writing back.
- Create an analytical view of the operational system that can be used as a basis for running algorithms.
- Produce snapshots of analytical results and persistent them for archiving and inspection.
- Share analytical results within the organization.

Syntax

Export a projected graph to a new database in the Neo4j databases directory:

```
CALL gds.graph.export(graphName: String, configuration: Map)
YIELD
    dbName: String,
    graphName: String,
    nodeCount: Integer,
    nodePropertyCount: Integer,
    relationshipCount: Integer,
    relationshipTypeCount: Integer,
    relationshipPropertyCount: Integer,
    writeMillis: Integer
```

Table 131. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
configuration	Map	no	Additional parameters to configure the database export.

Table 132. Graph export configuration

Name	Type	Default	Optional	Description
dbName	String	none	No	The name of the exported Neo4j database.
writeConcurrency	Boolean	4	yes	The number of concurrent threads used for writing the database.
enableDebugLog	Boolean	false	yes	Prints debug information to Neo4j log files.
batchSize	Integer	10000	yes	Number of entities processed by one single thread at a time.
defaultRelationshipType	String	__ALL__	yes	Relationship type used for * relationship projections.
additionalNodeProperties	String, List or Map	{}	yes	Allows for exporting additional node properties from the original graph backing the in-memory graph.

Table 133. Results

Name	Type	Description
dbName	String	The name of the exported Neo4j database.
graphName	String	The name under which the graph is stored in the catalog.
nodeCount	Integer	The number of nodes exported.

Name	Type	Description
nodePropertyCount	Integer	The number of node properties exported.
relationshipCount	Integer	The number of relationships exported.
relationshipTypeCount	Integer	The number of relationship types exported.
relationshipPropertyCount	Integer	The number of relationship properties exported.
writeMillis	Integer	Milliseconds for writing the graph into the new database.

Example

Export the `my-graph` from GDS into a Neo4j database called `mydatabase`:

```
CALL gds.graph.export('my-graph', { dbName: 'mydatabase' })
```

The new database can be started using databases management commands.

The database must not exist when using the export procedure. It needs to be created manually using the following commands.

After running exporting the graph, we can start a new database and query the exported graph:

```
:use system
CREATE DATABASE mydatabase;
:use mydatabase
MATCH (n) RETURN n;
```

Example with additional node properties

Suppose we have a graph `my-db-graph` in the Neo4j database that has a string node property `myproperty`, and that we have a corresponding in-memory graph called `my-in-memory-graph` which does not have the `myproperty` node property. If we want to export `my-in-memory-graph` but additionally add the `myproperty` properties from `my-db-graph` we can use the `additionalProperties` configuration parameter.

Export the `my-in-memory-graph` from GDS with `myproperty` from `my-db-graph` into a Neo4j database called `mydatabase`:

```
CALL gds.graph.export('my-graph', { dbName: 'mydatabase', additionalNodeProperties: ['myproperty']})
```

The new database can be started using databases management commands.

The original database (`my-db-graph`) must not have changed since loading the in-memory representation (`my-in-memory-graph`) that we export in order for the export to work correctly.

The `additionalNodeProperties` parameter uses the same syntax as `nodeProperties` of the graph project procedure. So we could for instance define a default value for our `myproperty`.

Export the `my-in-memory-graph` *from GDS with* `myproperty` *from* `my-db-graph` *with default value into a Neo4j database called* `mydatabase`:

```
CALL gds.graph.export('my-graph', { dbName: 'mydatabase', additionalNodeProperties: [{ myproperty:
{defaultValue: 'my-default-value'}}] })
```

Chapter 5. Export a named graph to CSV

We can export projected graphs stored in the graph catalog to a set of CSV files. All nodes, relationships and properties present in a projected graph are exported. This includes data that has been projected with `gds.graph.project` and data that has been added by running algorithms in `mutate` mode. The location of the exported CSV files can be configured via the configuration parameter `gds.export.location` in the `neo4j.conf`. All files will be stored in a subfolder using the specified export name. The export will fail if a folder with the given export name already exists.

The `gds.export.location` parameter must be configured for this feature.

5.1. Syntax

Export a named graph to a set of CSV files:

```
CALL gds.beta.graph.export.csv(graphName: String, configuration: Map)
YIELD
    graphName: String,
    exportName: String,
    nodeCount: Integer,
    nodePropertyCount: Integer,
    relationshipCount: Integer,
    relationshipTypeCount: Integer,
    relationshipPropertyCount: Integer,
    writeMillis: Integer
```

Table 134. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
configuration	Map	no	Additional parameters to configure the database export.

Table 135. Graph export configuration

Name	Type	Default	Optional	Description
exportName	String	none	No	The name of the directory where the graph is exported to. The absolute path of the exported CSV files depends on the configuration parameter `gds.export.location` in the `neo4j.conf`.
writeConcurrency	Boolean	4	yes	The number of concurrent threads used for writing the database.
defaultRelationshipType	String	`__ALL__`	yes	Relationship type used for `*` relationship projections.
additionalNodeProperties	String, List or Map	{}	yes	Allows for exporting additional node properties from the original graph backing the projected graph.

Table 136. Results

Name	Type	Description
graphName	String	The name under which the graph is stored in the catalog.
exportName	String	The name of the directory where the graph is exported to.
nodeCount	Integer	The number of nodes exported.
nodePropertyCount	Integer	The number of node properties exported.
relationshipCount	Integer	The number of relationships exported.
relationshipTypeCount	Integer	The number of relationship types exported.
relationshipPropertyCount	Integer	The number of relationship properties exported.
writeMillis	Integer	Milliseconds for writing the graph into the new database.

5.2. Estimation

As many other procedures in GDS, export to csv has an estimation mode. For more details see Memory Estimation. Using the `gds.beta.graph.export.csv.estimate` procedure, it is possible to estimate the required disk space of the exported CSV files. The estimation uses sampling to generate a more accurate estimate.

Estimate the required disk space for exporting a named graph to CSV files.:

```
CALL gds.beta.graph.export.csv.estimate(graphName:String, configuration: Map)
YIELD
  nodeCount: Integer,
  relationshipCount: Integer,
  requiredMemory: String,
  treeView: String,
  mapView: Map,
  bytesMin: Integer,
  bytesMax: Integer,
  heapPercentageMin: Float,
  heapPercentageMax: Float;
```

Table 137. Parameters

Name	Type	Optional	Description
graphName	String	no	The name under which the graph is stored in the catalog.
configuration	Map	no	Additional parameters to configure the database export.

Table 138. Graph export estimate configuration

Name	Type	Default	Optional	Description
exportName	String	none	no	Name of the folder the exported CSV files are saved at.
samplingFactor	Double	0.001	yes	The fraction of nodes and relationships to sample for the estimation.
writeConcurrency	Boolean	4	yes	The number of concurrent threads used for writing the database.

Name	Type	Default	Optional	Description
defaultRelationshipType	String	`__ALL__`	yes	Relationship type used for `*` relationship projections.

Table 139. Results

Name	Type	Description
`nodeCount`	Integer	The number of nodes in the graph.
`relationshipCount`	Integer	The number of relationships in the graph.
`requiredMemory`	String	An estimation of the required memory in a human readable format.
`treeView`	String	A more detailed representation of the required memory, including estimates of the different components in human readable format.
`mapView`	Map	A more detailed representation of the required memory, including estimates of the different components in structured format.
`bytesMin`	Integer	The minimum number of bytes required.
`bytesMax`	Integer	The maximum number of bytes required.
`heapPercentageMin`	Float	The minimum percentage of the configured maximum heap required.
`heapPercentageMax`	Float	The maximum percentage of the configured maximum heap required.

5.3. Export format

The format of the exported CSV files is based on the format that is supported by the Neo4j Admin import command.

5.3.1. Nodes

Nodes are exported into files grouped by the nodes labels, i.e., for every label combination that exists in the graph a set of export files is created. The naming schema of the exported files is: `nodes_LABELS_INDEX.csv`, where:

- `LABELS` is the ordered list of labels joined by `_`.
- `INDEX` is a number between 0 and concurrency.

For each label combination one or more data files are created, as each exporter thread exports into a separate file.

Additionally, each label combination produces a single header file, which contains a single line describing the columns in the data files More information about the header files can be found here: CSV header format.

For example a Graph with the node combinations `:A`, `:B` and `:A:B` might create the following files

```
nodes_A_header.csv
nodes_A_0.csv
nodes_B_header.csv
nodes_B_0.csv
nodes_B_2.csv
nodes_A_B_header.csv
nodes_A_B_0.csv
nodes_A_B_1.csv
nodes_A_B_2.csv
```

5.3.2. Relationships

The format of the relationship files is similar to those of the nodes. Relationships are exported into files grouped by the relationship type. The naming schema of the exported files is: `relationships_TYPE_INDEX.csv`, where:

- `TYPE` is the relationship type
- `INDEX` is a number between 0 and concurrency.

For each relationship type one or more data files are created, as each exporter thread exports into a separate file.

Additionally, each relationship type produces a single header file, which contains a single line describing the columns in the data files.

For example a Graph with the relationship types `:KNOWS`, `:LIVES_IN` might create the following files

```
relationships_KNOWS_header.csv
relationships_KNOWS_0.csv
relationships_LIVES_IN_header.csv
relationships_LIVES_IN_0.csv
relationships_LIVES_IN_2.csv
```

5.4. Example

Export the `my-graph` from GDS into a directory `my-export`:

```
CALL gds.beta.graph.export.csv('my-graph', { exportName: 'my-export' })
```

5.5. Example with additional node properties

Suppose we have a graph `my-db-graph` in the Neo4j database that has a string node property `myproperty`, and that we have a corresponding in-memory graph called `my-in-memory-graph` which does not have the `myproperty` node property. If we want to export `my-in-memory-graph` but additionally add the `myproperty` properties from `my-db-graph` we can use the `additionalProperties` configuration parameter.

Export the `my-in-memory-graph` from GDS with the `myproperty` from `my-db-graph` into a directory `my-export`:

```
CALL gds.beta.graph.export.csv('my-graph', { exportName: 'my-export', additionalNodeProperties:
['myproperty']})
```

The original database (`my-db-graph`) must not have changed since loading the in-memory representation (`my-in-memory-graph`) that we export in order for the export to work correctly.

The `additionalNodeProperties` parameter uses the same syntax as `nodeProperties` of the graph project procedure. So we could for instance define a default value for our `myproperty`.

Export the `my-in-memory-graph` from GDS with `myproperty` from `my-db-graph` with default value into a directory called `my-export`:

```
CALL gds.beta.graph.export.csv('my-graph', { exportName: 'my-export', additionalNodeProperties: [{
myproperty: {defaultValue: 'my-default-value'}}] })
```

5.6. Node Properties

This section explains the currently supported node properties.

The Neo4j Graph Data Science Library is capable of augmenting nodes with additional properties. These properties can be loaded from the database when the graph is projected. Many algorithms can also persist their result as one or more node properties when they are run using the `mutate` mode.

5.6.1. Supported types

The Neo4j Graph Data Science library does not support all property types that are supported by the Neo4j database. Every supported type also defines a fallback value, which is used to indicate that the value of this property is not set.

The following table lists the supported property types, as well as, their corresponding fallback values.

- `Long` - `Long.MIN_VALUE`
- `Double` - `NaN`
- `Long Array` - `null`
- `Float Array` - `null`
- `Double Array` - `null`

5.6.2. Defining the type of a node property

When creating a graph projection that specifies a set of node properties, the type of these properties is automatically determined using the first property value that is read by the loader for any specified property. All integral numerical types are interpreted as `Long` values, all floating point values are interpreted as `Double` values. Array values are explicitly defined by the type of the values that the array contains, i.e. a conversion of, for example, an `Integer Array` into a `Long Array` is not supported. Arrays with mixed content types are not supported.

5.6.3. Automatic type conversion

Most algorithms that are capable of using node properties require a specific property type. In cases of a mismatch between the type of the provided property and the required type, the library will try to convert the property value into the required type. This automatic conversion only happens when the following conditions are satisfied:

- Neither the given, nor the expected type are an `Array` type.
- The conversion is loss-less
  - `Long` to `Double`: The Long values does not exceed the supported range of the Double type.
  - `Double` to `Long`: The Double value does not have any decimal places.

The algorithm computation will fail if any of these conditions are not satisfied for any node property value.

The automatic conversion is computationally more expensive and should therefore be avoided in performance critical applications.

5.7. Utility functions

This section provides explanations and examples for each of the utility functions in the Neo4j Graph Data Science library.

5.7.1. System Functions

Name	Description
`gds.version`	Return the version of the installed Neo4j Graph Data Science library.

Usage:

```
RETURN gds.version() AS version
```

Table 140. Results

version
"2.0.6"

5.7.2. Numeric Functions

Table 141. Numeric Functions

Name	Description
`gds.util.NaN`	Returns NaN as a Cypher value.
`gds.util.infinity`	Return infinity as a Cypher value.

Name	Description
gds.util.isFinite	Return false if the given argument is ±Infinity, NaN, or null.
gds.util.isInfinite	Return true if the given argument is ±Infinity, NaN, or null.

Syntax

Name	Parameter
gds.util.NaN()	-
gds.util.infinity()	-
gds.util.isFinite(value: NUMBER)	value to be checked if it is finite.
gds.util.isInfinite(value: NUMBER)	value to be checked if it is infinite.

Examples

Example for gds.util.IsFinite:

```
UNWIND [1.0, gds.util.NaN(), gds.util.infinity()] AS value
RETURN gds.util.isFinite(value) AS isFinite
```

Table 142. Results

isFinite
true
false
false

Example for gds.util.isInfinite():

```
UNWIND [1.0, gds.util.NaN(), gds.util.infinity()] AS value
RETURN gds.util.isInfinite(value) AS isInfinite
```

Table 143. Results

isInfinite
false
true
true

A common usage of gds.util.IsFinite and gds.util.IsInfinite is for filtering streamed results, as for instance seen in the examples of gds.alpha.allShortestPaths.

5.7.3. Node id functions

Table 144. Node id functions

Name	Description
gds.util.asNode	Return the node object for the given node id or null if none exists.
gds.util.asNodes	Return the node objects for the given node ids or an empty list if none exists.

Syntax

Name	Parameters
gds.util.asNode(nodeId: NUMBER)	nodeId of a node in the neo4j-graph
gds.util.asNodes(nodeIds: List of NUMBER)	list of nodeIds of nodes in the neo4j-graph

Examples

Consider the graph created by the following Cypher statement:

Example graph:

```
CREATE  (nAlice:User {name: 'Alice'})
CREATE  (nBridget:User {name: 'Bridget'})
CREATE  (nCharles:User {name: 'Charles'})
CREATE  (nAlice)-[:LINK]->(nBridget)
CREATE  (nBridget)-[:LINK]->(nCharles)
```

Example for gds.util.asNode:

```
MATCH (u:User{name: 'Alice'})
WITH id(u) AS nodeId
RETURN gds.util.asNode(nodeId).name AS node
```

Table 145. Results

node
"Alice"

Example for gds.util.asNodes:

```
MATCH (u:User)
WHERE NOT u.name = 'Charles'
WITH collect(id(u)) AS nodeIds
RETURN [x in gds.util.asNodes(nodeIds)| x.name] AS nodes
```

Table 146. Results

nodes
[Alice, Bridget]

As many algorithms streaming mode only return the node id, `gds.util.asNode` and `gds.util.asNodes` can be used to retrieve the whole node from the neo4j database.

5.8. Cypher on GDS graph Enterprise edition

This chapter explains how to execute Cypher queries on named graphs in the Neo4j Graph Data Science library.

This feature is in the alpha tier.

This feature is not available in AuraDS

Exploring projected graphs after loading them and potentially executing algorithms in mutate mode can be tricky in the Neo4j Graph Data Science library. A natural way to achieve this in the Neo4j database is to use Cypher queries. Cypher queries allow for example to get a hold of which properties are present on a node among many other things. Executing Cypher queries on a projected graph can be achieved by leveraging the `gds.alpha.create.cypherdb` procedure. This procedure will create a new impermanent database which you can switch to. That database will then use data from the projected graph as compared to the store files for usual Neo4j databases.

5.8.1. Limitations

Although it is possible to execute arbitrary Cypher queries on the database created by the `gds.alpha.create.cypherdb` procedure, not every aspect of Cypher is implemented yet. Some known limitations are listed below:

- Dropping the newly created database
  - Restarting the DBMS will remove the database instead
- Writes
  - All queries that attempt to write things, such as nodes, properties or labels, will fail

5.8.2. Syntax

```
CALL gds.alpha.create.cypherdb(
    dbName: String
    graphName: String
)
YIELD
    dbName: String,
    graphName: String,
    createMillis: Integer
```

Table 147. Parameters

Name	Type	Optional	Description
dbName	String	no	The name under which the new database is stored.
graphName	String	no	The name under which the graph is stored in the catalog.

Table 148. Results

Name	Type	Description
dbName	String	The name under which the new database is stored.
graphName	String	The name under which the graph is stored in the catalog.
createMillis	Integer	Milliseconds for creating the database.

5.8.3. Example

To demonstrate how to execute cypher statements on projected graphs we are going to create a simple social network graph. We will use this graph to create a new database which we will execute our statements on.

```
CREATE
  (alice:Person { name: 'Alice', age: 23 }),
  (bob:Person { name: 'Bob', age: 42 }),
  (carl:Person { name: 'Carl', age: 31 }),

  (alice)-[:KNOWS]->(bob),
  (bob)-[:KNOWS]->(alice),
  (alice)-[:KNOWS]->(carl)
```

We will now load a graph projection of the created graph via the graph project procedure:

Project `Person` nodes and `KNOWS` relationships:

```
CALL gds.graph.project(
  'social_network',
  'Person',
  'KNOWS',
  { nodeProperties: 'age' }
)
YIELD
  graphName, nodeCount, relationshipCount
```

Table 149. Results

graph	nodeCont	relationshipCount
"social_network"	3	3

With a named graph loaded into the Neo4j Graph Data Science library, we can proceed to create the new database using the loaded graph as underlying data.

Create a new database `gdsdb` using our `social_network` graph:

```
CALL gds.alpha.create.cypherdb(
  'gdsdb',
  'social_network'
)
```

In order to verify that the new database was created successfully we can use the Neo4j database administration commands.

```
SHOW DATABASES
```

Table 150. Results

name	address	role	requestedStatus	currentStatus	error	default	home
"neo4j"	"localhost:7687"	"standalone"	"online"	"online"	""	true	true
"system"	"localhost:7687"	"standalone"	"online"	"online"	""	false	false
"gdsdb"	"localhost:7687"	"standalone"	"online"	"online"	""	false	false

We can now switch to the newly created database.

```
:use gdsdb
```

Finally, we are set up to execute cypher queries on our in-memory graph.

```
MATCH (n:Person)-[:KNOWS]->(m:Person) RETURN n.age AS age1, m.age AS age2
```

Table 151. Results

age1	age2
23	42
42	23
23	31

We can see that the returned ages correspond to the structure of the original graph.

5.9. Administration

This section explains administration capabilities in the Neo4j Graph Data Science library.

The GDS catalog offers elevated access to administrator users. Any user granted a role with the name `admin` is considered an administrator by GDS.

A GDS administrator has access to graphs projected by any other user. This includes the ability to list, drop and run algorithms over these graphs.

5.9.1. Disambiguating identically named graphs

Sometimes, several users (including the admin user themselves) could have a graph with the same name. To disambiguate between these graphs, the `username` configuration parameter can be used.

5.9.2. Examples

We will illustrate the administrator capabilities using a small example. In this example we have three users where one is an administrator. We create the users and set up the roles using the following Cypher commands:

```
CREATE USER alice SET PASSWORD $alice_pw CHANGE NOT REQUIRED;
CREATE USER bob SET PASSWORD $bob_pw CHANGE NOT REQUIRED;
CREATE USER carol SET PASSWORD $carol_pw CHANGE NOT REQUIRED;

GRANT ROLE reader TO alice;
GRANT ROLE reader TO bob;
GRANT ROLE admin TO carol;
```

As we can see, `alice` and `bob` are standard users with read access to the database. `carol` is an administrator by virtue of being granted the `admin` role (for more information about this role see the Cypher manual).

Now `alice` and `bob` each project a few graphs. They both project a graph called `graphA` and `bob` also projects a graph called `graphB`.

Listing

To list all graphs from all users, `carol` simply uses the graph list procedure.

Listing all graphs as administrator user:

```
CALL gds.graph.list()
YIELD graphName
```

Table 152. Results

graphName
"graphA"
"graphA"
"graphB"

Notice that all graphs from all users are visible to `carol` since they are considered a GDS admin.

Running algorithms with other users' graphs

`carol` may use `graphB` by simply naming it.

`carol` *can run WCC on the* `graphB` *graph owned by* `bob`*:*

```
CALL gds.wcc.stats('graphB')
YIELD componentCount
```

To use the `graphA` owned by `alice`, `carol` must use the `username` override.

carol can run WCC on graphA owned by alice:

```
CALL gds.wcc.stats('graphA', { username: 'alice' })
YIELD componentCount
```

Dropping other users' graphs

Unlike for listing, the full procedure signature must be used when using the username override to disambiguate. In the query below we have used the default values for the second and third parameter for the drop procedure. username is the fourth parameter. For more details see Dropping graphs.

To drop graphA owned by bob, carol can run the following:

```
CALL gds.graph.drop('graphA', true, '', 'bob')
YIELD graphName
```

5.10. Backup and Restore

> *This section explains how to back up and restore graphs and models in the Neo4j Graph Data Science library.*

This feature is not available in AuraDS

In the Neo4j Graph Data Science library, graphs and machine learning models are stored in-memory. This is necessary mainly for performance reasons but has the disadvantage that data will be lost after shutting down the database. There are already concepts to circumvent this limitation, such as running algorithms in write mode, exporting graphs to csv or storing models. The back-up and restore procedures described in this section will provide a simple and uniform way of saving graphs and models in order to load them back into memory after a database restart.

The gds.export.location parameter must be configured for this feature.

5.10.1. Syntax

Back-up in-memory graphs and models

```
CALL gds.alpha.backup
YIELD
  backupId: String,
  backupTime: LocalDateTime,
  exportMillis: Long
```

Table 153. Results

Name	Type	Description
graphName	String	The name of the persisted graph or an empty string if a model was persisted instead.

Name	Type	Description
modelName	String	The name of the persisted model or an empty string if a graph was persisted instead.
exportPath	String	Path where the backups are stored at.
backupTime	LocalDateTime	Point in time when the backup was created.
exportMillis	Long	Milliseconds for creating the backup
status	String	Status of the persistence operation. Either `SUCCESSFUL` or `FAILED`.

Restore graphs and models

```
CALL gds.alpha.restore
YIELD
  restoredGraph: String,
  restoredModel: String,
  status: String,
  restoreMillis: Long
```

Table 154. Results

Name	Type	Description
restoredGraph	String	The name of the restored graph or an empty string if a model was restored instead.
restoredModel	String	The name of the restored model or an empty string if a graph was restored instead.
status	String	Status of the restore operation. Either `SUCCESSFUL` or an error message.
restoreMillis	Long	Amount of time restoring took in milliseconds.

5.10.2. Examples

First we need to create a graph in the corresponding Neo4j database.

The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:Person {name: 'Alice'}),
  (bridget:Person {name: 'Bridget'}),

  (alice)-[:KNOWS]->(bridget),
```

Now we need to project an in-memory graph which we want to back-up.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'Person',
  'KNOWS'
)
```

We can now run the back-up procedure in order to store the in-memory graph on disk.

The following will run the back-up procedure:

```
CALL gds.alpha.backup
YIELD graphName, status
```

Table 155. Results

graphName	status
"myGraph"	"SUCCESSFUL"

It is now safe to drop the in-memory graph or shutdown the db, as we can restore it at a later point.

The following will drop the in-memory graph:

```
CALL gds.graph.drop('myGraph')
```

If we want to restore the backed-up graph, we can simply run the restore procedure to load it back into memory.

The following will run the restore procedure:

```
CALL gds.restore
YIELD restoredGraphs
```

Table 156. Results

restoredGraph	"myGraph"

As we can see, one graph with name `myGraph` was restored by the procedure.

Chapter 6. Graph Algorithms

This chapter describes each of the graph algorithms in the Neo4j Graph Data Science library, including algorithm tiers, execution modes and general syntax.

The Neo4j Graph Data Science (GDS) library contains many graph algorithms. The algorithms are divided into categories which represent different problem classes. The categories are listed in this chapter.

Algorithms exist in one of three tiers of maturity:

- Production-quality
  - Indicates that the algorithm has been tested with regards to stability and scalability.
  - Algorithms in this tier are prefixed with `gds.<algorithm>`.
- Beta
  - Indicates that the algorithm is a candidate for the production-quality tier.
  - Algorithms in this tier are prefixed with `gds.beta.<algorithm>`.
- Alpha
  - Indicates that the algorithm is experimental and might be changed or removed at any time.
  - Algorithms in this tier are prefixed with `gds.alpha.<algorithm>`.

This chapter is divided into the following sections:

6.1. Syntax overview

This section describes the general syntax for running algorithms in the Neo4j Graph Data Science library, including execution modes and common configuration parameters.

The general algorithm syntax involves referencing a previously loaded named graph.

Additionally, different execution modes are provided:

- `stream`
  - Returns the result of the algorithm as a stream of records.
- `stats`
  - Returns a single record of summary statistics, but does not write to the Neo4j database.
- `mutate`
  - Writes the results of the algorithm to the projected graph and returns a single record of summary statistics.
- `write`
  - Writes the results of the algorithm to the Neo4j database and returns a single record of summary statistics.

Finally, an execution mode may be estimated by appending the command with `estimate`.

Only the production-quality tier guarantees availability of all execution modes and estimation procedures.

Including all of the above mentioned elements leads to the following syntax outline:

Syntax composition:

```
CALL gds[.<tier>].<algorithm>.<execution-mode>[.<estimate>](
  graphName: String,
  configuration: Map
)
```

When using the estimation mode it is also possible to inline the graph creation into the algorithm configuration and omit the graph name. The syntax looks as follows:

Syntax composition for memory estimation:

```
CALL gds[.<tier>].<algorithm>.<execution-mode>.estimate(
  configuration: Map
)
```

The detailed sections in this chapter include concrete syntax overviews and examples.

6.2. Centrality

> *This chapter provides explanations and examples for each of the centrality algorithms in the Neo4j Graph Data Science library.*

Centrality algorithms are used to determine the importance of distinct nodes in a network. The Neo4j GDS library includes the following centrality algorithms, grouped by quality tier:

- Production-quality

- Page Rank
- Article Rank
- Eigenvector Centrality
- Betweenness Centrality
- Degree Centrality

- Beta
  - Closeness Centrality
- Alpha
  - Harmonic Centrality
  - HITS
  - Influence Maximization

6.2.1. PageRank

This section describes the PageRank algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The PageRank algorithm measures the importance of each node within the graph, based on the number incoming relationships and the importance of the corresponding source nodes. The underlying assumption roughly speaking is that a page is only as important as the pages that link to it.

PageRank is introduced in the original Google paper as a function that solves the following equation:

$$PR(A) = (1-d) + d(\frac{PR(T_1)}{(T_1)} + ... + \frac{PR(T_n)}{(T_n)})$$

where,

- we assume that a page A has pages T_1 to T_n which point to it.
- d is a damping factor which can be set between 0 (inclusive) and 1 (exclusive). It is usually set to 0.85.
- C(A) is defined as the number of links going out of page A.

This equation is used to iteratively update a candidate solution and arrive at an approximate solution to the same equation.

For more information on this algorithm, see:

- The original google paper
- An Efficient Partition-Based Parallel PageRank Algorithm
- PageRank beyond the web for use cases

Running this algorithm requires sufficient memory availability. Before running this algorithm, we recommend that you read Memory Estimation.

Considerations

There are some things to be aware of when using the PageRank algorithm:

- If there are no relationships from within a group of pages to outside the group, then the group is considered a spider trap.
- Rank sink can occur when a network of pages is forming an infinite cycle.
- Dead-ends occur when pages have no outgoing relationship.

Changing the damping factor can help with all the considerations above. It can be interpreted as a probability of a web surfer to sometimes jump to a random page and therefore not getting stuck in sinks.

Syntax

This section covers the syntax used to execute the PageRank algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

PageRank syntax per mode

Run PageRank in stream mode on a named graph.

```
CALL gds.pageRank.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  score: Float
```

Table 157. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 158. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 159. Algorithm specific configuration

Name	Type	Default	Optional	Description
dampingFactor	Float	0.85	yes	The damping factor of the Page Rank calculation. Must be in [0, 1).
maxIterations	Integer	20	yes	The maximum number of iterations of Page Rank to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	[]	yes	The nodes or node ids to use for computing Personalized Page Rank.
scaler	String	None	yes	The name of the scaler applied for the final scores. Supported values are None, MinMax, Max, Mean, Log, L1Norm, L2Norm and StdScore.

Table 160. Results

Name	Type	Description
nodeId	Integer	Node ID.
score	Float	PageRank score.

Run PageRank in stats mode on a named graph.

```
CALL gds.pageRank.stats(
  graphName: String,
  configuration: Map
)
YIELD
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  centralityDistribution: Map,
  configuration: Map
```

Table 161. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 162. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 163. Algorithm specific configuration

Name	Type	Default	Optional	Description
dampingFactor	Float	0.85	yes	The damping factor of the Page Rank calculation. Must be in [0, 1).
maxIterations	Integer	20	yes	The maximum number of iterations of Page Rank to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	[]	yes	The nodes or node ids to use for computing Personalized Page Rank.
scaler	String	None	yes	The name of the scaler applied for the final scores. Supported values are None, MinMax, Max, Mean, Log, L1Norm, L2Norm and StdScore.

Table 164. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the `centralityDistribution`.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	The configuration used for running the algorithm.

Run PageRank in mutate mode on a named graph.

```
CALL gds.pageRank.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  nodePropertiesWritten: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  centralityDistribution: Map,
  configuration: Map
```

Table 165. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 166. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 167. Algorithm specific configuration

Name	Type	Default	Optional	Description
dampingFactor	Float	0.85	yes	The damping factor of the Page Rank calculation. Must be in [0, 1).
maxIterations	Integer	20	yes	The maximum number of iterations of Page Rank to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	[]	yes	The nodes or node ids to use for computing Personalized Page Rank.

Name	Type	Default	Optional	Description
scaler	String	`None`	yes	The name of the scaler applied for the final scores. Supported values are `None`, `MinMax`, `Max`, `Mean`, `Log`, `L1Norm`, `L2Norm` and `StdScore`.

Table 168. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the `centralityDistribution`.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
nodePropertiesWritten	Integer	The number of properties that were written to the projected graph.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	The configuration used for running the algorithm.

Run PageRank in write mode on a named graph.

```
CALL gds.pageRank.write(
  graphName: String,
  configuration: Map
)
YIELD
  nodePropertiesWritten: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  centralityDistribution: Map,
  configuration: Map
```

Table 169. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 170. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 171. Algorithm specific configuration

Name	Type	Default	Optional	Description
dampingFactor	Float	0.85	yes	The damping factor of the Page Rank calculation. Must be in [0, 1).
maxIterations	Integer	20	yes	The maximum number of iterations of Page Rank to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

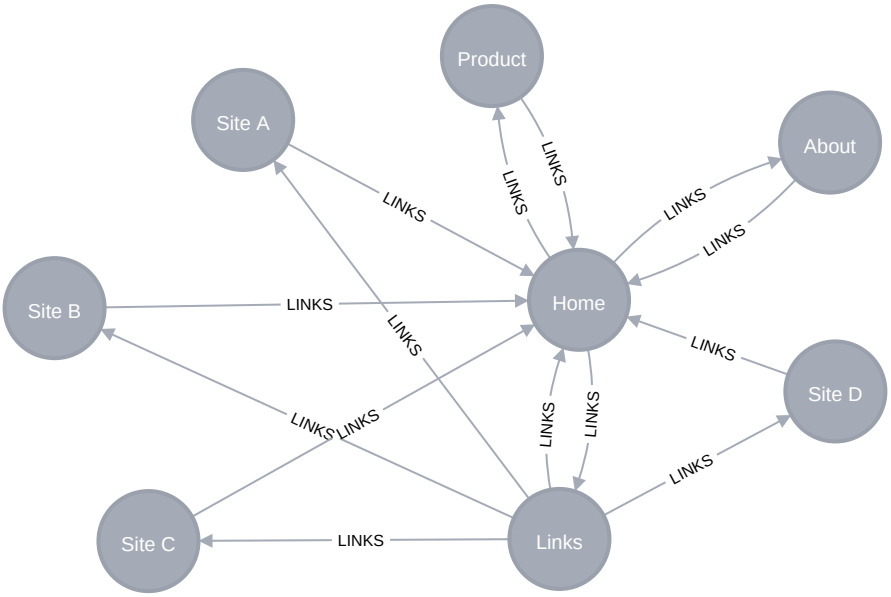
Name	Type	Default	Optional	Description
sourceNodes	List or Node or Number	`[]`	yes	The nodes or node ids to use for computing Personalized Page Rank.
scaler	String	`None`	yes	The name of the scaler applied for the final scores. Supported values are `None`, `MinMax`, `Max`, `Mean`, `Log`, `L1Norm`, `L2Norm` and `StdScore`.

Table 172. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the `centralityDistribution`.
writeMillis	Integer	Milliseconds for writing result data back.
nodePropertiesWritten	Integer	The number of properties that were written to Neo4j.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the PageRank algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small web network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (home:Page {name:'Home'}),
  (about:Page {name:'About'}),
  (product:Page {name:'Product'}),
  (links:Page {name:'Links'}),
  (a:Page {name:'Site A'}),
  (b:Page {name:'Site B'}),
  (c:Page {name:'Site C'}),
  (d:Page {name:'Site D'}),

  (home)-[:LINKS {weight: 0.2}]->(about),
  (home)-[:LINKS {weight: 0.2}]->(links),
  (home)-[:LINKS {weight: 0.6}]->(product),
  (about)-[:LINKS {weight: 1.0}]->(home),
  (product)-[:LINKS {weight: 1.0}]->(home),
  (a)-[:LINKS {weight: 1.0}]->(home),
  (b)-[:LINKS {weight: 1.0}]->(home),
  (c)-[:LINKS {weight: 1.0}]->(home),
  (d)-[:LINKS {weight: 1.0}]->(home),
  (links)-[:LINKS {weight: 0.8}]->(home),
  (links)-[:LINKS {weight: 0.05}]->(a),
  (links)-[:LINKS {weight: 0.05}]->(b),
  (links)-[:LINKS {weight: 0.05}]->(c),
  (links)-[:LINKS {weight: 0.05}]->(d);
```

This graph represents eight pages, linking to one another. Each relationship has a property called `weight`, which describes the importance of the relationship.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'Page',
  'LINKS',
  {
    relationshipProperties: 'weight'
  }
)
```

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.pageRank.write.estimate('myGraph', {
  writeProperty: 'pageRank',
  maxIterations: 20,
  dampingFactor: 0.85
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 173. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
8	14	696	696	"696 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the score for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode:

```
CALL gds.pageRank.stream('myGraph')
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 174. Results

name	score
"Home"	3.215681999884452
"About"	1.0542700552146722
"Links"	1.0542700552146722
"Product"	1.0542700552146722
"Site A"	0.3278578964488539
"Site B"	0.3278578964488539
"Site C"	0.3278578964488539

name	score
"Site D"	0.3278578964488539

The above query is running the algorithm in `stream` mode as `unweighted` and the returned scores are not normalized. Below, one can find an example for weighted graphs. Another example shows the application of a scaler to normalize the final scores.

While we are using the `stream` mode to illustrate running the algorithm as `weighted` or `unweighted`, all the algorithm modes support this configuration parameter.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm and returns the result in form of statistical and measurement values

```
CALL gds.pageRank.stats('myGraph', {
  maxIterations: 20,
  dampingFactor: 0.85
})
YIELD centralityDistribution
RETURN centralityDistribution.max AS max
```

Table 175. Results

max
3.2156810760498047

The centrality histogram can be useful for inspecting the computed scores or perform normalizations.

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the score for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.pageRank.mutate('myGraph', {
  maxIterations: 20,
  dampingFactor: 0.85,
  mutateProperty: 'pagerank'
})
YIELD nodePropertiesWritten, ranIterations
```

Table 176. Results

nodePropertiesWritten	ranIterations
8	20

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the score for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.pageRank.write('myGraph', {
  maxIterations: 20,
  dampingFactor: 0.85,
  writeProperty: 'pagerank'
})
YIELD nodePropertiesWritten, ranIterations
```

Table 177. Results

nodePropertiesWritten	ranIterations
8	20

Weighted

By default, the algorithm is considering the relationships of the graph to be `unweighted`, to change this behaviour we can use configuration parameter called `relationshipWeightProperty`. In the `weighted` case, the previous score of a node send to its neighbors, is multiplied by the relationship weight and then divided by the sum of the weights of its outgoing relationships. If the value of the relationship property is negative it will be ignored during computation. Below is an example of running the algorithm using the relationship property.

The following will run the algorithm in `stream` mode using relationship weights:

```
CALL gds.pageRank.stream('myGraph', {
  maxIterations: 20,
  dampingFactor: 0.85,
  relationshipWeightProperty: 'weight'
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 178. Results

name	score
"Home"	3.53751028396339
"Product"	1.9357838291651097
"About"	0.7452612763883698
"Links"	0.7452612763883698
"Site A"	0.18152677135466103
"Site B"	0.18152677135466103
"Site C"	0.18152677135466103
"Site D"	0.18152677135466103

We are using `stream` mode to illustrate running the algorithm as `weighted` or `unweighted`, all the algorithm modes support this configuration parameter.

Tolerance

The `tolerance` configuration parameter denotes the minimum change in scores between iterations. If all scores change less than the configured `tolerance` value the result stabilises, and the algorithm returns.

The following will run the algorithm in `stream` mode using bigger `tolerance` value:

```
CALL gds.pageRank.stream('myGraph', {
  maxIterations: 20,
  dampingFactor: 0.85,
  tolerance: 0.1
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 179. Results

name	score
"Home"	1.5812450669583336
"About"	0.5980194356381945
"Links"	0.5980194356381945

name	score
"Product"	0.5980194356381945
"Site A"	0.23374955154166668
"Site B"	0.23374955154166668
"Site C"	0.23374955154166668
"Site D"	0.23374955154166668

In this example we are using `tolerance: 0.1`, so the results are a bit different compared to the ones from stream example which is using the default value of `tolerance`. Note that the nodes 'About', 'Link' and 'Product' now have the same score, while with the default value of `tolerance` the node 'Product' has higher score than the other two.

Damping Factor

The damping factor configuration parameter accepts values between 0 (inclusive) and 1 (exclusive). If its value is too high then problems of sinks and spider traps may occur, and the values may oscillate so that the algorithm does not converge. If it's too low then all scores are pushed towards 1, and the result will not sufficiently reflect the structure of the graph.

The following will run the algorithm in `stream` mode using smaller `dampingFactor` value:

```
CALL gds.pageRank.stream('myGraph', {
  maxIterations: 20,
  dampingFactor: 0.05
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 180. Results

name	score
"Home"	1.2487309425844906
"About"	0.9708121818724536
"Links"	0.9708121818724536
"Product"	0.9708121818724536
"Site A"	0.9597081216238426
"Site B"	0.9597081216238426
"Site C"	0.9597081216238426
"Site D"	0.9597081216238426

Compared to the results from the stream example which is using the default value of `dampingFactor` the score values are closer to each other when using `dampingFactor: 0.05`. Also, note that the nodes 'About', 'Link' and 'Product' now have the same score, while with the default value of `dampingFactor` the node

'Product' has higher score than the other two.

Personalised PageRank

Personalized PageRank is a variation of PageRank which is biased towards a set of `sourceNodes`. This variant of PageRank is often used as part of recommender systems.

The following examples show how to run PageRank centered around 'Site A'.

The following will run the algorithm and stream results:

```
MATCH (siteA:Page {name: 'Site A'})
CALL gds.pageRank.stream('myGraph', {
  maxIterations: 20,
  dampingFactor: 0.85,
  sourceNodes: [siteA]
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 181. Results

name	score
"Home"	0.39902290442518784
"Site A"	0.16890325301726694
"About"	0.11220151747374331
"Links"	0.11220151747374331
"Product"	0.11220151747374331
"Site B"	0.01890325301726691
"Site C"	0.01890325301726691
"Site D"	0.01890325301726691

Comparing these results to the ones from the stream example (which is not using `sourceNodes` configuration parameter) shows that the 'Site A' node that we used in the `sourceNodes` list now scores second instead of fourth.

Scaling centrality scores

To normalize the final scores as part of the algorithm execution, one can use the `scaler` configuration parameter. A common scaler is the `L1Norm`, which normalizes each score to a value between 0 and 1. A description of all available scalers can be found in the documentation for the `scaleProperties` procedure.

The following will run the algorithm in `stream` mode and returns normalized results:

```
CALL gds.pageRank.stream('myGraph', {
  scaler: "L1Norm"
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 182. Results

name	score
"Home"	0.4181682554824872
"About"	0.1370975954128506
"Links"	0.1370975954128506
"Product"	0.1370975954128506
"Site A"	0.04263473956974027
"Site B"	0.04263473956974027
"Site C"	0.04263473956974027
"Site D"	0.04263473956974027

Comparing the results with the stream example, we can see that the relative order of scores is the same.

6.2.2. Article Rank

This section describes the Article Rank algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

ArticleRank is a variant of the Page Rank algorithm, which measures the **transitive** influence of nodes.

Page Rank follows the assumption that relationships originating from low-degree nodes have a higher influence than relationships from high-degree nodes. Article Rank lowers the influence of low-degree nodes by lowering the scores being sent to their neighbors in each iteration.

The Article Rank of a node v at iteration *i* is defined as:

$$ArticleRank_i(v) = (1-d) + d \sum_{w \in N_{in}(v)} \frac{ArticleRank_{i-1}(w)}{|N_{out}(w)| + \overline{N_{out}}}$$

where,

- $N_{in}(v)$ denotes incoming neighbors and $N_{out}(v)$ denotes outgoing neighbors of node *v*.
- *d* is a damping factor in *[0, 1]*.
- N_{out} is the average out-degree

For more information, see ArticleRank: a PageRank-based alternative to numbers of citations for analysing citation networks.

Considerations

There are some things to be aware of when using the Article Rank algorithm:

- If there are no relationships from within a group of pages to outside the group, then the group is considered a spider trap.
- Rank sink can occur when a network of pages is forming an infinite cycle.
- Dead-ends occur when pages have no outgoing relationship.

Changing the damping factor can help with all the considerations above. It can be interpreted as a probability of a web surfer to sometimes jump to a random page and therefore not getting stuck in sinks.

Syntax

This section covers the syntax used to execute the Article Rank algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Article Rank syntax per mode

Run Article Rank in stream mode on a named graph.

```
CALL gds.articleRank.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  score: Float
```

Table 183. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 184. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 185. Algorithm specific configuration

Name	Type	Default	Optional	Description
dampingFactor	Float	0.85	yes	The damping factor of the Page Rank calculation. Must be in [0, 1).
maxIterations	Integer	20	yes	The maximum number of iterations of Article Rank to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable, and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	[]	yes	The nodes or node ids to use for computing Personalized Page Rank.
scaler	String	None	yes	The name of the scaler applied for the final scores. Supported values are None, MinMax, Max, Mean, Log, L1Norm, L2Norm and StdScore.

Table 186. Results

Name	Type	Description
nodeId	Integer	Node ID.
score	Float	Eigenvector score.

Run Article Rank in stats mode on a named graph.

```
CALL gds.articleRank.stats(
  graphName: String,
  configuration: Map
)
YIELD
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  centralityDistribution: Map,
  configuration: Map
```

Table 187. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 188. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 189. Algorithm specific configuration

Name	Type	Default	Optional	Description
dampingFactor	Float	0.85	yes	The damping factor of the Page Rank calculation. Must be in [0, 1).
maxIterations	Integer	20	yes	The maximum number of iterations of Article Rank to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable, and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	[]	yes	The nodes or node ids to use for computing Personalized Page Rank.
scaler	String	None	yes	The name of the scaler applied for the final scores. Supported values are None, MinMax, Max, Mean, Log, L1Norm, L2Norm and StdScore.

Table 190. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the `centralityDistribution`.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	The configuration used for running the algorithm.

Run Article Rank in mutate mode on a named graph.

```
CALL gds.articleRank.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  nodePropertiesWritten: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  centralityDistribution: Map,
  configuration: Map
```

Table 191. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 192. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 193. Algorithm specific configuration

Name	Type	Default	Optional	Description
dampingFactor	Float	0.85	yes	The damping factor of the Page Rank calculation. Must be in [0, 1).
maxIterations	Integer	20	yes	The maximum number of iterations of Article Rank to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable, and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	[]	yes	The nodes or node ids to use for computing Personalized Page Rank.

Name	Type	Default	Optional	Description
scaler	String	None	yes	The name of the scaler applied for the final scores. Supported values are None, MinMax, Max, Mean, Log, L1Norm, L2Norm and StdScore.

Table 194. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the centralityDistribution.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
nodePropertiesWritten	Integer	The number of properties that were written to the projected graph.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	The configuration used for running the algorithm.

Run Article Rank in write mode on a named graph.

```
CALL gds.articleRank.write(
  graphName: String,
  configuration: Map
)
YIELD
  nodePropertiesWritten: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  centralityDistribution: Map,
  configuration: Map
```

Table 195. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 196. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 197. Algorithm specific configuration

Name	Type	Default	Optional	Description
dampingFactor	Float	0.85	yes	The damping factor of the Page Rank calculation. Must be in [0, 1).
maxIterations	Integer	20	yes	The maximum number of iterations of Article Rank to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable, and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

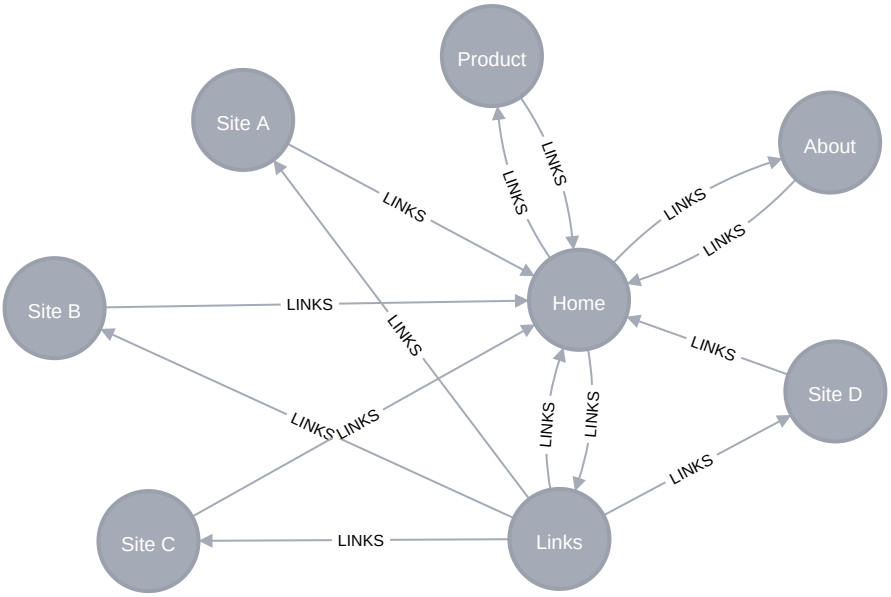
Name	Type	Default	Optional	Description
sourceNodes	List or Node or Number	`[]`	yes	The nodes or node ids to use for computing Personalized Page Rank.
scaler	String	`None`	yes	The name of the scaler applied for the final scores. Supported values are `None`, `MinMax`, `Max`, `Mean`, `Log`, `L1Norm`, `L2Norm` and `StdScore`.

Table 198. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the `centralityDistribution`.
writeMillis	Integer	Milliseconds for writing result data back.
nodePropertiesWritten	Integer	The number of properties that were written to Neo4j.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Article Rank algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small web network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (home:Page {name:'Home'}),
  (about:Page {name:'About'}),
  (product:Page {name:'Product'}),
  (links:Page {name:'Links'}),
  (a:Page {name:'Site A'}),
  (b:Page {name:'Site B'}),
  (c:Page {name:'Site C'}),
  (d:Page {name:'Site D'}),

  (home)-[:LINKS {weight: 0.2}]->(about),
  (home)-[:LINKS {weight: 0.2}]->(links),
  (home)-[:LINKS {weight: 0.6}]->(product),
  (about)-[:LINKS {weight: 1.0}]->(home),
  (product)-[:LINKS {weight: 1.0}]->(home),
  (a)-[:LINKS {weight: 1.0}]->(home),
  (b)-[:LINKS {weight: 1.0}]->(home),
  (c)-[:LINKS {weight: 1.0}]->(home),
  (d)-[:LINKS {weight: 1.0}]->(home),
  (links)-[:LINKS {weight: 0.8}]->(home),
  (links)-[:LINKS {weight: 0.05}]->(a),
  (links)-[:LINKS {weight: 0.05}]->(b),
  (links)-[:LINKS {weight: 0.05}]->(c),
  (links)-[:LINKS {weight: 0.05}]->(d);
```

This graph represents eight pages, linking to one another. Each relationship has a property called `weight`, which describes the importance of the relationship.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'Page',
  'LINKS',
  {
    relationshipProperties: 'weight'
  }
)
```

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.articleRank.write.estimate('myGraph', {
  writeProperty: 'centrality',
  maxIterations: 20
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 199. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
8	14	696	696	"696 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the score for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode:

```
CALL gds.articleRank.stream('myGraph')
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 200. Results

name	score
"Home"	0.5607071761939444
"About"	0.250337073634706
"Links"	0.250337073634706
"Product"	0.250337073634706
"Site A"	0.18152391630760797
"Site B"	0.18152391630760797
"Site C"	0.18152391630760797

name	score
"Site D"	0.18152391630760797

The above query is running the algorithm in `stream` mode as `unweighted`. Below, one can find an example for weighted graphs.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm and return statistics about the centrality scores.

```
CALL gds.articleRank.stats('myGraph')
YIELD centralityDistribution
RETURN centralityDistribution.max AS max
```

Table 201. Results

max
0.5607099533081055

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the score for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.articleRank.mutate('myGraph', {
  mutateProperty: 'centrality'
})
YIELD nodePropertiesWritten, ranIterations
```

Table 202. Results

nodePropertiesWritten	ranIterations
8	19

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the score for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.articleRank.write('myGraph', {
  writeProperty: 'centrality'
})
YIELD nodePropertiesWritten, ranIterations
```

Table 203. Results

nodePropertiesWritten	ranIterations
8	19

Weighted

By default, the algorithm considers the relationships of the graph to be unweighted. To change this behaviour, we can use the `relationshipWeightProperty` configuration parameter. If the parameter is set, the associated property value is used as relationship weight. In the `weighted` case, the previous score of a node sent to its neighbors is multiplied by the normalized relationship weight. Note, that negative relationship weights are ignored during the computation.

In the following example, we use the `weight` property of the input graph as relationship weight property.

The following will run the algorithm in `stream` mode using relationship weights:

```
CALL gds.articleRank.stream('myGraph', {
  relationshipWeightProperty: 'weight'
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 204. Results

name	score
"Home"	0.5160810726222141
"Product"	0.24570958074084706
"About"	0.1819031935802824
"Links"	0.1819031935802824
"Site A"	0.15281123078335393
"Site B"	0.15281123078335393

name	score
"Site C"	0.15281123078335393
"Site D"	0.15281123078335393

As in the unweighted example, the "Home" node has the highest score. In contrast, the "Product" now has the second highest instead of the fourth highest score.

We are using `stream` mode to illustrate running the algorithm as `weighted`, however, all the algorithm modes support the `relationshipWeightProperty` configuration parameter.

Tolerance

The `tolerance` configuration parameter denotes the minimum change in scores between iterations. If all scores change less than the configured tolerance, the iteration is aborted and considered converged. Note, that setting a higher tolerance leads to earlier convergence, but also to less accurate centrality scores.

The following will run the algorithm in `stream` mode using a high `tolerance` value:

```
CALL gds.articleRank.stream('myGraph', {
  tolerance: 0.1
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 205. Results

name	score
"Home"	0.4470707070707072
"About"	0.23000212652844235
"Links"	0.23000212652844235
"Product"	0.23000212652844235
"Site A"	0.16888888888888892
"Site B"	0.16888888888888892
"Site C"	0.16888888888888892
"Site D"	0.16888888888888892

We are using `tolerance: 0.1`, which leads to slightly different results compared to the stream example. However, the computation converges after four iterations, and we can already observe a trend in the resulting scores.

Personalised Article Rank

Personalized Article Rank is a variation of Article Rank which is biased towards a set of `sourceNodes`. By

default, the power iteration starts with the same value for all nodes: `1 / |V|`. For a given set of source nodes `S`, the initial value of each source node is set to `1 / |S|` and to `0` for all remaining nodes.

The following examples show how to run Eigenvector centrality centered around 'Site A' and 'Site B'.

The following will run the algorithm and stream results:

```
MATCH (siteA:Page {name: 'Site A'}), (siteB:Page {name: 'Site B'})
CALL gds.articleRank.stream('myGraph', {
  maxIterations: 20,
  sourceNodes: [siteA, siteB]
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 206. Results

name	score
"Site A"	0.15249052775314756
"Site B"	0.15249052775314756
"Home"	0.1105231342997017
"About"	0.019777824032578193
"Links"	0.019777824032578193
"Product"	0.019777824032578193
"Site C"	0.002490527753147571
"Site D"	0.002490527753147571

Comparing these results to the ones from the stream example (which is not using `sourceNodes` configuration parameter) shows the 'Site A' and `Site B` nodes we used in the `sourceNodes` list now score second and third instead of fourth and fifth.

Scaling centrality scores

To normalize the final scores as part of the algorithm execution, one can use the `scaler` configuration parameter. A common scaler is the `L1Norm`, which normalizes each score to a value between 0 and 1. A description of all available scalers can be found in the documentation for the `scaleProperties` procedure.

The following will run the algorithm in `stream` mode and returns normalized results:

```
CALL gds.articleRank.stream('myGraph', {
  scaler: "L1Norm"
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 207. Results

name	score
"Home"	0.275151294006312
"About"	0.12284588582564794
"Links"	0.12284588582564794
"Product"	0.12284588582564794
"Site A"	0.08907776212918608
"Site B"	0.08907776212918608
"Site C"	0.08907776212918608
"Site D"	0.08907776212918608

Comparing the results with the stream example, we can see that the relative order of scores is the same.

6.2.3. Eigenvector Centrality

> *This section describes the Eigenvector Centrality algorithm in the Neo4j Graph Data Science library.*

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

Eigenvector Centrality is an algorithm that measures the **transitive** influence of nodes. Relationships originating from high-scoring nodes contribute more to the score of a node than connections from low-scoring nodes. A high eigenvector score means that a node is connected to many nodes who themselves have high scores.

The algorithm computes the eigenvector associated with the largest absolute eigenvalue. To compute that eigenvalue, the algorithm applies the power iteration approach. Within each iteration, the centrality score for each node is derived from the scores of its incoming neighbors. In the power iteration method, the eigenvector is L2-normalized after each iteration, leading to normalized results by default.

The PageRank algorithm is a variant of Eigenvector Centrality with an additional jump probability.

Considerations

There are some things to be aware of when using the Eigenvector centrality algorithm:

- Centrality scores for nodes with no incoming relationships will converge to `0`.
- Due to missing degree normalization, high-degree nodes have a very strong influence on their neighbors' score.

Syntax

This section covers the syntax used to execute the Eigenvector Centrality algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Eigenvector Centrality syntax per mode

Run Eigenvector Centrality in stream mode on a named graph.

```
CALL gds.eigenvector.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  score: Float
```

Table 208. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 209. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 210. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	20	yes	The maximum number of iterations of Eigenvector Centrality to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	[]	yes	The nodes or node ids to use for computing Personalized Page Rank.
scaler	String	None	yes	The name of the scaler applied for the final scores. Supported values are None, MinMax, Max, Mean, Log, L1Norm, L2Norm and StdScore.

Table 211. Results

Name	Type	Description
nodeId	Integer	Node ID.

Name	Type	Description
score	Float	Eigenvector score.

Run Eigenvector Centrality in stats mode on a named graph.

```
CALL gds.eigenvector.stats(
  graphName: String,
  configuration: Map
)
YIELD
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  centralityDistribution: Map,
  configuration: Map
```

Table 212. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 213. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm.

Table 214. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	`20`	yes	The maximum number of iterations of Eigenvector Centrality to run.
tolerance	Float	`0.0000001`	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable and the algorithm returns.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	`[]`	yes	The nodes or node ids to use for computing Personalized Page Rank.
scaler	String	`None`	yes	The name of the scaler applied for the final scores. Supported values are `None`, `MinMax`, `Max`, `Mean`, `Log`, `L1Norm`, `L2Norm` and `StdScore`.

Table 215. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the `centralityDistribution`.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	The configuration used for running the algorithm.

Run Eigenvector Centrality in mutate mode on a named graph.

```
CALL gds.eigenvector.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  nodePropertiesWritten: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  centralityDistribution: Map,
  configuration: Map
```

Table 216. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 217. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 218. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	20	yes	The maximum number of iterations of Eigenvector Centrality to run.
tolerance	Float	0.0000001	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable and the algorithm returns.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	[]	yes	The nodes or node ids to use for computing Personalized Page Rank.
scaler	String	None	yes	The name of the scaler applied for the final scores. Supported values are None, MinMax, Max, Mean, Log, L1Norm, L2Norm and StdScore.

Table 219. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the `centralityDistribution`.
mutateMillis	Integer	Milliseconds for adding properties to the in-memory graph.
nodePropertiesWritten	Integer	The number of properties that were written to the in-memory graph.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	The configuration used for running the algorithm.

Run Eigenvector Centrality in write mode on a named graph.

```
CALL gds.eigenvector.write(
  graphName: String,
  configuration: Map
)
YIELD
  nodePropertiesWritten: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  centralityDistribution: Map,
  configuration: Map
```

Table 220. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 221. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 222. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	`20`	yes	The maximum number of iterations of Eigenvector Centrality to run.
tolerance	Float	`0.0000001`	yes	Minimum change in scores between iterations. If all scores change less than the tolerance value the result is considered stable and the algorithm returns.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
sourceNodes	List or Node or Number	`[]`	yes	The nodes or node ids to use for computing Personalized Page Rank.

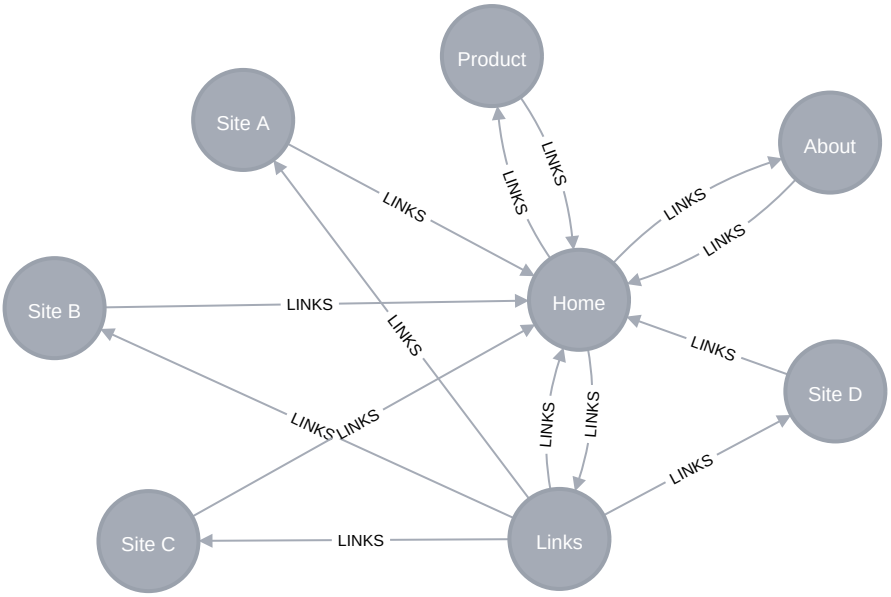
Name	Type	Default	Optional	Description
scaler	String	`None`	yes	The name of the scaler applied for the final scores. Supported values are `None`, `MinMax`, `Max`, `Mean`, `Log`, `L1Norm`, `L2Norm` and `StdScore`.

Table 223. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the `centralityDistribution`.
writeMillis	Integer	Milliseconds for writing result data back.
nodePropertiesWritten	Integer	The number of properties that were written to Neo4j.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Eigenvector Centrality algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small web network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (home:Page {name:'Home'}),
  (about:Page {name:'About'}),
  (product:Page {name:'Product'}),
  (links:Page {name:'Links'}),
  (a:Page {name:'Site A'}),
  (b:Page {name:'Site B'}),
  (c:Page {name:'Site C'}),
  (d:Page {name:'Site D'}),

  (home)-[:LINKS {weight: 0.2}]->(about),
  (home)-[:LINKS {weight: 0.2}]->(links),
  (home)-[:LINKS {weight: 0.6}]->(product),
  (about)-[:LINKS {weight: 1.0}]->(home),
  (product)-[:LINKS {weight: 1.0}]->(home),
  (a)-[:LINKS {weight: 1.0}]->(home),
  (b)-[:LINKS {weight: 1.0}]->(home),
  (c)-[:LINKS {weight: 1.0}]->(home),
  (d)-[:LINKS {weight: 1.0}]->(home),
  (links)-[:LINKS {weight: 0.8}]->(home),
  (links)-[:LINKS {weight: 0.05}]->(a),
  (links)-[:LINKS {weight: 0.05}]->(b),
  (links)-[:LINKS {weight: 0.05}]->(c),
  (links)-[:LINKS {weight: 0.05}]->(d);
```

This graph represents eight pages, linking to one another. Each relationship has a property called `weight`, which describes the importance of the relationship.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'Page',
  'LINKS',
  {
    relationshipProperties: 'weight'
  }
)
```

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.eigenvector.write.estimate('myGraph', {
  writeProperty: 'centrality',
  maxIterations: 20
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 224. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
8	14	696	696	"696 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the score for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode:

```
CALL gds.eigenvector.stream('myGraph')
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 225. Results

name	score
"Home"	0.7465574981728249
"About"	0.33997520529777137
"Links"	0.33997520529777137
"Product"	0.33997520529777137
"Site A"	0.15484062876886298
"Site B"	0.15484062876886298
"Site C"	0.15484062876886298

name	score
"Site D"	0.15484062876886298

The above query is running the algorithm in `stream` mode as `unweighted`. Below, one can find an example for weighted graphs.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm and return statistics about the centrality scores.

```
CALL gds.eigenvector.stats('myGraph', {
  maxIterations: 20
})
YIELD centralityDistribution
RETURN centralityDistribution.max AS max
```

Table 226. Results

max
0.7465581893920898

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the score for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.eigenvector.mutate('myGraph', {
  maxIterations: 20,
  mutateProperty: 'centrality'
})
YIELD nodePropertiesWritten, ranIterations
```

Table 227. Results

nodePropertiesWritten	ranIterations
8	20

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the score for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.eigenvector.write('myGraph', {
  maxIterations: 20,
  writeProperty: 'centrality'
})
YIELD nodePropertiesWritten, ranIterations
```

Table 228. Results

nodePropertiesWritten	ranIterations
8	20

Weighted

By default, the algorithm considers the relationships of the graph to be unweighted. To change this behaviour, we can use the `relationshipWeightProperty` configuration parameter. If the parameter is set, the associated property value is used as relationship weight. In the `weighted` case, the previous score of a node sent to its neighbors is multiplied by the normalized relationship weight. Note, that negative relationship weights are ignored during the computation.

In the following example, we use the `weight` property of the input graph as relationship weight property.

The following will run the algorithm in `stream` mode using relationship weights:

```
CALL gds.eigenvector.stream('myGraph', {
  maxIterations: 20,
  relationshipWeightProperty: 'weight'
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 229. Results

name	score
"Home"	0.8328163407319487
"Product"	0.5004775834976313
"About"	0.1668258611658771
"Links"	0.1668258611658771
"Site A"	0.008327591469710233

name	score
"Site B"	0.008327591469710233
"Site C"	0.008327591469710233
"Site D"	0.008327591469710233

As in the unweighted example, the "Home" node has the highest score. In contrast, the "Product" now has the second highest instead of the fourth highest score.

We are using `stream` mode to illustrate running the algorithm as `weighted`, however, all the algorithm modes support the `relationshipWeightProperty` configuration parameter.

Tolerance

The `tolerance` configuration parameter denotes the minimum change in scores between iterations. If all scores change less than the configured tolerance, the iteration is aborted and considered converged. Note, that setting a higher tolerance leads to earlier convergence, but also to less accurate centrality scores.

The following will run the algorithm in `stream` mode using a high `tolerance` value:

```
CALL gds.eigenvector.stream('myGraph', {
  maxIterations: 20,
  tolerance: 0.1
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 230. Results

name	score
"Home"	0.7108273818583551
"About"	0.3719400001993262
"Links"	0.3719400001993262
"Product"	0.3719400001993262
"Site A"	0.14116155811301126
"Site B"	0.14116155811301126
"Site C"	0.14116155811301126
"Site D"	0.14116155811301126

We are using `tolerance: 0.1`, which leads to slightly different results compared to the stream example. However, the computation converges after three iterations, and we can already observe a trend in the resulting scores.

Personalised Eigenvector Centrality

Personalized Eigenvector Centrality is a variation of Eigenvector Centrality which is biased towards a set of `sourceNodes`. By default, the power iteration starts with the same value for all nodes: `1 / |V|`. For a given set of source nodes `S`, the initial value of each source node is set to `1 / |S|` and to `0` for all remaining nodes.

The following examples show how to run Eigenvector centrality centered around 'Site A'.

The following will run the algorithm and stream results:

```
MATCH (siteA:Page {name: 'Site A'}), (siteB:Page {name: 'Site B'})
CALL gds.eigenvector.stream('myGraph', {
  maxIterations: 20,
  sourceNodes: [siteA, siteB]
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 231. Results

name	score
"Home"	0.7465645391567868
"About"	0.33997203172449453
"Links"	0.33997203172449453
"Product"	0.33997203172449453
"Site A"	0.15483736775159632
"Site B"	0.15483736775159632
"Site C"	0.15483736775159632
"Site D"	0.15483736775159632

Scaling centrality scores

Internally, centrality scores are scaled after each iteration using L2 normalization. As a consequence, the final values are already normalized. This behavior cannot be changed as it is part of the power iteration method.

However, to normalize the final scores as part of the algorithm execution, one can use the `scaler` configuration parameter. A common scaler is the `L1Norm`, which normalizes each score to a value between 0 and 1. A description of all available scalers can be found in the documentation for the `scaleProperties` procedure.

The following will run the algorithm in `stream` mode and returns normalized results:

```
CALL gds.eigenvector.stream('myGraph', {
  scaler: "L1Norm"
})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY score DESC, name ASC
```

Table 232. Results

name	score
"Home"	0.31291106560043064
"About"	0.1424967320371402
"Links"	0.1424967320371402
"Product"	0.1424967320371402
"Site A"	0.06489968457203725
"Site B"	0.06489968457203725
"Site C"	0.06489968457203725
"Site D"	0.06489968457203725

Comparing the results with the stream example, we can see that the relative order of scores is the same.

6.2.4. Betweenness Centrality

> *This section describes the Betweenness Centrality algorithm in the Neo4j Graph Data Science library.*

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

Betweenness centrality is a way of detecting the amount of influence a node has over the flow of information in a graph. It is often used to find nodes that serve as a bridge from one part of a graph to another.

The algorithm calculates unweighted shortest paths between all pairs of nodes in a graph. Each node receives a score, based on the number of shortest paths that pass through the node. Nodes that more

frequently lie on shortest paths between other nodes will have higher betweenness centrality scores.

The GDS implementation is based on Brandes' approximate algorithm for unweighted graphs. The implementation requires $O(n + m)$ space and runs in $O(n * m)$ time, where n is the number of nodes and m the number of relationships in the graph.

For more information on this algorithm, see:

- A Faster Algorithm for Betweenness Centrality
- Centrality Estimation in Large Networks
- A Set of Measures of Centrality Based on Betweenness

Running this algorithm requires sufficient memory availability. Before running this algorithm, we recommend that you read Memory Estimation.

Considerations and sampling

The Betweenness Centrality algorithm can be very resource-intensive to compute. Brandes' approximate algorithm computes single-source shortest paths (SSSP) for a set of source nodes. When all nodes are selected as source nodes, the algorithm produces an exact result. However, for large graphs this can potentially lead to very long runtimes. Thus, approximating the results by computing the SSSPs for only a subset of nodes can be useful. In GDS we refer to this technique as *sampling*, where the size of the source node set is the *sampling size*.

There are two things to consider when executing the algorithm on large graphs:

- A higher parallelism leads to higher memory consumption as each thread executes SSSPs for a subset of source nodes sequentially.
  - In the worst case, a single SSSP requires the whole graph to be duplicated in memory.
- A higher sampling size leads to more accurate results, but also to a potentially much longer execution time.

Changing the values of the configuration parameters `concurrency` and `samplingSize`, respectively, can help to manage these considerations.

Sampling strategies

Brandes defines several strategies for selecting source nodes. The GDS implementation is based on the random degree selection strategy, which selects nodes with a probability proportional to their degree. The idea behind this strategy is that such nodes are likely to lie on many shortest paths in the graph and thus have a higher contribution to the betweenness centrality score.

Syntax

This section covers the syntax used to execute the Betweenness Centrality algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general

syntax variants, see Syntax overview.

Betweenness Centrality syntax per mode

Run Betweenness Centrality in stream mode on a named graph.

```
CALL gds.betweenness.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  score: Float
```

Table 233. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 234. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 235. Algorithm specific configuration

Name	Type	Default	Optional	Description
samplingSize	Integer	node count	yes	The number of source nodes to consider for computing centrality scores.
samplingSeed	Integer	null	yes	The seed value for the random number generator that selects start nodes.

Table 236. Results

Name	Type	Description
nodeId	Integer	Node ID.
score	Float	Betweenness Centrality score.

Run Betweenness Centrality in stats mode on a named graph.

```
CALL gds.betweenness.stats(
  graphName: String,
  configuration: Map
)
YIELD
  centralityDistribution: Map,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  configuration: Map
```

Table 237. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 238. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 239. Algorithm specific configuration

Name	Type	Default	Optional	Description
samplingSize	Integer	node count	yes	The number of source nodes to consider for computing centrality scores.
samplingSeed	Integer	null	yes	The seed value for the random number generator that selects start nodes.

Table 240. Results

Name	Type	Description
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the statistics.

Name	Type	Description
configuration	Map	Configuration used for running the algorithm.

Run Betweenness Centrality in mutate mode on a named graph.

```
CALL gds.betweenness.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  centralityDistribution: Map,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 241. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 242. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 243. Algorithm specific configuration

Name	Type	Default	Optional	Description
samplingSize	Integer	node count	yes	The number of source nodes to consider for computing centrality scores.
samplingSeed	Integer	null	yes	The seed value for the random number generator that selects start nodes.

Table 244. Results

Name	Type	Description
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
postProcessingMillis	Integer	Milliseconds for computing the statistics.
mutateMillis	Integer	Milliseconds for adding properties to the in-memory graph.
nodePropertiesWritten	Integer	Number of properties added to the in-memory graph.
configuration	Map	Configuration used for running the algorithm.

Run Betweenness Centrality in write mode on a named graph.

```
CALL gds.betweenness.write(
  graphName: String,
  configuration: Map
)
YIELD
  centralityDistribution: Map,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 245. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 246. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 247. Algorithm specific configuration

Name	Type	Default	Optional	Description
samplingSize	Integer	`node count`	yes	The number of source nodes to consider for computing centrality scores.
samplingSeed	Integer	`null`	yes	The seed value for the random number generator that selects start nodes.

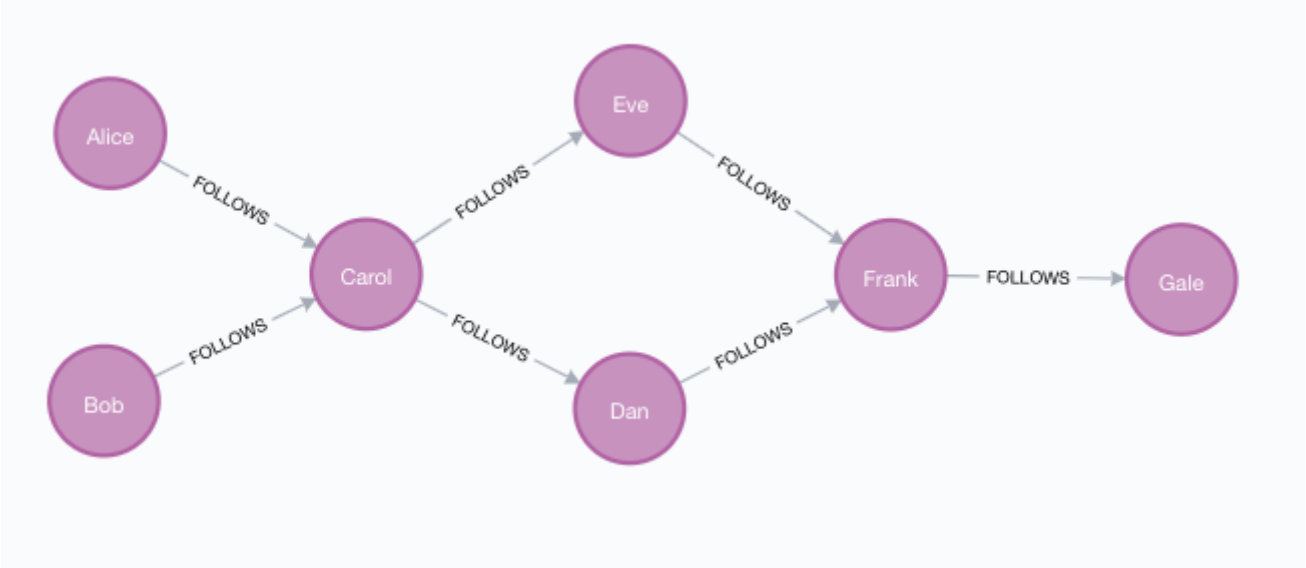
Table 248. Results

Name	Type	Description
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.

Name	Type	Description
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the statistics.
writeMillis	Integer	Milliseconds for writing result data back.
nodePropertiesWritten	Integer	Number of properties written to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Betweenness Centrality algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:User {name: 'Alice'}),
  (bob:User {name: 'Bob'}),
  (carol:User {name: 'Carol'}),
  (dan:User {name: 'Dan'}),
  (eve:User {name: 'Eve'}),
  (frank:User {name: 'Frank'}),
  (gale:User {name: 'Gale'}),

  (alice)-[:FOLLOWS]->(carol),
  (bob)-[:FOLLOWS]->(carol),
  (carol)-[:FOLLOWS]->(dan),
  (carol)-[:FOLLOWS]->(eve),
  (dan)-[:FOLLOWS]->(frank),
  (eve)-[:FOLLOWS]->(frank),
  (frank)-[:FOLLOWS]->(gale);
```

With the graph in Neo4j we can now project it into the graph catalog to prepare it for algorithm execution. We do this using a native projection targeting the `User` nodes and the `FOLLOWS` relationships.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will create a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project('myGraph', 'User', 'FOLLOWS')
```

In the following examples we will demonstrate using the Betweenness Centrality algorithm on this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.betweenness.write.estimate('myGraph', { writeProperty: 'betweenness' })
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 249. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
7	7	2912	2912	"2912 Bytes"

As is discussed in Considerations and sampling we can configure the memory requirements using the `concurrency` configuration parameter.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.betweenness.write.estimate('myGraph', { writeProperty: 'betweenness', concurrency: 1 })
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 250. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
7	7	848	848	"848 Bytes"

Here we can note that the estimated memory requirements were lower than when running with the default concurrency setting. Similarly, using a higher value will increase the estimated memory

requirements.

Stream

In the `stream` execution mode, the algorithm returns the centrality for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode:

```
CALL gds.betweenness.stream('myGraph')
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY name ASC
```

Table 251. Results

name	score
"Alice"	0.0
"Bob"	0.0
"Carol"	8.0
"Dan"	3.0
"Eve"	3.0
"Frank"	5.0
"Gale"	0.0

We note that the 'Carol' node has the highest score, followed by the 'Frank' node. Studying the example graph we can see that these nodes are in bottleneck positions in the graph. The 'Carol' node connects the 'Alice' and 'Bob' nodes to all other nodes, which increases its score. In particular, the shortest path from 'Alice' or 'Bob' to any other reachable node passes through 'Carol'. Similarly, all shortest paths that lead to the 'Gale' node passes through the 'Frank' node. Since 'Gale' is reachable from each other node, this causes the score for 'Frank' to be high.

Conversely, there are no shortest paths that pass through either of the nodes 'Alice', 'Bob' or 'Gale' which causes their betweenness centrality score to be zero.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm in `stats` mode:

```
CALL gds.betweenness.stats('myGraph')
YIELD centralityDistribution
RETURN centralityDistribution.min AS minimumScore, centralityDistribution.mean AS meanScore
```

Table 252. Results

minimumScore	meanScore
0.0	2.714292253766741

Comparing this to the results we saw in the stream example, we can find our minimum and maximum values from the table. It is worth noting that unless the graph has a particular shape involving a directed cycle, the minimum score will almost always be zero.

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the centrality for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.betweenness.mutate('myGraph', { mutateProperty: 'betweenness' })
YIELD centralityDistribution, nodePropertiesWritten
RETURN centralityDistribution.min AS minimumScore, centralityDistribution.mean AS meanScore,
nodePropertiesWritten
```

Table 253. Results

minimumScore	meanScore	nodePropertiesWritten
0.0	2.714292253766741	7

The returned result is the same as in the `stats` example. Additionally, the graph 'myGraph' now has a node property `betweenness` which stores the betweenness centrality score for each node. To find out how to inspect the new schema of the in-memory graph, see Listing graphs.

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the centrality for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.betweenness.write('myGraph', { writeProperty: 'betweenness' })
YIELD centralityDistribution, nodePropertiesWritten
RETURN centralityDistribution.min AS minimumScore, centralityDistribution.mean AS meanScore,
nodePropertiesWritten
```

Table 254. Results

minimumScore	meanScore	nodePropertiesWritten
0.0	2.714292253766741	7

The returned result is the same as in the `stats` example. Additionally, each of the seven nodes now has a new property `betweenness` in the Neo4j database, containing the betweenness centrality score for that node.

Sampling

Betweenness Centrality can be very resource-intensive to compute. To help with this, it is possible to approximate the results using a sampling technique. The configuration parameters `samplingSize` and `samplingSeed` are used to control the sampling. We illustrate this on our example graph by approximating Betweenness Centrality with a sampling size of two. The seed value is an arbitrary integer, where using the same value will yield the same results between different runs of the procedure.

The following will run the algorithm in `stream` mode with a sampling size of two:

```
CALL gds.betweenness.stream('myGraph', {samplingSize: 2, samplingSeed: 0})
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY name ASC
```

Table 255. Results

name	score
"Alice"	0.0
"Bob"	0.0
"Carol"	4.0
"Dan"	2.0
"Eve"	2.0
"Frank"	2.0
"Gale"	0.0

Here we can see that the 'Carol' node has the highest score, followed by a three-way tie between the 'Dan', 'Eve', and 'Frank' nodes. We are only sampling from two nodes, where the probability of a node being picked for the sampling is proportional to its outgoing degree. The 'Carol' node has the maximum degree and is the most likely to be picked. The 'Gale' node has an outgoing degree of zero and is very unlikely to be picked. The other nodes all have the same probability to be picked.

With our selected sampling seed of 0, we seem to have selected either of the 'Alice' and 'Bob' nodes, as well as the 'Carol' node. We can see that because either of 'Alice' and 'Bob' would add four to the score of the 'Carol' node, and each of 'Alice', 'Bob', and 'Carol' adds one to all of 'Dan', 'Eve', and 'Frank'.

To increase the accuracy of our approximation, the sampling size could be increased. In fact, setting the `samplingSize` to the node count of the graph (seven, in our case) will produce exact results.

Undirected

Betweenness Centrality can also be run on undirected graphs. To illustrate this, we will project our example graph using the `UNDIRECTED` orientation.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myUndirectedGraph'.

```
CALL gds.graph.project('myUndirectedGraph', 'User', {FOLLOWS: {orientation: 'UNDIRECTED'}})
```

Now we can run Betweenness Centrality on our undirected graph. The algorithm automatically figures out that the graph is undirected.

Running the algorithm on an undirected graph is about twice as computationally intensive compared to a directed graph.

The following will run the algorithm in `stream` mode on the undirected graph:

```
CALL gds.betweenness.stream('myUndirectedGraph')
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score
ORDER BY name ASC
```

Table 256. Results

name	score
"Alice"	0.0
"Bob"	0.0
"Carol"	9.5
"Dan"	3.0
"Eve"	3.0
"Frank"	5.5
"Gale"	0.0

The central nodes now have slightly higher scores, due to the fact that there are more shortest paths in the graph, and these are more likely to pass through the central nodes. The 'Dan' and 'Eve' nodes retain the same centrality scores as in the directed case.

6.2.5. Degree Centrality

This section describes the Degree Centrality algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Degree Centrality algorithm can be used to find popular nodes within a graph. Degree centrality measures the number of incoming or outgoing (or both) relationships from a node, depending on the orientation of a relationship projection. For more information on relationship orientations, see the relationship projection syntax section. It can be applied to either weighted or unweighted graphs. In the weighted case the algorithm computes the sum of all positive weights of adjacent relationships of a node, for each node in the graph. Non-positive weights are ignored.

For more information on this algorithm, see:

- Linton C. Freeman: Centrality in Social Networks Conceptual Clarification, 1979.

Use-cases

The Degree Centrality algorithm has been shown to be useful in many different applications. For example:

- Degree centrality is an important component of any attempt to determine the most important people in a social network. For example, in BrandWatch's most influential men and women on Twitter 2017 the top 5 people in each category have over 40m followers each, which is a lot higher than the average degree.
- Weighted degree centrality has been used to help separate fraudsters from legitimate users of an online auction. The weighted centrality for fraudsters is significantly higher because they tend to collude with each other to artificially increase the price of items. Read more in Two Step graph-based semi-supervised Learning for Online Auction Fraud Detection

Syntax

This section covers the syntax used to execute the Degree Centrality algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Degree Centrality syntax per mode

Run Degree Centrality in stream mode on a named graph.

```
CALL gds.degree.stream(
  graphName: String,
  configuration: Map
) YIELD
  nodeId: Integer,
  score: Float
```

Table 257. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 258. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 259. Algorithm specific configuration

Name	Type	Default	Optional	Description
orientation	String	NATURAL	yes	The orientation used to compute node degrees. Supported orientations are NATURAL, REVERSE and UNDIRECTED.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use for weighted degree computation. If unspecified, the algorithm runs unweighted.

Table 260. Results

Name	Type	Description
nodeId	Integer	Node ID.
score	Float	Degree Centrality score.

Run Degree Centrality in stats mode on a named graph.

```
CALL gds.degree.stats(
  graphName: String,
  configuration: Map
) YIELD
  centralityDistribution: Map,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  configuration: Map
```

Table 261. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 262. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 263. Algorithm specific configuration

Name	Type	Default	Optional	Description
orientation	String	NATURAL	yes	The orientation used to compute node degrees. Supported orientations are NATURAL, REVERSE and UNDIRECTED.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use for weighted degree computation. If unspecified, the algorithm runs unweighted.

Table 264. Results

Name	Type	Description
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
postProcessingMillis	Integer	Milliseconds for computing the statistics.
configuration	Map	Configuration used for running the algorithm.

Run Degree Centrality in mutate mode on a named graph.

```
CALL gds.degree.mutate(
  graphName: String,
  configuration: Map
) YIELD
  centralityDistribution: Map,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 265. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 266. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 267. Algorithm specific configuration

Name	Type	Default	Optional	Description
orientation	String	NATURAL	yes	The orientation used to compute node degrees. Supported orientations are NATURAL, REVERSE and UNDIRECTED.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use for weighted degree computation. If unspecified, the algorithm runs unweighted.

Table 268. Results

Name	Type	Description
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
postProcessingMillis	Integer	Milliseconds for computing the statistics.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
nodePropertiesWritten	Integer	Number of properties added to the projected graph.
configuration	Map	Configuration used for running the algorithm.

Run Degree Centrality in write mode on a named graph.

```
CALL gds.degree.write(
  graphName: String,
  configuration: Map
) YIELD
  centralityDistribution: Map,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 269. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 270. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 271. Algorithm specific configuration

Name	Type	Default	Optional	Description
orientation	String	`NATURAL`	yes	The orientation used to compute node degrees. Supported orientations are `NATURAL`, `REVERSE` and `UNDIRECTED`.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use for weighted degree computation. If unspecified, the algorithm runs unweighted.

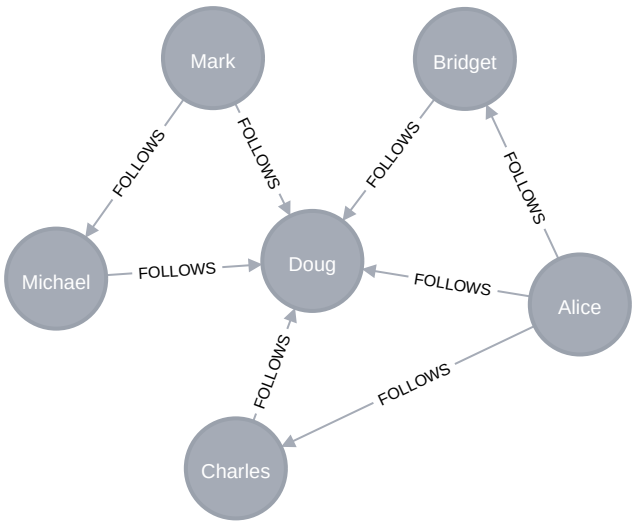
Table 272. Results

Name	Type	Description
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the statistics.
writeMillis	Integer	Milliseconds for writing result data back.
nodePropertiesWritten	Integer	Number of properties written to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Degree Centrality algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:User {name: 'Alice'}),
  (bridget:User {name: 'Bridget'}),
  (charles:User {name: 'Charles'}),
  (doug:User {name: 'Doug'}),
  (mark:User {name: 'Mark'}),
  (michael:User {name: 'Michael'}),

  (alice)-[:FOLLOWS {score: 1}]->(doug),
  (alice)-[:FOLLOWS {score: -2}]->(bridget),
  (alice)-[:FOLLOWS {score: 5}]->(charles),
  (mark)-[:FOLLOWS {score: 1.5}]->(doug),
  (mark)-[:FOLLOWS {score: 4.5}]->(michael),
  (bridget)-[:FOLLOWS {score: 1.5}]->(doug),
  (charles)-[:FOLLOWS {score: 2}]->(doug),
  (michael)-[:FOLLOWS {score: 1.5}]->(doug)
```

With the graph in Neo4j we can now project it into the graph catalog to prepare it for algorithm execution. We do this using a native projection targeting the `User` nodes and the `FOLLOWS` relationships.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a reverse projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'User',
  {
    FOLLOWS: {
      orientation: 'REVERSE',
      properties: ['score']
    }
  }
)
```

The graph is projected in a `REVERSE` orientation in order to retrieve people with the most followers in the following examples. This will be demonstrated using the Degree Centrality algorithm on this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.degree.write.estimate('myGraph', { writeProperty: 'degree' })
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 273. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	8	32	32	"32 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the degree centrality for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode:

```
CALL gds.degree.stream('myGraph')
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score AS followers
ORDER BY followers DESC, name DESC
```

Table 274. Results

name	followers
"Doug"	5.0
"Michael"	1.0
"Charles"	1.0
"Bridget"	1.0
"Mark"	0.0
"Alice"	0.0

We can see that Doug is the most popular user in our imaginary social network graph, with 5 followers - all other users follow them, but they don't follow anybody back. In a real social network, celebrities have very high follower counts but tend to follow only very few people. We could therefore consider Doug quite the celebrity!

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm in `stats` mode:

```
CALL gds.degree.stats('myGraph')
YIELD centralityDistribution
RETURN centralityDistribution.min AS minimumScore, centralityDistribution.mean AS meanScore
```

Table 275. Results

minimumScore	meanScore
0.0	1.3333358764648438

Comparing this to the results we saw in the stream example, we can find our minimum and mean values from the table.

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the degree centrality for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.degree.mutate('myGraph', { mutateProperty: 'degree' })
YIELD centralityDistribution, nodePropertiesWritten
RETURN centralityDistribution.min AS minimumScore, centralityDistribution.mean AS meanScore,
nodePropertiesWritten
```

Table 276. Results

minimumScore	meanScore	nodePropertiesWritten
0.0	1.3333358764648438	6

The returned result is the same as in the `stats` example. Additionally, the graph 'myGraph' now has a node property `degree` which stores the degree centrality score for each node. To find out how to inspect the new schema of the in-memory graph, see Listing graphs in the catalog.

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the degree centrality for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.degree.write('myGraph', { writeProperty: 'degree' })
YIELD centralityDistribution, nodePropertiesWritten
RETURN centralityDistribution.min AS minimumScore, centralityDistribution.mean AS meanScore,
nodePropertiesWritten
```

Table 277. Results

minimumScore	meanScore	nodePropertiesWritten
0.0	1.3333358764648438	6

The returned result is the same as in the `stats` example. Additionally, each of the seven nodes now has a new property `degree` in the Neo4j database, containing the degree centrality score for that node.

Weighted Degree Centrality example

This example will explain the weighted Degree Centrality algorithm. This algorithm is a variant of the Degree Centrality algorithm, that measures the sum of positive weights of incoming and outgoing relationships.

The following will run the algorithm in `stream` mode, showing which users have the highest weighted degree centrality:

```
CALL gds.degree.stream(
    'myGraph',
    { relationshipWeightProperty: 'score' }
)
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score AS weightedFollowers
ORDER BY weightedFollowers DESC, name DESC
```

Table 278. Results

name	weightedFollowers
"Doug"	7.5
"Charles"	5.0
"Michael"	4.5
"Mark"	0.0
"Bridget"	0.0
"Alice"	0.0

Doug still remains our most popular user, but there isn't such a big gap to the next person. Charles and Michael both only have one follower, but those relationships have a high relationship weight. Note that Bridget also has a weighted score of 0.0, despite having a connection from Alice. That is because the `score` property value between Bridget and Alice is negative and will be ignored by the algorithm.

Setting an orientation

By default, node centrality uses the `NATURAL` orientation to compute degrees. For some use-cases it makes

sense to analyze a different orientation, for example, if we want to find out how many users follow another user. In order to change the orientation, we can use the `orientation` configuration key. Supported values are `NATURAL` (default), `REVERSE` and `UNDIRECTED`.

The following will run the algorithm in `stream` mode, showing which users have the highest in-degree centrality using the reverse orientation of the relationships:

```
CALL gds.degree.stream(
    'myGraph',
    { orientation: 'REVERSE' }
)
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).name AS name, score AS followees
ORDER BY followees DESC, name DESC
```

Table 279. Results

name	followees
"Alice"	3.0
"Mark"	2.0
"Michael"	1.0
"Charles"	1.0
"Bridget"	1.0
"Doug"	0.0

The example shows that when looking at the reverse orientation, `Alice` is more central in the network than `Doug`.

6.2.6. Closeness Centrality Beta

> *This section describes the Closeness Centrality algorithm in the Neo4j Graph Data Science library.*

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

Closeness centrality is a way of detecting nodes that are able to spread information very efficiently through a graph.

The closeness centrality of a node measures its average farness (inverse distance) to all other nodes. Nodes with a high closeness score have the shortest distances to all other nodes.

For each node *u*, the Closeness Centrality algorithm calculates the sum of its distances to all other nodes, based on calculating the shortest paths between all pairs of nodes. The resulting sum is then inverted to determine the closeness centrality score for that node.

The **raw closeness centrality** of a node *u* is calculated using the following formula:

```
raw closeness centrality(u) = 1 / sum(distance from u to all other nodes)
```

It is more common to normalize this score so that it represents the average length of the shortest paths rather than their sum. This adjustment allow comparisons of the closeness centrality of nodes of graphs of different sizes

The formula for **normalized closeness centrality** of node *u* is as follows:

```
normalized closeness centrality(u) = (number of nodes - 1) / sum(distance from u to all other
nodes)
```

Wasserman and Faust have proposed an improved formula for dealing with unconnected graphs. Assuming that *n* is the number of nodes reachable from *u* (counting also itself), their corrected formula for a given node *u* is given as follows:

```
Wasserman-Faust normalized closeness centrality(u) = (n-1)^2/ number of nodes - 1) *
sum(distance from u to all other nodes
```

Note that in the case of a directed graph, closeness centrality is defined alternatively. That is, rather than considering distances from *u* to every other node, we instead sum and average the distance from every other node to *u*.

Use-cases - when to use the Closeness Centrality algorithm

- Closeness centrality is used to research organizational networks, where individuals with high closeness centrality are in a favourable position to control and acquire vital information and resources within the organization. One such study is "Mapping Networks of Terrorist Cells" by Valdis E. Krebs.
- Closeness centrality can be interpreted as an estimated time of arrival of information flowing through telecommunications or package delivery networks where information flows through shortest paths to a predefined target. It can also be used in networks where information spreads through all shortest paths simultaneously, such as infection spreading through a social network. Find more details in "Centrality and network flow" by Stephen P. Borgatti.
- Closeness centrality has been used to estimate the importance of words in a document, based on a graph-based keyphrase extraction process. This process is described by Florian Boudin in "A Comparison of Centrality Measures for Graph-Based Keyphrase Extraction".

Constraints - when not to use the Closeness Centrality algorithm

- Academically, closeness centrality works best on connected graphs. If we use the original formula on

an unconnected graph, we can end up with an infinite distance between two nodes in separate connected components. This means that we'll end up with an infinite closeness centrality score when we sum up all the distances from that node.

In practice, a variation on the original formula is used so that we don't run into these issues.

Syntax

This section covers the syntax used to execute the Closeness Centrality algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Closeness Centrality syntax per mode

Run Closeness Centrality in stream mode on a named graph.

```
CALL gds.beta.closeness.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  score: Float
```

Table 280. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 281. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 282. Algorithm specific configuration

Name	Type	Default	Optional	Description
useWassermanFaust	Boolean	false	yes	Use the improved Wasserman-Faust formula for closeness computation.

Table 283. Results

Name	Type	Description
nodeId	Integer	Node ID.
score	Float	Closeness centrality score.

Run Closeness Centrality in stats mode on a named graph.

```
CALL gds.beta.closeness.stats(
  graphName: String,
  configuration: Map
)
YIELD
  centralityDistribution: Map,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  preProcessingMillis: Integer,
  configuration: Map
```

Table 284. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 285. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 286. Algorithm specific configuration

Name	Type	Default	Optional	Description
useWassermanFaust	Boolean	false	yes	Use the improved Wasserman-Faust formula for closeness computation.

Table 287. Results

Name	Type	Description
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the statistics.
configuration	Map	Configuration used for running the algorithm.

Run Betweenness Centrality in mutate mode on a named graph.

```
CALL gds.beta.closeness.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  mutateProperty: String,
  centralityDistribution: Map,
  configuration: Map
```

Table 288. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 289. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 290. Algorithm specific configuration

Name	Type	Default	Optional	Description
useWassermanFaust	Boolean	false	yes	Use the improved Wasserman-Faust formula for closeness computation.

Table 291. Results

Name	Type	Description
nodePropertiesWritten	Integer	Number of properties added to the in-memory graph.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the statistics.

Name	Type	Description
mutateMillis	Integer	Milliseconds for mutating the GDS graph.
mutateProperty	String	The node property updated in the GDS graph.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	Configuration used for running the algorithm.

Run Closeness Centrality in write mode on a named graph.

```
CALL gds.beta.closeness.write(
  graphName: String,
  configuration: Map
)
YIELD
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  writeProperty: String,
  centralityDistribution: Map,
  configuration: Map
```

Table 292. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 293. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 294. Algorithm specific configuration

Name	Type	Default	Optional	Description
useWassermanFaust	Boolean	`false`	yes	Use the improved Wasserman-Faust formula for closeness computation.

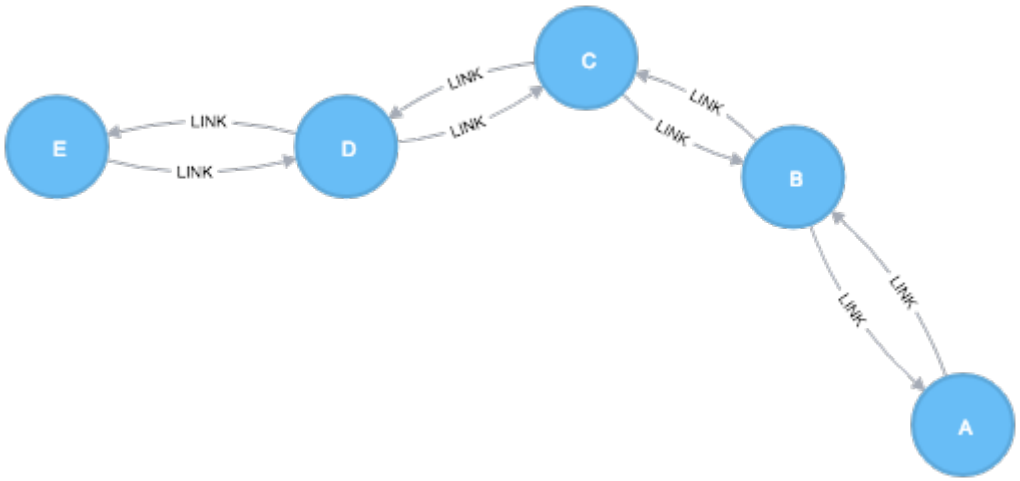
Table 295. Results

Name	Type	Description
nodePropertiesWritten	Integer	Number of properties written to Neo4j.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.

Name	Type	Description
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the statistics.
writeMillis	Integer	Milliseconds for mutating the GDS graph.
writeProperty	String	The node property updated in the GDS graph.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.
configuration	Map	Configuration used for running the algorithm.

Examples

In this section we will show examples of running the Closeness Centrality algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small sample graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE (a:Node {id:"A"}),
       (b:Node {id:"B"}),
       (c:Node {id:"C"}),
       (d:Node {id:"D"}),
       (e:Node {id:"E"}),
       (a)-[:LINK]->(b),
       (b)-[:LINK]->(a),
       (b)-[:LINK]->(c),
       (c)-[:LINK]->(b),
       (c)-[:LINK]->(d),
       (d)-[:LINK]->(c),
       (d)-[:LINK]->(e),
       (e)-[:LINK]->(d);
```

With the graph in Neo4j we can now project it into the graph catalog to prepare it for algorithm execution.

We do this using a native projection targeting the `Node` nodes and the `LINK` relationships.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will create a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project('myGraph', 'Node', 'LINK')
```

In the following examples we will demonstrate using the Closeness Centrality algorithm on this graph.

Stream

In the `stream` execution mode, the algorithm returns the centrality for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode:

```
CALL gds.beta.closeness.stream('myGraph')
YIELD nodeId, score
RETURN gds.util.asNode(nodeId).id AS id, score
ORDER BY score DESC
```

Table 296. Results

id	score
"C"	0.6666666666666666
"B"	0.5714285714285714
"D"	0.5714285714285714
"A"	0.4
"E"	0.4

C is the best connected node in this graph, although B and D aren't far behind. A and E don't have close ties to many other nodes, so their scores are lower. Any node that has a direct connection to all other nodes would score 1.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm in `stats` mode:

```
CALL gds.beta.closeness.stats('myGraph')
YIELD centralityDistribution
RETURN centralityDistribution.min AS minimumScore, centralityDistribution.mean AS meanScore
```

Table 297. Results

minimumScore	meanScore
0.399999618530273	0.521904373168945

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the centrality for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.beta.closeness.mutate('myGraph', { mutateProperty: 'centrality' })
YIELD centralityDistribution, nodePropertiesWritten
RETURN centralityDistribution.min AS minimumScore, centralityDistribution.mean AS meanScore,
nodePropertiesWritten
```

Table 298. Results

minimumScore	meanScore	nodePropertiesWritten
0.399999618530273	0.521904373168945	5

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the centrality for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.beta.closeness.write('myGraph', { writeProperty: 'centrality' })
YIELD centralityDistribution, nodePropertiesWritten
RETURN centralityDistribution.min AS minimumScore, centralityDistribution.mean AS meanScore,
nodePropertiesWritten
```

Table 299. Results

minimumScore	meanScore	nodePropertiesWritten
0.399999618530273	0.521904373168945	5

6.2.7. Harmonic Centrality Alpha

This section describes the Harmonic Centrality algorithm

Harmonic centrality (also known as valued centrality) is a variant of closeness centrality, that was invented to solve the problem the original formula had when dealing with unconnected graphs. As with many of the centrality algorithms, it originates from the field of social network analysis.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

Harmonic centrality was proposed by Marchiori and Latora in Harmony in the Small World while trying to come up with a sensible notion of "average shortest path".

They suggested a different way of calculating the average distance to that used in the Closeness Centrality algorithm. Rather than summing the distances of a node to all other nodes, the harmonic centrality algorithm sums the inverse of those distances. This enables it deal with infinite values.

The **raw harmonic centrality** for a node is calculated using the following formula:

```
raw harmonic centrality(node) = sum(1 / distance from node to every other node excluding
itself)
```

As with closeness centrality, we can also calculate a **normalized harmonic centrality** with the following formula:

```
normalized harmonic centrality(node) = sum(1 / distance from node to every other node excluding
itself) / (number of nodes - 1)
```

In this formula, ∞ values are handled cleanly.

Use-cases - when to use the Harmonic Centrality algorithm

Harmonic centrality was proposed as an alternative to closeness centrality, and therefore has similar use cases.

For example, we might use it if we're trying to identify where in the city to place a new public service so that it's easily accessible for residents. If we're trying to spread a message on social media we could use the algorithm to find the key influencers that can help us achieve our goal.

Syntax

The following will run the algorithm and write back results:

```
CALL gds.alpha.closeness.harmonic.write(configuration: Map)
YIELD nodes, preProcessingMillis, computeMillis, writeMillis, centralityDistribution
```

Table 300. Parameters

Name	Type	Default	Optional	Description
concurrency	int	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'.
readConcurrency	int	value of 'concurrency'	yes	The number of concurrent threads used for reading the graph.
writeConcurrency	int	value of 'concurrency'	yes	The number of concurrent threads used for writing the result.
writeProperty	string	'centrality'	yes	The property name written back to.

Table 301. Results

Name	Type	Description
nodes	int	The number of nodes considered.
preProcessingMillis	int	Milliseconds for preprocessing the data.
computeMillis	int	Milliseconds for running the algorithm.
writeMillis	int	Milliseconds for writing result data back.
writeProperty	string	The property name written back to.
centralityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of centrality values.

The following will run the algorithm and stream results:

```
CALL gds.alpha.closeness.harmonic.stream(configuration: Map)
YIELD nodeId, centrality
```

Table 302. Parameters

Name	Type	Default	Optional	Description
concurrency	int	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'.
readConcurrency	int	value of 'concurrency'	yes	The number of concurrent threads used for reading the graph.

Table 303. Results

Name	Type	Description
node	long	Node ID

Name	Type	Description
centrality	float	Harmonic centrality score

Harmonic Centrality algorithm sample

The following will create a sample graph:

```
CREATE (a:Node{id:"A"}),
       (b:Node{id:"B"}),
       (c:Node{id:"C"}),
       (d:Node{id:"D"}),
       (e:Node{id:"E"}),
       (a)-[:LINK]->(b),
       (b)-[:LINK]->(c),
       (d)-[:LINK]->(e)
```

The following will project and store a named graph:

```
CALL gds.graph.project(
  'graph',
  'Node',
  'LINK'
)
```

The following will run the algorithm and stream results:

```
CALL gds.alpha.closeness.harmonic.stream('graph', {})
YIELD nodeId, centrality
RETURN gds.util.asNode(nodeId).name AS user, centrality
ORDER BY centrality DESC
```

Table 304. Results

Name	Centrality weight
B	0.5
A	0.375
c	0.375
D	0.25
E	0.25

The following will run the algorithm and write back results:

```
CALL gds.alpha.closeness.harmonic.write('graph', {})
YIELD nodes, writeProperty
```

Table 305. Results

nodes	writeProperty
5	"centrality"

6.2.8. HITS Alpha

This section describes the HITS algorithm in the Neo4j Graph Data Science library.

Introduction

The Hyperlink-Induced Topic Search (HITS) is a link analysis algorithm that rates nodes based on two scores, a `hub` score and an `authority` score. The `authority` score estimates the importance of the node within the network. The `hub` score estimates the value of its relationships to other nodes. The GDS implementation is based on the Authoritative Sources in a Hyperlinked Environment publication by Jon M. Kleinberg.

Syntax

This section covers the syntax used to execute the HITS algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Run HITS in stream mode on a named graph.

```
CALL gds.alpha.hits.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  values: Map
```

Table 306. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 307. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 308. Algorithm specific configuration

Name	Type	Default	Optional	Description
hitsIterations	Integer	n/a	no	The number of hits iterations to run. The number of pregel iterations will be equal to `hitsIterations * 4 + 1`
authProperty	String	"auth"	yes	The name that is used for the auth property when using `STREAM`, `MUTATE` or `WRITE` modes.
hubProperty	String	"hub"	yes	The name that is used for the hub property when using `STREAM`, `MUTATE` or `WRITE` modes.

Table 309. Results

Name	Type	Description
nodeId	Integer	Node ID.
values	Map	A map containing the `auth` and `hub` keys.

Run HITS in stats mode on a named graph.

```
CALL gds.alpha.hits.stats(
  graphName: String,
  configuration: Map
)
YIELD
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  configuration: Map
```

Table 310. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 311. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm.

Table 312. Algorithm specific configuration

Name	Type	Default	Optional	Description
hitsIterations	Integer	n/a	no	The number of hits iterations to run. The number of pregel iterations will be equal to `hitsIterations * 4 + 1`
authProperty	String	"auth"	yes	The name that is used for the auth property when using `STREAM`, `MUTATE` or `WRITE` modes.
hubProperty	String	"hub"	yes	The name that is used for the hub property when using `STREAM`, `MUTATE` or `WRITE` modes.

Table 313. Results

Name	Type	Description
ranIterations	Integer	Number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.

Name	Type	Description
computeMillis	Integer	Milliseconds for running the algorithm.
configuration	Map	Configuration used for running the algorithm.

Run HITS in mutate mode on a named graph.

```
CALL gds.alpha.hits.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 314. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 315. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm.

Table 316. Algorithm specific configuration

Name	Type	Default	Optional	Description
hitsIterations	Integer	n/a	no	The number of hits iterations to run. The number of pregel iterations will be equal to `hitsIterations * 4 + 1`
authProperty	String	"auth"	yes	The name that is used for the auth property when using `STREAM`, `MUTATE` or `WRITE` modes.
hubProperty	String	"hub"	yes	The name that is used for the hub property when using `STREAM`, `MUTATE` or `WRITE` modes.

Table 317. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.

Name	Type	Description
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
nodePropertiesWritten	Integer	The number of properties that were written to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Run HITS in write mode on a named graph.

```
CALL gds.alpha.hits.write(
  graphName: String,
  configuration: Map
)
YIELD
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 318. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 319. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 320. Algorithm specific configuration

Name	Type	Default	Optional	Description
hitsIterations	Integer	n/a	no	The number of hits iterations to run. The number of pregel iterations will be equal to `hitsIterations * 4 + 1`
authProperty	String	"auth"	yes	The name that is used for the auth property when using `STREAM`, `MUTATE` or `WRITE` modes.
hubProperty	String	"hub"	yes	The name that is used for the hub property when using `STREAM`, `MUTATE` or `WRITE` modes.

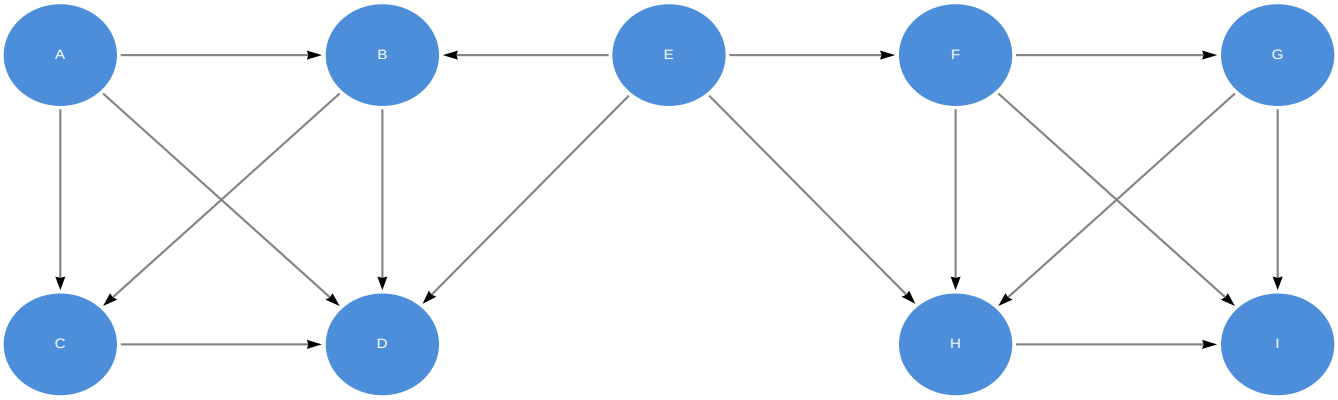
Table 321. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.

Name	Type	Description
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back.
nodePropertiesWritten	Integer	The number of properties that were written to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the HITS algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (a:Website {name: 'A'}),
  (b:Website {name: 'B'}),
  (c:Website {name: 'C'}),
  (d:Website {name: 'D'}),
  (e:Website {name: 'E'}),
  (f:Website {name: 'F'}),
  (g:Website {name: 'G'}),
  (h:Website {name: 'H'}),
  (i:Website {name: 'I'}),

  (a)-[:LINK]->(b),
  (a)-[:LINK]->(c),
  (a)-[:LINK]->(d),
  (b)-[:LINK]->(c),
  (b)-[:LINK]->(d),
  (c)-[:LINK]->(d),

  (e)-[:LINK]->(b),
  (e)-[:LINK]->(d),
  (e)-[:LINK]->(f),
  (e)-[:LINK]->(h),

  (f)-[:LINK]->(g),
  (f)-[:LINK]->(i),
  (f)-[:LINK]->(h),
  (g)-[:LINK]->(h),
  (g)-[:LINK]->(i),
  (h)-[:LINK]->(i);
```

In the example, we will use the HITS algorithm to calculate the authority and hub scores.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
  'myGraph',
  'Website',
  'LINK'
);
```

In the following examples we will demonstrate using the HITS algorithm on this graph.

Stream

In the `stream` execution mode, the algorithm returns the authority and hub scores for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm, and stream results:

```
CALL gds.alpha.hits.stream('myGraph', {hitsIterations: 20})
YIELD nodeId, values
RETURN gds.util.asNode(nodeId).name AS Name, values.auth AS auth, values.hub as hub
ORDER BY Name ASC
```

Table 322. Results

Name	auth	hub
"A"	0.0	0.5147630377521207
"B"	0.42644630743935796	0.3573686670593437
"C"	0.3218729455718005	0.23857061715828276
"D"	0.6463862608483191	0.0
"E"	0.0	0.640681017095129
"F"	0.23646490227616518	0.2763222153580397
"G"	0.10200264424057169	0.23867470447760597
"H"	0.426571816146601	0.0812340105698113
"I"	0.22009646020698218	0.0

6.2.9. Influence Maximization

This chapter provides explanations and examples for each of the influence maximization algorithms in the Neo4j Graph Data Science library.

The objective of influence maximization is to find a small subset of k nodes from a network in order to achieve maximization to the total number of nodes influenced by these k nodes. The Neo4j GDS library includes the following alpha influence maximization algorithms:

- Alpha
  - Greedy
  - CELF

CELF Alpha

This section describes the Cost Effective Lazy Forward (CELF) influence maximization algorithm in the Neo4j Graph Data Science library.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

This topic includes:

- Introduction
- Syntax
- Examples
  - Stream

Introduction

The CELF algorithm for influence maximization aims to find `k` nodes that maximize the expected spread of influence in the network. It simulates the influence spread using the Independent Cascade model, which calculates the expected spread by taking the average spread over the `mc` Monte-Carlo simulations. In the propagation process, a node is influenced in case that a uniform random draw is less than the probability `p`.

Leskovec et al. 2007 introduced the CELF algorithm in their study Cost-effective Outbreak Detection in Networks to deal with the NP-hard problem of influence maximization. The CELF algorithm is based on a "lazy-forward" optimization. The CELF algorithm dramatically improves the efficiency of the Greedy algorithm and should be preferred for large networks.

Syntax

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

Run CELF in stream mode on a named graph.

```
CALL gds.alpha.influenceMaximization.celf.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  spread: Float
```

Table 323. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 324. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 325. Algorithm specific configuration

Name	Type	Default	Optional	Description
seedSetSize	Integer	n/a	no	The number of nodes that maximize the expected spread in the network.
monteCarloSimulations	Integer	1000	yes	The number of Monte-Carlo simulations.
propagationProbability	Float	0.1	yes	The probability of a node being activated by an active neighbour node.

Table 326. Results

Name	Type	Description
nodeId	Integer	Node ID.
spread	Float	The spread gained by selecting the node.

Run CELF in stats mode on a named graph.

```
CALL gds.alpha.influenceMaximization.celf.stats(
  graphName: String,
  configuration: Map
)
YIELD
  nodes: Integer,
  computeMillis: Integer,
```

Table 327. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 328. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 329. Algorithm specific configuration

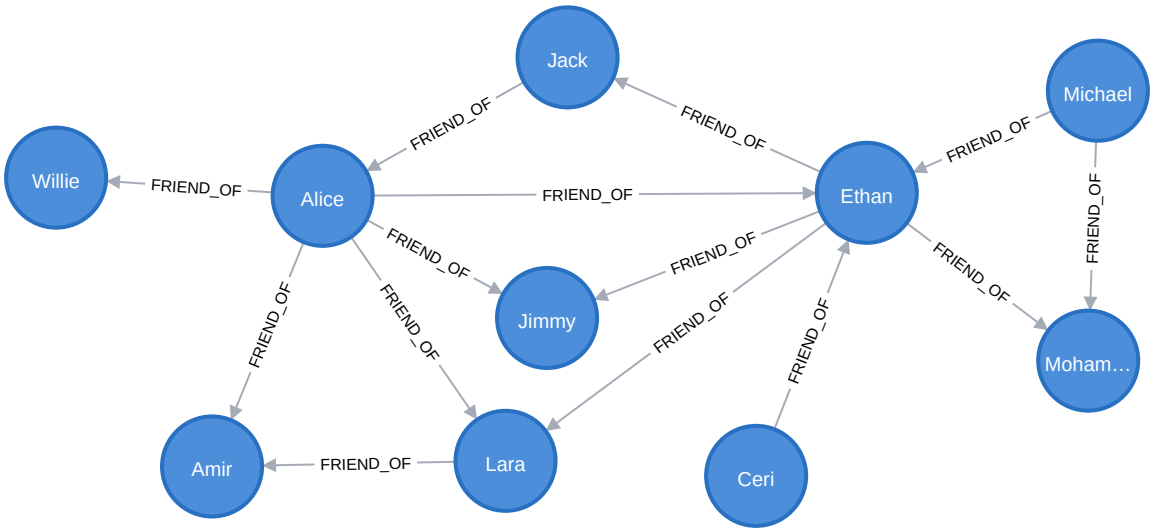
Name	Type	Default	Optional	Description
seedSetSize	Integer	n/a	no	The number of nodes that maximize the expected spread in the network.
monteCarloSimulations	Integer	1000	yes	The number of Monte-Carlo simulations.
propagationProbability	Float	0.1	yes	The probability of a node being activated by an active neighbour node.

Table 330. Results

Name	Type	Description
nodes	Integer	The number of nodes in the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Examples

In this section we will show examples of running the CELF algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (a:Person {name: 'Jimmy'}),
  (b:Person {name: 'Jack'}),
  (c:Person {name: 'Alice'}),
  (d:Person {name: 'Ceri'}),
  (e:Person {name: 'Mohammed'}),
  (f:Person {name: 'Michael'}),
  (g:Person {name: 'Ethan'}),
  (h:Person {name: 'Lara'}),
  (i:Person {name: 'Amir'}),
  (j:Person {name: 'Willie'}),

  (b)-[:FRIEND_OF]->(c),
  (c)-[:FRIEND_OF]->(a),
  (c)-[:FRIEND_OF]->(g),
  (c)-[:FRIEND_OF]->(h),
  (c)-[:FRIEND_OF]->(i),
  (c)-[:FRIEND_OF]->(j),
  (d)-[:FRIEND_OF]->(g),
  (f)-[:FRIEND_OF]->(e),
  (f)-[:FRIEND_OF]->(g),
  (g)-[:FRIEND_OF]->(a),
  (g)-[:FRIEND_OF]->(b),
  (g)-[:FRIEND_OF]->(h),
  (g)-[:FRIEND_OF]->(e),
  (h)-[:FRIEND_OF]->(i);
```

In the example, we will use the CELF algorithm to find k nodes subset.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
  'myGraph',
  'Person',
  'FRIEND_OF'
);
```

In the following examples we will demonstrate using the CELF algorithm on this graph.

Stream

In the `stream` execution mode, the algorithm returns the spread for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm, and stream results:

```
CALL gds.alpha.influenceMaximization.celf.stream('myGraph', {seedSetSize: 3, concurrency: 4})
YIELD nodeId, spread
RETURN gds.util.asNode(nodeId).name AS Name, spread
ORDER BY spread ASC
```

Table 331. Results

Name	spread
"Alice"	1.519
"Ethan"	2.701
"Michael"	3.8

Greedy Alpha

> *This section describes the Greedy influence maximization algorithm in the Neo4j Graph Data Science library.*

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

This topic includes:

- Introduction
- Syntax
- Examples
  - Stream

Introduction

The Greedy algorithm for influence maximization aims to find k nodes that maximize the expected spread of influence in a network. It simulates the influence spread using the Independent Cascade model, which calculates the expected spread by taking the average spread over the `mc` Monte-Carlo simulations. In the propagation process, a node is influenced in case that a uniform random draw is less than the probability `p`.

Kempe et al. 2003 introduced the Greedy algorithm in their study Maximizing the Spread of Influence

through a Social Network to deal with the NP-hard problem of influence maximization. The Greedy algorithm successively selecting the node within the maximum marginal gain approximation in polynomial time. For large networks CELF algorithm should be used.

Syntax

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

Greedy syntax per mode

Run Greedy in stream mode on a named graph.

```
CALL gds.alpha.influenceMaximization.greedy.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  spread : Float
```

Table 332. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 333. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 334. Algorithm specific configuration

Name	Type	Default	Optional	Description
seedSetSize	Integer	n/a	no	The number of nodes that maximize the expected spread in the network.
monteCarloSimulations	Integer	1000	yes	The number of Monte-Carlo simulations.
propagationProbability	Float	0.1	yes	The probability of a node being activated by an active neighbour node.

Table 335. Results

Name	Type	Description
nodeId	Integer	Node ID.
spread	Float	The spread gained by selecting the node.

Run Greedy in stats mode on a named graph.

```
CALL gds.alpha.influenceMaximization.greedy.stats(
  graphName: String,
  configuration: Map
)
YIELD
  nodes: Integer,
  computeMillis: Integer,
```

Table 336. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 337. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 338. Algorithm specific configuration

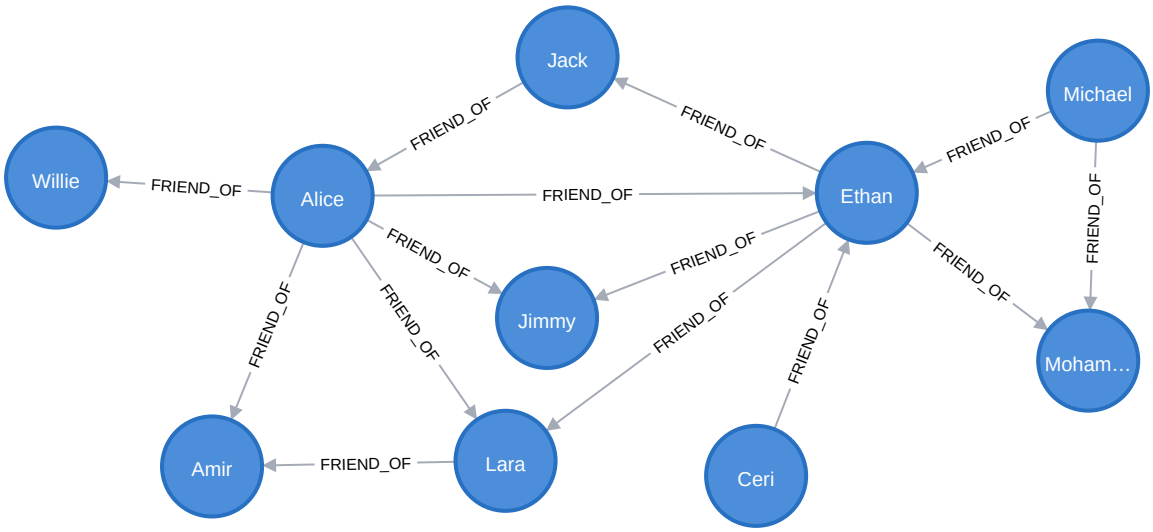
Name	Type	Default	Optional	Description
seedSetSize	Integer	n/a	no	The number of nodes that maximize the expected spread in the network.
monteCarloSimulations	Integer	1000	yes	The number of Monte-Carlo simulations.
propagationProbability	Float	0.1	yes	The probability of a node being activated by an active neighbour node.

Table 339. Results

Name	Type	Description
nodes	Integer	The number of nodes in the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Examples

In this section we will show examples of running the Greedy algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (a:Person {name: 'Jimmy'}),
  (b:Person {name: 'Jack'}),
  (c:Person {name: 'Alice'}),
  (d:Person {name: 'Ceri'}),
  (e:Person {name: 'Mohammed'}),
  (f:Person {name: 'Michael'}),
  (g:Person {name: 'Ethan'}),
  (h:Person {name: 'Lara'}),
  (i:Person {name: 'Amir'}),
  (j:Person {name: 'Willie'}),

  (b)-[:FRIEND_OF]->(c),
  (c)-[:FRIEND_OF]->(a),
  (c)-[:FRIEND_OF]->(g),
  (c)-[:FRIEND_OF]->(h),
  (c)-[:FRIEND_OF]->(i),
  (c)-[:FRIEND_OF]->(j),
  (d)-[:FRIEND_OF]->(g),
  (f)-[:FRIEND_OF]->(e),
  (f)-[:FRIEND_OF]->(g),
  (g)-[:FRIEND_OF]->(a),
  (g)-[:FRIEND_OF]->(b),
  (g)-[:FRIEND_OF]->(h),
  (g)-[:FRIEND_OF]->(e),
  (h)-[:FRIEND_OF]->(i);
```

In the example, we will use the Greedy algorithm to find k nodes subset.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
  'myGraph',
  'Person',
  'FRIEND_OF'
);
```

In the following examples we will demonstrate using the Greedy algorithm on this graph.

Stream

In the `stream` execution mode, the algorithm returns the spread for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm, and stream results:

```
CALL gds.alpha.influenceMaximization.greedy.stream('myGraph', {seedSetSize: 3, concurrency: 4})
YIELD nodeId, spread
RETURN gds.util.asNode(nodeId).name AS Name, spread
ORDER BY spread ASC
```

Table 340. Results

Name	spread
"Alice"	1.519
"Ethan"	2.701
"Michael"	3.8

6.3. Community detection

> *This chapter provides explanations and examples for each of the community detection algorithms in the Neo4j Graph Data Science library.*

Community detection algorithms are used to evaluate how groups of nodes are clustered or partitioned, as well as their tendency to strengthen or break apart. The Neo4j GDS library includes the following community detection algorithms, grouped by quality tier:

- Production-quality
  - Louvain
  - Label Propagation
  - Weakly Connected Components
  - Triangle Count
  - Local Clustering Coefficient
- Beta
  - K-1 Coloring
  - Modularity Optimization
- Alpha
  - Strongly Connected Components

- Speaker-Listener Label Propagation
- Approximate Maximum k-cut
- Conductance metric

6.3.1. Louvain

This section describes the Louvain algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Louvain method is an algorithm to detect communities in large networks. It maximizes a modularity score for each community, where the modularity quantifies the quality of an assignment of nodes to communities. This means evaluating how much more densely connected the nodes within a community are, compared to how connected they would be in a random network.

The Louvain algorithm is a hierarchical clustering algorithm, that recursively merges communities into a single node and executes the modularity clustering on the condensed graphs.

For more information on this algorithm, see:

- Lu, Hao, Mahantesh Halappanavar, and Ananth Kalyanaraman "Parallel heuristics for scalable community detection."
- https://en.wikipedia.org/wiki/Louvain_modularity

Running this algorithm requires sufficient memory availability. Before running this algorithm, we recommend that you read Memory Estimation.

Syntax

This section covers the syntax used to execute the Louvain algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Louvain syntax per mode

Run Louvain in stream mode on a named graph.

```
CALL gds.louvain.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  communityId: Integer,
  intermediateCommunityIds: List of Integer
```

Table 341. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 342. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 343. Algorithm specific configuration

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	Used to set the initial community for a node. The property value needs to be a number.
maxLevels	Integer	10	yes	The maximum number of levels in which the graph is clustered and then condensed.
maxIterations	Integer	10	yes	The maximum number of iterations that the modularity optimization will run for each level.
tolerance	Float	0.0001	yes	Minimum change in modularity between iterations. If the modularity changes less than the tolerance value, the result is considered stable and the algorithm returns.
includeIntermediateCommunities	Boolean	false	yes	Indicates whether to write intermediate communities. If set to false, only the final community is persisted.

Name	Type	Default	Optional	Description
consecutiveIds	Boolean	`false`	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory). Cannot be used in combination with the `includeIntermediateCommunities` flag.

Table 344. Results

Name	Type	Description
nodeId	Integer	Node ID.
communityId	Integer	The community ID of the final level.
intermediateCommunityIds	List of Integer	Community IDs for each level. `Null` if `includeIntermediateCommunities` is set to false.

Run Louvain in stats mode on a named graph.

```
CALL gds.louvain.stats(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  communityCount: Integer,
  ranLevels: Integer,
  modularity: Float,
  modularities: List of Float,
  communityDistribution: Map,
  configuration: Map
```

Table 345. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 346. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 347. Algorithm specific configuration

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	Used to set the initial community for a node. The property value needs to be a number.
maxLevels	Integer	10	yes	The maximum number of levels in which the graph is clustered and then condensed.
maxIterations	Integer	10	yes	The maximum number of iterations that the modularity optimization will run for each level.
tolerance	Float	0.0001	yes	Minimum change in modularity between iterations. If the modularity changes less than the tolerance value, the result is considered stable and the algorithm returns.

Name	Type	Default	Optional	Description
includeIntermediateCommunities	Boolean	`false`	yes	Indicates whether to write intermediate communities. If set to false, only the final community is persisted.
consecutiveIds	Boolean	`false`	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory). Cannot be used in combination with the `includeIntermediateCommunities` flag.

Table 348. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing percentiles and community count.
communityCount	Integer	The number of communities found.
ranLevels	Integer	The number of supersteps the algorithm actually ran.
modularity	Float	The final modularity score.
modularities	List of Float	The modularity scores for each level.
communityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of community size for the last level.
configuration	Map	The configuration used for running the algorithm.

Run Louvain in mutate mode on a named graph.

```
CALL gds.louvain.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  postProcessingMillis: Integer,
  communityCount: Integer,
  ranLevels: Integer,
  modularity: Float,
  modularities: List of Float,
  nodePropertiesWritten: Integer,
  communityDistribution: Map,
  configuration: Map
```

Table 349. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 350. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 351. Algorithm specific configuration

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	Used to set the initial community for a node. The property value needs to be a number.
maxLevels	Integer	10	yes	The maximum number of levels in which the graph is clustered and then condensed.
maxIterations	Integer	10	yes	The maximum number of iterations that the modularity optimization will run for each level.
tolerance	Float	0.0001	yes	Minimum change in modularity between iterations. If the modularity changes less than the tolerance value, the result is considered stable and the algorithm returns.

Name	Type	Default	Optional	Description
includeIntermediateCommunities	Boolean	`false`	yes	Indicates whether to write intermediate communities. If set to false, only the final community is persisted.
consecutiveIds	Boolean	`false`	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory). Cannot be used in combination with the `includeIntermediateCommunities` flag.

Table 352. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
postProcessingMillis	Integer	Milliseconds for computing percentiles and community count.
communityCount	Integer	The number of communities found.
ranLevels	Integer	The number of supersteps the algorithm actually ran.
modularity	Float	The final modularity score.
modularities	List of Float	The modularity scores for each level.
nodePropertiesWritten	Integer	Number of properties added to the projected graph.
communityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of community size for the last level.
configuration	Map	The configuration used for running the algorithm.

Run Louvain in write mode on a named graph.

```
CALL gds.louvain.write(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  postProcessingMillis: Integer,
  nodePropertiesWritten: Integer,
  communityCount: Integer,
  ranLevels: Integer,
  modularity: Float,
  modularities: List of Float,
  communityDistribution: Map,
  configuration: Map
```

Table 353. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 354. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 355. Algorithm specific configuration

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	`n/a`	yes	Used to set the initial community for a node. The property value needs to be a number.
maxLevels	Integer	`10`	yes	The maximum number of levels in which the graph is clustered and then condensed.
maxIterations	Integer	`10`	yes	The maximum number of iterations that the modularity optimization will run for each level.

Name	Type	Default	Optional	Description
tolerance	Float	`0.0001`	yes	Minimum change in modularity between iterations. If the modularity changes less than the tolerance value, the result is considered stable and the algorithm returns.
includeIntermediateCommunities	Boolean	`false`	yes	Indicates whether to write intermediate communities. If set to false, only the final community is persisted.
consecutiveIds	Boolean	`false`	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory). Cannot be used in combination with the `includeIntermediateCommunities` flag.
minCommunitySize	Integer	`0`	yes	Only community ids of communities with a size greater than or equal to the given value are written to Neo4j.

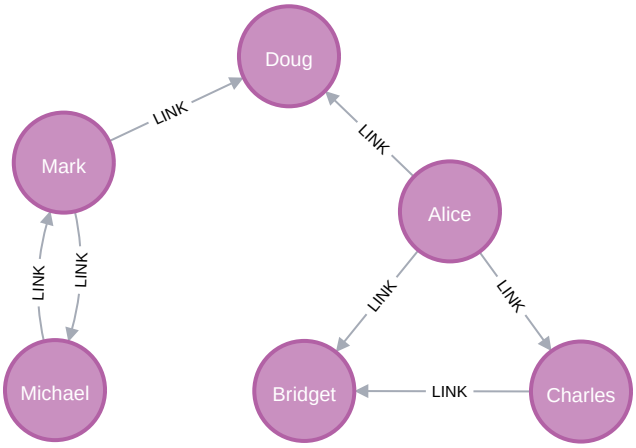
Table 356. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back.
postProcessingMillis	Integer	Milliseconds for computing percentiles and community count.
nodePropertiesWritten	Integer	The number of node properties written.
communityCount	Integer	The number of communities found.
ranLevels	Integer	The number of supersteps the algorithm actually ran.
modularity	Float	The final modularity score.
modularities	List of Float	The modularity scores for each level.
communityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of community size for the last level.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Louvain community detection algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes

connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (nAlice:User {name: 'Alice', seed: 42}),
  (nBridget:User {name: 'Bridget', seed: 42}),
  (nCharles:User {name: 'Charles', seed: 42}),
  (nDoug:User {name: 'Doug'}),
  (nMark:User {name: 'Mark'}),
  (nMichael:User {name: 'Michael'}),

  (nAlice)-[:LINK {weight: 1}]->(nBridget),
  (nAlice)-[:LINK {weight: 1}]->(nCharles),
  (nCharles)-[:LINK {weight: 1}]->(nBridget),

  (nAlice)-[:LINK {weight: 5}]->(nDoug),

  (nMark)-[:LINK {weight: 1}]->(nDoug),
  (nMark)-[:LINK {weight: 1}]->(nMichael),
  (nMichael)-[:LINK {weight: 1}]->(nMark);
```

This graph has two clusters of *Users*, that are closely connected. Between those clusters there is one single edge. The relationships that connect the nodes in each component have a property `weight` which determines the strength of the relationship.

We can now project the graph and store it in the graph catalog. We load the `LINK` relationships with orientation set to `UNDIRECTED` as this works best with the Louvain algorithm.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
    'myGraph',
    'User',
    {
        LINK: {
            orientation: 'UNDIRECTED'
        }
    },
    {
        nodeProperties: 'seed',
        relationshipProperties: 'weight'
    }
)
```

In the following examples we will demonstrate using the Louvain algorithm on this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.louvain.write.estimate('myGraph', { writeProperty: 'community' })
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 357. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	14	5313	563880	"[5313 Bytes ... 550 KiB]"

Stream

In the `stream` execution mode, the algorithm returns the community ID for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm and stream results:

```
CALL gds.louvain.stream('myGraph')
YIELD nodeId, communityId, intermediateCommunityIds
RETURN gds.util.asNode(nodeId).name AS name, communityId, intermediateCommunityIds
ORDER BY name ASC
```

Table 358. Results

name	communityId	intermediateCommunityIds
"Alice"	2	null
"Bridget"	2	null
"Charles"	2	null
"Doug"	5	null
"Mark"	5	null
"Michael"	5	null

We use default values for the procedure configuration parameter. Levels and `innerIterations` are set to 10 and the tolerance value is 0.0001. Because we did not set the value of `includeIntermediateCommunities` to `true`, the column communities is always `null`.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm and returns the result in form of statistical and measurement values

```
CALL gds.louvain.stats('myGraph')
YIELD communityCount
```

Table 359. Results

communityCount
2

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the community ID for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm and store the results in `myGraph`:

```
CALL gds.louvain.mutate('myGraph', { mutateProperty: 'communityId' })
YIELD communityCount, modularity, modularities
```

Table 360. Results

communityCount	modularity	modularities
2	0.3571428571428571	[0.3571428571428571]

In `mutate` mode, only a single row is returned by the procedure. The result contains meta information, like the number of identified communities and the modularity values. In contrast to the `write` mode the result is written to the GDS in-memory graph instead of the Neo4j database.

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the community ID for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following run the algorithm, and write back results:

```
CALL gds.louvain.write('myGraph', { writeProperty: 'community' })
YIELD communityCount, modularity, modularities
```

Table 361. Results

communityCount	modularity	modularities
2	0.3571428571428571	[0.3571428571428571]

When writing back the results, only a single row is returned by the procedure. The result contains meta information, like the number of identified communities and the modularity values.

Weighted

The Louvain algorithm can also run on weighted graphs, taking the given relationship weights into concern when calculating the modularity.

The following will run the algorithm on a weighted graph and stream results:

```
CALL gds.louvain.stream('myGraph', { relationshipWeightProperty: 'weight' })
YIELD nodeId, communityId, intermediateCommunityIds
RETURN gds.util.asNode(nodeId).name AS name, communityId, intermediateCommunityIds
ORDER BY name ASC
```

Table 362. Results

name	communityId	intermediateCommunityIds
"Alice"	3	null
"Bridget"	2	null
"Charles"	2	null
"Doug"	3	null
"Mark"	5	null
"Michael"	5	null

Using the weighted relationships, we see that `Alice` and `Doug` have formed their own community, as their link is much stronger than all the others.

Seeded

The Louvain algorithm can be run incrementally, by providing a seed property. With the seed property an initial community mapping can be supplied for a subset of the loaded nodes. The algorithm will try to keep the seeded community IDs.

The following will run the algorithm and stream results:

```
CALL gds.louvain.stream('myGraph', { seedProperty: 'seed' })
YIELD nodeId, communityId, intermediateCommunityIds
RETURN gds.util.asNode(nodeId).name AS name, communityId, intermediateCommunityIds
ORDER BY name ASC
```

Table 363. Results

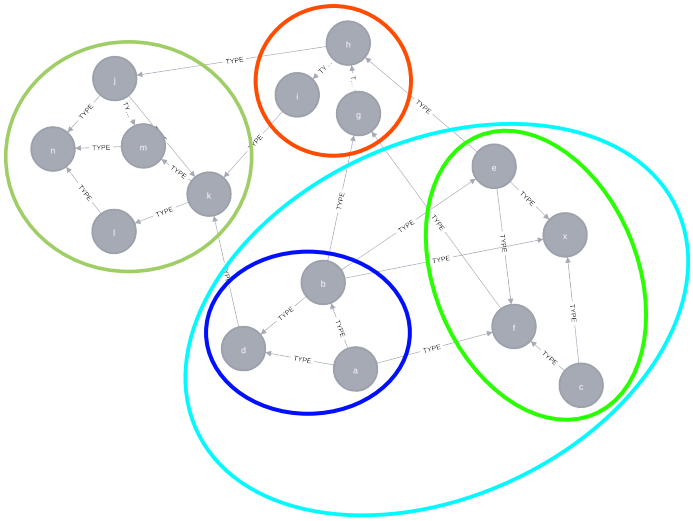
name	communityId	intermediateCommunityIds
"Alice"	42	null
"Bridget"	42	null
"Charles"	42	null
"Doug"	47	null
"Mark"	47	null
"Michael"	47	null

Using the seeded graph, we see that the community around `Alice` keeps its initial community ID of `42`. The other community is assigned a new community ID, which is guaranteed to be larger than the largest seeded community ID. Note that the `consecutiveIds` configuration option cannot be used in combination with seeding in order to retain the seeding values.

Stream intermediate communities

As described before, Louvain is a hierarchical clustering algorithm. That means that after every clustering step all nodes that belong to the same cluster are reduced to a single node. Relationships between nodes of the same cluster become self-relationships, relationships to nodes of other clusters connect to the clusters representative. This condensed graph is then used to run the next level of clustering. The process is repeated until the clusters are stable.

In order to demonstrate this iterative behavior, we need to construct a more complex graph.



```
CREATE (a:Node {name: 'a'})
CREATE (b:Node {name: 'b'})
CREATE (c:Node {name: 'c'})
CREATE (d:Node {name: 'd'})
CREATE (e:Node {name: 'e'})
CREATE (f:Node {name: 'f'})
CREATE (g:Node {name: 'g'})
CREATE (h:Node {name: 'h'})
CREATE (i:Node {name: 'i'})
CREATE (j:Node {name: 'j'})
CREATE (k:Node {name: 'k'})
CREATE (l:Node {name: 'l'})
CREATE (m:Node {name: 'm'})
CREATE (n:Node {name: 'n'})
CREATE (x:Node {name: 'x'})

CREATE (a)-[:TYPE]->(b)
CREATE (a)-[:TYPE]->(d)
CREATE (a)-[:TYPE]->(f)
CREATE (b)-[:TYPE]->(d)
CREATE (b)-[:TYPE]->(x)
CREATE (b)-[:TYPE]->(g)
CREATE (b)-[:TYPE]->(e)
CREATE (c)-[:TYPE]->(x)
CREATE (c)-[:TYPE]->(f)
CREATE (d)-[:TYPE]->(k)
CREATE (e)-[:TYPE]->(x)
CREATE (e)-[:TYPE]->(f)
CREATE (e)-[:TYPE]->(h)
CREATE (f)-[:TYPE]->(g)
CREATE (g)-[:TYPE]->(h)
CREATE (h)-[:TYPE]->(i)
CREATE (h)-[:TYPE]->(j)
CREATE (i)-[:TYPE]->(k)
CREATE (j)-[:TYPE]->(k)
CREATE (j)-[:TYPE]->(m)
CREATE (j)-[:TYPE]->(n)
CREATE (k)-[:TYPE]->(m)
CREATE (k)-[:TYPE]->(l)
CREATE (l)-[:TYPE]->(n)
CREATE (m)-[:TYPE]->(n);
```

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
    'myGraph2',
    'Node',
    {
        TYPE: {
            type: 'TYPE',
            orientation: 'undirected',
            aggregation: 'NONE'
        }
    }
)
```

The following run the algorithm and stream results including the intermediate communities:

```
CALL gds.louvain.stream('myGraph2', { includeIntermediateCommunities: true })
YIELD nodeId, communityId, intermediateCommunityIds
RETURN gds.util.asNode(nodeId).name AS name, communityId, intermediateCommunityIds
ORDER BY name ASC
```

Table 364. Results

name	communityId	intermediateCommunityIds
"a"	14	[3, 14]
"b"	14	[3, 14]
"c"	14	[14, 14]
"d"	14	[3, 14]
"e"	14	[14, 14]
"f"	14	[14, 14]
"g"	7	[7, 7]
"h"	7	[7, 7]
"i"	7	[7, 7]
"j"	12	[12, 12]
"k"	12	[12, 12]
"l"	12	[12, 12]
"m"	12	[12, 12]
"n"	12	[12, 12]
"x"	14	[14, 14]

In this example graph, after the first iteration we see 4 clusters, which in the second iteration are reduced to three.

6.3.2. Label Propagation

This section describes the Label Propagation algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Label Propagation algorithm (LPA) is a fast algorithm for finding communities in a graph. It detects these communities using network structure alone as its guide, and doesn't require a pre-defined objective function or prior information about the communities.

LPA works by propagating labels throughout the network and forming communities based on this process of label propagation.

The intuition behind the algorithm is that a single label can quickly become dominant in a densely connected group of nodes, but will have trouble crossing a sparsely connected region. Labels will get trapped inside a densely connected group of nodes, and those nodes that end up with the same label when the algorithms finish can be considered part of the same community.

The algorithm works as follows:

- Every node is initialized with a unique community label (an identifier).
- These labels propagate through the network.
- At every iteration of propagation, each node updates its label to the one that the maximum numbers of its neighbours belongs to. Ties are broken arbitrarily but deterministically.
- LPA reaches convergence when each node has the majority label of its neighbours.
- LPA stops if either convergence, or the user-defined maximum number of iterations is achieved.

As labels propagate, densely connected groups of nodes quickly reach a consensus on a unique label. At the end of the propagation only a few labels will remain - most will have disappeared. Nodes that have the same community label at convergence are said to belong to the same community.

One interesting feature of LPA is that nodes can be assigned preliminary labels to narrow down the range of solutions generated. This means that it can be used as semi-supervised way of finding communities where we hand-pick some initial communities.

For more information on this algorithm, see:

- "Near linear time algorithm to detect community structures in large-scale networks"
- Use cases:
    - Twitter polarity classification with label propagation over lexical links and the follower graph

- Label Propagation Prediction of Drug-Drug Interactions Based on Clinical Side Effects
- "Feature Inference Based on Label Propagation on Wikidata Graph for DST"

Running this algorithm requires sufficient memory availability. Before running this algorithm, we recommend that you read Memory Estimation.

Syntax

This section covers the syntax used to execute the Label Propagation algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Label Propagation syntax per mode

Run Label Propagation in stream mode on a named graph.

```
CALL gds.labelPropagation.stream(
  graphName: String,
  configuration: Map
)
YIELD
    nodeId: Integer,
    communityId: Integer
```

Table 365. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 366. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 367. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	10	yes	The maximum number of iterations to run.
nodeWeightProperty	String	null	yes	The name of a node property that contains node weights.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	The name of a node property that defines an initial numeric label.
consecutiveIds	Boolean	false	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).

Table 368. Results

Name	Type	Description
nodeId	Integer	Node ID.
communityId	Integer	Community ID.

Run Label Propagation in stats mode on a named graph.

```
CALL gds.labelPropagation.stats(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  communityCount: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  communityDistribution: Map,
  configuration: Map
```

Table 369. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 370. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 371. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	10	yes	The maximum number of iterations to run.
nodeWeightProperty	String	null	yes	The name of a node property that contains node weights.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	The name of a node property that defines an initial numeric label.
consecutiveIds	Boolean	false	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).

Table 372. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing percentiles and community count.
communityCount	Integer	The number of communities found.
ranIterations	Integer	The number of iterations that were executed.
didConverge	Boolean	True if the algorithm did converge to a stable labelling within the provided number of maximum iterations.
communityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of community size.
configuration	Map	The configuration used for running the algorithm.

Run Label Propagation in mutate mode on a named graph.

```
CALL gds.labelPropagation.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  postProcessingMillis: Integer,
  nodePropertiesWritten: Integer,
  communityCount: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  communityDistribution: Map,
  configuration: Map
```

Table 373. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 374. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 375. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	10	yes	The maximum number of iterations to run.
nodeWeightProperty	String	null	yes	The name of a node property that contains node weights.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	The name of a node property that defines an initial numeric label.
consecutiveIds	Boolean	false	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).

Table 376. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the in-memory graph.
postProcessingMillis	Integer	Milliseconds for computing percentiles and community count.
nodePropertiesWritten	Integer	The number of node properties written.
communityCount	Integer	The number of communities found.
ranIterations	Integer	The number of iterations that were executed.
didConverge	Boolean	True if the algorithm did converge to a stable labelling within the provided number of maximum iterations.
communityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of community size.
configuration	Map	The configuration used for running the algorithm.

Run Label Propagation in write mode on a named graph.

```
CALL gds.labelPropagation.write(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  postProcessingMillis: Integer,
  nodePropertiesWritten: Integer,
  communityCount: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  communityDistribution: Map,
  configuration: Map
```

Table 377. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 378. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 379. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	10	yes	The maximum number of iterations to run.
nodeWeightProperty	String	null	yes	The name of a node property that contains node weights.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	The name of a node property that defines an initial numeric label.

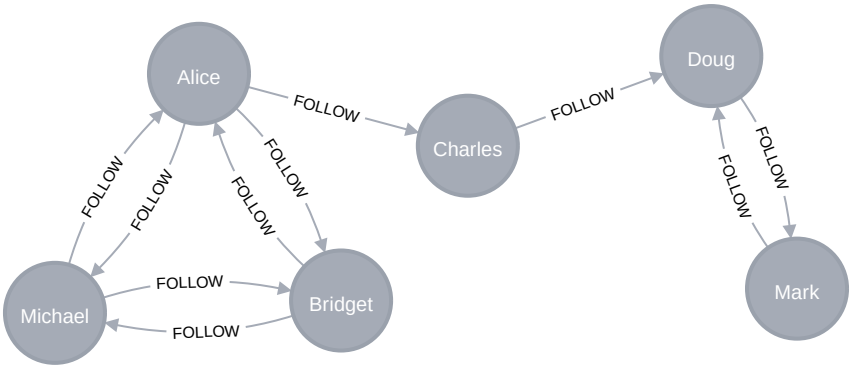
Name	Type	Default	Optional	Description
consecutiveIds	Boolean	false	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).
minCommunitySize	Integer	0	yes	Only community ids of communities with a size greater than or equal to the given value are written to Neo4j.

Table 380. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back.
postProcessingMillis	Integer	Milliseconds for computing percentiles and community count.
nodePropertiesWritten	Integer	The number of node properties written.
communityCount	Integer	The number of communities found.
ranIterations	Integer	The number of iterations that were executed.
didConverge	Boolean	True if the algorithm did converge to a stable labelling within the provided number of maximum iterations.
communityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of community size.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Label Propagation algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:User {name: 'Alice', seed_label: 52}),
  (bridget:User {name: 'Bridget', seed_label: 21}),
  (charles:User {name: 'Charles', seed_label: 43}),
  (doug:User {name: 'Doug', seed_label: 21}),
  (mark:User {name: 'Mark', seed_label: 19}),
  (michael:User {name: 'Michael', seed_label: 52}),

  (alice)-[:FOLLOW {weight: 1}]->(bridget),
  (alice)-[:FOLLOW {weight: 10}]->(charles),
  (mark)-[:FOLLOW {weight: 1}]->(doug),
  (bridget)-[:FOLLOW {weight: 1}]->(michael),
  (doug)-[:FOLLOW {weight: 1}]->(mark),
  (michael)-[:FOLLOW {weight: 1}]->(alice),
  (alice)-[:FOLLOW {weight: 1}]->(michael),
  (bridget)-[:FOLLOW {weight: 1}]->(alice),
  (michael)-[:FOLLOW {weight: 1}]->(bridget),
  (charles)-[:FOLLOW {weight: 1}]->(doug)
```

This graph represents six users, some of whom follow each other. Besides a `name` property, each user also has a `seed_label` property. The `seed_label` property represents a value in the graph used to seed the node with a label. For example, this can be a result from a previous run of the Label Propagation algorithm. In addition, each relationship has a weight property.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
    'myGraph',
    'User',
    'FOLLOW',
    {
        nodeProperties: 'seed_label',
        relationshipProperties: 'weight'
    }
)
```

In the following examples we will demonstrate using the Label Propagation algorithm on this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done

with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in write mode:

```
CALL gds.labelPropagation.write.estimate('myGraph', { writeProperty: 'community' })
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 381. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	10	1608	1608	"1608 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the community ID for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm and stream results:

```
CALL gds.labelPropagation.stream('myGraph')
YIELD nodeId, communityId AS Community
RETURN gds.util.asNode(nodeId).name AS Name, Community
ORDER BY Community, Name
```

Table 382. Results

Name	Community
"Alice"	1
"Bridget"	1
"Michael"	1
"Charles"	4
"Doug"	4
"Mark"	4

In the above example we can see that our graph has two communities each containing three nodes. The default behaviour of the algorithm is to run `unweighted`, e.g. without using `node` or `relationship` weights. The `weighted` option will be demonstrated in Weighted

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm in `stats` mode:

```
CALL gds.labelPropagation.stats('myGraph')
YIELD communityCount, ranIterations, didConverge
```

Table 383. Results

communityCount	ranIterations	didConverge
2	3	true

As we can see from the example above the algorithm finds two communities and converges in three iterations. Note that we ran the algorithm `unweighted`.

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the community ID for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm and write back results:

```
CALL gds.labelPropagation.mutate('myGraph', { mutateProperty: 'community' })
YIELD communityCount, ranIterations, didConverge
```

Table 384. Results

communityCount	ranIterations	didConverge
2	3	true

The returned result is the same as in the `stats` example. Additionally, the graph 'myGraph' now has a node property `community` which stores the community ID for each node. To find out how to inspect the new schema of the in-memory graph, see Listing graphs.

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the community ID for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm and write back results:

```
CALL gds.labelPropagation.write('myGraph', { writeProperty: 'community' })
YIELD communityCount, ranIterations, didConverge
```

Table 385. Results

communityCount	ranIterations	didConverge
2	3	true

The returned result is the same as in the `stats` example. Additionally, each of the six nodes now has a new property `community` in the Neo4j database, containing the community ID for that node.

Weighted

The Label Propagation algorithm can also be configured to use node and/or relationship weights into account. By specifying a node weight via the `nodeWeightProperty` key, we can control the influence of a nodes community onto its neighbors. During the computation of the weight of a specific community, the node property will be multiplied by the weight of that nodes relationships.

When we projected `myGraph`, we also projected the relationship property `weight`. In order to tell the algorithm to consider this property as a relationship weight, we have to set the `relationshipWeightProperty` configuration parameter to `weight`.

The following will run the algorithm on a graph with weighted relationships and stream results:

```
CALL gds.labelPropagation.stream('myGraph', { relationshipWeightProperty: 'weight' })
YIELD nodeId, communityId AS Community
RETURN gds.util.asNode(nodeId).name AS Name, Community
ORDER BY Community, Name
```

Table 386. Results

Name	Community
"Bridget"	2
"Michael"	2
"Alice"	4
"Charles"	4
"Doug"	4

Name	Community
"Mark"	4

Compared to the unweighted run of the algorithm we still have two communities, but they contain two and four nodes respectively. Using the weighted relationships, the nodes `Alice` and `Charles` are now in the same community as there is a strong link between them.

We have used the `stream` mode to demonstrate running the algorithm using weights, the configuration parameters are available for all the modes of the algorithm.

Seeded communities

At the beginning of the algorithm computation, every node is initialized with a unique label, and the labels propagate through the network.

An initial set of labels can be provided by setting the `seedProperty` configuration parameter. When we projected `myGraph`, we also projected the node property `seed_label`. We can use this node property as `seedProperty`.

The algorithm first checks if there is a seed label assigned to the node. If no seed label is present, the algorithm assigns new unique label to the node. Using this preliminary set of labels, it then sequentially updates each node's label to a new one, which is the most frequent label among its neighbors at every iteration of label propagation.

The `consecutiveIds` configuration option cannot be used in combination with `seedProperty` in order to retain the seeding values.

The following will run the algorithm with pre-defined labels:

```
CALL gds.labelPropagation.stream('myGraph', { seedProperty: 'seed_label' })
YIELD nodeId, communityId AS Community
RETURN gds.util.asNode(nodeId).name AS Name, Community
ORDER BY Community, Name
```

Table 387. Results

Name	Community
"Charles"	19
"Doug"	19
"Mark"	19
"Alice"	21
"Bridget"	21
"Michael"	21

As we can see, the communities are based on the `seed_label` property, concretely `19` is from the node `Mark` and `21` from `Doug`.

We have used the `stream` mode to demonstrate running the algorithm using `seedProperty`, this configuration parameter is available for all the modes of the algorithm.

6.3.3. Weakly Connected Components

This section describes the Weakly Connected Components (WCC) algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The WCC algorithm finds sets of connected nodes in an undirected graph, where all nodes in the same set form a connected component. WCC is often used early in an analysis to understand the structure of a graph. Using WCC to understand the graph structure enables running other algorithms independently on an identified cluster. As a preprocessing step for directed graphs, it helps quickly identify disconnected groups.

For more information on this algorithm, see:

- "An efficient domain-independent algorithm for detecting approximately duplicate database records".
- One study uses WCC to work out how well connected the network is, and then to see whether the connectivity remains if 'hub' or 'authority' nodes are moved from the graph: "Characterizing and Mining Citation Graph of Computer Science Literature"

Running this algorithm requires sufficient memory availability. Before running this algorithm, we recommend that you read Memory Estimation.

Syntax

This section covers the syntax used to execute the Weakly Connected Components algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

WCC syntax per mode

Run WCC in stream mode on a named graph.

```
CALL gds.wcc.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  componentId: Integer
```

Table 388. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 389. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 390. Algorithm specific configuration

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	Used to set the initial component for a node. The property value needs to be a number.
threshold	Float	null	yes	The value of the weight above which the relationship is considered in the computation.
consecutiveIds	Boolean	false	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).

Table 391. Results

Name	Type	Description
nodeId	Integer	Node ID.
componentId	Integer	Component ID.

Run WCC in stats mode on a named graph.

```
CALL gds.wcc.stats(
  graphName: String,
  configuration: Map
)
YIELD
  componentCount: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  componentDistribution: Map,
  configuration: Map
```

Table 392. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 393. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 394. Algorithm specific configuration

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	Used to set the initial component for a node. The property value needs to be a number.
threshold	Float	null	yes	The value of the weight above which the relationship is considered in the computation.
consecutiveIds	Boolean	false	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).

Table 395. Results

Name	Type	Description
componentCount	Integer	The number of computed components.

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing component count and distribution statistics.
componentDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of component sizes.
configuration	Map	The configuration used for running the algorithm.

Run WCC in mutate mode on a named graph.

```
CALL gds.wcc.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  componentCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  postProcessingMillis: Integer,
  componentDistribution: Map,
  configuration: Map
```

Table 396. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 397. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 398. Algorithm specific configuration

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	n/a	yes	Used to set the initial component for a node. The property value needs to be a number.
threshold	Float	null	yes	The value of the weight above which the relationship is considered in the computation.
consecutiveIds	Boolean	false	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).

Table 399. Results

Name	Type	Description
componentCount	Integer	The number of computed components.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
postProcessingMillis	Integer	Milliseconds for computing component count and distribution statistics.
componentDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of component sizes.
configuration	Map	The configuration used for running the algorithm.

Run WCC in write mode on a named graph.

```
CALL gds.wcc.write(
  graphName: String,
  configuration: Map
)
YIELD
  componentCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  postProcessingMillis: Integer,
  componentDistribution: Map,
  configuration: Map
```

Table 400. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 401. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 402. Algorithm specific configuration

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
seedProperty	String	`n/a`	yes	Used to set the initial component for a node. The property value needs to be a number.
threshold	Float	`null`	yes	The value of the weight above which the relationship is considered in the computation.
consecutiveIds	Boolean	`false`	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).

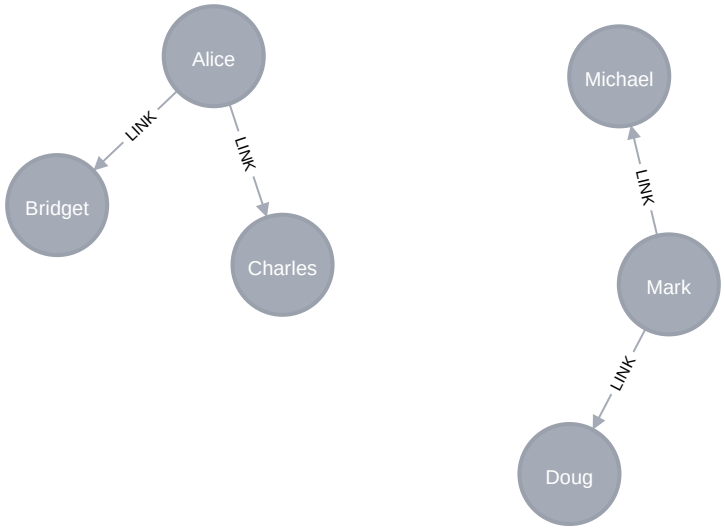
Name	Type	Default	Optional	Description
minComponentSize	Integer	`0`	yes	Only component ids of components with a size greater than or equal to the given value are written to Neo4j.

Table 403. Results

Name	Type	Description
componentCount	Integer	The number of computed components.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result back to Neo4j.
postProcessingMillis	Integer	Milliseconds for computing component count and distribution statistics.
componentDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of component sizes.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Weakly Connected Components algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small user network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (nAlice:User {name: 'Alice'}),
  (nBridget:User {name: 'Bridget'}),
  (nCharles:User {name: 'Charles'}),
  (nDoug:User {name: 'Doug'}),
  (nMark:User {name: 'Mark'}),
  (nMichael:User {name: 'Michael'}),

  (nAlice)-[:LINK {weight: 0.5}]->(nBridget),
  (nAlice)-[:LINK {weight: 4}]->(nCharles),
  (nMark)-[:LINK {weight: 1.1}]->(nDoug),
  (nMark)-[:LINK {weight: 2}]->(nMichael);
```

This graph has two connected components, each with three nodes. The relationships that connect the nodes in each component have a property `weight` which determines the strength of the relationship.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'User',
  'LINK',
  {
    relationshipProperties: 'weight'
  }
)
```

In the following examples we will demonstrate using the Weakly Connected Components algorithm on this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in write mode:

```
CALL gds.wcc.write.estimate('myGraph', { writeProperty: 'component' })
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 404. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	4	168	168	"168 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the component ID for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm and stream results:

```
CALL gds.wcc.stream('myGraph')
YIELD nodeId, componentId
RETURN gds.util.asNode(nodeId).name AS name, componentId
ORDER BY componentId, name
```

Table 405. Results

name	componentId
"Alice"	0
"Bridget"	0
"Charles"	0
"Doug"	3
"Mark"	3
"Michael"	3

The result shows that the algorithm identifies two components. This can be verified in the example graph.

The default behaviour of the algorithm is to run `unweighted`, e.g. without using `relationship` weights. The `weighted` option will be demonstrated in Weighted

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm in `stats` mode:

```
CALL gds.wcc.stats('myGraph')
YIELD componentCount
```

Table 406. Results

componentCount
2

The result shows that `myGraph` has two components and this can be verified by looking at the example graph.

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the component ID for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.wcc.mutate('myGraph', { mutateProperty: 'componentId' })
YIELD nodePropertiesWritten, componentCount;
```

Table 407. Results

nodePropertiesWritten	componentCount
6	2

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the component ID for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.wcc.write('myGraph', { writeProperty: 'componentId' })
YIELD nodePropertiesWritten, componentCount;
```

Table 408. Results

nodePropertiesWritten	componentCount
6	2

As we can see from the results, the nodes connected to one another are calculated by the algorithm as

belonging to the same connected component.

Weighted

By configuring the algorithm to use a weight we can increase granularity in the way the algorithm calculates component assignment. We do this by specifying the property key with the `relationshipWeightProperty` configuration parameter. Additionally, we can specify a threshold for the weight value. Then, only weights greater than the threshold value will be considered by the algorithm. We do this by specifying the threshold value with the `threshold` configuration parameter.

If a relationship does not have the specified weight property, the algorithm falls back to using a default value of zero.

The following will run the algorithm and stream results:

```
CALL gds.wcc.stream('myGraph', {
  relationshipWeightProperty: 'weight',
  threshold: 1.0
}) YIELD nodeId, componentId
RETURN gds.util.asNode(nodeId).name AS Name, componentId AS ComponentId
ORDER BY ComponentId, Name
```

Table 409. Results

Name	ComponentId
"Alice"	0
"Charles"	0
"Bridget"	1
"Doug"	3
"Mark"	3
"Michael"	3

As we can see from the results, the node named 'Bridget' is now in its own component, due to its relationship weight being less than the configured threshold and thus ignored.

We are using stream mode to illustrate running the algorithm as weighted or unweighted, all the other algorithm modes also support this configuration parameter.

Seeded components

It is possible to define preliminary component IDs for nodes using the `seedProperty` configuration parameter. This is helpful if we want to retain components from a previous run and it is known that no components have been split by removing relationships. The property value needs to be a number.

The algorithm first checks if there is a seeded component ID assigned to the node. If there is one, that component ID is used. Otherwise, a new unique component ID is assigned to the node.

Once every node belongs to a component, the algorithm merges components of connected nodes. When

components are merged, the resulting component is always the one with the lower component ID. Note that the `consecutiveIds` configuration option cannot be used in combination with seeding in order to retain the seeding values.

The algorithm assumes that nodes with the same seed value do in fact belong to the same component. If any two nodes in different components have the same seed, behavior is undefined. It is then recommended running WCC without seeds.

To demonstrate this in practice, we will go through a few steps:

1. We will run the algorithm and write the results to Neo4j.
2. Then we will add another node to our graph, this node will not have the property computed in Step 1.
3. We will project a new graph that has the result from Step 1 as `nodeProperty`
4. And then we will run the algorithm again, this time in `stream` mode, and we will use the `seedProperty` configuration parameter.

We will use the weighted variant of WCC.

Step 1

The following will run the algorithm in `write` mode:

```
CALL gds.wcc.write('myGraph', {
  writeProperty: 'componentId',
  relationshipWeightProperty: 'weight',
  threshold: 1.0
})
YIELD nodePropertiesWritten, componentCount;
```

Table 410. Results

nodePropertiesWritten	componentCount
6	3

Step 2

After the algorithm has finished writing to Neo4j we want to create a new node in the database.

The following will create a new node in the Neo4j graph, with no component ID:

```
MATCH (b:User {name: 'Bridget'})
CREATE (b)-[:LINK {weight: 2.0}]->(new:User {name: 'Mats'})
```

Step 3

Note, that we cannot use our already projected graph as it does not contain the component id. We will therefore project a second graph that contains the previously computed component id.

The following will project a new graph containing the previously computed component id:

```
CALL gds.graph.project(
  'myGraph-seeded',
  'User',
  'LINK',
  {
    nodeProperties: 'componentId',
    relationshipProperties: 'weight'
  }
)
```

Step 4

The following will run the algorithm in `stream` mode using `seedProperty`:

```
CALL gds.wcc.stream('myGraph-seeded', {
  seedProperty: 'componentId',
  relationshipWeightProperty: 'weight',
  threshold: 1.0
}) YIELD nodeId, componentId
RETURN gds.util.asNode(nodeId).name AS name, componentId
ORDER BY componentId, name
```

Table 411. Results

name	componentId
"Alice"	0
"Charles"	0
"Bridget"	1
"Mats"	1
"Doug"	3
"Mark"	3
"Michael"	3

The result shows that despite not having the `seedProperty` when it was projected, the node 'Mats' has been assigned to the same component as the node 'Bridget'. This is correct because these two nodes are connected.

Writing Seeded components

In the previous section we demonstrated the `seedProperty` usage in `stream` mode. It is also available in the other modes of the algorithm. Below is an example on how to use `seedProperty` in `write` mode. Note that the example below relies on Steps 1 - 3 from the previous section.

The following will run the algorithm in `write` mode using `seedProperty`:

```
CALL gds.wcc.write('myGraph-seeded', {
  seedProperty: 'componentId',
  writeProperty: 'componentId',
  relationshipWeightProperty: 'weight',
  threshold: 1.0
})
YIELD nodePropertiesWritten, componentCount;
```

Table 412. Results

nodePropertiesWritten	componentCount
1	3

If the `seedProperty` configuration parameter has the same value as `writeProperty`, the algorithm only writes properties for nodes where the component ID has changed. If they differ, the algorithm writes properties for all nodes.

6.3.4. Triangle Count

This section describes the Triangle Count algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Triangle Count algorithm counts the number of triangles for each node in the graph. A triangle is a set of three nodes where each node has a relationship to the other two. In graph theory terminology, this is sometimes referred to as a 3-clique. The Triangle Count algorithm in the GDS library only finds triangles in undirected graphs.

Triangle counting has gained popularity in social network analysis, where it is used to detect communities and measure the cohesiveness of those communities. It can also be used to determine the stability of a graph, and is often used as part of the computation of network indices, such as clustering coefficients. The Triangle Count algorithm is also used to compute the Local Clustering Coefficient.

For more information on this algorithm, see:

- Triangle count and clustering coefficient have been shown to be useful as features for classifying a

given website as spam, or non-spam, content. This is described in "Efficient Semi-streaming Algorithms for Local Triangle Counting in Massive Graphs".

Syntax

This section covers the syntax used to execute the Triangle Count algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

The named graphs must be projected in the `UNDIRECTED` orientation for the Triangle Count algorithm.

Triangle Count syntax per mode

Run Triangle Count in stream mode on a named graph:

```
CALL gds.triangleCount.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  triangleCount: Integer
```

Table 413. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 414. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 415. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxDegree	Integer	$2^{63} - 1$	Yes	If a node has a degree higher than this it will not be considered by the algorithm. The triangle count for these nodes will be -1.

Table 416. Results

Name	Type	Description
nodeId	Integer	Node ID.
triangleCount	Integer	Number of triangles the node is part of. Is -1 if the node has been excluded from computation using the maxDegree configuration parameter.

Run Triangle Count in stats mode on a named graph:

```
CALL gds.triangleCount.stats(
  graphName: String,
  configuration: Map
)
YIELD
  globalTriangleCount: Integer,
  nodeCount: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  configuration: Map
```

Table 417. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 418. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 419. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxDegree	Integer	$2^{63} - 1$	Yes	If a node has a degree higher than this it will not be considered by the algorithm. The triangle count for these nodes will be -1.

Table 420. Results

Name	Type	Description
globalTriangleCount	Integer	Total number of triangles in the graph.
nodeCount	Integer	Number of nodes in the graph.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the global metrics.

Name	Type	Description
configuration	Map	The configuration used for running the algorithm.

Run Triangle Count in mutate mode on a named graph:

```
CALL gds.triangleCount.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  globalTriangleCount: Integer,
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 421. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 422. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 423. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxDegree	Integer	$2^{63} - 1$	Yes	If a node has a degree higher than this it will not be considered by the algorithm. The triangle count for these nodes will be -1.

Table 424. Results

Name	Type	Description
globalTriangleCount	Integer	Total number of triangles in the graph.
nodeCount	Integer	Number of nodes in the graph.
nodePropertiesWritten	Integer	Number of properties added to the projected graph.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.

Name	Type	Description
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the global metrics.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
configuration	Map	The configuration used for running the algorithm.

Run Triangle Count in write mode on a named graph:

```
CALL gds.triangleCount.write(
  graphName: String,
  configuration: Map
)
YIELD
  globalTriangleCount: Integer,
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 425. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 426. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 427. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxDegree	Integer	$2^{63} - 1$	Yes	If a node has a degree higher than this it will not be considered by the algorithm. The triangle count for these nodes will be -1.

Table 428. Results

Name	Type	Description
globalTriangleCount	Integer	Total number of triangles in the graph.
nodeCount	Integer	Number of nodes in the graph.
nodePropertiesWritten	Integer	Number of properties written to Neo4j.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.

Name	Type	Description
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the global metrics.
writeMillis	Integer	Milliseconds for writing results back to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Triangles listing

In addition to the standard execution modes there is an `alpha` procedure `gds.alpha.triangles` that can be used to list all triangles in the graph.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

The following will return a stream of node IDs for each triangle:

```
CALL gds.alpha.triangles(
  graphName: String,
  configuration: Map
)
YIELD nodeA, nodeB, nodeC
```

Table 429. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 430. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm.

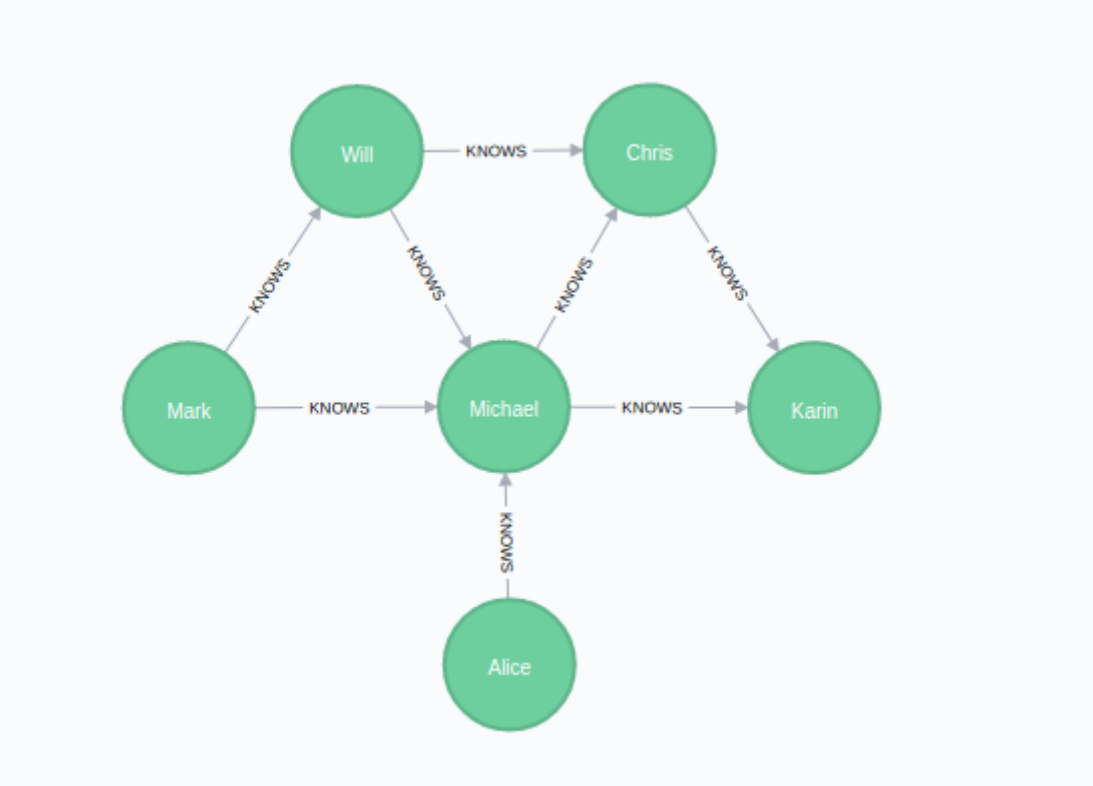
Table 431. Results

Name	Type	Description
nodeA	Integer	The ID of the first node in the given triangle.
nodeB	Integer	The ID of the second node in the given triangle.

Name	Type	Description
nodeC	Integer	The ID of the third node in the given triangle.

Examples

In this section we will show examples of running the Triangle Count algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:Person {name: 'Alice'}),
  (michael:Person {name: 'Michael'}),
  (karin:Person {name: 'Karin'}),
  (chris:Person {name: 'Chris'}),
  (will:Person {name: 'Will'}),
  (mark:Person {name: 'Mark'}),

  (michael)-[:KNOWS]->(karin),
  (michael)-[:KNOWS]->(chris),
  (will)-[:KNOWS]->(michael),
  (mark)-[:KNOWS]->(michael),
  (mark)-[:KNOWS]->(will),
  (alice)-[:KNOWS]->(michael),
  (will)-[:KNOWS]->(chris),
  (chris)-[:KNOWS]->(karin)
```

With the graph in Neo4j we can now project it into the graph catalog to prepare it for algorithm execution. We do this using a native projection targeting the `Person` nodes and the `KNOWS` relationships. For the relationships we must use the `UNDIRECTED` orientation. This is because the Triangle Count algorithm is defined only for undirected graphs.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'Person',
  {
    KNOWS: {
      orientation: 'UNDIRECTED'
    }
  }
)
```

The Triangle Count algorithm requires the graph to be projected using the `UNDIRECTED` orientation for relationships.

In the following examples we will demonstrate using the Triangle Count algorithm on this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in write mode:

```
CALL gds.triangleCount.write.estimate('myGraph', { writeProperty: 'triangleCount' })
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 432. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	16	152	152	"152 Bytes"

Note that the relationship count is 16, although we only projected 8 relationships in the original Cypher statement. This is because we used the `UNDIRECTED` orientation, which will project each relationship in each direction, effectively doubling the number of relationships.

Stream

In the `stream` execution mode, the algorithm returns the triangle count for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode:

```
CALL gds.triangleCount.stream('myGraph')
YIELD nodeId, triangleCount
RETURN gds.util.asNode(nodeId).name AS name, triangleCount
ORDER BY triangleCount DESC
```

Table 433. Results

name	triangleCount
"Michael"	3
"Chris"	2
"Will"	2
"Karin"	1
"Mark"	1
"Alice"	0

Here we find that the 'Michael' node has the most triangles. This can be verified in the example graph. Since the 'Alice' node only `KNOWS` one other node, it can not be part of any triangle, and indeed the algorithm reports a count of zero.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm in `stats` mode:

```
CALL gds.triangleCount.stats('myGraph')
YIELD globalTriangleCount, nodeCount
```

Table 434. Results

globalTriangleCount	nodeCount
3	6

Here we can see that the graph has six nodes with a total number of three triangles. Comparing this to the stream example we can see that the 'Michael' node has a triangle count equal to the global triangle count. In other words, that node is part of all of the triangles in the graph and thus has a very central position in the graph.

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the triangle count for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.triangleCount.mutate('myGraph', {
  mutateProperty: 'triangles'
})
YIELD globalTriangleCount, nodeCount
```

Table 435. Results

globalTriangleCount	nodeCount
3	6

The returned result is the same as in the `stats` example. Additionally, the graph 'myGraph' now has a node property `triangles` which stores the triangle count for each node. To find out how to inspect the new schema of the in-memory graph, see Listing graphs.

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the triangle count for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.triangleCount.write('myGraph', {
  writeProperty: 'triangles'
})
YIELD globalTriangleCount, nodeCount
```

Table 436. Results

globalTriangleCount	nodeCount
3	6

The returned result is the same as in the `stats` example. Additionally, each of the six nodes now has a new property `triangles` in the Neo4j database, containing the triangle count for that node.

Maximum Degree

The Triangle Count algorithm supports a `maxDegree` configuration parameter that can be used to exclude nodes from processing if their degree is greater than the configured value. This can be useful to speed up the computation when there are nodes with a very high degree (so-called super nodes) in the graph. Super nodes have a great impact on the performance of the Triangle Count algorithm. To learn about the degree distribution of your graph, see Listing graphs.

The nodes excluded from the computation get assigned a triangle count of `-1`.

The following will run the algorithm in `stream` mode with the `maxDegree` parameter:

```
CALL gds.triangleCount.stream('myGraph', {
  maxDegree: 4
})
YIELD nodeId, triangleCount
RETURN gds.util.asNode(nodeId).name AS name, triangleCount
ORDER BY name ASC
```

Table 437. Results

name	triangleCount
"Alice"	0
"Chris"	0
"Karin"	0
"Mark"	0
"Michael"	-1
"Will"	0

Running the algorithm on the example graph with `maxDegree: 4` excludes the 'Michael' node from the computation, as it has a degree of 5.

As this node is part of all the triangles in the example graph excluding it results in no triangles.

Triangles listing

It is also possible to list all the triangles in the graph. To do this we make use of the `alpha` procedure `gds.alpha.triangles`.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

The following will compute a stream of node IDs for each triangle and return the name property of the nodes:

```
CALL gds.alpha.triangles('myGraph')
YIELD nodeA, nodeB, nodeC
RETURN
  gds.util.asNode(nodeA).name AS nodeA,
  gds.util.asNode(nodeB).name AS nodeB,
  gds.util.asNode(nodeC).name AS nodeC
```

Table 438. Results

nodeA	nodeB	nodeC
"Michael"	"Karin"	"Chris"
"Michael"	"Chris"	"Will"
"Michael"	"Will"	"Mark"

We can see that there are three triangles in the graph: "Will, Michael, and Chris", "Will, Mark, and Michael", and "Michael, Karin, and Chris". The node "Alice" is not part of any triangle and thus does not appear in the triangles listing.

6.3.5. Local Clustering Coefficient

> *This section describes the Local Clustering Coefficient algorithm in the Neo4j Graph Data Science library.*

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Local Clustering Coefficient algorithm computes the local clustering coefficient for each node in the graph. The local clustering coefficient C_n of a node *n* describes the likelihood that the neighbours of *n* are also connected. To compute C_n we use the number of triangles a node is a part of T_n, and the degree of the node d_n. The formula to compute the local clustering coefficient is as follows:

$$C_n = \frac{2T_n}{d_n(d_n - 1)}$$

As we can see the triangle count is required to compute the local clustering coefficient. To do this the Triangle Count algorithm is utilised.

Additionally, the algorithm can compute the *average clustering coefficient* for the whole graph. This is the normalised sum over all the local clustering coefficients.

For more information, see Clustering Coefficient.

Syntax

This section covers the syntax used to execute the Local Clustering Coefficient algorithm in each of its

execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Run Local Clustering Coefficient in stream mode on a named graph:

```
CALL gds.localClusteringCoefficient.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  localClusteringCoefficient: Double
```

Table 439. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 440. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 441. Algorithm specific configuration

Name	Type	Default	Optional	Description
triangleCountProperty	String	n/a	Yes	Node property that contains pre-computed triangle count.

Table 442. Results

Name	Type	Description
nodeId	Integer	Node ID.
localClusteringCoefficient	Double	Local clustering coefficient.

Run Local Clustering Coefficient in stats mode on a named graph:

```
CALL gds.localClusteringCoefficient.stats(
  graphName: String,
  configuration: Map
)
YIELD
  averageClusteringCoefficient: Double,
  nodeCount: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  configuration: Map
```

Table 443. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 444. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 445. Algorithm specific configuration

Name	Type	Default	Optional	Description
triangleCountProperty	String	n/a	Yes	Node property that contains pre-computed triangle count.

Table 446. Results

Name	Type	Description
averageClusteringCoefficient	Double	The average clustering coefficient.
nodeCount	Integer	Number of nodes in the graph.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the global metrics.

Name	Type	Description
configuration	Map	The configuration used for running the algorithm.

Run Local Clustering Coefficient in mutate mode on a named graph:

```
CALL gds.localClusteringCoefficient.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  averageClusteringCoefficient: Double,
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 447. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 448. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 449. Algorithm specific configuration

Name	Type	Default	Optional	Description
triangleCountProperty	String	n/a	Yes	Node property that contains pre-computed triangle count.

Table 450. Results

Name	Type	Description
averageClusteringCoefficient	Double	The average clustering coefficient.
nodeCount	Integer	Number of nodes in the graph.
nodePropertiesWritten	Integer	Number of properties added to the projected graph.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
postProcessingMillis	Integer	Milliseconds for computing the global metrics.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
configuration	Map	The configuration used for running the algorithm.

Run Local Clustering Coefficient in write mode on a named graph:

```
CALL gds.localClusteringCoefficient.write(
  graphName: String,
  configuration: Map
)
YIELD
  averageClusteringCoefficient: Double,
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 451. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 452. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 453. Algorithm specific configuration

Name	Type	Default	Optional	Description
triangleCountProperty	String	n/a	Yes	Node property that contains pre-computed triangle count.

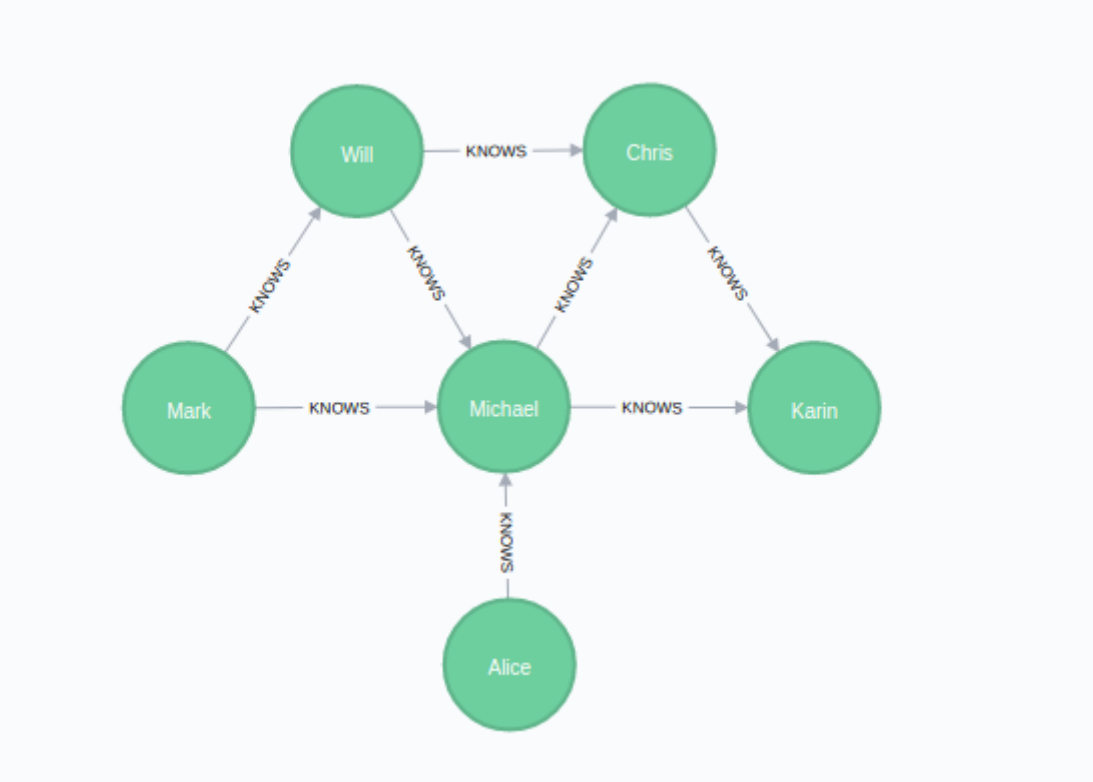
Table 454. Results

Name	Type	Description
averageClusteringCoefficient	Double	The average clustering coefficient.
nodeCount	Integer	Number of nodes in the graph.
nodePropertiesWritten	Integer	Number of properties written to Neo4j.

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the global metrics.
writeMillis	Integer	Milliseconds for writing results back to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Local Clustering Coefficient algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:Person {name: 'Alice'}),
  (michael:Person {name: 'Michael'}),
  (karin:Person {name: 'Karin'}),
  (chris:Person {name: 'Chris'}),
  (will:Person {name: 'Will'}),
  (mark:Person {name: 'Mark'}),

  (michael)-[:KNOWS]->(karin),
  (michael)-[:KNOWS]->(chris),
  (will)-[:KNOWS]->(michael),
  (mark)-[:KNOWS]->(michael),
  (mark)-[:KNOWS]->(will),
  (alice)-[:KNOWS]->(michael),
  (will)-[:KNOWS]->(chris),
  (chris)-[:KNOWS]->(karin)
```

With the graph in Neo4j we can now project it into the graph catalog to prepare it for algorithm execution. We do this using a native projection targeting the `Person` nodes and the `KNOWS` relationships. For the relationships we must use the `UNDIRECTED` orientation. This is because the Local Clustering Coefficient algorithm is defined only for undirected graphs.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'Person',
  {
    KNOWS: {
      orientation: 'UNDIRECTED'
    }
  }
)
```

The Local Clustering Coefficient algorithm requires the graph to be created using the `UNDIRECTED` orientation for relationships.

In the following examples we will demonstrate using the Local Clustering Coefficient algorithm on 'myGraph'.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.localClusteringCoefficient.write.estimate('myGraph', {
  writeProperty: 'localClusteringCoefficient'
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 455. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	16	288	288	"288 Bytes"

Note that the relationship count is 16 although we only created 8 relationships in the original Cypher statement. This is because we used the `UNDIRECTED` orientation, which will project each relationship in each direction, effectively doubling the number of relationships.

Stream

In the `stream` execution mode, the algorithm returns the local clustering coefficient for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode:

```
CALL gds.localClusteringCoefficient.stream('myGraph')
YIELD nodeId, localClusteringCoefficient
RETURN gds.util.asNode(nodeId).name AS name, localClusteringCoefficient
ORDER BY localClusteringCoefficient DESC
```

Table 456. Results

name	localClusteringCoefficient
"Karin"	1.0
"Mark"	1.0
"Chris"	0.6666666666666666
"Will"	0.6666666666666666
"Michael"	0.3
"Alice"	0.0

From the results we can see that the nodes 'Karin' and 'Mark' have the highest local clustering coefficients. This shows that they are the best at introducing their friends - all the people who know them, know each other! This can be verified in the example graph.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm

result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm in `stats` mode:

```
CALL gds.localClusteringCoefficient.stats('myGraph')
YIELD averageClusteringCoefficient, nodeCount
```

Table 457. Results

averageClusteringCoefficient	nodeCount
0.6055555555555555	6

The result shows that on average each node of our example graph has approximately 60% of its neighbours connected.

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the local clustering coefficient for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.localClusteringCoefficient.mutate('myGraph', {
  mutateProperty: 'localClusteringCoefficient'
})
YIELD averageClusteringCoefficient, nodeCount
```

Table 458. Results

averageClusteringCoefficient	nodeCount
0.6055555555555555	6

The returned result is the same as in the `stats` example. Additionally, the graph 'myGraph' now has a node property `localClusteringCoefficient` which stores the local clustering coefficient for each node. To find out how to inspect the new schema of the in-memory graph, see Listing graphs.

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the local clustering coefficient for each node as a property to the Neo4j database. The name of the new property is

specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.localClusteringCoefficient.write('myGraph', {
  writeProperty: 'localClusteringCoefficient'
})
YIELD averageClusteringCoefficient, nodeCount
```

Table 459. Results

averageClusteringCoefficient	nodeCount
0.6055555555555555	6

The returned result is the same as in the `stats` example. Additionally, each of the six nodes now has a new property `localClusteringCoefficient` in the Neo4j database, containing the local clustering coefficient for that node.

Pre-computed Counts

By default, the Local Clustering Coefficient algorithm executes Triangle Count as part of its computation. It is also possible to avoid the triangle count computation by configuring the Local Clustering Coefficient algorithm to read the triangle count from a node property. In order to do that we specify the `triangleCountProperty` configuration parameter. Please note that the Local Clustering Coefficient algorithm depends on the property holding actual triangle counts and not another number for the results to be actual local clustering coefficients.

To illustrate this we make use of the Triangle Count algorithm in `mutate` mode. The Triangle Count algorithm is going to store its result back into 'myGraph'. It is also possible to obtain the property value from the Neo4j database using a graph projection with a node property when creating the in-memory graph.

The following computes the triangle counts and stores the result into the in-memory graph:

```
CALL gds.triangleCount.mutate('myGraph', {
  mutateProperty: 'triangles'
})
```

The following will run the algorithm in `stream` mode using pre-computed triangle counts:

```
CALL gds.localClusteringCoefficient.stream('myGraph', {
  triangleCountProperty: 'triangles'
})
YIELD nodeId, localClusteringCoefficient
RETURN gds.util.asNode(nodeId).name AS name, localClusteringCoefficient
ORDER BY localClusteringCoefficient DESC
```

Table 460. Results

name	localClusteringCoefficient
"Karin"	1.0
"Mark"	1.0
"Chris"	0.6666666666666666
"Will"	0.6666666666666666
"Michael"	0.3
"Alice"	0.0

As we can see the results are the same as in the `stream` example where we did not specify a `triangleCountProperty`.

6.3.6. K-1 Coloring Beta

This section describes the K-1 Coloring algorithm in the Neo4j Graph Data Science library.

This algorithm is in the beta tier. For more information on algorithm tiers, see Graph Algorithms.

Introduction

The K-1 Coloring algorithm assigns a color to every node in the graph, trying to optimize for two objectives:

1. To make sure that every neighbor of a given node has a different color than the node itself.
2. To use as few colors as possible.

Note that the graph coloring problem is proven to be NP-complete, which makes it intractable on anything but trivial graph sizes. For that reason the implemented algorithm is a greedy algorithm. Thus it is neither guaranteed that the result is an optimal solution, using as few colors as theoretically possible, nor does it always produce a correct result where no two neighboring nodes have different colors. However the precision of the latter can be controlled by the number of iterations this algorithm runs.

For more information on this algorithm, see:

- Çatalyürek, Ümit V., et al. "Graph coloring algorithms for multi-core and massively multithreaded architectures."
- https://en.wikipedia.org/wiki/Graph_coloring#Vertex_coloring

Running this algorithm requires sufficient memory availability. Before running this algorithm, we recommend that you read Memory Estimation.

Syntax

The following describes the API for running the algorithm and stream results:

```
CALL gds.beta.k1coloring.stream(graphName: String, configuration: Map)
YIELD nodeId, color
```

Table 461. Parameters

Name	Type	Default	Optional	Description
graphName	String	null	yes	The name of an existing graph on which to run the algorithm. If no graph name is provided, the configuration map must contain configuration for creating a graph.
configuration	Map	{}	yes	Additional configuration, see below.

Table 462. Configuration

Name	Type	Default	Optional	Description
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'. This is dependent on the Neo4j edition; for more information, see CPU.
maxIterations	Integer	10	yes	The maximum number of iterations of K1 Coloring to run.

Table 463. Results

Name	Type	Description
nodeId	Integer	The ID of the Node
color	Integer	The color of the Node

The following describes the API for running the algorithm and returning the computation statistics:

```
CALL gds.beta.k1coloring.stats(
    graphName: String,
    configuration: Map
)
YIELD
    nodeCount,
    colorCount,
    ranIterations,
    didConverge,
    configuration,
    preProcessingMillis,
    computeMillis
```

Table 464. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	Name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

Table 465. Configuration

Name	Type	Default	Optional	Description
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'. This is dependent on the Neo4j edition; for more information, see CPU.
maxIterations	Integer	10	yes	The maximum number of iterations of K1 Coloring to run.

Table 466. Results

Name	Type	Description
nodeCount	Integer	The number of nodes considered.
ranIterations	Integer	The actual number of iterations the algorithm ran.
didConverge	Boolean	An indicator of whether the algorithm found a correct coloring.
colorCount	Integer	The number of colors used.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
configuration	Map	The configuration used for running the algorithm.

The following describes the API for running the algorithm and mutating the projected graph:

```
CALL gds.beta.k1coloring.mutate(graphName: String, configuration: Map)
YIELD nodeCount, colorCount, ranIterations, didConverge, configuration, preProcessingMillis,
computeMillis, mutateMillis
```

Table 467. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	Name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

The configuration for the `mutate` mode is similar to the `write` mode. Instead of specifying a `writeProperty`, we need to specify a `mutateProperty`. Also, specifying `writeConcurrency` is not possible in `mutate` mode.

Table 468. Results

Name	Type	Description
nodeCount	Integer	The number of nodes considered.
ranIterations	Integer	The actual number of iterations the algorithm ran.
didConverge	Boolean	An indicator of whether the algorithm found a correct coloring.
colorCount	Integer	The number of colors used.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
configuration	Map	The configuration used for running the algorithm.

The following describes the API for running the algorithm and writing results back to Neo4j:

```
CALL gds.beta.k1coloring.write(graphName: String, configuration: Map)
YIELD nodeCount, colorCount, ranIterations, didConverge, configuration, preProcessingMillis,
computeMillis, writeMillis
```

Table 469. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	Name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

Table 470. Configuration

Name	Type	Default	Optional	Description
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'. This is dependent on the Neo4j edition; for more information, see CPU.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result.
maxIterations	Integer	10	yes	The maximum number of iterations of K1 Coloring to run.
writeProperty	String	n/a	no	The node property this procedure writes the color to.

Table 471. Results

Name	Type	Description
nodeCount	Integer	The number of nodes considered.
ranIterations	Integer	The actual number of iterations the algorithm ran.
didConverge	Boolean	An indicator of whether the algorithm found a correct coloring.
colorCount	Integer	The number of colors used.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

Consider the graph created by the following Cypher statement:

```
CREATE (alice:User {name: 'Alice'}),
       (bridget:User {name: 'Bridget'}),
       (charles:User {name: 'Charles'}),
       (doug:User {name: 'Doug'}),

       (alice)-[:LINK]->(bridget),
       (alice)-[:LINK]->(charles),
       (alice)-[:LINK]->(doug),
       (bridget)-[:LINK]->(charles)
```

This graph has a super node with name "Alice" that connects to all other nodes. It should therefore not be possible for any other node to be assigned the same color as the Alice node.

```
CALL gds.graph.project(
    'myGraph',
    'User',
    {
        LINK : {
            orientation: 'UNDIRECTED'
        }
    }
)
```

We can now go ahead and project a graph with all the `User` nodes and the `LINK` relationships with `UNDIRECTED` orientation.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project('myGraph', 'Person', 'LIKES')
```

In the following examples we will demonstrate using the K-1 Coloring algorithm on this graph.

Running the K-1 Coloring algorithm in stream mode:

```
CALL gds.beta.k1coloring.stream('myGraph')
YIELD nodeId, color
RETURN gds.util.asNode(nodeId).name AS name, color
ORDER BY name
```

Table 472. Results

name	color
"Alice"	0
"Bridget"	1
"Charles"	2
"Doug"	1

It is also possible to write the assigned colors back to the database using the `write` mode.

Running the K-1 Coloring algorithm in write mode:

```
CALL gds.beta.k1coloring.write('myGraph', {writeProperty: 'color'})
YIELD nodeCount, colorCount, ranIterations, didConverge
```

Table 473. Results

nodeCount	colorCount	ranIterations	didConverge
4	3	1	true

When using `write` mode the procedure will return information about the algorithm execution. In this example we return the number of processed nodes, the number of colors used to color the graph, the number of iterations and information whether the algorithm converged.

To instead mutate the in-memory graph with the assigned colors, the `mutate` mode can be used as follows.

Running the K-1 Coloring algorithm in mutate mode:

```
CALL gds.beta.k1coloring.mutate('myGraph', {mutateProperty: 'color'})
YIELD nodeCount, colorCount, ranIterations, didConverge
```

Table 474. Results

nodeCount	colorCount	ranIterations	didConverge
4	3	1	true

Similar to the `write` mode, `stats` mode can run the algorithm and return only the execution statistics without persisting the results.

Running the K-1 Coloring algorithm in stats mode:

```
CALL gds.beta.k1coloring.stats('myGraph')
YIELD nodeCount, colorCount, ranIterations, didConverge
```

Table 475. Results

nodeCount	colorCount	ranIterations	didConverge
4	3	1	true

6.3.7. Modularity Optimization Beta

> *This section describes the Modularity Optimization algorithm in the Neo4j Graph Data Science library.*

This algorithm is in the beta tier. For more information on algorithm tiers, see Graph Algorithms.

Introduction

The Modularity Optimization algorithm tries to detect communities in the graph based on their *modularity*. *Modularity* is a measure of the structure of a graph, measuring the density of connections within a module

or community. Graphs with a high modularity score will have many connections within a community but only few pointing outwards to other communities. The algorithm will explore for every node if its modularity score might increase if it changes its community to one of its neighboring nodes.

For more information on this algorithm, see:

- MEJ Newman, M Girvan "Finding and evaluating community structure in networks"
- https://en.wikipedia.org/wiki/Modularity_(networks)

Running this algorithm requires sufficient memory availability. Before running this algorithm, we recommend that you read Memory Estimation.

Syntax

Modularity Optimization syntax per mode

Run Modularity Optimization in stream mode on a named graph.

```
CALL gds.beta.modularityOptimization.stream(graphName: String, configuration: Map)
YIELD
  nodeId: Integer,
  communityId: Integer
```

Table 476. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	Name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

Table 477. General configuration

Name	Type	Default	Optional	Description
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result (applicable in WRITE mode).

Table 478. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	10	yes	The maximum number of iterations to run.
tolerance	Float	0.0001	yes	Minimum change in modularity between iterations. If the modularity changes less than the tolerance value, the result is considered stable and the algorithm returns.
seedProperty	String	n/a	yes	Used to define initial set of labels (must be a number).
consecutiveIds	Boolean	false	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

Table 479. Results

Name	Type	Description
nodeId	Integer	Node ID
communityId	Integer	Community ID

Run Modularity Optimization in mutate mode on a named graph.

```
CALL gds.beta.modularityOptimization.mutate(graphName: String, configuration: Map})
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  communityCount: Integer,
  communityDistribution: Map,
  modularity: Float,
  ranIterations: Integer,
  didConverge: Boolean,
  nodes: Integer,
  configuration: Map
```

Table 480. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	Name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

The configuration for the `mutate` mode is similar to the `write` mode. Instead of specifying a `writeProperty`, we need to specify a `mutateProperty`. Also, specifying `writeConcurrency` is not possible in `mutate` mode.

Table 481. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
postProcessingMillis	Integer	Milliseconds for computing percentiles and community count.
nodes	Integer	The number of nodes considered.
didConverge	Boolean	True if the algorithm did converge to a stable modularity score within the provided number of maximum iterations.
ranIterations	Integer	The number of iterations run.
modularity	Float	The final modularity score.
communityCount	Integer	The number of communities found.
communityDistribution	Map	The containing min, max, mean as well as 50, 75, 90, 95, 99 and 999 percentile of community size.
configuration	Map	The configuration used for running the algorithm.

Run Modularity Optimization in write mode on a named graph.

```
CALL gds.beta.modularityOptimization.write(graphName: String, configuration: Map})
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  communityCount: Integer,
  communityDistribution: Map,
  modularity: Float,
  ranIterations: Integer,
  didConverge: Boolean,
  nodes: Integer,
  configuration: Map
```

Table 482. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	Name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

Table 483. General configuration

Name	Type	Default	Optional	Description
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result (applicable in WRITE mode).

Table 484. Algorithm specific configuration

Name	Type	Default	Optional	Description
seedProperty	String	n/a	yes	Used to set the initial community for a node. The property value needs to be a number.
writeProperty	String	n/a	yes	The property name written back the ID of the partition particular node belongs to.
maxIterations	Integer	10	yes	The maximum number of iterations that the modularity optimization will run for each level.
tolerance	Float	0.0001	yes	Minimum change in modularity between iterations. If the modularity changes less than the tolerance value, the result is considered stable and the algorithm returns.
consecutiveIds	Boolean	false	yes	Flag to decide whether component identifiers are mapped into a consecutive id space (requires additional memory).

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

Table 485. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back.
postProcessingMillis	Integer	Milliseconds for computing percentiles and community count.
nodes	Integer	The number of nodes considered.
didConverge	Boolean	True if the algorithm did converge to a stable modularity score within the provided number of maximum iterations.
ranIterations	Integer	The number of iterations run.
modularity	Float	The final modularity score.
communityCount	Integer	The number of communities found.
communityDistribution	Map	The containing min, max, mean as well as 50, 75, 90, 95, 99 and 999 percentile of community size.
configuration	Map	The configuration used for running the algorithm.

Examples

Consider the graph created by the following Cypher statement:

```
CREATE
  (a:Person {name:'Alice'})
, (b:Person {name:'Bridget'})
, (c:Person {name:'Charles'})
, (d:Person {name:'Doug'})
, (e:Person {name:'Elton'})
, (f:Person {name:'Frank'})
, (a)-[:KNOWS {weight: 0.01}]->(b)
, (a)-[:KNOWS {weight: 5.0}]->(e)
, (a)-[:KNOWS {weight: 5.0}]->(f)
, (b)-[:KNOWS {weight: 5.0}]->(c)
, (b)-[:KNOWS {weight: 5.0}]->(d)
, (c)-[:KNOWS {weight: 0.01}]->(e)
, (f)-[:KNOWS {weight: 0.01}]->(d)
```

This graph consists of two center nodes "Alice" and "Bridget" each of which have two more neighbors.

Additionally, each neighbor of "Alice" is connected to one of the neighbors of "Bridget". Looking at the weights of the relationships, it can be seen that the connections from the two center nodes to their neighbors are very strong, while connections between those groups are weak. Therefore the Modularity Optimization algorithm should detect two communities: "Alice" and "Bob" together with their neighbors respectively.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
    'myGraph',
    'Person',
    {
        KNOWS: {
            type: 'KNOWS',
            orientation: 'UNDIRECTED',
            properties: ['weight']
        }
    })
```

The following example demonstrates using the Modularity Algorithm on this weighted graph.

Running the Modularity Optimization algorithm in stream mode:

```
CALL gds.beta.modularityOptimization.stream('myGraph', { relationshipWeightProperty: 'weight' })
YIELD nodeId, communityId
RETURN gds.util.asNode(nodeId).name AS name, communityId
ORDER BY name
```

Table 486. Results

name	communityId
"Alice"	4
"Bridget"	1
"Charles"	1
"Doug"	1
"Elton"	4
"Frank"	4

It is also possible to write the assigned community ids back to the database using the `write` mode.

Running the Modularity Optimization algorithm in write mode:

```
CALL gds.beta.modularityOptimization.write('myGraph', { relationshipWeightProperty: 'weight',
writeProperty: 'community' })
YIELD nodes, communityCount, ranIterations, didConverge
```

Table 487. Results

nodes	communityCount	ranIterations	didConverge
6	2	3	true

When using `write` mode the procedure will return information about the algorithm execution. In this example we return the number of processed nodes, the number of communities assigned to the nodes in the graph, the number of iterations and information whether the algorithm converged.

Running the algorithm without specifying the `relationshipWeightProperty` will default all relationship weights to 1.0.

To instead mutate the in-memory graph with the assigned community ids, the `mutate` mode is used.

Running the Modularity Optimization algorithm in mutate mode:

```
CALL gds.beta.modularityOptimization.mutate('myGraph', { relationshipWeightProperty: 'weight',
mutateProperty: 'community' })
YIELD nodes, communityCount, ranIterations, didConverge
```

Table 488. Results

nodes	communityCount	ranIterations	didConverge
6	2	3	true

When using `mutate` mode the procedure will return information about the algorithm execution as in `write` mode.

6.3.8. Strongly Connected Components Alpha

This section describes the Strongly Connected Components algorithm in the Neo4j Graph Data Science library.

The Strongly Connected Components (SCC) algorithm finds maximal sets of connected nodes in a directed graph. A set is considered a strongly connected component if there is a directed path between each pair of nodes within the set. It is often used early in a graph analysis process to help us get an idea of how our graph is structured.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

SCC is one of the earliest graph algorithms, and the first linear-time algorithm was described by Tarjan in 1972. Decomposing a directed graph into its strongly connected components is a classic application of the depth-first search algorithm.

Use-cases - when to use the Strongly Connected Components algorithm

- In the analysis of powerful transnational corporations, SCC can be used to find the set of firms in which every member owns directly and/or indirectly owns shares in every other member. Although it has

benefits, such as reducing transaction costs and increasing trust, this type of structure can weaken market competition. Read more in "The Network of Global Corporate Control".

- SCC can be used to compute the connectivity of different network configurations when measuring routing performance in multihop wireless networks. Read more in "Routing performance in the presence of unidirectional links in multihop wireless networks"
- Strongly Connected Components algorithms can be used as a first step in many graph algorithms that work only on strongly connected graph. In social networks, a group of people are generally strongly connected (For example, students of a class or any other common place). Many people in these groups generally like some common pages, or play common games. The SCC algorithms can be used to find such groups, and suggest the commonly liked pages or games to the people in the group who have not yet liked those pages or games.

Syntax

The following will run the algorithm and write back results:

```
CALL gds.alpha.scc.write(
  graphName: string,
  configuration: map
)
YIELD preProcessingMillis, computeMillis, writeMillis, setCount, maxSetSize, minSetSize
```

Table 489. Parameters

Name	Type	Default	Optional	Description
writeProperty	String	'componentId'	yes	The property name written back to.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'.
readConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for reading the graph.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result.

Table 490. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back.
postProcessingMillis	Integer	Milliseconds for computing percentiles and community count.
nodes	Integer	The number of nodes considered.
communityCount	Integer	The number of communities found.

Name	Type	Description
p1	Float	The 1 percentile of community size.
p5	Float	The 5 percentile of community size.
p10	Float	The 10 percentile of community size.
p25	Float	The 25 percentile of community size.
p50	Float	The 50 percentile of community size.
p75	Float	The 75 percentile of community size.
p90	Float	The 90 percentile of community size.
p95	Float	The 95 percentile of community size.
p99	Float	The 99 percentile of community size.
p100	Float	The 100 percentile of community size.
writeProperty	String	The property name written back to.

The following will run the algorithm and stream results:

```
CALL gds.alpha.scc.stream(graphName: String, configuration: Map)
YIELD nodeId, componentId
```

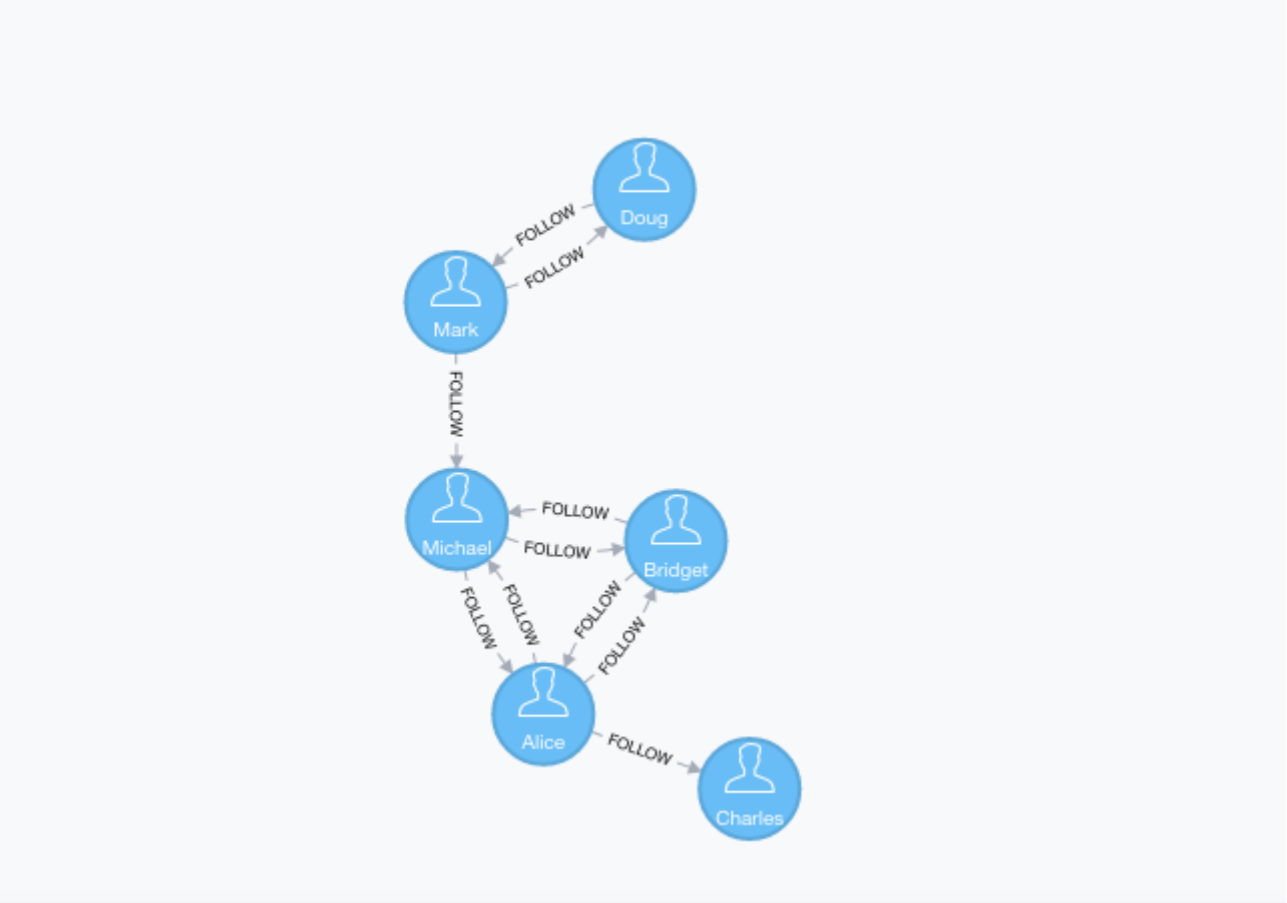
Table 491. Parameters

Name	Type	Default	Optional	Description
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency'.
readConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for reading the graph.

Table 492. Results

Name	Type	Description
nodeId	Integer	Node ID.
componentId	Integer	Component ID.

Strongly Connected Components algorithm example



The following will create a sample graph:

```
CREATE (nAlice:User {name:'Alice'})
CREATE (nBridget:User {name:'Bridget'})
CREATE (nCharles:User {name:'Charles'})
CREATE (nDoug:User {name:'Doug'})
CREATE (nMark:User {name:'Mark'})
CREATE (nMichael:User {name:'Michael'})

CREATE (nAlice)-[:FOLLOW]->(nBridget)
CREATE (nAlice)-[:FOLLOW]->(nCharles)
CREATE (nMark)-[:FOLLOW]->(nDoug)
CREATE (nMark)-[:FOLLOW]->(nMichael)
CREATE (nBridget)-[:FOLLOW]->(nMichael)
CREATE (nDoug)-[:FOLLOW]->(nMark)
CREATE (nMichael)-[:FOLLOW]->(nAlice)
CREATE (nAlice)-[:FOLLOW]->(nMichael)
CREATE (nBridget)-[:FOLLOW]->(nAlice)
CREATE (nMichael)-[:FOLLOW]->(nBridget);
```

The following will project and store a named graph:

```
CALL gds.graph.project('graph', 'User', 'FOLLOW')
```

The following will run the algorithm and write back results:

```
CALL gds.alpha.scc.write('graph', {
  writeProperty: 'componentId'
})
YIELD setCount, maxSetSize, minSetSize;
```

Table 493. Results

setCount	maxSetSize	minSetSize
3	3	1

The following will run the algorithm and stream back results:

```
CALL gds.alpha.scc.stream('graph', {})
YIELD nodeId, componentId
RETURN gds.util.asNode(nodeId).name AS Name, componentId AS Component
ORDER BY Component DESC
```

Table 494. Results

Name	Component
"Doug"	3
"Mark"	3
"Charles"	2
"Alice"	0
"Bridget"	0
"Michael"	0

We have 3 strongly connected components in our sample graph.

The first, and biggest, component has members Alice, Bridget, and Michael, while the second component has Doug and Mark. Charles ends up in his own component because there isn't an outgoing relationship from that node to any of the others.

The following will find the largest partition:

```
MATCH (u:User)
RETURN u.componentId AS Component, count(*) AS ComponentSize
ORDER BY ComponentSize DESC
LIMIT 1
```

Table 495. Results

Component	ComponentSize
0	3

References

- https://pdfs.semanticscholar.org/61db/6892a92d1d5bdc83e52cc18041613cf895fa.pdf
- http://code.activestate.com/recipes/578507-strongly-connected-components-of-a-directed-graph/
- http://www.sandia.gov/~srajama/publications/BFS_and_Coloring.pdf

6.3.9. Speaker-Listener Label Propagation Alpha

This section describes the Speaker-Listener Label Propagation algorithm in the Neo4j Graph Data Science library.

Introduction

The Speaker-Listener Label Propagation Algorithm (SLLPA) is a variation of the Label Propagation algorithm that is able to detect multiple communities per node. The GDS implementation is based on the SLPA: Uncovering Overlapping Communities in Social Networks via A Speaker-listener Interaction Dynamic Process publication by Xie et al.

The algorithm is randomized in nature and will not produce deterministic results. To accommodate this, we recommend using a higher number of iterations.

Syntax

This section covers the syntax used to execute the SLLPA algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

SLLPA syntax per mode

Run SLLPA in stream mode on a named graph.

```
CALL gds.alpha.sllpa.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  values: Map {
    communtiyIds: List of Integer
  }
```

Table 496. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 497. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 498. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	n/a	no	Maximum number of iterations to run.
minAssociationStrength	String	0.2	yes	Minimum influence required for a community to retain a node.

Table 499. Results

Name	Type	Description
nodeId	Integer	Node ID.
values	Map	A map that contains the key `communityIds`.

Run SLLPA in stats mode on a named graph.

```
CALL gds.alpha.sllpa.stats(
  graphName: String,
  configuration: Map
)
YIELD
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  configuration: Map
```

Table 500. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 501. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 502. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	n/a	no	Maximum number of iterations to run.
minAssociationStrength	String	0.2	yes	Minimum influence required for a community to retain a node.

Table 503. Results

Name	Type	Description
ranIterations	Integer	Number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
configuration	Map	Configuration used for running the algorithm.

Run SLLPA in mutate mode on a named graph.

```
CALL gds.alpha.sllpa.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 504. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 505. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 506. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	n/a	no	Maximum number of iterations to run.
minAssociationStrength	String	0.2	yes	Minimum influence required for a community to retain a node.

Table 507. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
nodePropertiesWritten	Integer	The number of properties that were written to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Run SLLPA in write mode on a named graph.

```
CALL gds.alpha.sllpa.write(
  graphName: String,
  configuration: Map
)
YIELD
  ranIterations: Integer,
  didConverge: Boolean,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 508. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 509. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 510. Algorithm specific configuration

Name	Type	Default	Optional	Description
maxIterations	Integer	n/a	no	Maximum number of iterations to run.
minAssociationStrength	String	0.2	yes	Minimum influence required for a community to retain a node.

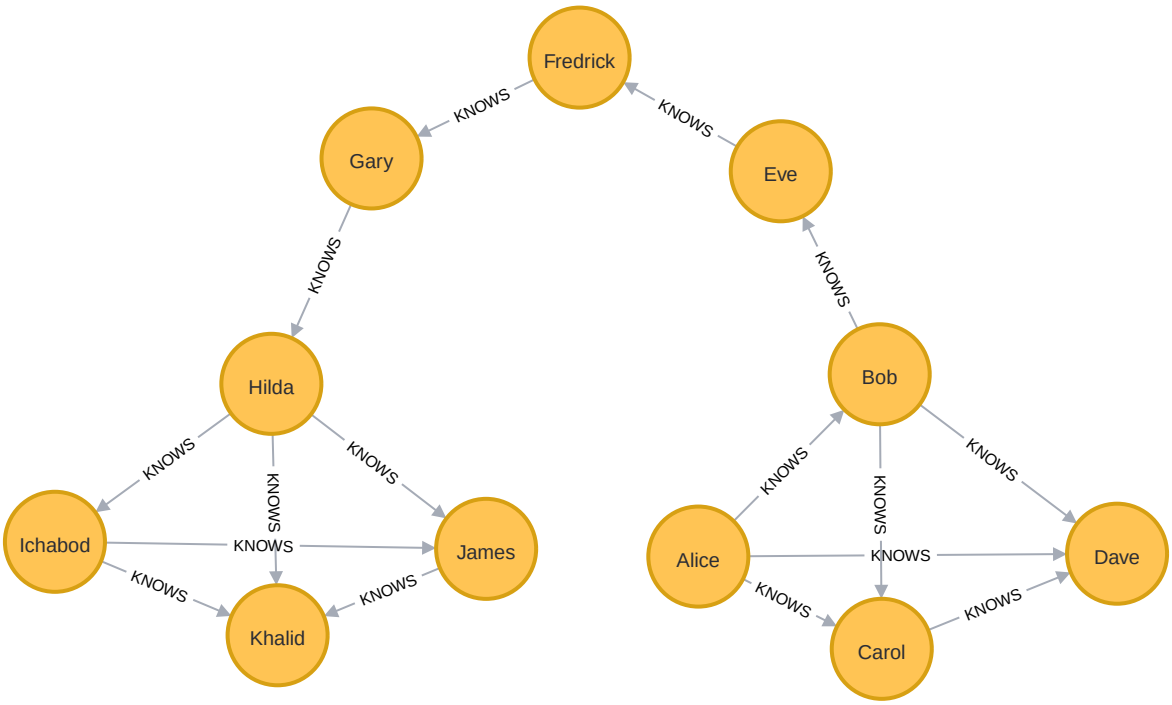
Table 511. Results

Name	Type	Description
ranIterations	Integer	The number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.

Name	Type	Description
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back.
nodePropertiesWritten	Integer	The number of properties that were written to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the SLLPA algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (a:Person {name: 'Alice'}),
  (b:Person {name: 'Bob'}),
  (c:Person {name: 'Carol'}),
  (d:Person {name: 'Dave'}),
  (e:Person {name: 'Eve'}),
  (f:Person {name: 'Fredrick'}),
  (g:Person {name: 'Gary'}),
  (h:Person {name: 'Hilda'}),
  (i:Person {name: 'Ichabod'}),
  (j:Person {name: 'James'}),
  (k:Person {name: 'Khalid'}),

  (a)-[:KNOWS]->(b),
  (a)-[:KNOWS]->(c),
  (a)-[:KNOWS]->(d),
  (b)-[:KNOWS]->(c),
  (b)-[:KNOWS]->(d),
  (c)-[:KNOWS]->(d),

  (b)-[:KNOWS]->(e),
  (e)-[:KNOWS]->(f),
  (f)-[:KNOWS]->(g),
  (g)-[:KNOWS]->(h),

  (h)-[:KNOWS]->(i),
  (h)-[:KNOWS]->(j),
  (h)-[:KNOWS]->(k),
  (i)-[:KNOWS]->(j),
  (i)-[:KNOWS]->(k),
  (j)-[:KNOWS]->(k);
```

In the example, we will use the SLLPA algorithm to find the communities in the graph.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
  'myGraph',
  'Person',
  {
    KNOWS: {
      orientation: 'UNDIRECTED'
    }
  }
);
```

In the following examples we will demonstrate using the SLLPA algorithm on this graph.

Stream

In the `stream` execution mode, the algorithm returns the community IDs for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm, and stream results:

```
CALL gds.alpha.sllpa.stream('myGraph', {maxIterations: 100, minAssociationStrength: 0.1})
YIELD nodeId, values
RETURN gds.util.asNode(nodeId).name AS Name, values.communityIds AS communityIds
  ORDER BY Name ASC
```

Table 512. Results

Name	communityIds
"Alice"	[0]
"Bob"	[0]
"Carol"	[0]
"Dave"	[0]
"Eve"	[0, 1]
"Fredrick"	[0, 1]
"Gary"	[0, 1]
"Hilda"	[1]
"Ichabod"	[1]
"James"	[1]
"Khalid"	[1]

Due to the randomness of the algorithm, the results will tend to vary between runs.

6.3.10. Approximate Maximum k-cut Alpha

This section describes the Approximate Maximum k-cut algorithm in the Neo4j Graph Data Science library.

Introduction

A k-cut of a graph is an assignment of its nodes into k disjoint communities. So for example a 2-cut of a graph with nodes `a,b,c,d` could be the communities `{a,b,c}` and `{d}`.

A Maximum k-cut is a k-cut such that the total weight of relationships between nodes from different communities in the k-cut is maximized. That is, a k-cut that maximizes the sum of weights of relationships whose source and target nodes are assigned to different communities in the k-cut. Suppose in the simple `a,b,c,d` node set example above we only had one relationship `b → c`, and it was of weight `1.0`. The 2-cut we outlined above would then not be a maximum 2-cut (with a cut cost of `0.0`), whereas for example the 2-cut with communities `{a,b}` and `{c,d}` would be one (with a cut cost of `1.0`).

Maximum k-cut is the same as Maximum Cut when `k = 2`.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

Applications

Finding the maximum k-cut for a graph has several known applications, for example it is used to:

- analyze protein interaction
- design circuit (VLSI) layouts
- solve wireless communication problems
- analyze cryptocurrency transaction patterns
- design computer networks

Approximation

In practice, finding the best cut is not feasible for larger graphs and only an approximation can be computed in reasonable time.

The approximate heuristic algorithm implemented in GDS is a parallelized GRASP style algorithm optionally enhanced (via config) with variable neighborhood search (VNS).

For detailed information about a serial version of the algorithm, with a slightly different construction phase, when `k = 2` see `GRASP+VNR` in the paper:

- Festa et al. Randomized Heuristics for the Max-Cut Problem, 2002.

To see how the algorithm above performs in terms of solution quality compared to other algorithms when `k = 2` see `FES02GV` in the paper:

- Dunning et al. What Works Best When? A Systematic Evaluation of Heuristics for Max-Cut and QUBO, 2018.

By the stochastic nature of the algorithm, the results it yields will not be deterministic unless running single-threaded (`concurrency = 1`) and using the same random seed (`randomSeed = SOME_FIXED_VALUE`).

Tuning the algorithm parameters

There are two important algorithm specific parameters which lets you trade solution quality for shorter runtime.

Iterations

GRASP style algorithms are iterative by nature. Every iteration they run the same well-defined steps to derive a solution, but each time with a different random seed yielding solutions that (highly likely) are different too. In the end the highest scoring solution is picked as the winner.

VNS max neighborhood order

Variable neighborhood search (VNS) works by slightly perturbing a locally optimal solution derived from the previous steps in an iteration of the algorithm, followed by locally optimizing this perturbed solution.

Perturb in this case means to randomly move some nodes from their current (locally optimal) community to another community.

VNS will in turn move `1,2,…,vnsMaxNeighborhoodOrder` random nodes and using each of the resulting solutions try to find a new locally optimal solution that's better. This means that although potentially better solutions can be derived using VNS it will take more time, and additionally some more memory will be needed to temporarily store the perturbed solutions.

By default, VNS is not used (`vnsMaxNeighborhoodOrder = 0`). To use it, experimenting with a maximum order equal to `20` is a good place to start.

Syntax

This section covers the syntax used to execute the Approximate Maximum k-cut algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Example 1. Approximate Maximum k-cut syntax per mode

Run Approximate Maximum k-cut in stream mode on a named graph.

```
CALL gds.alpha.maxkcut.stream(
  graphName: String,
  configuration: Map
) YIELD
  nodeId: Integer,
  communityId: Integer
```

Table 513. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 514. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm.

Table 515. Algorithm specific configuration

Name	Type	Default	Optional	Description
k	Integer	`2`	yes	The number of disjoint communities the nodes will be divided into.
iterations	Integer	`8`	yes	The number of iterations the algorithm will run before returning the best solution among all the iterations.
vnsMaxNeighborhoodOrder	Integer	`0 (VNS off)`	yes	The maximum number of nodes VNS will swap when perturbing solutions.
randomSeed	Integer	`n/a`	yes	A random seed which is used for all randomness in the computation. Requires `concurrency = 1`.
relationshipWeightProperty	String	`null`	yes	If set, the values stored at the given property are used as relationship weights during the computation. If not set, the graph is considered unweighted.

Table 516. Results

Name	Type	Description
nodeId	Integer	Node ID.

Name	Type	Description
communityId	Integer	Community ID.

Run Approximate Maximum k-cut in mutate mode on a named graph.

```
CALL gds.alpha.maxkcut.mutate(
  graphName: String,
  configuration: Map
) YIELD
  cutCost: Float,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 517. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 518. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 519. Algorithm specific configuration

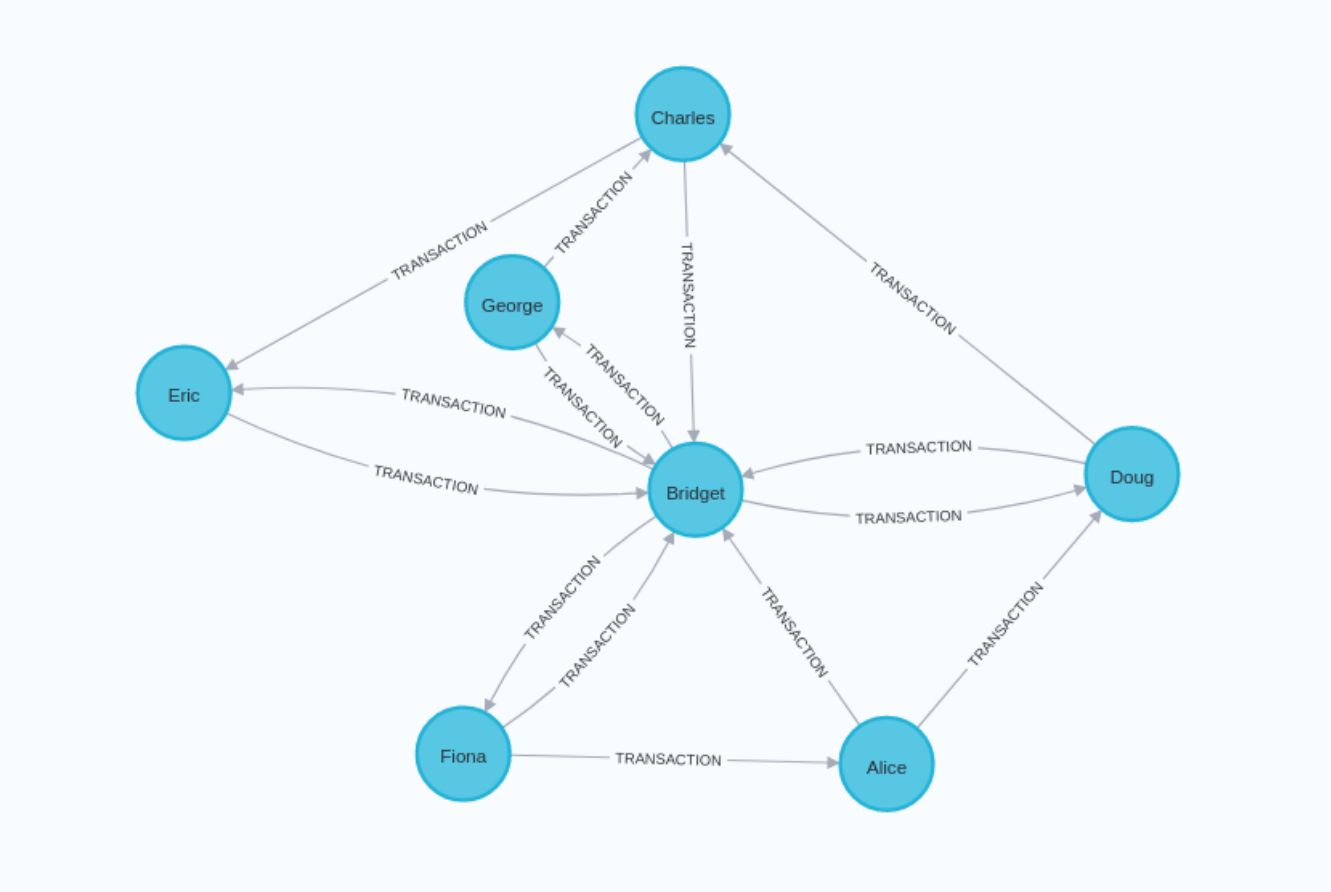
Name	Type	Default	Optional	Description
k	Integer	2	yes	The number of disjoint communities the nodes will be divided into.
iterations	Integer	8	yes	The number of iterations the algorithm will run before returning the best solution among all the iterations.
vnsMaxNeighborhoodOrder	Integer	0 (VNS off)	yes	The maximum number of nodes VNS will swap when perturbing solutions.
randomSeed	Integer	n/a	yes	A random seed which is used for all randomness in the computation. Requires `concurrency = 1`.
relationshipWeightProperty	String	null	yes	If set, the values stored at the given property are used as relationship weights during the computation. If not set, the graph is considered unweighted.

Table 520. Results

Name	Type	Description
cutCost	Float	Sum of weights of all relationships connecting nodes from different communities.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the statistics.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
nodePropertiesWritten	Integer	Number of properties added to the projected graph.
configuration	Map	Configuration used for running the algorithm.

Examples

In this section we will show examples of running the Approximate Maximum k-cut algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small Bitcoin transactions graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:Person {name: 'Alice'}),
  (bridget:Person {name: 'Bridget'}),
  (charles:Person {name: 'Charles'}),
  (doug:Person {name: 'Doug'}),
  (eric:Person {name: 'Eric'}),
  (fiona:Person {name: 'Fiona'}),
  (george:Person {name: 'George'}),
  (alice)-[:TRANSACTION {value: 81.0}]->(bridget),
  (alice)-[:TRANSACTION {value: 7.0}]->(doug),
  (bridget)-[:TRANSACTION {value: 1.0}]->(doug),
  (bridget)-[:TRANSACTION {value: 1.0}]->(eric),
  (bridget)-[:TRANSACTION {value: 1.0}]->(fiona),
  (bridget)-[:TRANSACTION {value: 1.0}]->(george),
  (charles)-[:TRANSACTION {value: 45.0}]->(bridget),
  (charles)-[:TRANSACTION {value: 3.0}]->(eric),
  (doug)-[:TRANSACTION {value: 3.0}]->(charles),
  (doug)-[:TRANSACTION {value: 1.0}]->(bridget),
  (eric)-[:TRANSACTION {value: 1.0}]->(bridget),
  (fiona)-[:TRANSACTION {value: 3.0}]->(alice),
  (fiona)-[:TRANSACTION {value: 1.0}]->(bridget),
  (george)-[:TRANSACTION {value: 1.0}]->(bridget),
  (george)-[:TRANSACTION {value: 4.0}]->(charles)
```

With the graph in Neo4j we can now project it into the graph catalog to prepare it for algorithm execution. We do this using a native projection targeting the `Person` nodes and the `TRANSACTION` relationships.

The following statement will project a graph store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'Person',
  {
    TRANSACTION: {
      properties: ['value']
    }
  }
)
```

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `mutate` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.alpha.maxkcut.mutate.estimate('myGraph', {mutateProperty: 'community'})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 521. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
7	15	488	488	"488 Bytes"

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the approximate maximum k-cut for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.alpha.maxkcut.mutate('myGraph', {mutateProperty: 'community'})
YIELD cutCost, nodePropertiesWritten
```

Table 522. Results

cutCost	nodePropertiesWritten
13.0	7

We can see that when relationship weight is not taken into account we derive a cut into two (since we didn't override the default `k = 2`) communities of cost `13.0`. The total cost is represented by the `cutCost` column here. This is the value we want to be as high as possible. Additionally, the graph 'myGraph' now has a node property `community` which stores the community to which each node belongs.

To inspect which community each node belongs to we can stream node properties.

Stream node properties:

```
CALL gds.graph.streamNodeProperty('myGraph', 'community')
YIELD nodeId, propertyValue
RETURN gds.util.asNode(nodeId).name as name, propertyValue AS community
```

Table 523. Results

name	community
"Alice"	0
"Bridget"	0
"Charles"	0
"Doug"	1
"Eric"	1
"Fiona"	1
"George"	1

Looking at our graph topology we can see that there are no relationships between the nodes of community 1, and two relationships between the nodes of community 0, namely Alice → Bridget and Charles → Bridget. However, since there are a total of eight relationships between Bridget and nodes of community 1, and our graph is unweighted assigning Bridget to community 1 would not yield a cut of a higher total weight. Thus, since the number of relationships connecting nodes of different communities greatly outnumber the number of relationships connecting nodes of the same community it seems like a good solution. In fact, this is the maximum 2-cut for this graph.

Because of the inherent randomness in the Approximate Maximum k-Cut algorithm (unless having concurrency = 1 and fixed randomSeed), running it another time might yield a different solution. For our case here it would be equally plausible to get the inverse solution, i.e. when our community 0 nodes are mapped to community 1 instead, and vice versa. Note however, that for that solution the cut cost would remain the same.

Mutate with relationship weights

In this example we will have a look at how adding relationship weight can affect our solution.

The following will run the algorithm in mutate mode, diving our nodes into two communities once again:

```
CALL gds.alpha.maxkcut.mutate(
   'myGraph',
   {
        relationshipWeightProperty: 'value',
        mutateProperty: 'weightedCommunity'
    }
)
YIELD cutCost, nodePropertiesWritten
```

Table 524. Results

cutCost	nodePropertiesWritten
146.0	7

Since the value properties on our TRANSACTION relationships were all at least 1.0 and several of a larger value it's not surprising that we obtain a cut with a larger cost in the weighted case.

Let us now stream node properties to once again inspect the node community distribution.

Stream node properties:

```
CALL gds.graph.streamNodeProperty('myGraph', 'weightedCommunity')
YIELD nodeId, propertyValue
RETURN gds.util.asNode(nodeId).name as name, propertyValue AS weightedCommunity
```

Table 525. Results

name	weightedCommunity
"Alice"	0
"Bridget"	1

name	weightedCommunity
"Charles"	0
"Doug"	1
"Eric"	1
"Fiona"	1
"George"	1

Comparing this result with that of unweighted case we can see that `Bridget` has moved to another community but the output is otherwise the same. Indeed, this makes sense by looking at our graph. `Bridget` is connected to nodes of community `1` by eight relationships, but these relationships all have weight `1.0`. And although `Bridget` is only connected to two community `0` nodes, these relationships are of weight `81.0` and `45.0`. Moving `Bridget` back to community `0` would lower the total cut cost of `81.0 + 45.0 - 8 * 1.0 = 118.0`. Hence, it does make sense that `Bridget` is now in community `1`. In fact, this is the maximum 2-cut in the weighted case.

Because of the inherent randomness in the Approximate Maximum k-Cut algorithm (unless having `concurrency = 1` and fixed `randomSeed`), running it another time might yield a different solution. For our case here it would be equally plausible to get the inverse solution, i.e. when our community `0` nodes are mapped to community `1` instead, and vice versa. Note however, that for that solution the cut cost would remain the same.

Stream

In the `stream` execution mode, the algorithm returns the approximate maximum k-cut for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode using default configuration parameters:

```
CALL gds.alpha.maxkcut.stream('myGraph')
YIELD nodeId, communityId
RETURN gds.util.asNode(nodeId).name AS name, communityId
```

Table 526. Results

name	communityId
"Alice"	0
"Bridget"	0
"Charles"	0
"Doug"	1
"Eric"	1
"Fiona"	1

name	communityId
"George"	1

We can see that the result is what we expect, namely the same as in the mutate unweighted example.

Because of the inherent randomness in the Approximate Maximum k-Cut algorithm (unless having `concurrency = 1` and fixed `randomSeed`), running it another time might yield a different solution. For our case here it would be equally plausible to get the inverse solution, i.e. when our community `0` nodes are mapped to community `1` instead, and vice versa. Note however, that for that solution the cut cost would remain the same.

6.3.11. Conductance metric Alpha

This section describes the Conductance algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

Conductance is a metric that allows you to evaluate the quality of a community detection. Relationships of nodes in a community `C` connect to nodes either within `C` or outside `C`. The conductance is the ratio between relationships that point outside `C` and the total number of relationships of `C`. The lower the conductance, the more "well-knit" a community is.

It was shown by Yang and Leskovec in the paper *"Defining and Evaluating Network Communities based on Ground-truth"* that conductance is a very good metric for evaluating actual communities of real world graphs.

The algorithm runs in time linear to the number of relationships in the graph.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

Syntax

This section covers the syntax used to execute the Conductance algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Example 2. Conductance syntax per mode

Run Conductance in stream mode on a named graph.

```
CALL gds.alpha.conductance.stream(
  graphName: String,
  configuration: Map
) YIELD
  community: Integer,
  conductance: Float
```

Table 527. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 528. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 529. Algorithm specific configuration

Name	Type	Default	Optional	Description
communityProperty	String	n/a	no	The node property that holds the community ID as an integer for each node. Note that only non-negative community IDs are considered valid and will have their conductance computed.

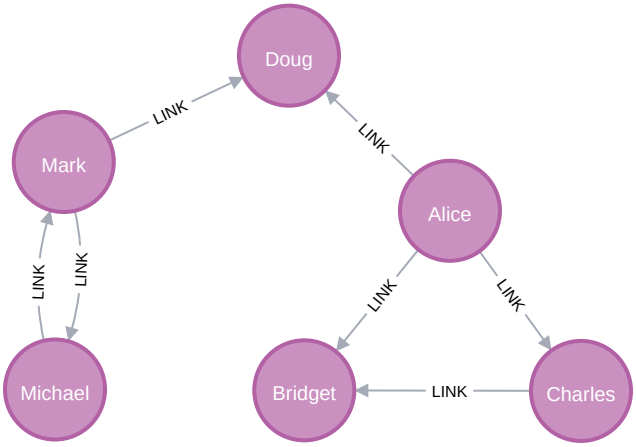
Table 530. Results

Name	Type	Description
community	Integer	Community ID.
conductance	Float	Conductance of the community.

Only non-negative community IDs are valid for identifying communities. Nodes with a negative community ID will only take part in the computation to the extent that they are connected to nodes in valid communities, and thus contribute to those valid communities' outward relationship counts.

Examples

In this section we will show examples of running the Conductance algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (nAlice:User {name: 'Alice', seed: 42}),
  (nBridget:User {name: 'Bridget', seed: 42}),
  (nCharles:User {name: 'Charles', seed: 42}),
  (nDoug:User {name: 'Doug'}),
  (nMark:User {name: 'Mark'}),
  (nMichael:User {name: 'Michael'}),

  (nAlice)-[:LINK {weight: 1}]->(nBridget),
  (nAlice)-[:LINK {weight: 1}]->(nCharles),
  (nCharles)-[:LINK {weight: 1}]->(nBridget),

  (nAlice)-[:LINK {weight: 5}]->(nDoug),

  (nMark)-[:LINK {weight: 1}]->(nDoug),
  (nMark)-[:LINK {weight: 1}]->(nMichael),
  (nMichael)-[:LINK {weight: 1}]->(nMark);
```

This graph has two clusters of *Users*, that are closely connected. Between those clusters there is one single edge. The relationships that connect the nodes in each component have a property `weight` which determines the strength of the relationship.

We can now project the graph and store it in the graph catalog. We load the `LINK` relationships with orientation set to `UNDIRECTED` as this works best with the Louvain algorithm which we will use to create the communities that we evaluate using Conductance.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
    'myGraph',
    'User',
    {
        LINK: {
            orientation: 'UNDIRECTED'
        }
    },
    {
        nodeProperties: 'seed',
        relationshipProperties: 'weight'
    }
)
```

We now run the Louvain algorithm to create a division of the nodes into communities that we can then evalutate.

The following will run the Louvain algorithm and store the results in `myGraph`:

```
CALL gds.louvain.mutate('myGraph', { mutateProperty: 'community', relationshipWeightProperty: 'weight' })
YIELD communityCount
```

Table 531. Results

communityCount
3

Now our in-memory graph `myGraph` is populated with node properties under the key `community` that we can set as input for our evaluation using Conductance. The nodes are now assigned to communities in the following way:

Table 532. Community assignments

name	community
"Alice"	3
"Bridget"	2
"Charles"	2
"Doug"	3
"Mark"	5
"Michael"	5

Please see the stream node properties procedure for how to obtain such an assignment table.

For more information about Louvain, see its algorithm page.

Stream

Since we now have a community detection, we can evaluate how good it is under the conductance metric. Note that we in this case we use the feature of relationships being weighted by a relationship property.

The Conductance stream procedure returns the conductance for each community. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the stream mode in general, see Stream.

The following will run the Conductance algorithm in `stream` mode:

```
CALL gds.alpha.conductance.stream('myGraph', { communityProperty: 'community', relationshipWeightProperty:
'weight' })
YIELD community, conductance
```

Table 533. Results

community	conductance
2	0.5
3	0.23076923076923078
5	0.2

We can see that the community of the weighted graph with the lowest conductance is community 5. This means that 5 is the community that is most "well-knit" in the sense that most of its relationship weights are internal to the community.

6.4. Similarity

> *This chapter provides explanations and examples for the similarity algorithms in the Neo4j Graph Data Science library.*

Similarity algorithms compute the similarity of pairs of nodes based on their neighborhoods or their properties. Several similarity metrics can be used to compute a similarity score. The Neo4j GDS library includes the following similarity algorithms:

- Node Similarity
- K-Nearest Neighbors

As well as a collection of different similarity functions for calculating similarity between arrays of numbers

6.4.1. Node Similarity

> *This section describes the Node Similarity algorithm in the Neo4j Graph Data Science library. The algorithm is based on the Jaccard and Overlap similarity metrics.*

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Node Similarity algorithm compares a set of nodes based on the nodes they are connected to. Two nodes are considered similar if they share many of the same neighbors. Node Similarity computes pair-wise similarities based on either the Jaccard metric, also known as the Jaccard Similarity Score, or the Overlap coefficient, also known as the Szymkiewicz–Simpson coefficient.

Given two sets `A` and `B`, the Jaccard Similarity is computed using the following formula:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

The Overlap coefficient is computed using the following formula:

$$O(A,B) = \frac{|A \cap B|}{min(|A|, |B|)}$$

The input of this algorithm is a bipartite, connected graph containing two disjoint node sets. Each relationship starts from a node in the first node set and ends at a node in the second node set.

The Node Similarity algorithm compares each node that has outgoing relationships with each other such node. For every node `n`, we collect the outgoing neighborhood `N(n)` of that node, that is, all nodes `m` such that there is a relationship from `n` to `m`. For each pair `n`, `m`, the algorithm computes a similarity for that pair that equals the outcome of the selected similarity metric for `N(n)` and `N(m)`.

Node Similarity has time complexity $O(n^3)$ and space complexity $O(n^2)$. We compute and store neighbour sets in time and space $O(n^2)$, then compute pairwise similarity scores in time $O(n^3)$.

In order to bound memory usage you can specify an explicit limit on the number of results to output per node, this is the 'topK' parameter. It can be set to any value, except 0. You will lose precision in the overall computation of course, and running time is unaffected - we still have to compute results before potentially throwing them away.

The output of the algorithm are new relationships between pairs of the first node set. Similarity scores are expressed via relationship properties.

For more information on this algorithm, see:

- Structural equivalence (Wikipedia)
- The Jaccard index (Wikipedia).
- The Overlap Coefficient (Wikipedia).
- Bipartite graphs (Wikipedia)

Running this algorithm requires sufficient available memory. Before running this algorithm, we recommend that you read Memory Estimation.

Syntax

This section covers the syntax used to execute the Node Similarity algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Node Similarity syntax per mode

Run Node Similarity in stream mode on a named graph.

```
CALL gds.nodeSimilarity.stream(
  graphName: String,
  configuration: Map
) YIELD
  node1: Integer,
  node2: Integer,
  similarity: Float
```

Table 534. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 535. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 536. Algorithm specific configuration

Name	Type	Default	Optional	Description
similarityCutoff	Float	1E-42	yes	Lower limit for the similarity score to be present in the result. Values must be between 0 and 1.
degreeCutoff	Integer	1	yes	Lower limit on the node degree for a node to be considered in the comparisons. This value can not be lower than 1.
topK	Integer	10	yes	Limit on the number of scores per node. The K largest results are returned. This value cannot be lower than 1.
bottomK	Integer	10	yes	Limit on the number of scores per node. The K smallest results are returned. This value cannot be lower than 1.
topN	Integer	0	yes	Global limit on the number of scores computed. The N largest total results are returned. This value cannot be negative, a value of 0 means no global limit.
bottomN	Integer	0	yes	Global limit on the number of scores computed. The N smallest total results are returned. This value cannot be negative, a value of 0 means no global limit.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

Name	Type	Default	Optional	Description
similarityMetric	String	`JACCARD`	yes	The metric used to compute similarity. Can be either `JACCARD` or `OVERLAP`.

Table 537. Results

Name	Type	Description
`node1`	Integer	Node ID of the first node.
`node2`	Integer	Node ID of the second node.
`similarity`	Float	Similarity score for the two nodes.

Run Node Similarity in stats mode on a named graph.

```
CALL gds.nodeSimilarity.stats(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  nodesCompared: Integer,
  similarityPairs: Integer,
  similarityDistribution: Map,
  configuration: Map
```

Table 538. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 539. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 540. Algorithm specific configuration

Name	Type	Default	Optional	Description
similarityCutoff	Float	1E-42	yes	Lower limit for the similarity score to be present in the result. Values must be between 0 and 1.
degreeCutoff	Integer	1	yes	Lower limit on the node degree for a node to be considered in the comparisons. This value can not be lower than 1.
topK	Integer	10	yes	Limit on the number of scores per node. The K largest results are returned. This value cannot be lower than 1.
bottomK	Integer	10	yes	Limit on the number of scores per node. The K smallest results are returned. This value cannot be lower than 1.
topN	Integer	0	yes	Global limit on the number of scores computed. The N largest total results are returned. This value cannot be negative, a value of 0 means no global limit.
bottomN	Integer	0	yes	Global limit on the number of scores computed. The N smallest total results are returned. This value cannot be negative, a value of 0 means no global limit.

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
similarityMetric	String	JACCARD	yes	The metric used to compute similarity. Can be either JACCARD or OVERLAP.

Table 541. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing component count and distribution statistics.
nodesCompared	Integer	The number of nodes for which similarity was computed.
similarityPairs	Integer	The number of similarities in the result.
similarityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of the computed similarity results.
configuration	Map	The configuration used for running the algorithm.

Run Node Similarity in mutate mode on a graph stored in the catalog.

```
CALL gds.nodeSimilarity.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  postProcessingMillis: Integer,
  relationshipsWritten: Integer,
  nodesCompared: Integer,
  similarityDistribution: Map,
  configuration: Map
```

Table 542. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 543. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 544. Algorithm specific configuration

Name	Type	Default	Optional	Description
similarityCutoff	Float	1E-42	yes	Lower limit for the similarity score to be present in the result. Values must be between 0 and 1.
degreeCutoff	Integer	1	yes	Lower limit on the node degree for a node to be considered in the comparisons. This value can not be lower than 1.
topK	Integer	10	yes	Limit on the number of scores per node. The K largest results are returned. This value cannot be lower than 1.
bottomK	Integer	10	yes	Limit on the number of scores per node. The K smallest results are returned. This value cannot be lower than 1.
topN	Integer	0	yes	Global limit on the number of scores computed. The N largest total results are returned. This value cannot be negative, a value of 0 means no global limit.

Name	Type	Default	Optional	Description
bottomN	Integer	`0`	yes	Global limit on the number of scores computed. The N smallest total results are returned. This value cannot be negative, a value of 0 means no global limit.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
similarityMetric	String	`JACCARD`	yes	The metric used to compute similarity. Can be either `JACCARD` or `OVERLAP`.

Table 545. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
postProcessingMillis	Integer	Milliseconds for computing percentiles.
nodesCompared	Integer	The number of nodes for which similarity was computed.
relationshipsWritten	Integer	The number of relationships created.
similarityDistribution	Map	Map containing min, max, mean, stdDev and p1, p5, p10, p25, p75, p90, p95, p99, p100 percentile values of the computed similarity results.
configuration	Map	The configuration used for running the algorithm.

Run Node Similarity in write mode on a graph stored in the catalog.

```
CALL gds.nodeSimilarity.write(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  postProcessingMillis: Integer,
  nodesCompared: Integer,
  relationshipsWritten: Integer,
  similarityDistribution: Map,
  configuration: Map
```

Table 546. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 547. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 548. Algorithm specific configuration

Name	Type	Default	Optional	Description
similarityCutoff	Float	`1E-42`	yes	Lower limit for the similarity score to be present in the result. Values must be between 0 and 1.
degreeCutoff	Integer	`1`	yes	Lower limit on the node degree for a node to be considered in the comparisons. This value can not be lower than 1.
topK	Integer	`10`	yes	Limit on the number of scores per node. The K largest results are returned. This value cannot be lower than 1.
bottomK	Integer	`10`	yes	Limit on the number of scores per node. The K smallest results are returned. This value cannot be lower than 1.

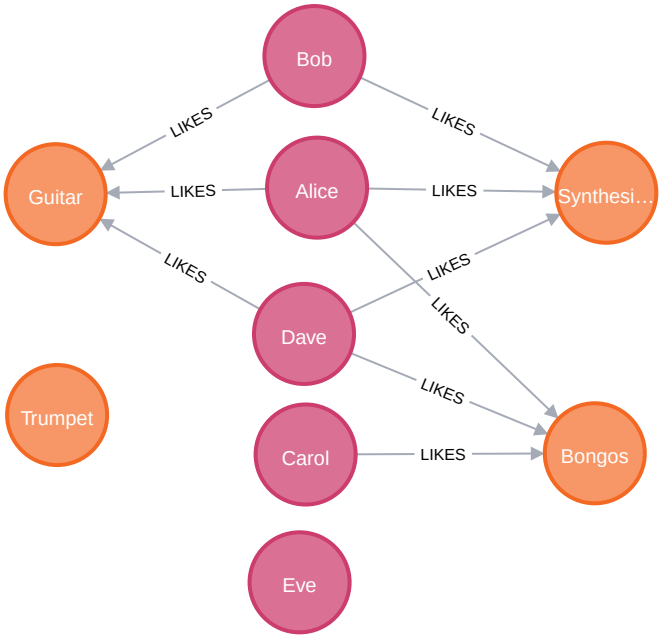
Name	Type	Default	Optional	Description
topN	Integer	`0`	yes	Global limit on the number of scores computed. The N largest total results are returned. This value cannot be negative, a value of 0 means no global limit.
bottomN	Integer	`0`	yes	Global limit on the number of scores computed. The N smallest total results are returned. This value cannot be negative, a value of 0 means no global limit.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
similarityMetric	String	`JACCARD`	yes	The metric used to compute similarity. Can be either `JACCARD` or `OVERLAP`.

Table 549. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
postProcessingMillis	Integer	Milliseconds for computing percentiles.
nodesCompared	Integer	The number of nodes for which similarity was computed.
relationshipsWritten	Integer	The number of relationships created.
similarityDistribution	Map	Map containing min, max, mean, stdDev and p1, p5, p10, p25, p75, p90, p95, p99, p100 percentile values of the computed similarity results.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Node Similarity algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small knowledge graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:Person {name: 'Alice'}),
  (bob:Person {name: 'Bob'}),
  (carol:Person {name: 'Carol'}),
  (dave:Person {name: 'Dave'}),
  (eve:Person {name: 'Eve'}),
  (guitar:Instrument {name: 'Guitar'}),
  (synth:Instrument {name: 'Synthesizer'}),
  (bongos:Instrument {name: 'Bongos'}),
  (trumpet:Instrument {name: 'Trumpet'}),

  (alice)-[:LIKES]->(guitar),
  (alice)-[:LIKES]->(synth),
  (alice)-[:LIKES {strength: 0.5}]->(bongos),
  (bob)-[:LIKES]->(guitar),
  (bob)-[:LIKES]->(synth),
  (carol)-[:LIKES]->(bongos),
  (dave)-[:LIKES]->(guitar),
  (dave)-[:LIKES]->(synth),
  (dave)-[:LIKES]->(bongos);
```

This bipartite graph has two node sets, Person nodes and Instrument nodes. The two node sets are connected via LIKES relationships. Each relationship starts at a Person node and ends at an Instrument node.

In the example, we want to use the Node Similarity algorithm to compare people based on the instruments they like.

The Node Similarity algorithm will only compute similarity for nodes that have a degree of at least 1. In the example graph, the Eve node will not be compared to other Person nodes.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
    'myGraph',
    ['Person', 'Instrument'],
    {
        LIKES: {
            type: 'LIKES',
            properties: {
                strength: {
                    property: 'strength',
                    defaultValue: 1.0
                }
            }
        }
    }
);
```

In the following examples we will demonstrate using the Node Similarity algorithm on this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.nodeSimilarity.write.estimate('myGraph', {
  writeRelationshipType: 'SIMILAR',
  writeProperty: 'score'
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 550. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
9	9	2592	2808	"[2592 Bytes ... 2808 Bytes]"

Stream

In the `stream` execution mode, the algorithm returns the similarity score for each relationship. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm, and stream results:

```
CALL gds.nodeSimilarity.stream('myGraph')
YIELD node1, node2, similarity
RETURN gds.util.asNode(node1).name AS Person1, gds.util.asNode(node2).name AS Person2, similarity
ORDER BY similarity DESCENDING, Person1, Person2
```

Table 551. Results

Person1	Person2	similarity
"Alice"	"Dave"	1.0
"Dave"	"Alice"	1.0
"Alice"	"Bob"	0.6666666666666666
"Bob"	"Alice"	0.6666666666666666
"Bob"	"Dave"	0.6666666666666666
"Dave"	"Bob"	0.6666666666666666
"Alice"	"Carol"	0.3333333333333333
"Carol"	"Alice"	0.3333333333333333
"Carol"	"Dave"	0.3333333333333333
"Dave"	"Carol"	0.3333333333333333

We use default values for the procedure configuration parameter. TopK is set to 10, topN is set to 0. Because of that the result set contains the top 10 similarity scores for each node.

If we would like to instead compare the Instruments to each other, we would then project the `LIKES` relationship type using `REVERSE` orientation. This would return similarities for pairs of Instruments and not compute any similarities between Persons.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm and returns the result in form of statistical and measurement values

```
CALL gds.nodeSimilarity.stats('myGraph')
YIELD nodesCompared, similarityPairs
```

Table 552. Results

nodesCompared	similarityPairs
4	10

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new relationship property containing the similarity score for that relationship. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm, and write back results to the in-memory graph:

```
CALL gds.nodeSimilarity.mutate('myGraph', {
    mutateRelationshipType: 'SIMILAR',
    mutateProperty: 'score'
})
YIELD nodesCompared, relationshipsWritten
```

Table 553. Results

nodesCompared	relationshipsWritten
4	10

As we can see from the results, the number of created relationships is equal to the number of rows in the streaming example.

The relationships that are produced by the mutation are always directed, even if the input graph is undirected. If `a → b` is topK for `a` and symmetrically `b → a` is topK for `b` (or both `a → b` and `b → a` are topN), it appears as though an undirected relationship is produced. However, they are just two directed relationships that have been independently produced.

Write

The `write` execution mode for each pair of nodes creates a relationship with their similarity score as a property to the Neo4j database. The type of the new relationship is specified using the mandatory configuration parameter `writeRelationshipType`. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics.

For more details on the `write` mode in general, see Write.

The following will run the algorithm, and write back results:

```
CALL gds.nodeSimilarity.write('myGraph', {
    writeRelationshipType: 'SIMILAR',
    writeProperty: 'score'
})
YIELD nodesCompared, relationshipsWritten
```

Table 554. Results

nodesCompared	relationshipsWritten
4	10

As we can see from the results, the number of created relationships is equal to the number of rows in the streaming example.

The relationships that are written are always directed, even if the input graph is undirected. If a → b is topK for a and symmetrically b → a is topK for b (or both a → b and b → a are topN), it appears as though an undirected relationship is written. However, they are just two directed relationships that have been independently written.

Limit results

There are four limits that can be applied to the similarity results. Top limits the result to the highest similarity scores. Bottom limits the result to the lowest similarity scores. Both top and bottom limits can apply to the result as a whole ("N"), or to the result per node ("K").

There must always be a "K" limit, either bottomK or topK, which is a positive number. The default value for topK and bottomK is 10.

Table 555. Result limits

	total results	results per node
highest score	topN	topK
lowest score	bottomN	bottomK

topK and bottomK

TopK and bottomK are limits on the number of scores computed per node. For topK, the K largest similarity scores per node are returned. For bottomK, the K smallest similarity scores per node are returned. TopK and bottomK cannot be 0, used in conjunction, and the default value is 10. If neither is specified, topK is used.

The following will run the algorithm, and stream the top 1 result per node:

```
CALL gds.nodeSimilarity.stream('myGraph', { topK: 1 })
YIELD node1, node2, similarity
RETURN gds.util.asNode(node1).name AS Person1, gds.util.asNode(node2).name AS Person2, similarity
ORDER BY Person1
```

Table 556. Results

Person1	Person2	similarity
"Alice"	"Dave"	1.0
"Bob"	"Alice"	0.6666666666666666
"Carol"	"Alice"	0.3333333333333333
"Dave"	"Alice"	1.0

The following will run the algorithm, and stream the bottom 1 result per node:

```
CALL gds.nodeSimilarity.stream('myGraph', { bottomK: 1 })
YIELD node1, node2, similarity
RETURN gds.util.asNode(node1).name AS Person1, gds.util.asNode(node2).name AS Person2, similarity
ORDER BY Person1
```

Table 557. Results

Person1	Person2	similarity
"Alice"	"Carol"	0.3333333333333333
"Bob"	"Alice"	0.6666666666666666
"Carol"	"Alice"	0.3333333333333333
"Dave"	"Carol"	0.3333333333333333

topN and bottomN

TopN and bottomN limit the number of similarity scores across all nodes. This is a limit on the total result set, in addition to the topK or bottomK limit on the results per node. For topN, the N largest similarity scores are returned. For bottomN, the N smallest similarity scores are returned. A value of 0 means no global limit is imposed and all results from topK or bottomK are returned.

The following will run the algorithm, and stream the 3 highest out of the top 1 results per node:

```
CALL gds.nodeSimilarity.stream('myGraph', { topK: 1, topN: 3 })
YIELD node1, node2, similarity
RETURN gds.util.asNode(node1).name AS Person1, gds.util.asNode(node2).name AS Person2, similarity
ORDER BY similarity DESC, Person1, Person2
```

Table 558. Results

Person1	Person2	similarity
"Alice"	"Dave"	1.0

Person1	Person2	similarity
"Dave"	"Alice"	1.0
"Bob"	"Alice"	0.6666666666666666

Degree cutoff and similarity cutoff

Degree cutoff is a lower limit on the node degree for a node to be considered in the comparisons. This value can not be lower than 1.

The following will ignore nodes with less than 3 LIKES relationships:

```
CALL gds.nodeSimilarity.stream('myGraph', { degreeCutoff: 3 })
YIELD node1, node2, similarity
RETURN gds.util.asNode(node1).name AS Person1, gds.util.asNode(node2).name AS Person2, similarity
ORDER BY Person1
```

Table 559. Results

Person1	Person2	similarity
"Alice"	"Dave"	1.0
"Dave"	"Alice"	1.0

Similarity cutoff is a lower limit for the similarity score to be present in the result. The default value is very small (1E-42) to exclude results with a similarity score of 0.

Setting similarity cutoff to 0 may yield a very large result set, increased runtime and memory consumption.

The following will ignore node pairs with a similarity score less than 0.5:

```
CALL gds.nodeSimilarity.stream('myGraph', { similarityCutoff: 0.5 })
YIELD node1, node2, similarity
RETURN gds.util.asNode(node1).name AS Person1, gds.util.asNode(node2).name AS Person2, similarity
ORDER BY Person1
```

Table 560. Results

Person1	Person2	similarity
"Alice"	"Dave"	1.0
"Alice"	"Bob"	0.6666666666666666
"Bob"	"Dave"	0.6666666666666666
"Bob"	"Alice"	0.6666666666666666
"Dave"	"Alice"	1.0
"Dave"	"Bob"	0.6666666666666666

Weighted Similarity

Relationship properties can be used to modify the similarity induced by certain relationships. For example a relationship value of 2 is equal to counting that relationship twice while computing the similarity.

Weighted similarity metrics are only defined for values greater or equal to 0.

The following query will respect relationship properties in the similarity computation:

```
CALL gds.nodeSimilarity.stream('myGraph', { relationshipWeightProperty: 'strength', similarityCutoff: 0.5
})
YIELD node1, node2, similarity
RETURN gds.util.asNode(node1).name AS Person1, gds.util.asNode(node2).name AS Person2, similarity
ORDER BY Person1
```

Table 561. Results

Person1	Person2	similarity
"Alice"	"Dave"	0.8333333333333334
"Alice"	"Bob"	0.8
"Bob"	"Alice"	0.8
"Bob"	"Dave"	0.6666666666666666
"Dave"	"Alice"	0.8333333333333334
"Dave"	"Bob"	0.6666666666666666

It can be seen that the similarity between Alice and Dave decreased compared to the non-weighted version of this algorithm. This is the case as the strength of the relationship between Alice and Bongos is reduced and both persons now only share 2.5 out of 3 possible instruments. Analogous the similarity between Alice and Bob increased as the missing liked instrument has a lower impact on the similarity score.

6.4.2. K-Nearest Neighbors

This section describes the K-Nearest Neighbors (KNN) algorithm in the Neo4j Graph Data Science library.

Introduction

The K-Nearest Neighbors algorithm computes a distance value for all node pairs in the graph and creates new relationships between each node and its k nearest neighbors. The distance is calculated based on node properties.

The input of this algorithm is a monopartite graph. The graph does not need to be connected, in fact, existing relationships between nodes will be ignored - apart from random walk sampling if that that initial sampling option is used. New relationships are created between each node and its k nearest neighbors.

The K-Nearest Neighbors algorithm compares given properties of each node. The k nodes where these

properties are most similar are the k-nearest neighbors.

The initial set of neighbors is picked at random and verified and refined in multiple iterations. The number of iterations is limited by the configuration parameter `maxIterations`. The algorithm may stop earlier if the neighbor lists only change by a small amount, which can be controlled by the configuration parameter `deltaThreshold`.

The particular implementation is based on Efficient k-nearest neighbor graph construction for generic similarity measures by Wei Dong et al. Instead of comparing every node with every other node, the algorithm selects possible neighbors based on the assumption, that the neighbors-of-neighbors of a node are most likely already the nearest one. The algorithm scales quasi-linear with respect to the node count, instead of being quadratic.

Furthermore, the algorithm only compares a sample of all possible neighbors on each iteration, assuming that eventually all possible neighbors will be seen. This can be controlled with the configuration parameter `sampleRate`:

- A valid sample rate must be in between 0 (exclusive) and 1 (inclusive).
- The default value is `0.5`.
- The parameter is used to control the trade-off between accuracy and runtime-performance.
- A higher sample rate will increase the accuracy of the result.
  - The algorithm will also require more memory and will take longer to compute.
- A lower sample rate will increase the runtime-performance.
  - Some potential nodes may be missed in the comparison and may not be included in the result.

When encountered neighbors have equal similarity to the least similar already known neighbor, randomly selecting which node to keep can reduce the risk of some neighborhoods not being explored. This behavior is controlled by the configuration parameter `perturbationRate`.

The output of the algorithm are new relationships between nodes and their k-nearest neighbors. Similarity scores are expressed via relationship properties.

For more information on this algorithm, see:

- Efficient k-nearest neighbor graph construction for generic similarity measures
- Nearest neighbor graph (Wikipedia)

Running this algorithm requires sufficient available memory. Before running this algorithm, we recommend that you read Memory Estimation.

Similarity metrics

The similarity measure used in the KNN algorithm depends on the type of the configured node properties. KNN supports both scalar numeric values and lists of numbers.

Scalar numbers

When a property is a scalar number, the similarity is computed as follows:

$$\frac{1}{1 + |p_s - p_t|}$$

Figure 2. one divided by one plus the absolute difference

This gives us a number in the range `(0, 1]`.

List of integers

When a property is a list of integers, similarity can be measured with either the Jaccard similarity or the Overlap coefficient.

Jaccard similarity

$$J(p_s, p_t) = \frac{|p_s \cap p_t|}{|p_s \cup p_t|}$$

Figure 3. size of intersection divided by size of union

Overlap coefficient

$$O(p_s, p_t) = \frac{|p_s \cap p_t|}{min(|p_s|, |p_t|)}$$

Figure 4. size of intersection divided by size of minimum set

Both of these metrics give a score in the range `[0, 1]` and no normalization needs to be performed. Jaccard similarity is used as the default option for comparing lists of integers when the metric is not specified.

List of floating-point numbers

When a property is a list of floating-point numbers, there are three alternatives for computing similarity between two nodes.

The default metric used is that of Cosine similarity.

Cosine similarity

$$cosine(p_s, p_t) = \frac{\sum_i p_s(i) \cdot p_t(i)}{\sqrt{\sum_i p_s(i)^2} \cdot \sqrt{\sum_i p_t(i)^2}}$$

Figure 5. dot product of the vectors divided by the product of their lengths

Notice that the above formula gives a score in the range of `[-1, 1]`. The score is normalized into the range `[0, 1]` by doing `score = (score + 1) / 2`.

The other two metrics include the Pearson correlation score and Normalized Euclidean similarity.

Pearson correlation score

$$pearson(p_s, p_t) = \frac{\sum_i (p_s(i) - \overline{p_s}) \cdot (p_t(i) - \overline{p_t})}{\sqrt{\sum_i (p_s(i) - \overline{p_s})^2} \cdot \sqrt{\sum_i (p_t(i) - \overline{p_t})^2}}$$

Figure 6. covariance divided by the product of the standard deviations

As above, the formula gives a score in the range `[-1, 1]`, which is normalized into the range `[0, 1]` similarly.

Euclidean similarity

$$ED(p_s, p_t) = \sqrt{\sum_i \left(p_s(i) - p_t(i)\right)^2}$$

Figure 7. the root of the sum of the square difference between each pair of elements

The result from this formula is a non-negative value, but is not necessarily bounded into the `[0, 1]` range. To bound the number into this range and obtain a similarity score, we return `score = 1 / (1 + distance)`, i.e., we perform the same normalization as in the case of scalar values.

Multiple properties

Finally, when multiple properties are specified, the similarity of the two neighbors is the mean of the similarities of the individual properties, i.e. the simple mean of the numbers, each of which is in the range `[0, 1]`, giving a total score also in the `[0, 1]` range.

The validity of this mean is highly context dependent, so take care when applying it to your data domain.

Node properties and metrics configuration

The node properties and metrics to use are specified with the `nodeProperties` configuration parameter. At least one node property must be specified.

This parameter accepts one of:

Table 562. nodeProperties syntax

a single property name	`nodeProperties: 'embedding'`
a Map of property keys to metrics	`nodeProperties: { embedding: 'COSINE', age: 'DEFAULT', lotteryNumbers: 'OVERLAP' }`

list of Strings and/or Maps	`nodeProperties: [ {embedding: 'COSINE'}, 'age', {lotteryNumbers: 'OVERLAP'} ]`

The available metrics by type are:

Table 563. Available metrics by type

type	metric
List of Integer	`JACCARD`, `OVERLAP`
List of Float	`COSINE`, `EUCLIDEAN`, `PEARSON`

For any property type, `DEFAULT` can also be specified to use the default metric. For scalar numbers, there is only the default metric.

Initial neighbor sampling

The algorithm starts off by picking `k` random neighbors for each node. There are two options for how this random sampling can be done.

Uniform

The first `k` neighbors for each node are chosen uniformly at random from all other nodes in the graph. This is the classic way of doing the initial sampling. It is also the algorithm's default. Note that this method does not actually use the topology of the input graph.

Random Walk

From each node we take a depth biased random walk and choose the first `k` unique nodes we visit on that walk as our initial random neighbors. If after some internally defined `O(k)` number of steps a random walk, `k` unique neighbors have not been visited, we will fill in the remaining neighbors using the uniform method described above. The random walk method makes use of the input graph's topology and may be suitable if it is more likely to find good similarity scores between topologically close nodes.

The random walk used is biased towards depth in the sense that it will more likely choose to go further away from its previously visited node, rather that go back to it or to a node equidistant to it. The intuition of this bias is that subsequent iterations of comparing neighbor-of-neighbors will likely cover the extended (topological) neighborhood of each node.

Syntax

This section covers the syntax used to execute the K-Nearest Neighbors algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

K-Nearest Neighbors syntax per mode

Run K-Nearest Neighbors in stream mode on a named graph.

```
CALL gds.knn.stream(
  graphName: String,
  configuration: Map
) YIELD
  node1: Integer,
  node2: Integer,
  similarity: Float
```

Table 564. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 565. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 566. Algorithm specific configuration

Name	Type	Default	Optional	Description
nodeProperties	String or Map or List of Strings / Maps	n/a	no	The node properties to use for similarity computation along with their selected similarity metrics. Accepts a single property key, a Map of property keys to metrics, or a List of property keys and/or Maps, as above. See Node properties and metrics configuration for details.
topK	Integer	10	yes	The number of neighbors to find for each node. The K-nearest neighbors are returned. This value cannot be lower than 1.
sampleRate	Float	0.5	yes	Sample rate to limit the number of comparisons per node. Value must be between 0 (exclusive) and 1 (inclusive).
deltaThreshold	Float	0.001	yes	Value as a percentage to determine when to stop early. If fewer updates than the configured value happen, the algorithm stops. Value must be between 0 (exclusive) and 1 (inclusive).
maxIterations	Integer	100	yes	Hard limit to stop the algorithm after that many iterations.

Name	Type	Default	Optional	Description
randomJoins	Integer	`10`	yes	Between every iteration, how many attempts are being made to connect new node neighbors based on random selection.
initialSampler	String	`"uniform"`	yes	The method used to sample the first `k` random neighbors for each node. "uniform" and "randomWalk", both case-insensitive, are valid inputs.
randomSeed	Integer	`n/a`	yes	The seed value to control the randomness of the algorithm. Note that `concurrency` must be set to 1 when setting this parameter.
similarityCutoff	Float	`0`	yes	Filter out from the list of K-nearest neighbors nodes with similarity below this threshold.
perturbationRate	Float	`0`	yes	The probability of replacing the least similar known neighbor with an encountered neighbor of equal similarity.

Table 567. Results

Name	Type	Description
`node1`	Integer	Node ID of the first node.
`node2`	Integer	Node ID of the second node.
`similarity`	Float	Similarity score for the two nodes.

Run K-Nearest Neighbors in stats mode on a named graph.

```
CALL gds.knn.stats(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  nodesCompared: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  nodePairsConsidered: Integer,
  similarityPairs: Integer,
  similarityDistribution: Map,
  configuration: Map
```

Table 568. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 569. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 570. Algorithm specific configuration

Name	Type	Default	Optional	Description
nodeProperties	String or Map or List of Strings / Maps	n/a	no	The node properties to use for similarity computation along with their selected similarity metrics. Accepts a single property key, a Map of property keys to metrics, or a List of property keys and/or Maps, as above. See Node properties and metrics configuration for details.
topK	Integer	10	yes	The number of neighbors to find for each node. The K-nearest neighbors are returned. This value cannot be lower than 1.
sampleRate	Float	0.5	yes	Sample rate to limit the number of comparisons per node. Value must be between 0 (exclusive) and 1 (inclusive).

Name	Type	Default	Optional	Description
deltaThreshold	Float	`0.001`	yes	Value as a percentage to determine when to stop early. If fewer updates than the configured value happen, the algorithm stops. Value must be between 0 (exclusive) and 1 (inclusive).
maxIterations	Integer	`100`	yes	Hard limit to stop the algorithm after that many iterations.
randomJoins	Integer	`10`	yes	Between every iteration, how many attempts are being made to connect new node neighbors based on random selection.
initialSampler	String	`"uniform"`	yes	The method used to sample the first `k` random neighbors for each node. "uniform" and "randomWalk", both case-insensitive, are valid inputs.
randomSeed	Integer	`n/a`	yes	The seed value to control the randomness of the algorithm. Note that `concurrency` must be set to 1 when setting this parameter.
similarityCutoff	Float	`0`	yes	Filter out from the list of K-nearest neighbors nodes with similarity below this threshold.
perturbationRate	Float	`0`	yes	The probability of replacing the least similar known neighbor with an encountered neighbor of equal similarity.

Table 571. Results

Name	Type	Description
ranIterations	Integer	Number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
nodePairsConsidered	Integer	The number of similarity computations.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing similarity value distribution statistics.
nodesCompared	Integer	The number of nodes for which similarity was computed.
similarityPairs	Integer	The number of similarities in the result.
similarityDistribution	Map	Map containing min, max, mean as well as p50, p75, p90, p95, p99 and p999 percentile values of the computed similarity results.
configuration	Map	The configuration used for running the algorithm.

Run K-Nearest Neighbors in mutate mode on a graph stored in the catalog.

```
CALL gds.knn.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  postProcessingMillis: Integer,
  relationshipsWritten: Integer,
  nodesCompared: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  nodePairsConsidered: Integer,
  similarityDistribution: Map,
  configuration: Map
```

Table 572. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 573. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 574. Algorithm specific configuration

Name	Type	Default	Optional	Description
nodeProperties	String or Map or List of Strings / Maps	n/a	no	The node properties to use for similarity computation along with their selected similarity metrics. Accepts a single property key, a Map of property keys to metrics, or a List of property keys and/or Maps, as above. See Node properties and metrics configuration for details.
topK	Integer	10	yes	The number of neighbors to find for each node. The K-nearest neighbors are returned. This value cannot be lower than 1.
sampleRate	Float	0.5	yes	Sample rate to limit the number of comparisons per node. Value must be between 0 (exclusive) and 1 (inclusive).

Name	Type	Default	Optional	Description
deltaThreshold	Float	`0.001`	yes	Value as a percentage to determine when to stop early. If fewer updates than the configured value happen, the algorithm stops. Value must be between 0 (exclusive) and 1 (inclusive).
maxIterations	Integer	`100`	yes	Hard limit to stop the algorithm after that many iterations.
randomJoins	Integer	`10`	yes	Between every iteration, how many attempts are being made to connect new node neighbors based on random selection.
initialSampler	String	`"uniform"`	yes	The method used to sample the first `k` random neighbors for each node. "uniform" and "randomWalk", both case-insensitive, are valid inputs.
randomSeed	Integer	`n/a`	yes	The seed value to control the randomness of the algorithm. Note that `concurrency` must be set to 1 when setting this parameter.
similarityCutoff	Float	`0`	yes	Filter out from the list of K-nearest neighbors nodes with similarity below this threshold.
perturbationRate	Float	`0`	yes	The probability of replacing the least similar known neighbor with an encountered neighbor of equal similarity.

Table 575. Results

Name	Type	Description
ranIterations	Integer	Number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
nodePairsConsidered	Integer	The number of similarity computations.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
postProcessingMillis	Integer	Milliseconds for computing similarity value distribution statistics.
nodesCompared	Integer	The number of nodes for which similarity was computed.
relationshipsWritten	Integer	The number of relationships created.
similarityDistribution	Map	Map containing min, max, mean, stdDev and p1, p5, p10, p25, p75, p90, p95, p99, p100 percentile values of the computed similarity results.

Name	Type	Description
configuration	Map	The configuration used for running the algorithm.

Run K-Nearest Neighbors in write mode on a graph stored in the catalog.

```
CALL gds.knn.write(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  postProcessingMillis: Integer,
  nodesCompared: Integer,
  ranIterations: Integer,
  didConverge: Boolean,
  nodePairsConsidered: Integer,
  relationshipsWritten: Integer,
  similarityDistribution: Map,
  configuration: Map
```

Table 576. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 577. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 578. Algorithm specific configuration

Name	Type	Default	Optional	Description
nodeProperties	String or Map or List of Strings / Maps	n/a	no	The node properties to use for similarity computation along with their selected similarity metrics. Accepts a single property key, a Map of property keys to metrics, or a List of property keys and/or Maps, as above. See Node properties and metrics configuration for details.
topK	Integer	10	yes	The number of neighbors to find for each node. The K-nearest neighbors are returned. This value cannot be lower than 1.

Name	Type	Default	Optional	Description
sampleRate	Float	`0.5`	yes	Sample rate to limit the number of comparisons per node. Value must be between 0 (exclusive) and 1 (inclusive).
deltaThreshold	Float	`0.001`	yes	Value as a percentage to determine when to stop early. If fewer updates than the configured value happen, the algorithm stops. Value must be between 0 (exclusive) and 1 (inclusive).
maxIterations	Integer	`100`	yes	Hard limit to stop the algorithm after that many iterations.
randomJoins	Integer	`10`	yes	Between every iteration, how many attempts are being made to connect new node neighbors based on random selection.
initialSampler	String	`"uniform"`	yes	The method used to sample the first `k` random neighbors for each node. "uniform" and "randomWalk", both case-insensitive, are valid inputs.
randomSeed	Integer	`n/a`	yes	The seed value to control the randomness of the algorithm. Note that `concurrency` must be set to 1 when setting this parameter.
similarityCutoff	Float	`0`	yes	Filter out from the list of K-nearest neighbors nodes with similarity below this threshold.
perturbationRate	Float	`0`	yes	The probability of replacing the least similar known neighbor with an encountered neighbor of equal similarity.

Table 579. Results

Name	Type	Description
ranIterations	Integer	Number of iterations run.
didConverge	Boolean	Indicates if the algorithm converged.
nodePairsConsidered	Integer	The number of similarity computations.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
postProcessingMillis	Integer	Milliseconds for computing similarity value distribution statistics.
nodesCompared	Integer	The number of nodes for which similarity was computed.
relationshipsWritten	Integer	The number of relationships created.

Name	Type	Description
similarityDistribution	Map	Map containing min, max, mean, stdDev and p1, p5, p10, p25, p75, p90, p95, p99, p100 percentile values of the computed similarity results.
configuration	Map	The configuration used for running the algorithm.

The KNN algorithm does not read any relationships, but the values for `relationshipProjection` or `relationshipQuery` are still being used and respected for the graph loading.

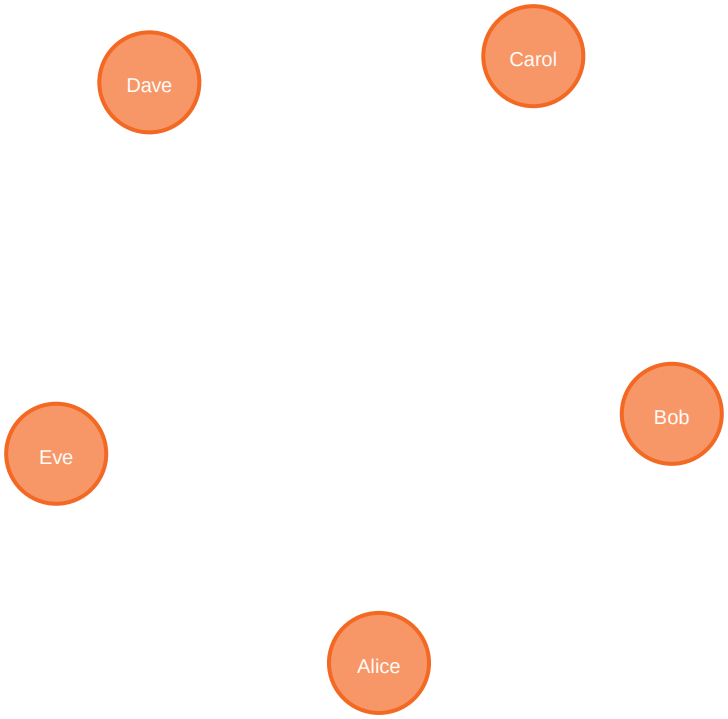
The results are the same as running write mode on a named graph, see write mode syntax above.

To get a deterministic result when running the algorithm:

- the `concurrency` parameter must be set to one
- the `randomSeed` must be explicitly set.

Examples

In this section we will show examples of running the KNN algorithm on a concrete graph. With the *Uniform sampler*, KNN samples initial neighbors uniformly at random, and doesn't take into account graph topology. This means KNN can run on a graph of only nodes, without any relationships. Consider the following graph of five disconnected Person nodes.



```
CREATE (alice:Person {name: 'Alice', age: 24, lotteryNumbers: [1, 3], embedding: [1.0, 3.0]})
CREATE (bob:Person {name: 'Bob', age: 73, lotteryNumbers: [1, 2, 3], embedding: [2.1, 1.6]})
CREATE (carol:Person {name: 'Carol', age: 24, lotteryNumbers: [3], embedding: [1.5, 3.1]})
CREATE (dave:Person {name: 'Dave', age: 48, lotteryNumbers: [2, 4], embedding: [0.6, 0.2]})
CREATE (eve:Person {name: 'Eve', age: 67, lotteryNumbers: [1, 5], embedding: [1.8, 2.7]});
```

In the example, we want to use the K-Nearest Neighbors algorithm to compare people based on either their age or a combination on all provided properties.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project(
    'myGraph',
    {
        Person: {
            label: 'Person',
            properties: ['age','lotteryNumbers','embedding']
        }
    },
    '*'
);
```

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.knn.write.estimate('myGraph', {
  nodeProperties: ['age'],
  writeRelationshipType: 'SIMILAR',
  writeProperty: 'score',
  topK: 1
})
YIELD nodeCount, bytesMin, bytesMax, requiredMemory
```

Table 580. Results

nodeCount	bytesMin	bytesMax	requiredMemory
5	2040	3096	"[2040 Bytes ... 3096 Bytes]"

Stream

In the `stream` execution mode, the algorithm returns the similarity score for each relationship. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm, and stream results:

```
CALL gds.knn.stream('myGraph', {
    topK: 1,
    nodeProperties: ['age'],
    // The following parameters are set to produce a deterministic result
    randomSeed: 1337,
    concurrency: 1,
    sampleRate: 1.0,
    deltaThreshold: 0.0
})
YIELD node1, node2, similarity
RETURN gds.util.asNode(node1).name AS Person1, gds.util.asNode(node2).name AS Person2, similarity
ORDER BY similarity DESCENDING, Person1, Person2
```

Table 581. Results

Person1	Person2	similarity
"Alice"	"Carol"	1.0
"Carol"	"Alice"	1.0
"Bob"	"Eve"	0.14285714285714285
"Eve"	"Bob"	0.14285714285714285
"Dave"	"Eve"	0.05

We use default values for the procedure configuration parameter for most parameters. The `randomSeed` and `concurrency` is set to produce the same result on every invocation. The `topK` parameter is set to 1 to only return the single nearest neighbor for every node. Notice that the similarity between Dave and Eve is very low. Setting the `similarityCutoff` parameter to 0.10 will filter the relationship between them, removing it from the result.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm and return the result in form of statistical and measurement values:

```
CALL gds.knn.stats('myGraph', {topK: 1, concurrency: 1, randomSeed: 42, nodeProperties: ['age']})
YIELD nodesCompared, similarityPairs
```

Table 582. Results

nodesCompared	similarityPairs
5	5

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new relationship property containing the similarity score for that relationship. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm, and write back results to the in-memory graph:

```
CALL gds.knn.mutate('myGraph', {
    mutateRelationshipType: 'SIMILAR',
    mutateProperty: 'score',
    topK: 1,
    randomSeed: 42,
    concurrency: 1,
    nodeProperties: ['age']
})
YIELD nodesCompared, relationshipsWritten
```

Table 583. Results

nodesCompared	relationshipsWritten
5	5

As we can see from the results, the number of created relationships is equal to the number of rows in the streaming example.

The relationships that are produced by the mutation are always directed, even if the input graph is undirected. If for example `a → b` is topK for `a` and symmetrically `b → a` is topK for `b`, it appears as though an undirected relationship is produced. However, they are just two directed relationships that have been independently produced.

Write

The `write` execution mode extends the `stats` mode with an important side effect: for each pair of nodes we create a relationship with the similarity score as a property to the Neo4j database. The type of the new relationship is specified using the mandatory configuration parameter `writeRelationshipType`. Each new relationship stores the similarity score between the two nodes it represents. The relationship property key is set using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics.

For more details on the `write` mode in general, see Write.

The following will run the algorithm, and write back results:

```
CALL gds.knn.write('myGraph', {
    writeRelationshipType: 'SIMILAR',
    writeProperty: 'score',
    topK: 1,
    randomSeed: 42,
    concurrency: 1,
    nodeProperties: ['age']
})
YIELD nodesCompared, relationshipsWritten
```

Table 584. Results

nodesCompared	relationshipsWritten
5	5

As we can see from the results, the number of created relationships is equal to the number of rows in the streaming example.

The relationships that are written are always directed, even if the input graph is undirected. If for example a → b is topK for a and symmetrically b → a is topK for b, it appears as though an undirected relationship is written. However, they are just two directed relationships that have been independently written.

Calculation with multiple properties

If we want to calculate similarity based on multiple metrics, we can calculate the similarity for each property individually and take their mean. As an example, we can use the Normalized Euclidean similarity metric for the embedding property and the Overlap metric for the lottery numbers property in addition to the age property.

The following shows an example of using multiple properties to calculate similarity and streams the results:

```
CALL gds.knn.stream('myGraph', {
    topK: 1,
    nodeProperties: [
        {embedding: "EUCLIDEAN"},
        'age',
        {lotteryNumbers: "OVERLAP"}
    ],
    // The following parameters are set to produce a deterministic result
    randomSeed: 1337,
    concurrency: 1,
    sampleRate: 1.0,
    deltaThreshold: 0.0
})
YIELD node1, node2, similarity
RETURN gds.util.asNode(node1).name AS Person1, gds.util.asNode(node2).name AS Person2, similarity
ORDER BY similarity DESCENDING, Person1, Person2
```

Table 585. Results

Person1	Person2	similarity
"Alice"	"Carol"	0.931216931216931

Person1	Person2	similarity
"Carol"	"Alice"	0.931216931216931
"Bob"	"Carol"	0.432336103416436
"Eve"	"Alice"	0.366920651602733
"Dave"	"Bob"	0.243466706038683

Note that the two distinct maps in the query could be merged to a single one.

6.4.3. Similarity functions

Definitions

The Neo4j GDS library provides a set of measures that can be used to calculate similarity between two arrays p_s, p_t of numbers.

The similarity functions can be classified into two groups. The first is `categorical` measures which treat the arrays as sets and calculate similarity based on the intersection between the two sets. The second is `numerical` measures which compute similarity based on how close the numbers at each position are to each other.

Similarity Function name	Formula	Type	Value range
`gds.similarity.jaccard`	$J(p_s, p_t) = \frac{\lvert p_s \cap p_t \rvert}{\lvert p_s \cup p_t \rvert}$	Categorical	`[0,1]`
`gds.similarity.overlap`	$O(p_s, p_t) = \frac{\lvert p_s \cap p_t \rvert}{min(\lvert p_s \rvert, \lvert p_t \rvert)}$	Categorical	`[0, 1]`
`gds.similarity.cosine`	$cosine(p_s, p_t) = \frac{\sum_i p_s(i) \cdot p_t(i)}{\sqrt{\sum_i p_s(i)^2} \cdot \sqrt{\sum_i p_t(i)^2}}$	Numerical	`[-1, 1]`
`gds.similarity.pearson`	$pearson(p_s, p_t) = \frac{\sum_i (p_s(i) - \overline{p_s}) \cdot (p_t(i) - \overline{p_t})}{\sqrt{\sum_i (p_s(i) - \overline{p_s})^2} \cdot \sqrt{\sum_i (p_t(i) - \overline{p_t})^2}}$	Numerical	`[-1, 1]`
`gds.similarity.euclideanDistance`	$ED(p_s, p_t) = \sqrt{\sum_i (p_s(i) - p_t(i))^2}$	Numerical	`[0, ∞)`
`gds.similarity.euclidean`	$euclidean(p_s, p_t) = \frac{1}{1 + \sqrt{\sum_i (p_s(i) - p_t(i))^2}}$	Numerical	`(0, 1]`

Examples

An example of usage for each function is provided below:

Jaccard similarity function

```
RETURN gds.similarity.jaccard(
  [1.0, 5.0, 3.0, 6.7],
  [5.0, 2.5, 3.1, 9.0]
) AS jaccardSimilarity
```

Table 586. Results

jaccardSimilarity
0.142857142857143

Overlap similarity function

```
RETURN gds.similarity.overlap(
  [1.0, 5.0, 3.0, 6.7],
  [5.0, 2.5, 3.1, 9.0]
) AS overlapSimilarity
```

Table 587. Results

overlapSimilarity
0.25

Cosine similarity function

```
RETURN gds.similarity.cosine(
  [1.0, 5.0, 3.0, 6.7],
  [5.0, 2.5, 3.1, 9.0]
) AS cosineSimilarity
```

Table 588. Results

cosineSimilarity
0.882757381034594

Pearson similarity function

```
RETURN gds.similarity.pearson(
  [1.0, 5.0, 3.0, 6.7],
  [5.0, 2.5, 3.1, 9.0]
) AS pearsonSimilarity
```

Table 589. Results

pearsonSimilarity
0.468277483648113

Euclidean similarity function

```
RETURN gds.similarity.euclidean(
  [1.0, 5.0, 3.0, 6.7],
  [5.0, 2.5, 3.1, 9.0]
)  AS euclideanSimilarity
```

Table 590. Results

euclideanSimilarity
0.160030485454022

Euclidean distance function

```
RETURN gds.similarity.euclideanDistance(
  [1.0, 5.0, 3.0, 6.7],
  [5.0, 2.5, 3.1, 9.0]
) AS euclideanDistance
```

Table 591. Results

euclideanDistance
5.248809388804284

The functions can also compute results when one or more values in the provided vectors are `null`. In the case of functions based on intersection such as Jaccard or Overlap, the null values are excluded from the set and the computation. In the rest of the functions the `null` value is replaced with a `0.0` value. See the examples below.

Jaccard with null values

```
RETURN gds.similarity.jaccard(
  [1.0, null, 3.0],
  [1.0, 2.0, 3.0]
) AS jaccardSimilarity
```

Table 592. Results

jaccardSimilarity
0.666666666666667

Cosine with null values

```
RETURN gds.similarity.cosine(
  [1.0, null, 3.0],
  [1.0, 2.0, 3.0]
) AS cosineSimilarity
```

Table 593. Results

cosineSimilarity
0.845154254728517

6.5. Path finding

This chapter provides explanations and examples for each of the path finding algorithms in the Neo4j Graph Data Science library.

Path finding algorithms find the path between two or more nodes or evaluate the availability and quality of paths. The Neo4j GDS library includes the following path finding algorithms, grouped by quality tier:

- Production-quality
  - Delta-Stepping Single-Source Shortest Path
  - Dijkstra Source-Target Shortest Path
  - Dijkstra Single-Source Shortest Path
  - A* Shortest Path
  - Yen's Shortest Path
  - Breadth First Search
  - Depth First Search
- Beta
  - Random Walk
- Alpha
  - Minimum Weight Spanning Tree
  - All Pairs Shortest Path

6.5.1. Delta-Stepping Single-Source Shortest Path

This section describes the Delta-Stepping Shortest Path algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Delta-Stepping Shortest Path algorithm computes all shortest paths between a source node and all reachable nodes in the graph. The algorithm supports weighted graphs with positive relationship weights. To compute the shortest path between a source and a single target node, Dijkstra Source-Target can be used.

In contrast to Dijkstra Single-Source, the Delta-Stepping algorithm is a distance correcting algorithm. This property allows it to traverse the graph in parallel. The algorithm is guaranteed to always find the shortest path between a source node and a target node. However, if multiple shortest paths exist between two

nodes, the algorithm is not guaranteed to return the same path in each computation.

The GDS implementation is based on [1] and incorporates the bucket fusion optimization discussed in [2]. The algorithm implementation is executed using multiple threads which can be defined in the procedure configuration.

For more information on this algorithm, see:

1. Ulrich Meyer and Peter Sanders. "δ-stepping: a parallelizable shortest path algorithm."
2. Yunming Zhang, Ajay Brahmakshatriya, Xinyi Chen, Laxman Dhulipala, Shoaib Kamil, Saman Amarasinghe, and Julian Shun. "Optimizing ordered graph algorithms with GraphIt."

Syntax

This section covers the syntax used to execute the Delta-Stepping algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Delta-Stepping syntax per mode

Run Delta-Stepping in stream mode on a named graph.

```
CALL gds.allShortestPaths.delta.stream(
  graphName: String,
  configuration: Map
)
YIELD
  index: Integer,
  sourceNode: Integer,
  targetNode: Integer,
  totalCost: Float,
  nodeIds: List of Integer,
  costs: List of Float,
  path: Path
```

Table 594. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 595. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 596. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

Table 597. Results

Name	Type	Description
index	Integer	0-based index of the found path.
sourceNode	Integer	Source node of the path.
targetNode	Integer	Target node of the path.
totalCost	Float	Total cost from source to target.
nodeIds	List of Integer	Node ids on the path in traversal order.

Name	Type	Description
costs	List of Float	Accumulated costs for each node on the path.
path	Path	The path represented as Cypher entity.

The mutate mode creates new relationships in the projected graph. Each relationship represents a path from the source node to the target node. The total cost of a path is stored via the `totalCost` relationship property.

Run Delta-Stepping in mutate mode on a named graph.

```
CALL gds.allShortestPaths.delta.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 598. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 599. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 600. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.

Table 601. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
mutateMillis	Integer	Milliseconds for adding relationships to the projected graph.

Name	Type	Description
relationshipsWritten	Integer	The number of relationships that were added.
configuration	Map	The configuration used for running the algorithm.

The write mode creates new relationships in the Neo4j database. Each relationship represents a path from the source node to the target node. Additional path information is stored using relationship properties. By default, the write mode stores a `totalCost` property. Optionally, one can also store `nodeIds` and `costs` of intermediate nodes on the path.

Run Delta-Stepping in write mode on a named graph.

```
CALL gds.allShortestPaths.delta.write(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 602. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 603. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 604. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	`n/a`	no	The Neo4j source node or node id.
writeNodeIds	Boolean	`false`	yes	If true, the written relationship has a nodeIds list property.
writeCosts	Boolean	`false`	yes	If true, the written relationship has a costs list property.

Table 605. Results

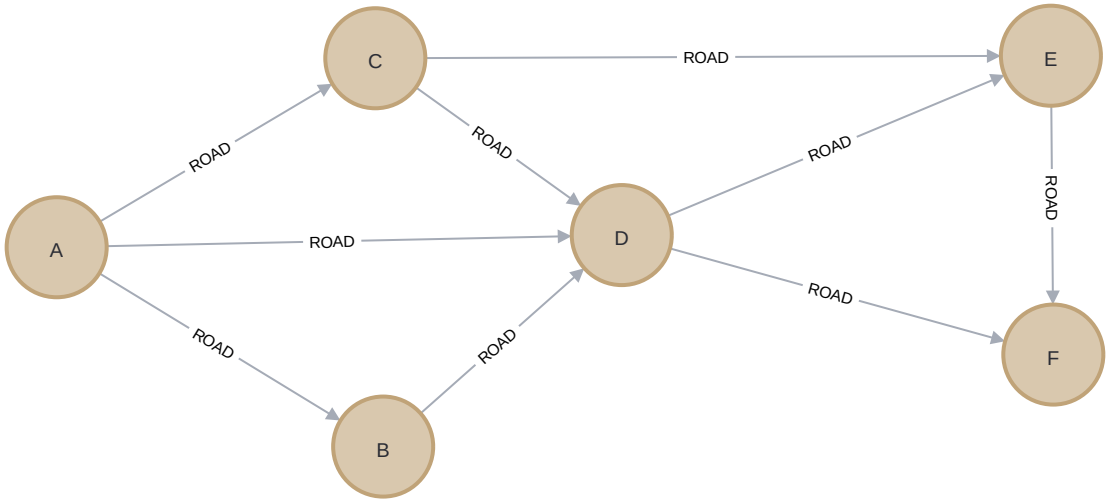
Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
writeMillis	Integer	Milliseconds for writing relationships to Neo4j.
relationshipsWritten	Integer	The number of relationships that were written.
configuration	Map	The configuration used for running the algorithm.

Delta

The `delta` parameter defines a range which is used to group nodes with the same tentative distance to the start node. The ranges are also called buckets. In each iteration of the algorithm, the non-empty bucket with the smallest tentative distance is processed in parallel. The `delta` parameter is the main tuning knob for the algorithm and controls the workload that can be processed in parallel. Generally, for power-law graphs, where many nodes can be reached within a few hops, a small delta (e.g. `2`) is recommended. For high-diameter graphs, e.g. transport networks, a high delta value (e.g. `10000`) is recommended. Note, that the value might vary depending on the graph topology and the value range of relationship properties.

Examples

In this section we will show examples of running the Delta-Stepping algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small transport network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE (a:Location {name: 'A'}),
       (b:Location {name: 'B'}),
       (c:Location {name: 'C'}),
       (d:Location {name: 'D'}),
       (e:Location {name: 'E'}),
       (f:Location {name: 'F'}),
       (a)-[:ROAD {cost: 50}]->(b),
       (a)-[:ROAD {cost: 50}]->(c),
       (a)-[:ROAD {cost: 100}]->(d),
       (b)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 80}]->(e),
       (d)-[:ROAD {cost: 30}]->(e),
       (d)-[:ROAD {cost: 80}]->(f),
       (e)-[:ROAD {cost: 40}]->(f);
```

This graph builds a transportation network with roads between locations. Like in the real world, the roads in the graph have different lengths. These lengths are represented by the `cost` relationship property.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
    'myGraph',
    'Location',
    'ROAD',
    {
        relationshipProperties: 'cost'
    }
)
```

In the following example we will demonstrate the use of the Delta-Stepping Shortest Path algorithm using this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in write mode:

```
MATCH (source:Location {name: 'A'})
CALL gds.allShortestPaths.delta.write.estimate('myGraph', {
    sourceNode: source,
    relationshipWeightProperty: 'cost',
    writeRelationshipType: 'PATH'
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
RETURN nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 606. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	9	368	576	"[368 Bytes ... 576 Bytes]"

Stream

In the `stream` execution mode, the algorithm returns the shortest path for each source-target-pair. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm and stream results:

```
MATCH (source:Location {name: 'A'})
CALL gds.allShortestPaths.delta.stream('myGraph', {
    sourceNode: source,
    relationshipWeightProperty: 'cost',
    delta: 3.0
})
YIELD index, sourceNode, targetNode, totalCost, nodeIds, costs, path
RETURN
    index,
    gds.util.asNode(sourceNode).name AS sourceNodeName,
    gds.util.asNode(targetNode).name AS targetNodeName,
    totalCost,
    [nodeId IN nodeIds | gds.util.asNode(nodeId).name] AS nodeNames,
    costs,
    nodes(path) as path
ORDER BY index
```

Table 607. Results

index	sourceNodeName	targetNodeName	totalCost	nodeNames	costs	path
0	"A"	"A"	0.0	[A]	[0.0]	[Node[0]]
1	"A"	"B"	50.0	[A, B]	[0.0, 50.0]	[Node[0], Node[1]]
2	"A"	"C"	50.0	[A, C]	[0.0, 50.0]	[Node[0], Node[2]]
3	"A"	"D"	90.0	[A, B, D]	[0.0, 50.0, 90.0]	[Node[0], Node[1], Node[3]]

index	sourceNodeName	targetNodeName	totalCost	nodeNames	costs	path
4	"A"	"E"	120.0	[A, B, D, E]	[0.0, 50.0, 90.0, 120.0]	[Node[0], Node[1], Node[3], Node[4]]
5	"A"	"F"	160.0	[A, B, D, E, F]	[0.0, 50.0, 90.0, 120.0, 160.0]	[Node[0], Node[1], Node[3], Node[4], Node[5]]

The result shows the total cost of the shortest path between node `A` and all other reachable nodes in the graph. It also shows ordered lists of node ids that were traversed to find the shortest paths as well as the accumulated costs of the visited nodes. This can be verified in the example graph. Cypher Path objects can be returned by the `path` return field. The Path objects contain the node objects and virtual relationships which have a `cost` property.

Mutate

The `mutate` execution mode updates the named graph with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the `mutateRelationshipType` option. The total path cost is stored using the `totalCost` property.

The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
MATCH (source:Location {name: 'A'})
CALL gds.allShortestPaths.delta.mutate('myGraph', {
    sourceNode: source,
    relationshipWeightProperty: 'cost',
    mutateRelationshipType: 'PATH'
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 608. Results

relationshipsWritten
6

After executing the above query, the in-memory graph will be updated with new relationships of type `PATH`. The new relationships will store a single property `totalCost`.

The relationships produced are always directed, even if the input graph is undirected.

Write

The `write` execution mode updates the Neo4j database with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the `writeRelationshipType` option. The total path cost is stored using the `totalCost` property. The intermediate node ids are stored using the `nodeIds` property. The accumulated costs to reach an intermediate node are stored using the `costs` property.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
MATCH (source:Location {name: 'A'})
CALL gds.allShortestPaths.delta.write('myGraph', {
    sourceNode: source,
    relationshipWeightProperty: 'cost',
    writeRelationshipType: 'PATH',
    writeNodeIds: true,
    writeCosts: true
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 609. Results

relationshipsWritten
6

The above query will write 6 relationships of type `PATH` back to Neo4j. The relationships store three properties describing the path: `totalCost`, `nodeIds` and `costs`.

The relationships written are always directed, even if the input graph is undirected.

6.5.2. Dijkstra Source-Target Shortest Path

This section describes the Dijkstra Shortest Path algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Dijkstra Shortest Path algorithm computes the shortest path between nodes. The algorithm supports weighted graphs with positive relationship weights. The Dijkstra Source-Target algorithm computes the shortest path between a source and a target node. To compute all paths from a source node to all reachable nodes, Dijkstra Single-Source can be used.

The GDS implementation is based on the original description and uses a binary heap as priority queue. The implementation is also used for the A* and Yen's algorithms. The algorithm implementation is executed using a single thread. Altering the concurrency configuration has no effect.

Syntax

This section covers the syntax used to execute the Dijkstra algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Dijkstra syntax per mode

Run Dijkstra in stream mode on a named graph.

```
CALL gds.shortestPath.dijkstra.stream(
  graphName: String,
  configuration: Map
)
YIELD
  index: Integer,
  sourceNode: Integer,
  targetNode: Integer,
  totalCost: Float,
  nodeIds: List of Integer,
  costs: List of Float,
  path: Path
```

Table 610. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 611. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 612. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

Table 613. Results

Name	Type	Description
index	Integer	0-based index of the found path.
sourceNode	Integer	Source node of the path.
targetNode	Integer	Target node of the path.
totalCost	Float	Total cost from source to target.
nodeIds	List of Integer	Node ids on the path in traversal order.

Name	Type	Description
costs	List of Float	Accumulated costs for each node on the path.
path	Path	The path represented as Cypher entity.

The mutate mode creates new relationships in the projected graph. Each relationship represents a path from the source node to the target node. The total cost of a path is stored via the `totalCost` relationship property.

Run Dijkstra in mutate mode on a named graph.

```
CALL gds.shortestPath.dijkstra.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 614. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 615. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 616. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.

Table 617. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
mutateMillis	Integer	Milliseconds for adding relationships to the projected graph.

Name	Type	Description
relationshipsWritten	Integer	The number of relationships that were added.
configuration	Map	The configuration used for running the algorithm.

The write mode creates new relationships in the Neo4j database. Each relationship represents a path from the source node to the target node. Additional path information is stored using relationship properties. By default, the write mode stores a `totalCost` property. Optionally, one can also store `nodeIds` and `costs` of intermediate nodes on the path.

Run Dijkstra in write mode on a named graph.

```
CALL gds.shortestPath.dijkstra.write(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 618. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 619. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 620. Algorithm specific configuration

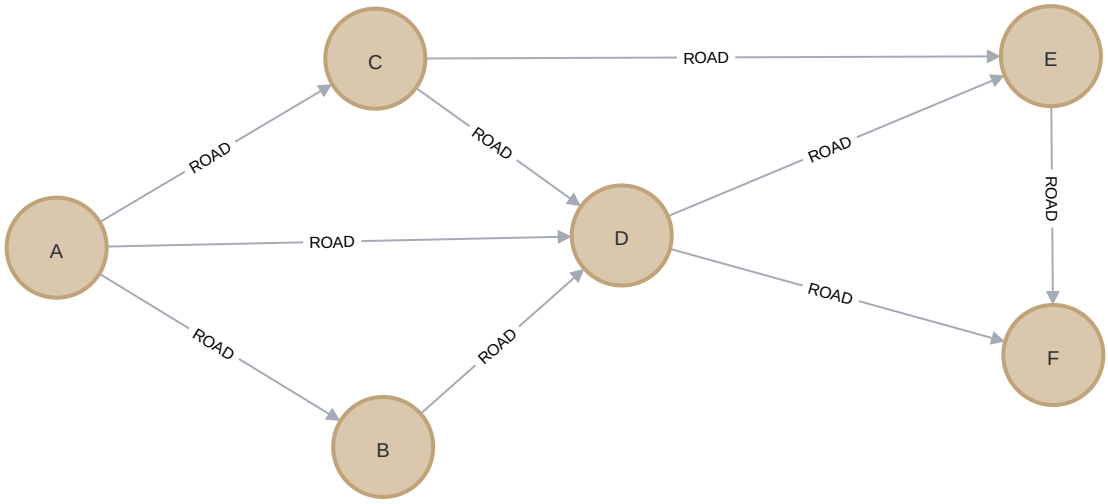
Name	Type	Default	Optional	Description
sourceNode	Integer	`n/a`	no	The Neo4j source node or node id.
writeNodeIds	Boolean	`false`	yes	If true, the written relationship has a nodeIds list property.
writeCosts	Boolean	`false`	yes	If true, the written relationship has a costs list property.

Table 621. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
writeMillis	Integer	Milliseconds for writing relationships to Neo4j.
relationshipsWritten	Integer	The number of relationships that were written.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Dijkstra algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small transport network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE (a:Location {name: 'A'}),
       (b:Location {name: 'B'}),
       (c:Location {name: 'C'}),
       (d:Location {name: 'D'}),
       (e:Location {name: 'E'}),
       (f:Location {name: 'F'}),
       (a)-[:ROAD {cost: 50}]->(b),
       (a)-[:ROAD {cost: 50}]->(c),
       (a)-[:ROAD {cost: 100}]->(d),
       (b)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 80}]->(e),
       (d)-[:ROAD {cost: 30}]->(e),
       (d)-[:ROAD {cost: 80}]->(f),
       (e)-[:ROAD {cost: 40}]->(f);
```

This graph builds a transportation network with roads between locations. Like in the real world, the roads in the graph have different lengths. These lengths are represented by the `cost` relationship property.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
    'myGraph',
    'Location',
    'ROAD',
    {
        relationshipProperties: 'cost'
    }
)
```

In the following example we will demonstrate the use of the Dijkstra Shortest Path algorithm using this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in write mode:

```
MATCH (source:Location {name: 'A'}), (target:Location {name: 'F'})
CALL gds.shortestPath.dijkstra.write.estimate('myGraph', {
    sourceNode: source,
    targetNode: target,
    relationshipWeightProperty: 'cost',
    writeRelationshipType: 'PATH'
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
RETURN nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 622. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	9	696	696	"696 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the shortest path for each source-target-pair. This

allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm and stream results:

```
MATCH (source:Location {name: 'A'}), (target:Location {name: 'F'})
CALL gds.shortestPath.dijkstra.stream('myGraph', {
    sourceNode: source,
    targetNode: target,
    relationshipWeightProperty: 'cost'
})
YIELD index, sourceNode, targetNode, totalCost, nodeIds, costs, path
RETURN
    index,
    gds.util.asNode(sourceNode).name AS sourceNodeName,
    gds.util.asNode(targetNode).name AS targetNodeName,
    totalCost,
    [nodeId IN nodeIds | gds.util.asNode(nodeId).name] AS nodeNames,
    costs,
    nodes(path) as path
ORDER BY index
```

Table 623. Results

index	sourceNodeName	targetNodeName	totalCost	nodeNames	costs	path
0	"A"	"F"	160.0	[A, B, D, E, F]	[0.0, 50.0, 90.0, 120.0, 160.0]	[Node[0], Node[1], Node[3], Node[4], Node[5]]

The result shows the total cost of the shortest path between node `A` and node `F`. It also shows an ordered list of node ids that were traversed to find the shortest path as well as the accumulated costs of the visited nodes. This can be verified in the example graph. Cypher Path objects can be returned by the `path` return field. The Path objects contain the node objects and virtual relationships which have a `cost` property.

Mutate

The `mutate` execution mode updates the named graph with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the `mutateRelationshipType` option. The total path cost is stored using the `totalCost` property.

The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
MATCH (source:Location {name: 'A'}), (target:Location {name: 'F'})
CALL gds.shortestPath.dijkstra.mutate('myGraph', {
    sourceNode: source,
    targetNode: target,
    relationshipWeightProperty: 'cost',
    mutateRelationshipType: 'PATH'
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 624. Results

relationshipsWritten
1

After executing the above query, the projected graph will be updated with a new relationship of type `PATH`. The new relationship will store a single property `totalCost`.

The relationship produced is always directed, even if the input graph is undirected.

Write

The `write` execution mode updates the Neo4j database with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the `writeRelationshipType` option. The total path cost is stored using the `totalCost` property. The intermediate node ids are stored using the `nodeIds` property. The accumulated costs to reach an intermediate node are stored using the `costs` property.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
MATCH (source:Location {name: 'A'}), (target:Location {name: 'F'})
CALL gds.shortestPath.dijkstra.write('myGraph', {
    sourceNode: source,
    targetNode: target,
    relationshipWeightProperty: 'cost',
    writeRelationshipType: 'PATH',
    writeNodeIds: true,
    writeCosts: true
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 625. Results

relationshipsWritten
1

The above query will write a single relationship of type `PATH` back to Neo4j. The relationship stores three properties describing the path: `totalCost`, `nodeIds` and `costs`.

The relationship written is always directed, even if the input graph is undirected.

6.5.3. Dijkstra Single-Source Shortest Path

This section describes the Dijkstra Shortest Path algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Dijkstra Shortest Path algorithm computes the shortest path between nodes. The algorithm supports weighted graphs with positive relationship weights. The Dijkstra Single-Source algorithm computes the shortest paths between a source node and all nodes reachable from that node. To compute the shortest path between a source and a target node, Dijkstra Source-Target can be used.

The GDS implementation is based on the original description and uses a binary heap as priority queue. The implementation is also used for the A* and Yen's algorithms. The algorithm implementation is executed using a single thread and altering the concurrency configuration has no effect. You can consider Delta-Stepping for an efficient parallel shortest path algorithm instead.

Syntax

This section covers the syntax used to execute the Dijkstra algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Dijkstra syntax per mode

Run Dijkstra in stream mode on a named graph.

```
CALL gds.allShortestPaths.dijkstra.stream(
  graphName: String,
  configuration: Map
)
YIELD
  index: Integer,
  sourceNode: Integer,
  targetNode: Integer,
  totalCost: Float,
  nodeIds: List of Integer,
  costs: List of Float,
  path: Path
```

Table 626. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 627. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 628. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

Table 629. Results

Name	Type	Description
index	Integer	0-based index of the found path.
sourceNode	Integer	Source node of the path.
targetNode	Integer	Target node of the path.
totalCost	Float	Total cost from source to target.
nodeIds	List of Integer	Node ids on the path in traversal order.

Name	Type	Description
costs	List of Float	Accumulated costs for each node on the path.
path	Path	The path represented as Cypher entity.

The mutate mode creates new relationships in the projected graph. Each relationship represents a path from the source node to the target node. The total cost of a path is stored via the `totalCost` relationship property.

Run Dijkstra in mutate mode on a named graph.

```
CALL gds.allShortestPaths.dijkstra.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 630. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 631. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 632. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.

Table 633. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
mutateMillis	Integer	Milliseconds for adding relationships to the projected graph.

Name	Type	Description
relationshipsWritten	Integer	The number of relationships that were added.
configuration	Map	The configuration used for running the algorithm.

The write mode creates new relationships in the Neo4j database. Each relationship represents a path from the source node to the target node. Additional path information is stored using relationship properties. By default, the write mode stores a `totalCost` property. Optionally, one can also store `nodeIds` and `costs` of intermediate nodes on the path.

Run Dijkstra in write mode on a named graph.

```
CALL gds.allShortestPaths.dijkstra.write(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 634. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 635. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 636. Algorithm specific configuration

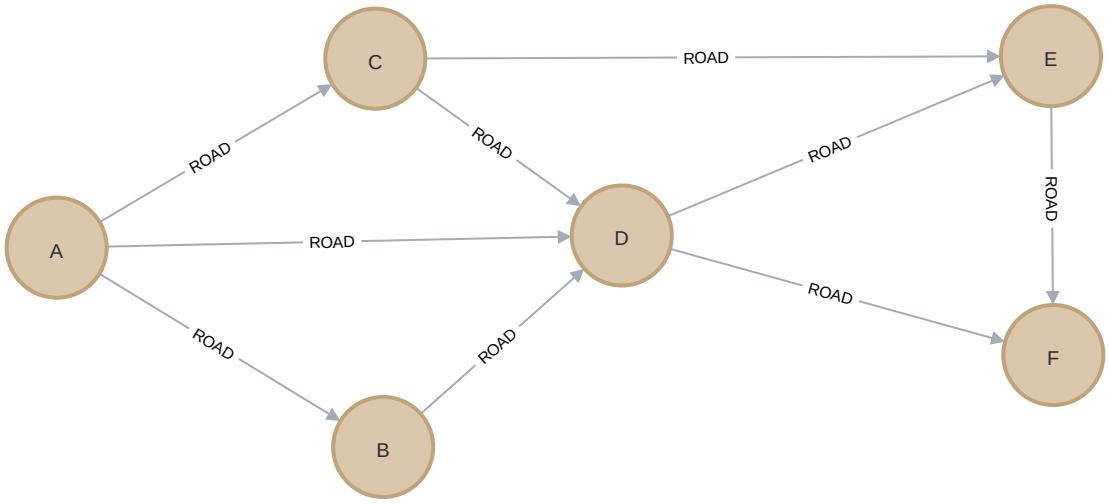
Name	Type	Default	Optional	Description
sourceNode	Integer	`n/a`	no	The Neo4j source node or node id.
writeNodeIds	Boolean	`false`	yes	If true, the written relationship has a nodeIds list property.
writeCosts	Boolean	`false`	yes	If true, the written relationship has a costs list property.

Table 637. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
writeMillis	Integer	Milliseconds for writing relationships to Neo4j.
relationshipsWritten	Integer	The number of relationships that were written.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Dijkstra algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small transport network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE (a:Location {name: 'A'}),
       (b:Location {name: 'B'}),
       (c:Location {name: 'C'}),
       (d:Location {name: 'D'}),
       (e:Location {name: 'E'}),
       (f:Location {name: 'F'}),
       (a)-[:ROAD {cost: 50}]->(b),
       (a)-[:ROAD {cost: 50}]->(c),
       (a)-[:ROAD {cost: 100}]->(d),
       (b)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 80}]->(e),
       (d)-[:ROAD {cost: 30}]->(e),
       (d)-[:ROAD {cost: 80}]->(f),
       (e)-[:ROAD {cost: 40}]->(f);
```

This graph builds a transportation network with roads between locations. Like in the real world, the roads in the graph have different lengths. These lengths are represented by the `cost` relationship property.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
    'myGraph',
    'Location',
    'ROAD',
    {
        relationshipProperties: 'cost'
    }
)
```

In the following example we will demonstrate the use of the Dijkstra Shortest Path algorithm using this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in write mode:

```
MATCH (source:Location {name: 'A'})
CALL gds.allShortestPaths.dijkstra.write.estimate('myGraph', {
    sourceNode: source,
    relationshipWeightProperty: 'cost',
    writeRelationshipType: 'PATH'
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
RETURN nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 638. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	9	696	696	"696 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the shortest path for each source-target-pair. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm and stream results:

```
MATCH (source:Location {name: 'A'})
CALL gds.allShortestPaths.dijkstra.stream('myGraph', {
    sourceNode: source,
    relationshipWeightProperty: 'cost'
})
YIELD index, sourceNode, targetNode, totalCost, nodeIds, costs, path
RETURN
    index,
    gds.util.asNode(sourceNode).name AS sourceNodeName,
    gds.util.asNode(targetNode).name AS targetNodeName,
    totalCost,
    [nodeId IN nodeIds | gds.util.asNode(nodeId).name] AS nodeNames,
    costs,
    nodes(path) as path
ORDER BY index
```

Table 639. Results

index	sourceNodeName	targetNodeName	totalCost	nodeNames	costs	path
0	"A"	"A"	0.0	[A]	[0.0]	[Node[0]]
1	"A"	"B"	50.0	[A, B]	[0.0, 50.0]	[Node[0], Node[1]]
2	"A"	"C"	50.0	[A, C]	[0.0, 50.0]	[Node[0], Node[2]]
3	"A"	"D"	90.0	[A, B, D]	[0.0, 50.0, 90.0]	[Node[0], Node[1], Node[3]]
4	"A"	"E"	120.0	[A, B, D, E]	[0.0, 50.0, 90.0, 120.0]	[Node[0], Node[1], Node[3], Node[4]]
5	"A"	"F"	160.0	[A, B, D, E, F]	[0.0, 50.0, 90.0, 120.0, 160.0]	[Node[0], Node[1], Node[3], Node[4], Node[5]]

The result shows the total cost of the shortest path between node `A` and all other reachable nodes in the graph. It also shows ordered lists of node ids that were traversed to find the shortest paths as well as the accumulated costs of the visited nodes. This can be verified in the example graph. Cypher Path objects can be returned by the `path` return field. The Path objects contain the node objects and virtual relationships which have a `cost` property.

Mutate

The `mutate` execution mode updates the named graph with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the

`mutateRelationshipType` option. The total path cost is stored using the `totalCost` property.

The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
MATCH (source:Location {name: 'A'})
CALL gds.allShortestPaths.dijkstra.mutate('myGraph', {
    sourceNode: source,
    relationshipWeightProperty: 'cost',
    mutateRelationshipType: 'PATH'
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 640. Results

relationshipsWritten
6

After executing the above query, the in-memory graph will be updated with new relationships of type `PATH`. The new relationships will store a single property `totalCost`.

The relationships produced are always directed, even if the input graph is undirected.

Write

The `write` execution mode updates the Neo4j database with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the `writeRelationshipType` option. The total path cost is stored using the `totalCost` property. The intermediate node ids are stored using the `nodeIds` property. The accumulated costs to reach an intermediate node are stored using the `costs` property.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
MATCH (source:Location {name: 'A'})
CALL gds.allShortestPaths.dijkstra.write('myGraph', {
    sourceNode: source,
    relationshipWeightProperty: 'cost',
    writeRelationshipType: 'PATH',
    writeNodeIds: true,
    writeCosts: true
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 641. Results

relationshipsWritten
6

The above query will write 6 relationships of type `PATH` back to Neo4j. The relationships store three properties describing the path: `totalCost`, `nodeIds` and `costs`.

The relationships written are always directed, even if the input graph is undirected.

6.5.4. A* Shortest Path

This section describes the A Shortest Path algorithm in the Neo4j Graph Data Science library.*

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The A* (pronounced "A-Star") Shortest Path algorithm computes the shortest path between two nodes. A* is an informed search algorithm as it uses a heuristic function to guide the graph traversal. The algorithm supports weighted graphs with positive relationship weights.

Unlike Dijkstra's shortest path algorithm, the next node to search from is not solely picked on the already computed distance. Instead, the algorithm combines the already computed distance with the result of a heuristic function. That function takes a node as input and returns a value that corresponds to the cost to reach the target node from that node. In each iteration, the graph traversal is continued from the node with the lowest combined cost.

In GDS, the A* algorithm is based on the Dijkstra's shortest path algorithm. The heuristic function is the haversine distance, which defines the distance between two points on a sphere. Here, the sphere is the earth and the points are geo-coordinates stored on the nodes in the graph.

The algorithm implementation is executed using a single thread. Altering the concurrency configuration has no effect.

Requirements

In GDS, the heuristic function used to guide the search is the haversine formula. The formula computes the distance between two points on a sphere given their longitudes and latitudes. The distance is computed in nautical miles.

In order to guarantee finding the optimal solution, i.e., the shortest path between two points, the heuristic must be admissible. To be admissible, the function must not overestimate the distance to the target, i.e.,

the lowest possible cost of a path must always be greater or equal to the heuristic.

This leads to a requirement on the relationship weights of the input graph. Relationship weights must represent the distance between two nodes and ideally scaled to nautical miles. Kilometers or miles also work, but the heuristic works best for nautical miles.

Syntax

This section covers the syntax used to execute the A* algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

A* syntax per mode

Run A in stream mode on a named graph.*

```
CALL gds.shortestPath.astar.stream(
  graphName: String,
  configuration: Map
)
YIELD
  index: Integer,
  sourceNode: Integer,
  targetNode: Integer,
  totalCost: Float,
  nodeIds: List of Integer,
  costs: List of Float,
  path: Path
```

Table 642. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 643. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 644. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

Table 645. Results

Name	Type	Description
index	Integer	0-based index of the found path.
sourceNode	Integer	Source node of the path.
targetNode	Integer	Target node of the path.
totalCost	Float	Total cost from source to target.
nodeIds	List of Integer	Node ids on the path in traversal order.

Name	Type	Description
costs	List of Float	Accumulated costs for each node on the path.
path	Path	The path represented as Cypher entity.

The mutate mode creates new relationships in the projected graph. Each relationship represents a path from the source node to the target node. The total cost of a path is stored via the `totalCost` relationship property.

Run A in mutate mode on a named graph.*

```
CALL gds.shortestPath.astar.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 646. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 647. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 648. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.

Table 649. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
mutateMillis	Integer	Milliseconds for adding relationships to the projected graph.

Name	Type	Description
relationshipsWritten	Integer	The number of relationships that were added.
configuration	Map	The configuration used for running the algorithm.

The write mode creates new relationships in the Neo4j database. Each relationship represents a path from the source node to the target node. Additional path information is stored using relationship properties. By default, the write mode stores a `totalCost` property. Optionally, one can also store `nodeIds` and `costs` of intermediate nodes on the path.

Run A in write mode on a named graph.*

```
CALL gds.shortestPath.astar.write(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 650. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 651. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 652. Algorithm specific configuration

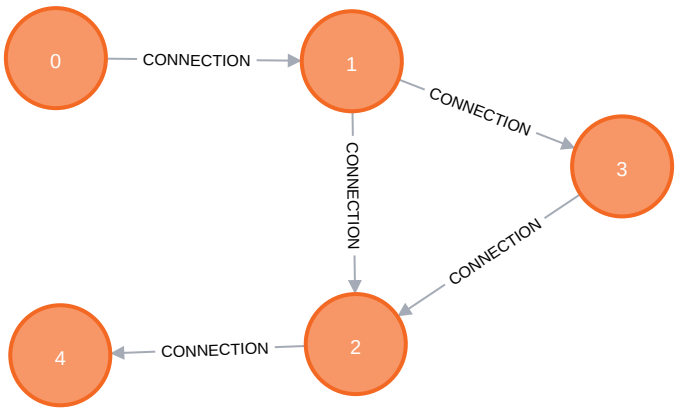
Name	Type	Default	Optional	Description
sourceNode	Integer	`n/a`	no	The Neo4j source node or node id.
writeNodeIds	Boolean	`false`	yes	If true, the written relationship has a nodeIds list property.
writeCosts	Boolean	`false`	yes	If true, the written relationship has a costs list property.

Table 653. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
writeMillis	Integer	Milliseconds for writing relationships to Neo4j.
relationshipsWritten	Integer	The number of relationships that were written.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the A* algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small transport network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE (a:Station {name: 'Kings Cross',         latitude: 51.5308, longitude: -0.1238}),
       (b:Station {name: 'Euston',              latitude: 51.5282, longitude: -0.1337}),
       (c:Station {name: 'Camden Town',         latitude: 51.5392, longitude: -0.1426}),
       (d:Station {name: 'Mornington Crescent', latitude: 51.5342, longitude: -0.1387}),
       (e:Station {name: 'Kentish Town',        latitude: 51.5507, longitude: -0.1402}),
       (a)-[:CONNECTION {distance: 0.7}]->(b),
       (b)-[:CONNECTION {distance: 1.3}]->(c),
       (b)-[:CONNECTION {distance: 0.7}]->(d),
       (d)-[:CONNECTION {distance: 0.6}]->(c),
       (c)-[:CONNECTION {distance: 1.3}]->(e)
```

The graph represents a transport network of stations. Each station has a geo-coordinate, expressed by `latitude` and `longitude` properties. Stations are connected via connections. We use the `distance` property as relationship weight which represents the distance between stations in kilometers. The algorithm will pick the next node in the search based on the already traveled distance and the distance to the target

station.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
    'myGraph',
    'Station',
    'CONNECTION',
    {
        nodeProperties: ['latitude', 'longitude'],
        relationshipProperties: 'distance'
    }
)
```

In the following example we will demonstrate the use of the A* Shortest Path algorithm using this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in write mode:

```
MATCH (source:Station {name: 'Kings Cross'}), (target:Station {name: 'Kentish Town'})
CALL gds.shortestPath.astar.write.estimate('myGraph', {
    sourceNode: source,
    targetNode: target,
    latitudeProperty: 'latitude',
    longitudeProperty: 'longitude',
    writeRelationshipType: 'PATH'
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
RETURN nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 654. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
5	5	984	984	"984 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the shortest path for each source-target-pair. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm and stream results:

```
MATCH (source:Station {name: 'Kings Cross'}), (target:Station {name: 'Kentish Town'})
CALL gds.shortestPath.astar.stream('myGraph', {
    sourceNode: source,
    targetNode: target,
    latitudeProperty: 'latitude',
    longitudeProperty: 'longitude',
    relationshipWeightProperty: 'distance'
})
YIELD index, sourceNode, targetNode, totalCost, nodeIds, costs, path
RETURN
    index,
    gds.util.asNode(sourceNode).name AS sourceNodeName,
    gds.util.asNode(targetNode).name AS targetNodeName,
    totalCost,
    [nodeId IN nodeIds | gds.util.asNode(nodeId).name] AS nodeNames,
    costs,
    nodes(path) as path
ORDER BY index
```

Table 655. Results

index	sourceNodeName	targetNodeName	totalCost	nodeNames	costs	path
0	"Kings Cross"	"Kentish Town"	3.3	[Kings Cross, Euston, Camden Town, Kentish Town]	[0.0, 0.7, 2.0, 3.3]	[Node[0], Node[1], Node[2], Node[4]]

The result shows the total cost of the shortest path between node `King's Cross` and `Kentish Town` in the graph. It also shows ordered lists of node ids that were traversed to find the shortest paths as well as the accumulated costs of the visited nodes. This can be verified in the example graph. Cypher Path objects can be returned by the `path` return field. The Path objects contain the node objects and virtual relationships which have a `cost` property.

Mutate

The `mutate` execution mode updates the named graph with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the `mutateRelationshipType` option. The total path cost is stored using the `totalCost` property.

The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
MATCH (source:Station {name: 'Kings Cross'}), (target:Station {name: 'Kentish Town'})
CALL gds.shortestPath.astar.mutate('myGraph', {
    sourceNode: source,
    targetNode: target,
    latitudeProperty: 'latitude',
    longitudeProperty: 'longitude',
    relationshipWeightProperty: 'distance',
    mutateRelationshipType: 'PATH'
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 656. Results

relationshipsWritten
1

After executing the above query, the in-memory graph will be updated with new relationships of type `PATH`. The new relationships will store a single property `totalCost`.

The relationship produced is always directed, even if the input graph is undirected.

Write

The `write` execution mode updates the Neo4j database with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the `writeRelationshipType` option. The total path cost is stored using the `totalCost` property. The intermediate node ids are stored using the `nodeIds` property. The accumulated costs to reach an intermediate node are stored using the `costs` property.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
MATCH (source:Station {name: 'Kings Cross'}), (target:Station {name: 'Kentish Town'})
CALL gds.shortestPath.astar.write('myGraph', {
    sourceNode: source,
    targetNode: target,
    latitudeProperty: 'latitude',
    longitudeProperty: 'longitude',
    relationshipWeightProperty: 'distance',
    writeRelationshipType: 'PATH',
    writeNodeIds: true,
    writeCosts: true
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 657. Results

relationshipsWritten
1

The above query will write one relationship of type `PATH` back to Neo4j. The relationship stores three

properties describing the path: `totalCost`, `nodeIds` and `costs`.

The relationship written is always directed, even if the input graph is undirected.

6.5.5. Yen's algorithm Shortest Path

This section describes the Yen's Shortest Path algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

Yen's Shortest Path algorithm computes a number of shortest paths between two nodes. The algorithm is often referred to as Yen's k-Shortest Path algorithm, where k is the number of shortest paths to compute. The algorithm supports weighted graphs with positive relationship weights. It also respects parallel relationships between the same two nodes when computing multiple shortest paths.

For `k = 1`, the algorithm behaves exactly like Dijkstra's shortest path algorithm and returns the shortest path. For `k = 2`, the algorithm returns the shortest path and the second shortest path between the same source and target node. Generally, for `k = n`, the algorithm computes at most `n` paths which are discovered in the order of their total cost.

The GDS implementation is based on the original description. For the actual path computation, Yen's algorithm uses Dijkstra's shortest path algorithm. The algorithm makes sure that an already discovered shortest path will not be traversed again.

The algorithm implementation is executed using a single thread. Altering the concurrency configuration has no effect.

Syntax

This section covers the syntax used to execute the Yen's algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Yen’s syntax per mode

Run Yen's in stream mode on a named graph.

```
CALL gds.shortestPath.yens.stream(
  graphName: String,
  configuration: Map
)
YIELD
  index: Integer,
  sourceNode: Integer,
  targetNode: Integer,
  totalCost: Float,
  nodeIds: List of Integer,
  costs: List of Float,
  path: Path
```

Table 658. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 659. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 660. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.

Table 661. Results

Name	Type	Description
index	Integer	0-based index of the found path.
sourceNode	Integer	Source node of the path.
targetNode	Integer	Target node of the path.
totalCost	Float	Total cost from source to target.
nodeIds	List of Integer	Node ids on the path in traversal order.

Name	Type	Description
costs	List of Float	Accumulated costs for each node on the path.
path	Path	The path represented as Cypher entity.

The mutate mode creates new relationships in the projected graph. Each relationship represents a path from the source node to the target node. The total cost of a path is stored via the `totalCost` relationship property.

Run Yen's in mutate mode on a named graph.

```
CALL gds.shortestPath.yens.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 662. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 663. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 664. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The Neo4j source node or node id.

Table 665. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
mutateMillis	Integer	Milliseconds for adding relationships to the projected graph.

Name	Type	Description
relationshipsWritten	Integer	The number of relationships that were added.
configuration	Map	The configuration used for running the algorithm.

The write mode creates new relationships in the Neo4j database. Each relationship represents a path from the source node to the target node. Additional path information is stored using relationship properties. By default, the write mode stores a `totalCost` property. Optionally, one can also store `nodeIds` and `costs` of intermediate nodes on the path.

Run Yen's in write mode on a named graph.

```
CALL gds.shortestPath.yens.write(
  graphName: String,
  configuration: Map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 666. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 667. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 668. Algorithm specific configuration

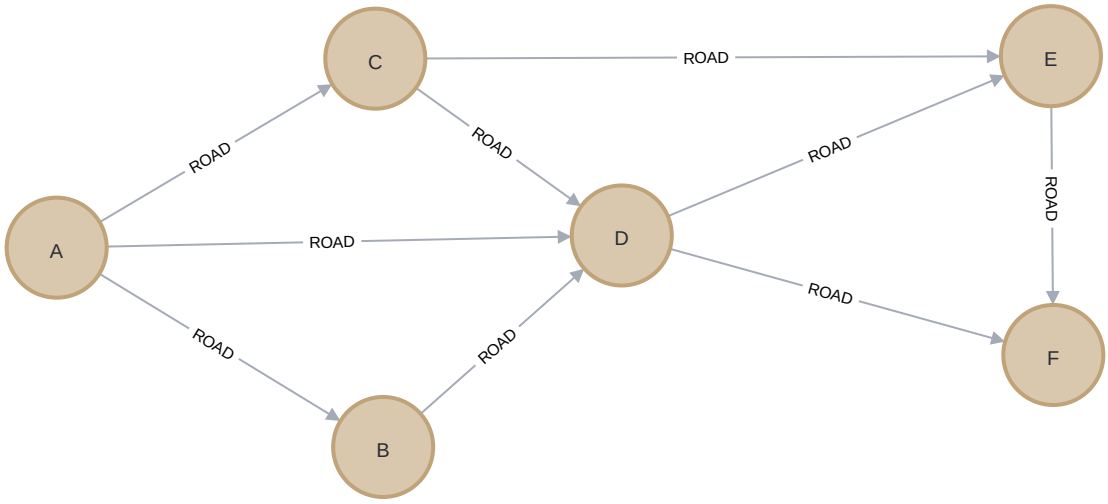
Name	Type	Default	Optional	Description
sourceNode	Integer	`n/a`	no	The Neo4j source node or node id.
writeNodeIds	Boolean	`false`	yes	If true, the written relationship has a nodeIds list property.
writeCosts	Boolean	`false`	yes	If true, the written relationship has a costs list property.

Table 669. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Unused.
writeMillis	Integer	Milliseconds for writing relationships to Neo4j.
relationshipsWritten	Integer	The number of relationships that were written.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Yen's algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small transport network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE (a:Location {name: 'A'}),
       (b:Location {name: 'B'}),
       (c:Location {name: 'C'}),
       (d:Location {name: 'D'}),
       (e:Location {name: 'E'}),
       (f:Location {name: 'F'}),
       (a)-[:ROAD {cost: 50}]->(b),
       (a)-[:ROAD {cost: 50}]->(c),
       (a)-[:ROAD {cost: 100}]->(d),
       (b)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 80}]->(e),
       (d)-[:ROAD {cost: 30}]->(e),
       (d)-[:ROAD {cost: 80}]->(f),
       (e)-[:ROAD {cost: 40}]->(f);
```

This graph builds a transportation network with roads between locations. Like in the real world, the roads in the graph have different lengths. These lengths are represented by the `cost` relationship property.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
    'myGraph',
    'Location',
    'ROAD',
    {
        relationshipProperties: 'cost'
    }
)
```

In the following example we will demonstrate the use of the Yen's Shortest Path algorithm using this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `write` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in write mode:

```
MATCH (source:Location {name: 'A'}), (target:Location {name: 'F'})
CALL gds.shortestPath.yens.write.estimate('myGraph', {
    sourceNode: source,
    targetNode: target,
    k: 3,
    relationshipWeightProperty: 'cost',
    writeRelationshipType: 'PATH'
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
RETURN nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 670. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
6	9	1008	1008	"1008 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the shortest path for each source-target-pair. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm and stream results:

```
MATCH (source:Location {name: 'A'}), (target:Location {name: 'F'})
CALL gds.shortestPath.yens.stream('myGraph', {
    sourceNode: source,
    targetNode: target,
    k: 3,
    relationshipWeightProperty: 'cost'
})
YIELD index, sourceNode, targetNode, totalCost, nodeIds, costs, path
RETURN
    index,
    gds.util.asNode(sourceNode).name AS sourceNodeName,
    gds.util.asNode(targetNode).name AS targetNodeName,
    totalCost,
    [nodeId IN nodeIds | gds.util.asNode(nodeId).name] AS nodeNames,
    costs,
    nodes(path) as path
ORDER BY index
```

Table 671. Results

index	sourceNodeName	targetNodeName	totalCost	nodeNames	costs	path
0	"A"	"F"	160.0	[A, B, D, E, F]	[0.0, 50.0, 90.0, 120.0, 160.0]	[Node[0], Node[1], Node[3], Node[4], Node[5]]
1	"A"	"F"	160.0	[A, C, D, E, F]	[0.0, 50.0, 90.0, 120.0, 160.0]	[Node[0], Node[2], Node[3], Node[4], Node[5]]
2	"A"	"F"	170.0	[A, B, D, F]	[0.0, 50.0, 90.0, 170.0]	[Node[0], Node[1], Node[3], Node[5]]

The result shows the three shortest paths between node `A` and node `F`. The first two paths have the same total cost, however the first one traversed from `A` to `D` via the `B` node, while the second traversed via the `C` node. The third path has a higher total cost as it goes directly from `D` to `F` using the relationship with a cost of `80`, whereas the detour via `E` for the first two paths costs `70`. This can be verified in the example graph. Cypher Path objects can be returned by the `path` return field. The Path objects contain the node objects and virtual relationships which have a `cost` property.

Mutate

The `mutate` execution mode updates the named graph with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the `mutateRelationshipType` option. The total path cost is stored using the `totalCost` property.

The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
MATCH (source:Location {name: 'A'}), (target:Location {name: 'F'})
CALL gds.shortestPath.yens.mutate('myGraph', {
    sourceNode: source,
    targetNode: target,
    k: 3,
    relationshipWeightProperty: 'cost',
    mutateRelationshipType: 'PATH'
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 672. Results

relationshipsWritten
3

After executing the above query, the projected graph will be updated with a new relationship of type `PATH`. The new relationship will store a single property `totalCost`.

The relationships produced are always directed, even if the input graph is undirected.

Write

The `write` execution mode updates the Neo4j database with new relationships. Each new relationship represents a path from source node to target node. The relationship type is configured using the `writeRelationshipType` option. The total path cost is stored using the `totalCost` property. The intermediate node ids are stored using the `nodeIds` property. The accumulated costs to reach an intermediate node are stored using the `costs` property.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
MATCH (source:Location {name: 'A'}), (target:Location {name: 'F'})
CALL gds.shortestPath.yens.write('myGraph', {
    sourceNode: source,
    targetNode: target,
    k: 3,
    relationshipWeightProperty: 'cost',
    writeRelationshipType: 'PATH',
    writeNodeIds: true,
    writeCosts: true
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 673. Results

relationshipsWritten
3

The above query will write a single relationship of type `PATH` back to Neo4j. The relationship stores three properties describing the path: `totalCost`, `nodeIds` and `costs`.

The relationships written are always directed, even if the input graph is undirected.

6.5.6. Minimum Weight Spanning Tree Alpha

This section describes the Minimum Weight Spanning Tree algorithm in the Neo4j Graph Data Science library.

The Minimum Weight Spanning Tree (MST) starts from a given node, and finds all its reachable nodes and the set of relationships that connect the nodes together with the minimum possible weight. Prim's algorithm is one of the simplest and best-known minimum spanning tree algorithms. The K-Means variant of this algorithm can be used to detect clusters in the graph.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

The first known algorithm for finding a minimum spanning tree was developed by the Czech scientist Otakar Borůvka in 1926, while trying to find an efficient electricity network for Moravia. Prim's algorithm was invented by Jarnik in 1930 and rediscovered by Prim in 1957. It is similar to Dijkstra's shortest path algorithm but, rather than minimizing the total length of a path ending at each relationship, it minimizes the length of each relationship individually. Unlike Dijkstra's, Prim's can tolerate negative-weight relationships.

The algorithm operates as follows:

- Start with a tree containing only one node (and no relationships).
- Select the minimal-weight relationship coming from that node, and add it to our tree.
- Repeatedly choose a minimal-weight relationship that joins any node in the tree to one that is not in

the tree, adding the new relationship and node to our tree.

- When there are no more nodes to add, the tree we have built is a minimum spanning tree.

Use-cases - when to use the Minimum Weight Spanning Tree algorithm

- Minimum spanning tree was applied to analyze airline and sea connections of Papua New Guinea, and minimize the travel cost of exploring the country. It could be used to help design low-cost tours that visit many destinations across the country. The research mentioned can be found in "An Application of Minimum Spanning Trees to Travel Planning".
- Minimum spanning tree has been used to analyze and visualize correlations in a network of currencies, based on the correlation between currency returns. This is described in "Minimum Spanning Tree Application in the Currency Market".
- Minimum spanning tree has been shown to be a useful tool to trace the history of transmission of infection, in an outbreak supported by exhaustive clinical research. For more information, see Use of the Minimum Spanning Tree Model for Molecular Epidemiological Investigation of a Nosocomial Outbreak of Hepatitis C Virus Infection.

Constraints - when not to use the Minimum Weight Spanning Tree algorithm

The MST algorithm only gives meaningful results when run on a graph, where the relationships have different weights. If the graph has no weights, or all relationships have the same weight, then any spanning tree is a minimum spanning tree.

Syntax

The following will run the algorithm and write back results:

```
CALL gds.alpha.spanningTree.write(
  graphName: string,
  configuration: map
)
YIELD preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount
```

The following will compute the minimum weight spanning tree and write the results:

```
CALL gds.alpha.spanningTree.minimum.write(
  graphName: string,
  configuration: map
)
YIELD preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount
```

The following will compute the maximum weight spanning tree and write the results:

```
CALL gds.alpha.spanningTree.maximum.write(
  graphName: string,
  configuration: map
)
YIELD preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount
```

Table 674. Configuration

Name	Type	Default	Optional	Description
startNodeId	Integer	null	no	The start node ID
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
writeProperty	String	'mst'	yes	The relationship type written back as result
weightWriteProperty	String	n/a	no	The weight property of the `writeProperty` relationship type written back

Table 675. Results

Name	Type	Description
effectiveNodeCount	Integer	The number of visited nodes
preProcessingMillis	Integer	Milliseconds for preprocessing the data
computeMillis	Integer	Milliseconds for running the algorithm
writeMillis	Integer	Milliseconds for writing result data back

The following will run the k-spanning tree algorithms and write back results:

```
CALL gds.alpha.spanningTree.kmin.write(
  graphName: string,
  configuration: map
)
YIELD preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount
```

```
CALL gds.alpha.spanningTree.kmax.write(
  graphName: string,
  configuration: map
)
YIELD preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount
```

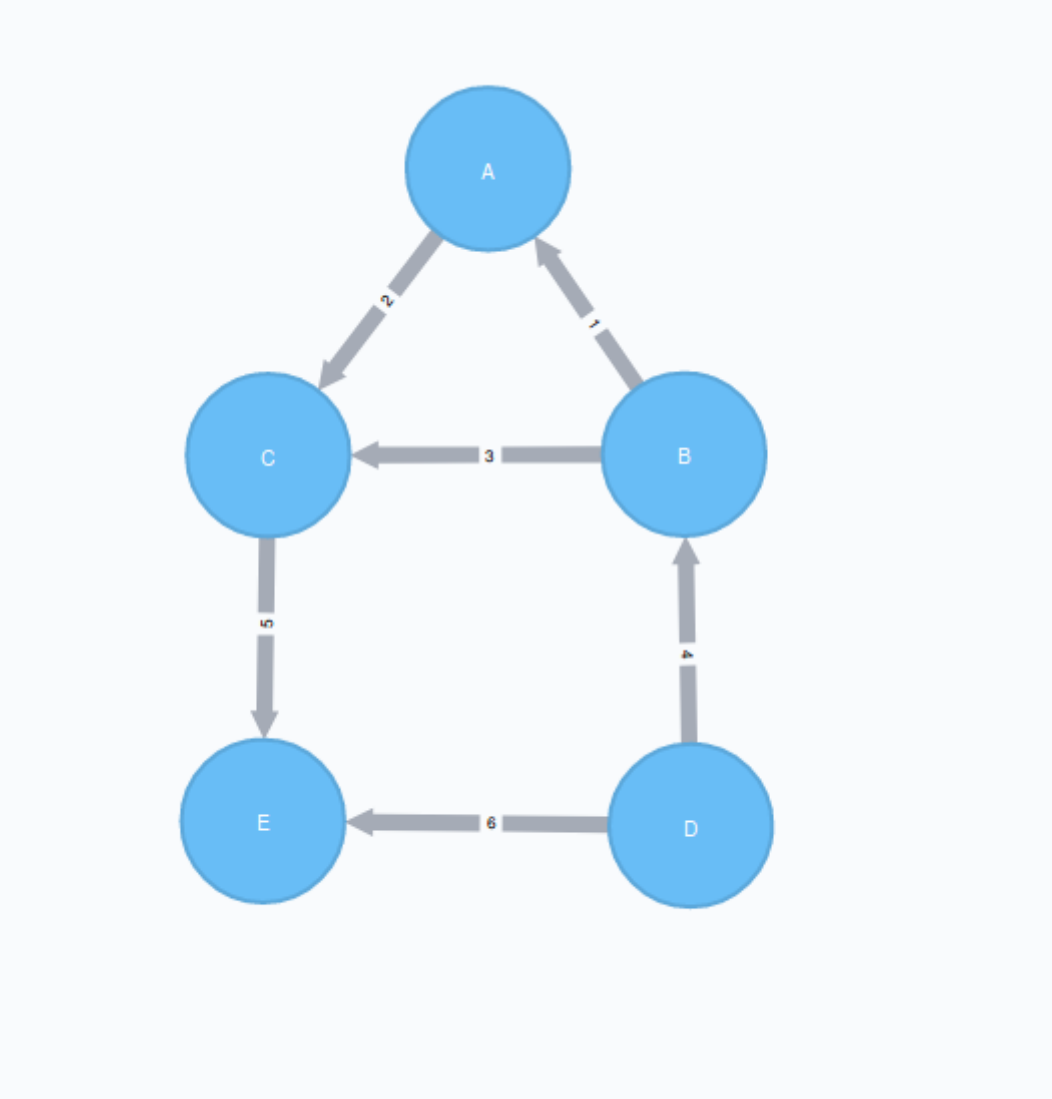
Table 676. Configuration

Name	Type	Default	Optional	Description
k	Integer	null	no	The result is a tree with `k` nodes and `k - 1` relationships
startNodeId	Integer	null	no	The start node ID
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
writeProperty	String	'MST'	yes	The relationship type written back as result
weightWriteProperty	String	n/a	no	The weight property of the `writeProperty` relationship type written back

Table 677. Results

Name	Type	Description
effectiveNodeCount	Integer	The number of visited nodes
preProcessingMillis	Integer	Milliseconds for preprocessing the data
computeMillis	Integer	Milliseconds for running the algorithm
writeMillis	Integer	Milliseconds for writing result data back

Minimum Weight Spanning Tree algorithm sample



The following will create a sample graph:

```
CREATE (a:Place {id: 'A'}),
       (b:Place {id: 'B'}),
       (c:Place {id: 'C'}),
       (d:Place {id: 'D'}),
       (e:Place {id: 'E'}),
       (f:Place {id: 'F'}),
       (g:Place {id: 'G'}),
       (d)-[:LINK {cost:4}]->(b),
       (d)-[:LINK {cost:6}]->(e),
       (b)-[:LINK {cost:1}]->(a),
       (b)-[:LINK {cost:3}]->(c),
       (a)-[:LINK {cost:2}]->(c),
       (c)-[:LINK {cost:5}]->(e),
       (f)-[:LINK {cost:1}]->(g);
```

The following will project and store a named graph:

```
CALL gds.graph.project(
  'graph',
  'Place',
  {
    LINK: {
      type: 'LINK',
      properties: 'cost',
      orientation: 'UNDIRECTED'
    }
  }
)
```

Minimum weight spanning tree visits all nodes that are in the same connected component as the starting node, and returns a spanning tree of all nodes in the component where the total weight of the relationships is minimized.

The following will run the Minimum Weight Spanning Tree algorithm and write back results:

```
MATCH (n:Place {id: 'D'})
CALL gds.alpha.spanningTree.minimum.write('graph', {
  startNodeId: id(n),
  relationshipWeightProperty: 'cost',
  writeProperty: 'MINST',
  weightWriteProperty: 'writeCost'
})
YIELD preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount
RETURN preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount;
```

To find all pairs of nodes included in our minimum spanning tree, run the following query:

```
MATCH path = (n:Place {id: 'D'})-[:MINST*]-()
WITH relationships(path) AS rels
UNWIND rels AS rel
WITH DISTINCT rel AS rel
RETURN startNode(rel).id AS source, endNode(rel).id AS destination, rel.writeCost AS cost
```

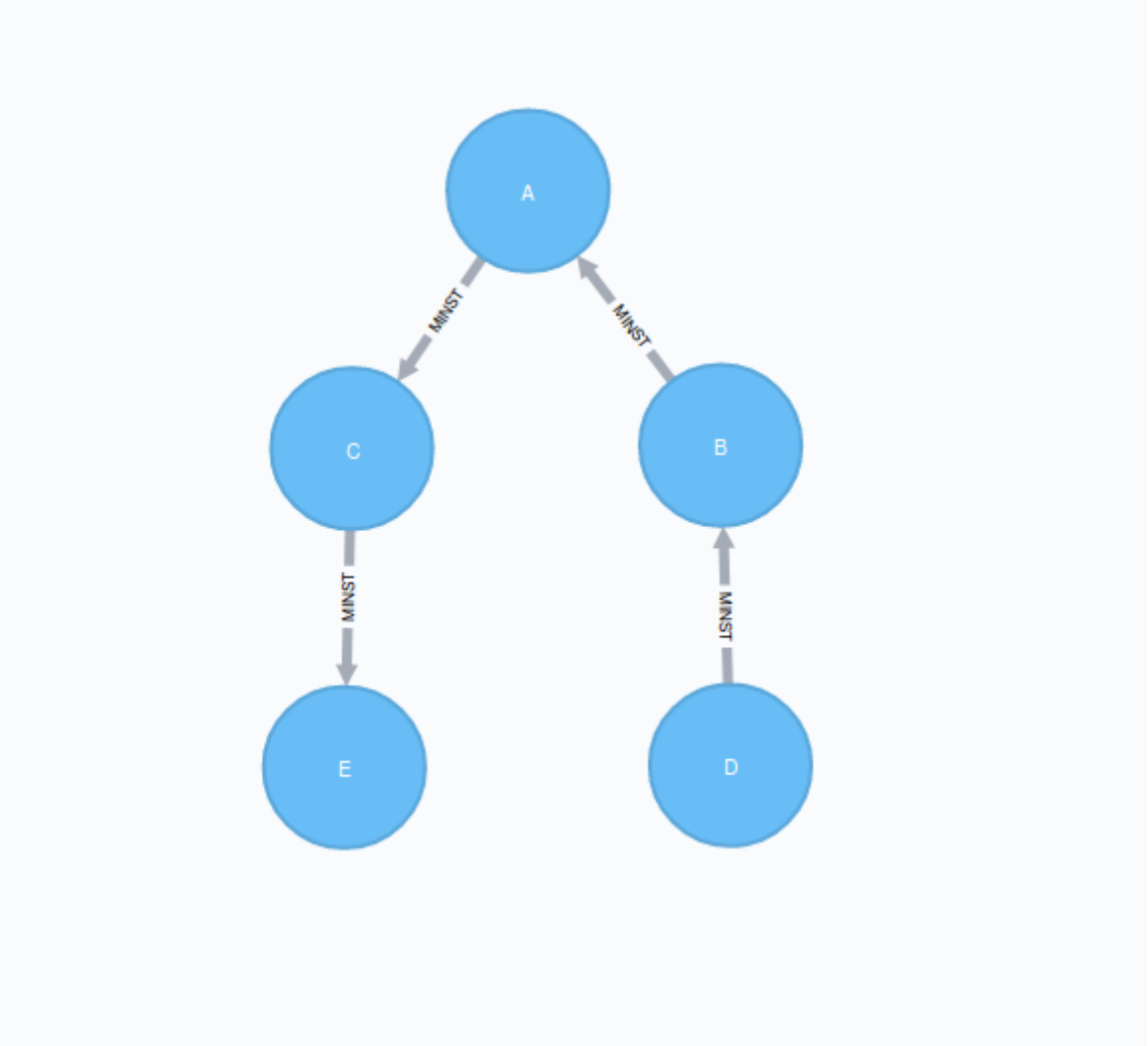


Figure 8. Results

Table 678. Results

Source	Destination	Cost
D	B	4
B	A	1
A	C	2
C	E	5

The minimum spanning tree excludes the relationship with cost 6 from D to E, and the one with cost 3 from B to C. Nodes F and G aren't included because they're unreachable from D.

Maximum weighted tree spanning algorithm is similar to the minimum one, except that it returns a spanning tree of all nodes in the component where the total weight of the relationships is maximized.

The following will run the maximum weight spanning tree algorithm and write back results:

```
MATCH (n:Place{id: 'D'})
CALL gds.alpha.spanningTree.maximum.write('graph', {
  startNodeId: id(n),
  relationshipWeightProperty: 'cost',
  writeProperty: 'MAXST',
  weightWriteProperty: 'writeCost'
})
YIELD preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount
RETURN preProcessingMillis,computeMillis, writeMillis, effectiveNodeCount;
```

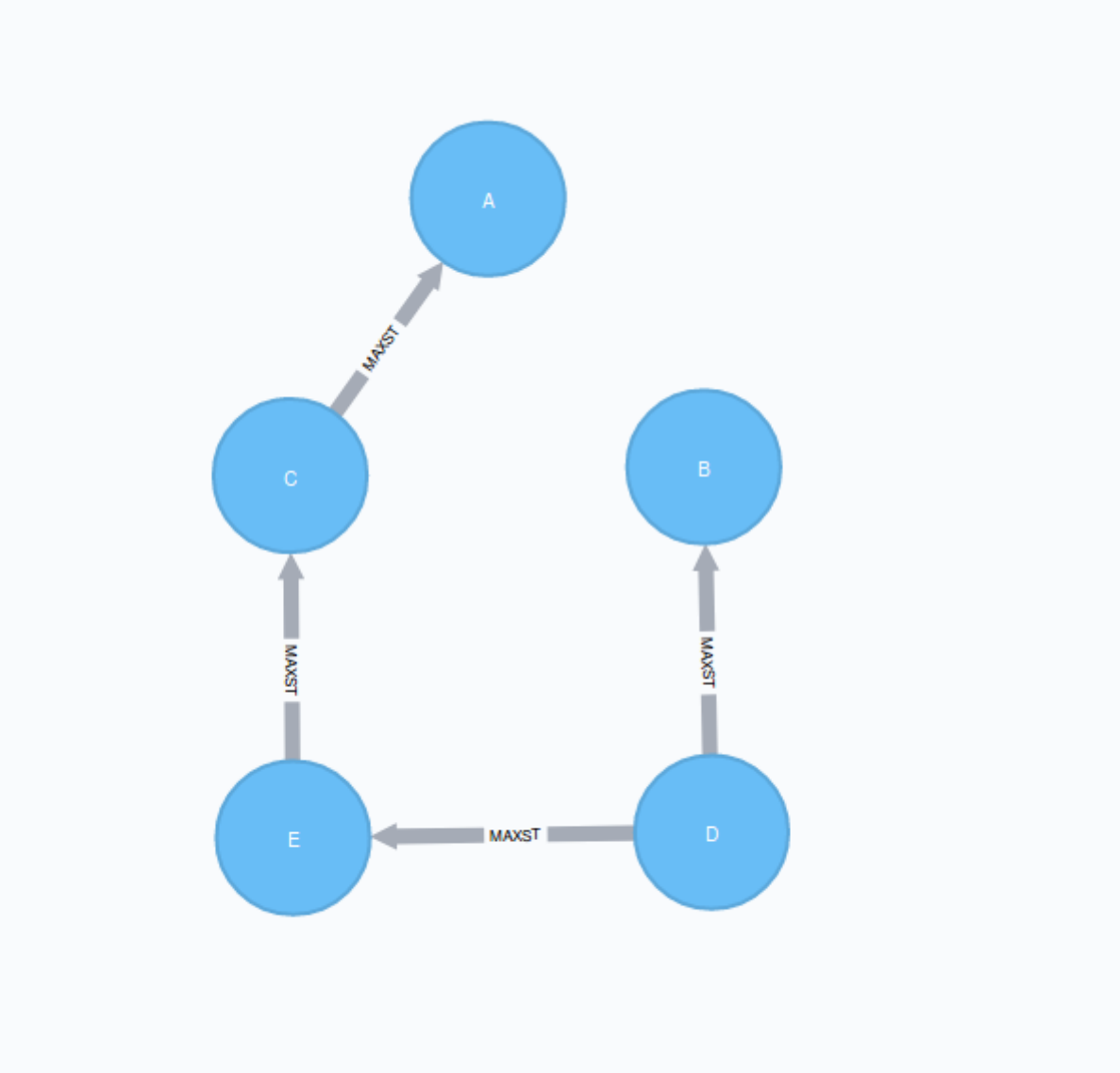


Figure 9. Results

K-Spanning tree

Sometimes we want to limit the size of our spanning tree result, as we are only interested in finding a smaller tree within our graph that does not span across all nodes. K-Spanning tree algorithm returns a tree with `k` nodes and `k - 1` relationships.

In our sample graph we have 5 nodes. When we ran MST above, we got a 5-minimum spanning tree returned, that covered all five nodes. By setting the `k=3`, we define that we want to get returned a 3-minimum spanning tree that covers 3 nodes and has 2 relationships.

The following will run the k-minimum spanning tree algorithm and write back results:

```
MATCH (n:Place{id: 'D'})
CALL gds.alpha.spanningTree.kmin.write('graph', {
  k: 3,
  startNodeId: id(n),
  relationshipWeightProperty: 'cost',
  writeProperty:'kminst'
})
YIELD preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount
RETURN preProcessingMillis,computeMillis,writeMillis, effectiveNodeCount;
```

Find nodes that belong to our k-spanning tree result:

```
MATCH (n:Place)
WITH n.id AS Place, n.kminst AS Partition, count(*) AS count
WHERE count = 3
RETURN Place, Partition
```

Table 679. Results

Place	Partition
A	1
B	1
C	1
D	3
E	4

Nodes A, B, and C are the result 3-minimum spanning tree of our graph.

The following will run the k-maximum spanning tree algorithm and write back results:

```
MATCH (n:Place{id: 'D'})
CALL gds.alpha.spanningTree.kmax.write('graph', {
  k: 3,
  startNodeId: id(n),
  relationshipWeightProperty: 'cost',
  writeProperty:'kmaxst'
})
YIELD preProcessingMillis, computeMillis, writeMillis, effectiveNodeCount
RETURN preProcessingMillis,computeMillis,writeMillis, effectiveNodeCount;
```

Find nodes that belong to our k-spanning tree result:

```
MATCH (n:Place)
WITH n.id AS Place, n.kmaxst AS Partition, count(*) AS count
WHERE count = 3
RETURN Place, Partition
```

Table 680. Results

Place	Partition
A	0
B	1
C	3

Place	Partition
D	3
E	3

Nodes C, D, and E are the result 3-maximum spanning tree of our graph.

6.5.7. All Pairs Shortest Path Alpha

This section describes the All Pairs Shortest Path algorithm in the Neo4j Graph Data Science library.

The All Pairs Shortest Path (APSP) calculates the shortest (weighted) path between all pairs of nodes. This algorithm has optimizations that make it quicker than calling the Single Source Shortest Path algorithm for every pair of nodes in the graph.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

Some pairs of nodes might not be reachable between each other, so no shortest path exists between these pairs. In this scenario, the algorithm will return `Infinity` value as a result between these pairs of nodes.

Plain cypher does not support filtering `Infinity` values, so `gds.util.isFinite` function was added to help filter `Infinity` values from results.

Use-cases - when to use the All Pairs Shortest Path algorithm

- The All Pairs Shortest Path algorithm is used in urban service system problems, such as the location of urban facilities or the distribution or delivery of goods. One example of this is determining the traffic load expected on different segments of a transportation grid. For more information, see Urban Operations Research.
- All pairs shortest path is used as part of the REWIRE data center design algorithm that finds a network with maximum bandwidth and minimal latency. There are more details about this approach in "REWIRE: An Optimization-based Framework for Data Center Network Design"

Syntax

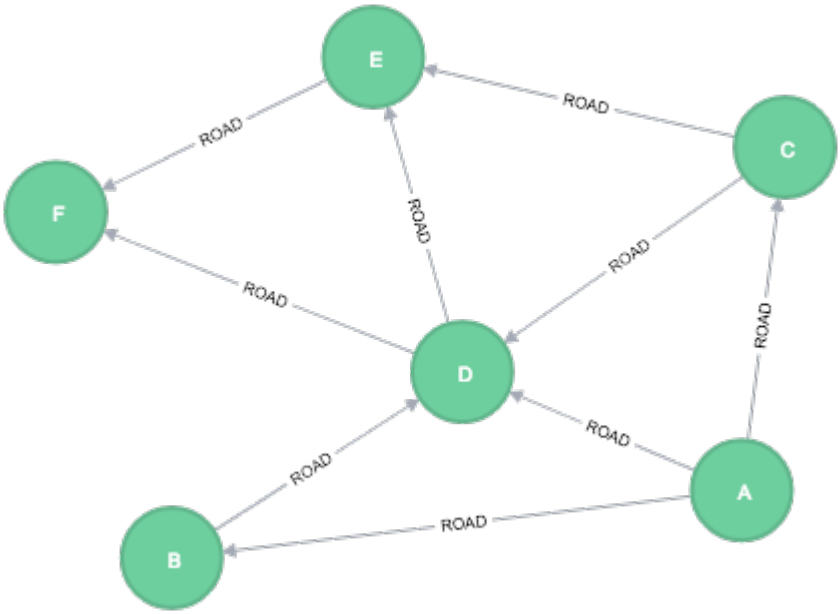
The following will run the algorithm and stream results:

```
CALL gds.alpha.allShortestPaths.stream(
  graphName: string,
  configuration: map
)
YIELD startNodeId, targetNodeId, distance
```

Table 681. Parameters

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'. This is dependent on the Neo4j edition; for more information, see CPU.
readConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for reading the graph.

All Pairs Shortest Path algorithm sample



The following will create a sample graph:

```
CREATE (a:Loc {name: 'A'}),
       (b:Loc {name: 'B'}),
       (c:Loc {name: 'C'}),
       (d:Loc {name: 'D'}),
       (e:Loc {name: 'E'}),
       (f:Loc {name: 'F'}),
       (a)-[:ROAD {cost: 50}]->(b),
       (a)-[:ROAD {cost: 50}]->(c),
       (a)-[:ROAD {cost: 100}]->(d),
       (b)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 40}]->(d),
       (c)-[:ROAD {cost: 80}]->(e),
       (d)-[:ROAD {cost: 30}]->(e),
       (d)-[:ROAD {cost: 80}]->(f),
       (e)-[:ROAD {cost: 40}]->(f);
```

The following will project and store a graph using native projection:

```
CALL gds.graph.project(
  'nativeGraph',
  'Loc',
  {
    ROAD: {
      type: 'ROAD',
      properties: 'cost'
    }
  }
)
YIELD graphName
```

The following will run the algorithm and stream results:

```
CALL gds.alpha.allShortestPaths.stream('nativeGraph', {
  relationshipWeightProperty: 'cost'
})
YIELD sourceNodeId, targetNodeId, distance
WITH sourceNodeId, targetNodeId, distance
WHERE gds.util.isFinite(distance) = true

MATCH (source:Loc) WHERE id(source) = sourceNodeId
MATCH (target:Loc) WHERE id(target) = targetNodeId
WITH source, target, distance WHERE source <> target

RETURN source.name AS source, target.name AS target, distance
ORDER BY distance DESC, source ASC, target ASC
LIMIT 10
```

Table 682. Results

Source	Target	Cost
A	F	160
A	E	120
B	F	110
C	F	110
A	D	90
B	E	70
C	E	70
D	F	70
A	B	50
A	C	50

This query returned the top 10 pairs of nodes that are the furthest away from each other. F and E appear to be quite distant from the others.

For now, only single-source shortest path support loading the relationship as undirected, but we can use Cypher loading to help us solve this. Undirected graph can be represented as Bidirected graph, which is a directed graph in which the reverse of every relationship is also a relationship.

We do not have to save this reversed relationship, we can project it using **Cypher loading**. Note that relationship query does not specify direction of the relationship. This is applicable to all other algorithms

that use Cypher loading.

The following will project and store an undirected graph using cypher projection:

```
CALL gds.graph.project.cypher(
  'cypherGraph',
  'MATCH (n:Loc) RETURN id(n) AS id',
  'MATCH (n:Loc)-[r:ROAD]-(p:Loc) RETURN id(n) AS source, id(p) AS target, r.cost AS cost'
)
YIELD graphName
```

The following will run the algorithm, treating the graph as undirected:

```
CALL gds.alpha.allShortestPaths.stream('cypherGraph', {
  relationshipWeightProperty: 'cost'
})
YIELD sourceNodeId, targetNodeId, distance
WITH sourceNodeId, targetNodeId, distance
WHERE gds.util.isFinite(distance) = true

MATCH (source:Loc) WHERE id(source) = sourceNodeId
MATCH (target:Loc) WHERE id(target) = targetNodeId
WITH source, target, distance WHERE source <> target

RETURN source.name AS source, target.name AS target, distance
ORDER BY distance DESC, source ASC, target ASC
LIMIT 10
```

Table 683. Results

Source	Target	Cost
A	F	160
F	A	160
A	E	120
E	A	120
B	F	110
C	F	110
F	B	110
F	C	110
A	D	90
D	A	90

6.5.8. Random Walk Beta

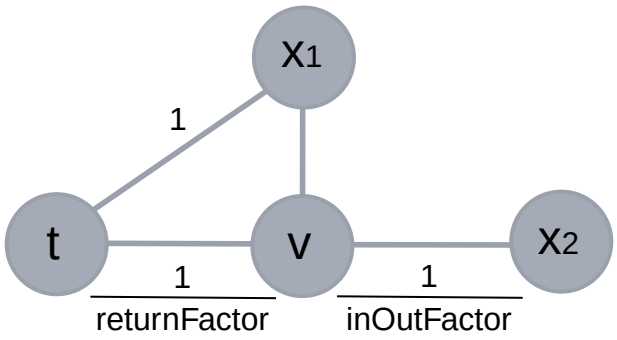
This section describes the Random Walk algorithm in the Neo4j Graph Data Science library.

Random Walk is an algorithm that provides random paths in a graph.

A random walk simulates a traversal of the graph in which the traversed relationships are chosen at random. In a classic random walk, each relationship has the same, possibly weighted, probability of being picked. This probability is not influenced by the previously visited nodes. The random walk implementation

of the Neo4j Graph Data Science library supports the concept of second order random walks. This method tries to model the transition probability based on the currently visited node `v`, the node `t` visited before the current one, and the node `x` which is the target of a candidate relationship. Random walks are thus influenced by two parameters: the `returnFactor` and the `inOutFactor`:

- The `returnFactor` is used if `t` equals `x`, i.e., the random walk returns to the previously visited node.
- The `inOutFactor` is used if the distance from `t` to `x` is equal to 2, i.e., the walk traverses further away from the node `t`



The probabilities for traversing a relationship during a random walk can be further influenced by specifying a `relationshipWeightProperty`. A relationship property value greater than 1 will increase the likelihood of a relationship being traversed, a property value between 0 and 1 will decrease that probability.

	To obtain a random walk where the transition probability is independent of the previously visited nodes both the `returnFactor` and the `inOutFactor` can be set to 1.0.

	Running this algorithm requires sufficient memory availability. Before running this algorithm, we recommend that you read Memory Estimation.

Syntax

RandomWalk syntax per mode

Run RandomWalk in stream mode on a named graph.

```
CALL gds.beta.randomWalk.stream(
  graphName: String,
  configuration: Map
) YIELD
YIELD
  nodeIds: List of Integer,
  path: Path
```

Table 684. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 685. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 686. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNodes	List of Integer	List of all nodes	yes	The list of nodes from which to do a random walk.
walkLength	Integer	80	yes	The number of steps in a single random walk.
walksPerNode	Integer	10	yes	The number of random walks generated for each node.
inOutFactor	Float	1.0	yes	Tendency of the random walk to stay close to the start node or fan out in the graph. Higher value means stay local.
returnFactor	Float	1.0	yes	Tendency of the random walk to return to the last visited node. A value below 1.0 means a higher tendency.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights to influence the probabilities of the random walks. The weights need to be >= 0. If unspecified, the algorithm runs unweighted.
randomSeed	Integer	random	yes	Seed value for the random number generator used to generate the random walks.

Name	Type	Default	Optional	Description
walkBufferSize	Integer	1000	yes	The number of random walks to complete before starting training.

Table 687. Results

Name	Type	Description
nodeIds	List of Integer	The nodes of the random walk.
path	Path	A Path object of the random walk.

Examples

Consider the graph created by the following Cypher statement:

```
CREATE (home:Page {name: 'Home'}),
       (about:Page {name: 'About'}),
       (product:Page {name: 'Product'}),
       (links:Page {name: 'Links'}),
       (a:Page {name: 'Site A'}),
       (b:Page {name: 'Site B'}),
       (c:Page {name: 'Site C'}),
       (d:Page {name: 'Site D'}),

       (home)-[:LINKS]->(about),
       (about)-[:LINKS]->(home),
       (product)-[:LINKS]->(home),
       (home)-[:LINKS]->(product),
       (links)-[:LINKS]->(home),
       (home)-[:LINKS]->(links),
       (links)-[:LINKS]->(a),
       (a)-[:LINKS]->(home),
       (links)-[:LINKS]->(b),
       (b)-[:LINKS]->(home),
       (links)-[:LINKS]->(c),
       (c)-[:LINKS]->(home),
       (links)-[:LINKS]->(d),
       (d)-[:LINKS]->(home)
```

```
CALL gds.graph.project(
    'myGraph',
    '*',
    { LINKS: { orientation: 'UNDIRECTED' } }
);
```

Without specified source nodes

Run the RandomWalk algorithm on `myGraph`

```
CALL gds.beta.randomWalk.stream(
  'myGraph',
  {
    walkLength: 3,
    walksPerNode: 1,
    randomSeed: 42,
    concurrency: 1
  }
)
YIELD nodeIds, path
RETURN nodeIds, [node IN nodes(path) | node.name ] AS pages
```

Table 688. Results

nodeIds	pages
[0, 5, 3]	[Home, Site B, Links]
[1, 0, 6]	[About, Home, Site C]
[2, 0, 5]	[Product, Home, Site B]
[3, 6, 3]	[Links, Site C, Links]
[4, 3, 4]	[Site A, Links, Site A]
[5, 3, 5]	[Site B, Links, Site B]
[6, 3, 7]	[Site C, Links, Site D]
[7, 3, 0]	[Site D, Links, Home]

With specified source nodes

Run the RandomWalk algorithm on `myGraph` with specified sourceNodes

```
MATCH (page:Page)
WHERE page.name IN ['Home', 'About']
WITH COLLECT(page) as sourceNodes
CALL gds.beta.randomWalk.stream(
  'myGraph',
  {
    sourceNodes: sourceNodes,
    walkLength: 3,
    walksPerNode: 1,
    randomSeed: 42,
    concurrency: 1
  }
)
YIELD nodeIds, path
RETURN nodeIds, [node IN nodes(path) | node.name ] AS pages
```

Table 689. Results

nodeIds	pages
[0, 5, 3]	[Home, Site B, Links]
[1, 0, 6]	[About, Home, Site C]

6.5.9. Breadth First Search

This section describes the Breadth First Search traversal algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Breadth First Search algorithm is a graph traversal algorithm that given a start node visits nodes in order of increasing distance, see https://en.wikipedia.org/wiki/Breadth-first_search. A related algorithm is the Depth First Search algorithm, Depth First Search. This algorithm is useful for searching when the likelihood of finding the node searched for decreases with distance. There are multiple termination conditions supported for the traversal, based on either reaching one of several target nodes, reaching a maximum depth, exhausting a given budget of traversed relationship cost, or just traversing the whole graph. The output of the procedure contains information about which nodes were visited and in what order.

Syntax

Breadth First Search syntax per mode

Run Breadth First Search in stream mode:

```
CALL gds.bfs.stream(
  graphName: string,
  configuration: map
)
YIELD
  sourceNode: int,
  nodeIds: int,
  path: Path
```

Table 690. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	Name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

Table 691. General configuration

Name	Type	Default	Optional	Description
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result (applicable in WRITE mode).

Table 692. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The node id of the node where to start the traversal.
targetNodes	List of Integer	empty list	yes	Ids for target nodes. Traversal terminates when any target node is visited.
maxDepth	Integer	-1	yes	The maximum distance from the source node at which nodes are visited.

Table 693. Results

Name	Type	Description
sourceNode	Integer	The node id of the node where to start the traversal.
nodeIds	List of Integer	The ids of all nodes that were visited during the traversal.
path	Path	A path containing all the nodes that were visited during the traversal.

Run Breadth First Search in stream mode:

```
CALL gds.bfs.mutate(
  graphName: string,
  configuration: map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 694. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	Name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

Table 695. General configuration for algorithm execution.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.
mutateRelationshipType	String	n/a	no	The relationship type used for the new relationships written to the projected graph.

Table 696. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The node id of the node where to start the traversal.
targetNodes	List of Integer	empty list	yes	Ids for target nodes. Traversal terminates when any target node is visited.
maxDepth	Integer	-1	yes	The maximum distance from the source node at which nodes are visited.

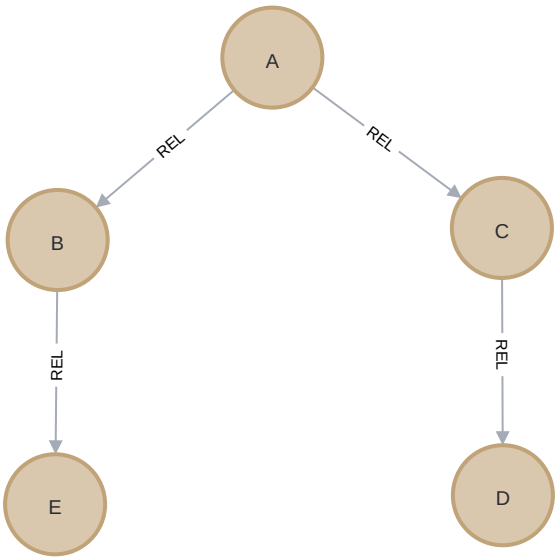
Table 697. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
postProcessingMillis	Integer	Unused.
mutateMillis	Integer	Milliseconds for adding relationships to the projected graph.
relationshipsWritten	Integer	The number of relationships that were added.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Breadth First Search algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small graph of a handful nodes connected in a particular pattern. The example graph looks like this:



Consider the graph projected by the following Cypher statement:

```
CREATE
       (nA:Node {name: 'A'}),
       (nB:Node {name: 'B'}),
       (nC:Node {name: 'C'}),
       (nD:Node {name: 'D'}),
       (nE:Node {name: 'E'}),

       (nA)-[:REL]->(nB),
       (nA)-[:REL]->(nC),
       (nB)-[:REL]->(nE),
       (nC)-[:REL]->(nD)
```

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project('myGraph', 'Node', 'REL')
```

In the following examples we will demonstrate using the Breadth First Search algorithm on this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `stream` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in stream mode:

```
MATCH (source:Node {name: 'A'})
CALL gds.bfs.stream.estimate('myGraph', {
    sourceNode: source
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
RETURN nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 698. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
5	4	536	536	"536 Bytes"

Stream

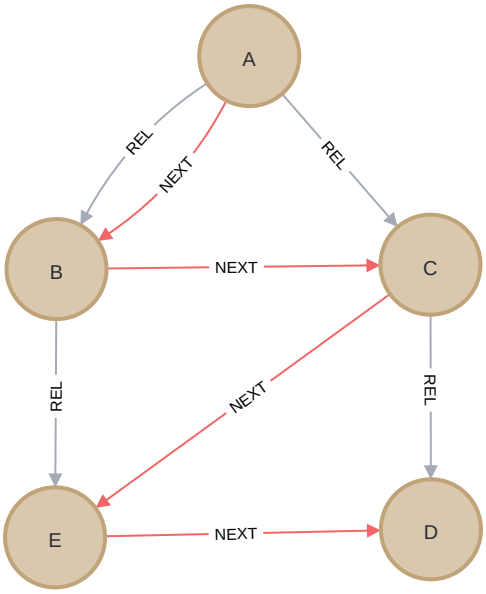
In the `stream` execution mode, the algorithm returns the path in traversal order for each relationship. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm and stream results:

```
MATCH (source:Node{name:'A'})
CALL gds.bfs.stream('myGraph', {
  sourceNode: source
})
YIELD path
RETURN path
```

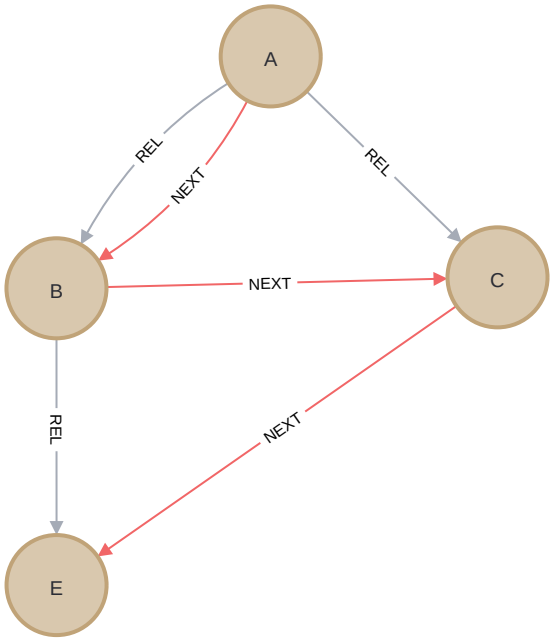
If we do not specify any of the options for early termination, the algorithm will traverse the entire graph. In the image below we can see the traversal order of the nodes, marked by relationship type `NEXT`:



Running the Breadth First Search algorithm with target nodes:

```
MATCH (a:Node{name:'A'}), (d:Node{name:'D'}), (e:Node{name:'E'})
WITH id(a) AS source, [id(d), id(e)] AS targetNodes
CALL gds.bfs.stream('myGraph', {
  sourceNode: source,
  targetNodes: targetNodes
})
YIELD path
RETURN path
```

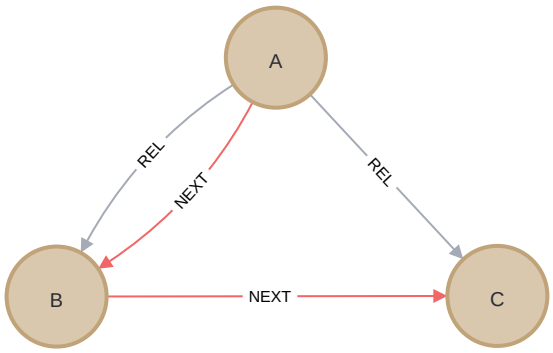
In the image below we can see the traversal order of the nodes, marked by relationship type `NEXT`. It is notable that the `D` node is not present in the picture, this is because the algorithm reached the target node `E` first and terminated the execution, leaving `D` unvisited.



Running the Breadth First Search algorithm with maxDepth:

```
MATCH (source:Node{name:'A'})
CALL gds.bfs.stream('myGraph', {
  sourceNode: source,
  maxDepth: 1
})
YIELD path
RETURN path
```

In the image below we can see the traversal order of the nodes, marked by relationship type `NEXT`. Nodes `D` and `E` were not visited since they are at distance 2 from node `A`.



Mutate

The `mutate` execution mode updates the named graph with new relationships. The path returned from the Breadth First Search algorithm is a line graph, where the nodes appear in the order they were visited by the algorithm. The relationship type has to be configured using the `mutateRelationshipType` option.

The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

Breadth First Search `mutate` supports the same early termination conditions as the `stream` mode.

The following will run the algorithm in `mutate` mode:

```
MATCH (source:Node{name:'A'})
CALL gds.bfs.mutate('myGraph', {
  sourceNode: source,
  mutateRelationshipType: 'BFS'
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 699. Results

relationshipsWritten
4

After executing the above query, the in-memory graph will be updated with new relationships of type `BFS`.

The relationships produced are always directed, even if the input graph is undirected.

6.5.10. Depth First Search

This section describes the Depth First Search traversal algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

The Depth First Search algorithm is a graph traversal that starts at a given node and explores as far as possible along each branch before backtracking, see https://en.wikipedia.org/wiki/Depth-first_search. A related algorithm is the Breath First Search algorithm, Breath First Search. This algorithm can be preferred over Breath First Search for example if one wants to find a target node at a large distance and exploring a random path has decent probability of success. There are multiple termination conditions supported for the traversal, based on either reaching one of several target nodes, reaching a maximum depth, exhausting a given budget of traversed relationship cost, or just traversing the whole graph. The output of the procedure contains information about which nodes were visited and in what order.

Syntax

Depth First Search syntax per mode

Run Depth First Search in stream mode:

```
CALL gds.dfs.stream(
  graphName: String,
  configuration: Map
)
YIELD
  sourceNode: Integer,
  nodeIds: Integer,
  path: Path
```

Table 700. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	Name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

Table 701. General configuration

Name	Type	Default	Optional	Description
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'readConcurrency' and 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result (applicable in WRITE mode).

The algorithm is single-threaded and changing the `concurrency` parameter has no effect on the runtime.

Table 702. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	`n/a`	no	The node id of the node where to start the traversal.
targetNodes	List of Integer	`empty list`	yes	Ids for target nodes. Traversal terminates when any target node is visited.
maxDepth	Integer	`-1`	yes	The maximum distance from the source node at which nodes are visited.

Table 703. Results

Name	Type	Description
sourceNode	Integer	The node id of the node where to start the traversal.
nodeIds	List of Integer	The ids of all nodes that were visited during the traversal.
path	Path	A path containing all the nodes that were visited during the traversal.

Run Depth First Search in stream mode:

```
CALL gds.dfs.mutate(
  graphName: string,
  configuration: map
)
YIELD
  relationshipsWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 704. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	Name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering. Must be empty if graphNameOrConfig is a Map.

Table 705. General configuration for algorithm execution.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.
mutateRelationshipType	String	n/a	no	The relationship type used for the new relationships written to the projected graph.

Table 706. Algorithm specific configuration

Name	Type	Default	Optional	Description
sourceNode	Integer	n/a	no	The node id of the node where to start the traversal.
targetNodes	List of Integer	empty list	yes	Ids for target nodes. Traversal terminates when any target node is visited.
maxDepth	Integer	-1	yes	The maximum distance from the source node at which nodes are visited.

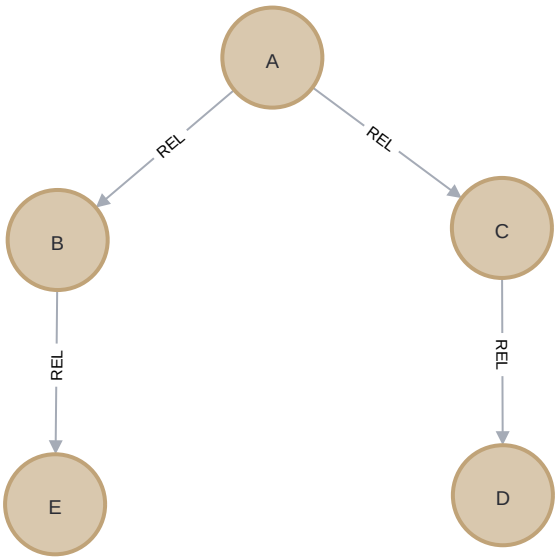
Table 707. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
postProcessingMillis	Integer	Unused.
mutateMillis	Integer	Milliseconds for adding relationships to the projected graph.
relationshipsWritten	Integer	The number of relationships that were added.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Depth First Search algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small graph of a handful nodes connected in a particular pattern. The example graph looks like this:



Consider the graph projected by the following Cypher statement:

```
CREATE
       (nA:Node {name: 'A'}),
       (nB:Node {name: 'B'}),
       (nC:Node {name: 'C'}),
       (nD:Node {name: 'D'}),
       (nE:Node {name: 'E'}),

       (nA)-[:REL]->(nB),
       (nA)-[:REL]->(nC),
       (nB)-[:REL]->(nE),
       (nC)-[:REL]->(nD)
```

The following statement will project the graph and store it in the graph catalog.

```
CALL gds.graph.project('myGraph', 'Node', 'REL')
```

In the following examples we will demonstrate using the Depth First Search algorithm on this graph.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `stream` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in stream mode:

```
MATCH (source:Node {name: 'A'})
CALL gds.dfs.stream.estimate('myGraph', {
  sourceNode: source
})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
RETURN nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 708. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
5	4	344	344	"344 Bytes"

Stream

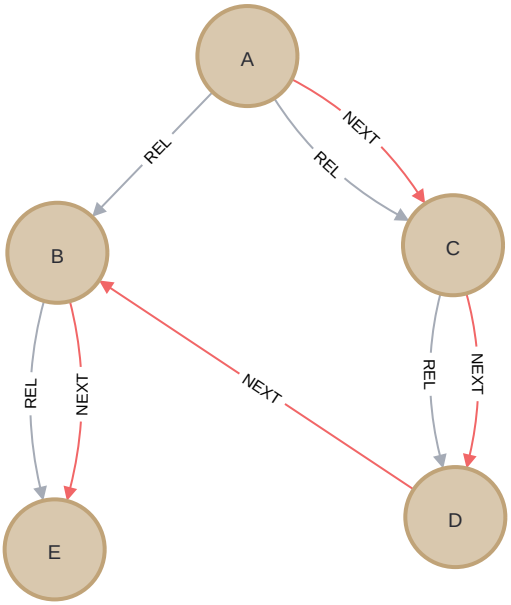
In the `stream` execution mode, the algorithm returns the path in traversal order for each relationship. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

Running the Depth First Search algorithm:

```
MATCH (source:Node{name:'A'})
CALL gds.dfs.stream('myGraph', {
  sourceNode: source
})
YIELD path
RETURN path
```

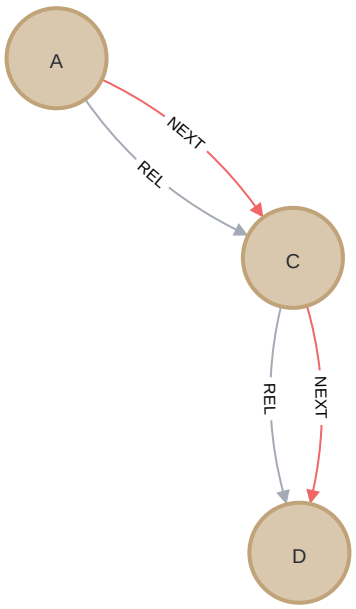
If we do not specify any of the options for early termination, the algorithm will traverse the entire graph: In the image below we can see the traversal order of the nodes, marked by relationship type `NEXT`:



Running the Depth First Search algorithm with target nodes:

```
MATCH (a:Node{name:'A'}), (d:Node{name:'D'}), (e:Node{name:'E'})
WITH id(a) AS source, [id(d), id(e)] AS targetNodes
CALL gds.dfs.stream('myGraph', {
  sourceNode: source,
  targetNodes: targetNodes
})
YIELD path
RETURN path
```

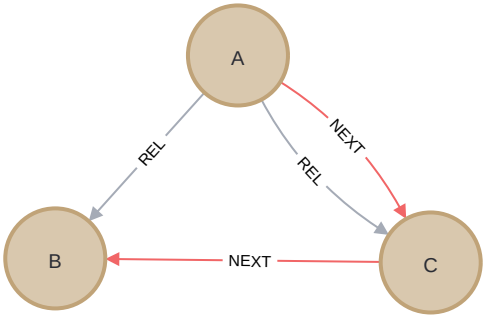
If specifying nodes `D` and `E` as target nodes, not all nodes at distance 1 will be visited due to the depth first traversal order, in which node `D` is reached before `B`.



Running the Depth First Search algorithm with maxDepth:

```
MATCH (source:Node{name:'A'})
CALL gds.dfs.stream('myGraph', {
  sourceNode: source,
  maxDepth: 1
})
YIELD path
RETURN path
```

In the above case, nodes `D` and `E` were not visited since they are at distance 2 from node `A`.



Mutate

The `mutate` execution mode updates the named graph with new relationships. The path returned from the Depth First Search algorithm is a line graph, where the nodes appear in the order they were visited by the algorithm. The relationship type has to be configured using the `mutateRelationshipType` option.

The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

Depth First Search `mutate` supports the same early termination conditions as the `stream` mode.

The following will run the algorithm in `mutate` mode:

```
MATCH (source:Node{name:'A'})
CALL gds.dfs.mutate('myGraph', {
  sourceNode: source,
  mutateRelationshipType: 'DFS'
})
YIELD relationshipsWritten
RETURN relationshipsWritten
```

Table 709. Results

relationshipsWritten
4

After executing the above query, the in-memory graph will be updated with new relationships of type `DFS`.

The relationships produced are always directed, even if the input graph is undirected.

6.6. Node embeddings

This chapter provides explanations and examples for the node embedding algorithms in the Neo4j Graph Data Science library.

Node embedding algorithms compute low-dimensional vector representations of nodes in a graph. These vectors, also called embeddings, can be used for machine learning. The Neo4j Graph Data Science library contains the following node embedding algorithms:

- Production-quality
  - FastRP
- Beta
  - GraphSAGE
  - Node2Vec

6.6.1. Fast Random Projection

This section describes the Fast Random Projection (FastRP) node embedding algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

Fast Random Projection, or FastRP for short, is a node embedding algorithm in the family of random projection algorithms. These algorithms are theoretically backed by the Johnsson-Lindenstrauss lemma according to which one can project n vectors of *arbitrary* dimension into $O(\log(n))$ dimensions and still approximately preserve pairwise distances among the points. In fact, a linear projection chosen in a random way satisfies this property.

Such techniques therefore allow for aggressive dimensionality reduction while preserving most of the distance information. The FastRP algorithm operates on graphs, in which case we care about preserving similarity between nodes and their neighbors. This means that two nodes that have similar neighborhoods should be assigned similar embedding vectors. Conversely, two nodes that are not similar should be not be assigned similar embedding vectors.

The FastRP algorithm initially assigns random vectors to all nodes using a technique called *very sparse random projection*, see (Achlioptas, 2003) below. Moreover, in GDS it is possible to use node properties for the creation of these *initial random vectors* in a way described below. We will also use *projection of a node* synonymously with the initial random vector of a node.

Starting with these random vectors and iteratively averaging over node neighborhoods, the algorithm constructs a sequence of *intermediate embeddings* e_n^i for each node *n*. More precisely,

$$e_n^i = \text{avg}(e_m^{i-1}),$$

where *m* ranges over neighbors of *n* and e_n^0 is the node's initial random vector.

The embedding e_n of node *n*, which is the output of the algorithm, is a combination of the vectors and embeddings defined above:

$$e_n = w_0 \cdot \text{normalize}(r_n) + \sum_{i=1}^{i=k} w_i \cdot \text{normalize}(e_n^i),$$

where `normalize` is the function which divides a vector with its L2 norm, the value of `nodeSelfInfluence` is w_0, and the values of `iterationWeights` are $[w_1, w_2, \ldots, w_k]$. We will return to Node Self Influence later on.

Therefore, each node's embedding depends on a neighborhood of radius equal to the number of iterations. This way FastRP exploits higher-order relationships in the graph while still being highly scalable.

The present implementation extends the original algorithm to support weighted graphs, which computes weighted averages of neighboring embeddings using the relationship weights. In order to make use of this, the `relationshipWeightProperty` parameter should be set to an existing relationship property.

The original algorithm is intended only for undirected graphs. We support running on both on directed graphs and undirected graph. For directed graphs we consider only the outgoing neighbors when computing the intermediate embeddings for a node. Therefore, using the orientations `NATURAL`, `REVERSE` or `UNDIRECTED` will all give different embeddings. In general, it is recommended to first use `UNDIRECTED` as this is what the original algorithm was evaluated on.

For more information on this algorithm see:

- H. Chen, S.F. Sultan, Y. Tian, M. Chen, S. Skiena: Fast and Accurate Network Embeddings via Very Sparse Random Projection, 2019.
- Dimitris Achlioptas. Database-friendly random projections: Johnson-Lindenstrauss with binary coins. Journal of Computer and System Sciences, 66(4):671–687, 2003.

Node properties

Most real-world graphs contain node properties which store information about the nodes and what they represent. The FastRP algorithm in the GDS library extends the original FastRP algorithm with a capability to take node properties into account. The resulting embeddings can therefore represent the graph more accurately.

The node property aware aspect of the algorithm is configured via the parameters `featureProperties` and `propertyRatio`. Each node property in `featureProperties` is associated with a randomly generated vector

of dimension `propertyDimension`, where `propertyDimension = embeddingDimension * propertyRatio`. Each node is then initialized with a vector of size `embeddingDimension` formed by concatenation of two parts:

1. The first part is formed like in the standard FastRP algorithm,
2. The second one is a linear combination of the property vectors, using the property values of the node as weights.

The algorithm then proceeds with the same logic as the FastRP algorithm. Therefore, the algorithm will output arrays of size `embeddingDimension`. The last `propertyDimension` coordinates in the embedding captures information about property values of nearby nodes (the "property part" below), and the remaining coordinates (`embeddingDimension` - `propertyDimension` of them; "topology part") captures information about nearby presence of nodes.

```
[0, 1, ...        | ...,   N - 1, N]
 ^^^^^^^^^^^^^^^^ | ^^^^^^^^^^^^^^^
  topology part   |  property part
                  ^
           property ratio
```

Tuning algorithm parameters

In order to improve the embedding quality using FastRP on one of your graphs, it is possible to tune the algorithm parameters. This process of finding the best parameters for your specific use case and graph is typically referred to as hyperparameter tuning. We will go through each of the configuration parameters and explain how they behave.

For statistically sound results, it is a good idea to reserve a test set excluded from parameter tuning. After selecting a set of parameter values, the embedding quality can be evaluated using a downstream machine learning task on the test set. By varying the parameter values and studying the precision of the machine learning task, it is possible to deduce the parameter values that best fit the concrete dataset and use case. To construct such a set you may want to use a dedicated node label in the graph to denote a subgraph without the test data.

Embedding dimension

The embedding dimension is the length of the produced vectors. A greater dimension offers a greater precision, but is more costly to operate over.

The optimal embedding dimension depends on the number of nodes in the graph. Since the amount of information the embedding can encode is limited by its dimension, a larger graph will tend to require a greater embedding dimension. A typical value is a power of two in the range 128 - 1024. A value of at least 256 gives good results on graphs in the order of 10^5 nodes, but in general increasing the dimension improves results. Increasing embedding dimension will however increase memory requirements and runtime linearly.

Normalization strength

The normalization strength is used to control how node degrees influence the embedding. Using a negative value will downplay the importance of high degree neighbors, while a positive value will instead increase their importance. The optimal normalization strength depends on the graph and on the task that the embeddings will be used for. In the original paper, hyperparameter tuning was done in the range of `[-1,0]` (no positive values), but we have found cases where a positive normalization strengths gives better results.

Iteration weights

The iteration weights parameter control two aspects: the number of iterations, and their relative impact on the final node embedding. The parameter is a list of numbers, indicating one iteration per number where the number is the weight applied to that iteration.

In each iteration, the algorithm will expand across all relationships in the graph. This has some implications:

- With a single iteration, only direct neighbors will be considered for each node embedding.
- With two iterations, direct neighbors and second-degree neighbors will be considered for each node embedding.
- With three iterations, direct neighbors, second-degree neighbors, and third-degree neighbors will be considered for each node embedding. Direct neighbors may be reached twice, in different iterations.
- In general, the embedding corresponding to the `i`:th iteration contains features depending on nodes reachable with paths of length `i`. If the graph is undirected, then a node reachable with a path of length `L` can also be reached with length `L+2k`, for any integer `k`.
- In particular, a node may reach back to itself on each even iteration (depending on the direction in the graph).

It is good to have at least one non-zero weight in an even and in an odd position. Typically, using at least a few iterations, for example three, is recommended. However, a too high value will consider nodes far away and may not be informative or even be detrimental. The intuition here is that as the projections reach further away from the node, the less specific the neighborhood becomes. Of course, a greater number of iterations will also take more time to complete.

Node Self Influence

Node Self Influence is a variation of the original FastRP algorithm.

How much a node's embedding is affected by the intermediate embedding at iteration *i* is controlled by the *i*'th element of `iterationWeights`. This can also be seen as how much the initial random vectors, or projections, of nodes that can be reached in *i* hops from a node affect the embedding of the node. Similarly, `nodeSelfInfluence` behaves like an iteration weight for a 0 th iteration, or the amount of influence the projection of a node has on the embedding of the same node.

A reason for setting this parameter to a non-zero value is if your graph has low connectivity or a significant

amount of isolated nodes. Isolated nodes combined with using `propertyRatio = 0.0` leads to embeddings that contain all zeros. However using node properties along with node self influence can thus produce more meaningful embeddings for such nodes. This can be seen as producing fallback features when graph structure is (locally) missing. Moreover, sometimes a node's own properties are simply informative features and are good to include even if connectivity is high. Finally, node self influence can be used for pure dimensionality reduction to compress node properties used for node classification.

If node properties are not used, using `nodeSelfInfluence` may also have a positive effect, depending on other settings and on the problem.

Orientation

Choosing the right orientation when creating the graph may have the single greatest impact. The FastRP algorithm is designed to work with undirected graphs, and we expect this to be the best in most cases. If you expect only outgoing or incoming relationships to be informative for a prediction task, then you may want to try using the orientations `NATURAL` or `REVERSE` respectively.

Syntax

This section covers the syntax used to execute the FastRP algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

FastRP syntax per mode

Run FastRP in stream mode on a named graph.

```
CALL gds.fastRP.stream(
  graphName: String,
  configuration: Map
) YIELD
  nodeId: Integer,
  embedding: List of Float
```

Table 710. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 711. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 712. Algorithm specific configuration

Name	Type	Default	Optional	Description
propertyRatio	Float	0.0	yes	The desired ratio of the property embedding dimension to the total `embeddingDimension`. A positive value requires `featureProperties` to be non-empty.
featureProperties	List of String	[]	yes	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	n/a	no	The dimension of the computed node embeddings. Minimum value is 1.
iterationWeights	List of Float	[0.0, 1.0, 1.0]	yes	Contains a weight for each iteration. The weight controls how much the intermediate embedding from the iteration contributes to the final embedding.
nodeSelfInfluence	Float	0.0	yes	Controls for each node how much its initial random vector contributes to its final embedding.
normalizationStrength	Float	0.0	yes	The initial random vector for each node is scaled by its degree to the power of `normalizationStrength`.
randomSeed	Integer	n/a	yes	A random seed which is used for all randomness in computing the embeddings.

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use for weighted random projection. If unspecified, the algorithm runs unweighted.
The number of iterations is equal to the length of `iterationWeights`.				
It is required that `iterationWeights` is non-empty or `nodeSelfInfluence` is non-zero.				

Table 713. Results

Name	Type	Description
nodeId	Integer	Node ID.
embedding	List of Float	FastRP node embedding.

Run FastRP in stats mode on a named graph.

```
CALL gds.fastRP.stats(
  graphName: String,
  configuration: Map
) YIELD
  nodeCount: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  configuration: Map
```

Table 714. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 715. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 716. Algorithm specific configuration

Name	Type	Default	Optional	Description
propertyRatio	Float	0.0	yes	The desired ratio of the property embedding dimension to the total `embeddingDimension`. A positive value requires `featureProperties` to be non-empty.
featureProperties	List of String	[]	yes	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	n/a	no	The dimension of the computed node embeddings. Minimum value is 1.
iterationWeights	List of Float	[0.0, 1.0, 1.0]	yes	Contains a weight for each iteration. The weight controls how much the intermediate embedding from the iteration contributes to the final embedding.
nodeSelfInfluence	Float	0.0	yes	Controls for each node how much its initial random vector contributes to its final embedding.
normalizationStrength	Float	0.0	yes	The initial random vector for each node is scaled by its degree to the power of `normalizationStrength`.
randomSeed	Integer	n/a	yes	A random seed which is used for all randomness in computing the embeddings.

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use for weighted random projection. If unspecified, the algorithm runs unweighted.
The number of iterations is equal to the length of `iterationWeights`.				
It is required that `iterationWeights` is non-empty or `nodeSelfInfluence` is non-zero.				

Table 717. Results

Name	Type	Description
nodeCount	Integer	Number of nodes processed.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
configuration	Map	Configuration used for running the algorithm.

Run FastRP in mutate mode on a named graph.

```
CALL gds.fastRP.mutate(
  graphName: String,
  configuration: Map
) YIELD
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 718. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 719. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm.

Table 720. Algorithm specific configuration

Name	Type	Default	Optional	Description
propertyRatio	Float	`0.0`	yes	The desired ratio of the property embedding dimension to the total `embeddingDimension`. A positive value requires `featureProperties` to be non-empty.
featureProperties	List of String	`[]`	yes	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	`n/a`	no	The dimension of the computed node embeddings. Minimum value is 1.
iterationWeights	List of Float	`[0.0, 1.0, 1.0]`	yes	Contains a weight for each iteration. The weight controls how much the intermediate embedding from the iteration contributes to the final embedding.
nodeSelfInfluence	Float	`0.0`	yes	Controls for each node how much its initial random vector contributes to its final embedding.
normalizationStrength	Float	`0.0`	yes	The initial random vector for each node is scaled by its degree to the power of `normalizationStrength`.

Name	Type	Default	Optional	Description
randomSeed	Integer	`n/a`	yes	A random seed which is used for all randomness in computing the embeddings.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use for weighted random projection. If unspecified, the algorithm runs unweighted.
The number of iterations is equal to the length of `iterationWeights`.				
It is required that `iterationWeights` is non-empty or `nodeSelfInfluence` is non-zero.				

Table 721. Results

Name	Type	Description
nodeCount	Integer	Number of nodes processed.
nodePropertiesWritten	Integer	Number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the in-memory graph.
configuration	Map	Configuration used for running the algorithm.

Run FastRP in write mode on a named graph.

```
CALL gds.fastRP.write(
  graphName: String,
  configuration: Map
) YIELD
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 722. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 723. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 724. Algorithm specific configuration

Name	Type	Default	Optional	Description
propertyRatio	Float	`0.0`	yes	The desired ratio of the property embedding dimension to the total `embeddingDimension`. A positive value requires `featureProperties` to be non-empty.
featureProperties	List of String	`[]`	yes	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	`n/a`	no	The dimension of the computed node embeddings. Minimum value is 1.
iterationWeights	List of Float	`[0.0, 1.0, 1.0]`	yes	Contains a weight for each iteration. The weight controls how much the intermediate embedding from the iteration contributes to the final embedding.
nodeSelfInfluence	Float	`0.0`	yes	Controls for each node how much its initial random vector contributes to its final embedding.

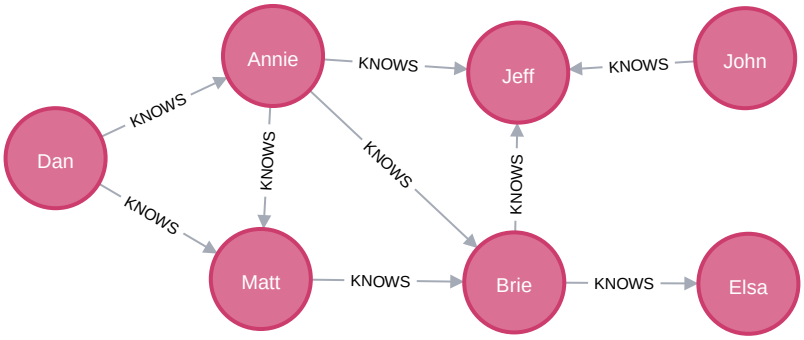
Name	Type	Default	Optional	Description
normalizationStrength	Float	`0.0`	yes	The initial random vector for each node is scaled by its degree to the power of `normalizationStrength`.
randomSeed	Integer	`n/a`	yes	A random seed which is used for all randomness in computing the embeddings.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use for weighted random projection. If unspecified, the algorithm runs unweighted.
The number of iterations is equal to the length of `iterationWeights`.				
It is required that `iterationWeights` is non-empty or `nodeSelfInfluence` is non-zero.				

Table 725. Results

Name	Type	Description
nodeCount	Integer	Number of nodes processed.
nodePropertiesWritten	Integer	Number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
configuration	Map	Configuration used for running the algorithm.

Examples

In this section we will show examples of running the FastRP node embedding algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (dan:Person {name: 'Dan', age: 18}),
  (annie:Person {name: 'Annie', age: 12}),
  (matt:Person {name: 'Matt', age: 22}),
  (jeff:Person {name: 'Jeff', age: 51}),
  (brie:Person {name: 'Brie', age: 45}),
  (elsa:Person {name: 'Elsa', age: 65}),
  (john:Person {name: 'John', age: 64}),

  (dan)-[:KNOWS {weight: 1.0}]->(annie),
  (dan)-[:KNOWS {weight: 1.0}]->(matt),
  (annie)-[:KNOWS {weight: 1.0}]->(matt),
  (annie)-[:KNOWS {weight: 1.0}]->(jeff),
  (annie)-[:KNOWS {weight: 1.0}]->(brie),
  (matt)-[:KNOWS {weight: 3.5}]->(brie),
  (brie)-[:KNOWS {weight: 1.0}]->(elsa),
  (brie)-[:KNOWS {weight: 2.0}]->(jeff),
  (john)-[:KNOWS {weight: 1.0}]->(jeff);
```

This graph represents seven people who know one another. A relationship property `weight` denotes the strength of the knowledge between two persons.

With the graph in Neo4j we can now project it into the graph catalog to prepare it for algorithm execution. We do this using a native projection targeting the `Person` nodes and the `KNOWS` relationships. For the relationships we will use the `UNDIRECTED` orientation. This is because the FastRP algorithm has been measured to compute more predictive node embeddings in undirected graphs. We will also add the `weight` relationship property which we will make use of when running the weighted version of FastRP.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'persons'.

```
CALL gds.graph.project(
  'persons',
  'Person',
  {
    KNOWS: {
      orientation: 'UNDIRECTED',
      properties: 'weight'
    }
  },
  { nodeProperties: ['age'] }
)
```

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `stream` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.fastRP.stream.estimate('persons', {embeddingDimension: 128})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 726. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
7	18	11424	11424	"11424 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the embedding for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm, and stream results:

```
CALL gds.fastRP.stream('persons',
  {
    embeddingDimension: 4,
    randomSeed: 42
  }
)
YIELD nodeId, embedding
```

Table 727. Results

nodeId	embedding
0	[0.4774002134799957, -0.6602408289909363, -0.36686956882476807, -1.7089111804962158]
1	[0.7989360094070435, -0.4918718934059143, -0.41281944513320923, -1.6314401626586914]
2	[0.47275322675704956, -0.49587157368659973, -0.3340468406677246, -1.7141895294189453]
3	[0.8290714025497437, -0.3260476291179657, -0.3317275643348694, -1.4370529651641846]
4	[0.7749264240264893, -0.4773247539997101, 0.0675133764743805, -1.5248265266418457]
5	[0.8408374190330505, -0.37151476740837097, 0.12121132016181946, -1.530960202217102]
6	[1.0, -0.11054422706365585, -0.3697933852672577, -0.9225144982337952]

The results of the algorithm are not very intuitively interpretable, as the node embedding format is a mathematical abstraction of the node within its neighborhood, designed for machine learning programs. What we can see is that the embeddings have four elements (as configured using `embeddingDimension`) and that the numbers are relatively small (they all fit in the range of `[-2, 2]`). The magnitude of the

numbers is controlled by the `embeddingDimension`, the number of nodes in the graph, and by the fact that FastRP performs euclidean normalization on the intermediate embedding vectors.

Due to the random nature of the algorithm the results will vary between the runs. However, this does not necessarily mean that the pairwise distances of two node embeddings vary as much.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm and returns the result in form of statistical and measurement values

```
CALL gds.fastRP.stats('persons', { embeddingDimension: 8 })
YIELD nodeCount
```

Table 728. Results

nodeCount
7

The `stats` mode does not currently offer any statistical results for the embeddings themselves. We can however see that the algorithm has successfully processed all seven nodes in our example graph.

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the embedding for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.fastRP.mutate(
  'persons',
  {
    embeddingDimension: 8,
    mutateProperty: 'fastrp-embedding'
  }
)
YIELD nodePropertiesWritten
```

Table 729. Results

nodePropertiesWritten
7

The returned result is similar to the `stats` example. Additionally, the graph 'persons' now has a node property `fastrp-embedding` which stores the node embedding for each node. To find out how to inspect the new schema of the in-memory graph, see Listing graphs.

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the embedding for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.fastRP.write(
  'persons',
  {
    embeddingDimension: 8,
    writeProperty: 'fastrp-embedding'
  }
)
YIELD nodePropertiesWritten
```

Table 730. Results

nodePropertiesWritten
7

The returned result is similar to the `stats` example. Additionally, each of the seven nodes now has a new property `fastrp-embedding` in the Neo4j database, containing the node embedding for that node.

Weighted

By default, the algorithm is considering the relationships of the graph to be unweighted. To change this behaviour we can use configuration parameter called `relationshipWeightProperty`. Below is an example of running the weighted variant of algorithm.

The following will run the algorithm, and stream results:

```
CALL gds.fastRP.stream(
  'persons',
  {
    embeddingDimension: 4,
    randomSeed: 42,
    relationshipWeightProperty: 'weight'
  }
)
YIELD nodeId, embedding
```

Table 731. Results

nodeId	embedding
0	[0.10945529490709305, -0.5032674074172974, 0.464673787355423, -1.7539862394332886]
1	[0.3639600872993469, -0.39210301637649536, 0.46271592378616333, -1.829423427581787]
2	[0.12314096093177795, -0.3213110864162445, 0.40100979804992676, -1.471055269241333]
3	[0.30704641342163086, -0.24944794178009033, 0.3947891891002655, -1.3463698625564575]
4	[0.23112300038337708, -0.30148714780807495, 0.584831714630127, -1.2822188138961792]
5	[0.14497177302837372, -0.2312137484550476, 0.5552002191543579, -1.2605633735656738]
6	[0.5139184594154358, -0.07954332232475281, 0.3690345287322998, -0.9176374077796936]

Since the initial state of the algorithm is randomised, it isn't possible to intuitively analyse the effect of the relationship weights.

Using node properties as features

To explain the novel initialization using node properties, let us consider an example where `embeddingDimension` is 10, `propertyRatio` is 0.2. The dimension of the embedded properties, `propertyDimension` is thus 2. Assume we have a property `f1` of scalar type, and a property `f2` storing arrays of length 2. This means that there are 3 features which we order like `f1` followed by the two values of `f2`. For each of these three features we sample a two dimensional random vector. Let's say these are `p1=[0.0, 2.4]`, `p2=[-2.4, 0.0]` and `p3=[2.4, 0.0]`. Consider now a node `(n {f1: 0.5, f2: [1.0, -1.0]})`. The linear combination mentioned above, is in concrete terms `0.5 * p1 + 1.0 * p2 - 1.0 * p3 = [-4.8, 1.2]`. The initial random vector for the node `n` contains first 8 values sampled as in the original FastRP paper, and then our computed values `-4.8` and `1.2`, totalling 10 entries.

In the example below, we again set the embedding dimension to 2, but we set `propertyRatio` to 1, which means the embedding is computed from node properties only.

The following will run FastRP with feature properties:

```
CALL gds.fastRP.stream('persons', {
    randomSeed: 42,
    embeddingDimension: 2,
    propertyRatio: 1.0,
    featureProperties: ['age'],
    iterationWeights: [1.0]
}) YIELD nodeId, embedding
```

Table 732. Results

nodeId	embedding
0	[0.0, -1.0]
1	[0.0, -1.0]
2	[0.0, -0.9999999403953552]
3	[0.0, -1.0]
4	[0.0, -0.9999999403953552]
5	[0.0, -1.0]
6	[0.0, -1.0]

In this example, the embeddings are based on the age property. Because of L2 normalization which is applied to each iteration (here only one iteration), all nodes have the same embedding despite having different age values (apart from rounding errors).

6.6.2. GraphSAGE Beta

> *This section describes the GraphSAGE node embedding algorithm in the Neo4j Graph Data Science library.*

GraphSAGE is an *inductive* algorithm for computing node embeddings. GraphSAGE is using node feature information to generate node embeddings on unseen nodes or graphs. Instead of training individual embeddings for each node, the algorithm learns a function that generates embeddings by sampling and aggregating features from a node's local neighborhood.

The algorithm is defined for UNDIRECTED graphs.

For more information on this algorithm see:

- William L. Hamilton, Rex Ying, and Jure Leskovec. "Inductive Representation Learning on Large Graphs." 2018.
- Amit Pande, Kai Ni and Venkataramani Kini. "SWAG: Item Recommendations using Convolutions on Weighted Graphs." 2019.

Considerations

If you are embedding a graph that has an isolated node, the aggregation step in GraphSAGE can only draw information from the node itself. When all the properties of that node are `0.0`, and the activation function is ReLU, this leads to an all-zero vector for that node. However, since GraphSAGE normalizes node embeddings using the L2-norm, and a zero vector cannot be normalized, we assign all-zero embeddings to such nodes under these special circumstances. In scenarios where you generate all-zero embeddings for orphan nodes, that may have impacts on downstream tasks such as nearest neighbor or other similarity algorithms. It may be more appropriate to filter out these disconnected nodes prior to running GraphSAGE.

When doing memory estimation of the training, the feature dimension is computed as if each feature property is scalar.

Syntax

GraphSAGE syntax per mode

Run GraphSAGE in train mode on a named graph.

```
CALL gds.beta.graphSage.train(
  graphName: String,
  configuration: Map
) YIELD
  modelInfo: Map,
  configuration: Map,
  trainMillis: Integer
```

Table 733. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 734. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 735. Algorithm specific configuration

Name	Type	Default	Optional	Description
modelName	String	n/a	no	The name of the model to train, must not exist in the Model Catalog.
featureProperties	List of String	n/a	no	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	64	yes	The dimension of the generated node embeddings as well as their hidden layer representations.
aggregator	String	"mean"	yes	The aggregator to be used by the layers. Supported values are "mean" and "pool".
activationFunction	String	"sigmoid"	yes	The activation function to be used in the model architecture. Supported values are "sigmoid" and "relu".
sampleSizes	List of Integer	[25, 10]	yes	A list of Integer values, the size of the list determines the number of layers and the values determine how many nodes will be sampled by the layers.

Name	Type	Default	Optional	Description
projectedFeatureDimension	Integer	`n/a`	yes	The dimension of the projected `featureProperties`. This enables multi-label GraphSage, where each label can have a subset of the `featureProperties`.
batchSize	Integer	`100`	yes	The number of nodes per batch.
tolerance	Float	`1e-4`	yes	Tolerance used for the early convergence of an epoch.
learningRate	Float	`0.1`	yes	The learning rate determines the step size at each iteration while moving toward a minimum of a loss function.
epochs	Integer	`1`	yes	Number of times to traverse the graph.
maxIterations	Integer	`10`	yes	Maximum number of weight updates per batch. Batches can also converge early based on `tolerance`.
searchDepth	Integer	`5`	yes	Maximum depth of the RandomWalks to sample nearby nodes for the training.
negativeSampleWeight	Integer	`20`	yes	The weight of the negative samples. Higher values increase the impact of negative samples in the loss.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
randomSeed	Integer	`random`	yes	A random seed which is used to control the randomness in computing the embeddings.

Table 736. Results

Name	Type	Description
`modelInfo`	Map	Details of the trained model.
`configuration`	Map	The configuration used to run the procedure.
`trainMillis`	Integer	Milliseconds to train the model.

Table 737. Details on `modelInfo`

Name	Type	Description
`name`	String	The name of the trained model.
`type`	String	The type of the trained model. Always `graphSage`.
`metrics`	Map	Metrics related to running the training, details in the table below.

Table 738. Metrics collected during training

Name	Type	Description
ranEpochs	Integer	The number of ran epochs during training.
epochLosses	List	Ordered list of the losses after each epoch.
didConverge	Boolean	Indicates if the training has converged.

Run GraphSAGE in stream mode on a named graph.

```
CALL gds.beta.graphSage.stream(
  graphName: String,
  configuration: Map
) YIELD
  nodeId: Integer,
  embedding: List
```

Table 739. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 740. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 741. Algorithm specific configuration

Name	Type	Default	Optional	Description
batchSize	Integer	100	yes	The number of nodes per batch.

Table 742. Results

Name	Type	Description
nodeId	Integer	The Neo4j node ID.
embedding	List of Float	The computed node embedding.

Run GraphSAGE in mutate mode on a graph stored in the catalog.

```
CALL gds.beta.graphSage.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 743. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 744. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 745. Algorithm specific configuration

Name	Type	Default	Optional	Description
batchSize	Integer	100	yes	The number of nodes per batch.

Table 746. Results

Name	Type	Description
nodeCount	Integer	The number of nodes processed.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for writing result data back to the projected graph.
configuration	Map	The configuration used for running the algorithm.

Run GraphSAGE in write mode on a graph stored in the catalog.

```
CALL gds.beta.graphSage.write(
  graphName: String,
  configuration: Map
)
YIELD
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 747. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 748. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 749. Algorithm specific configuration

Name	Type	Default	Optional	Description
batchSize	Integer	100	yes	The number of nodes per batch.

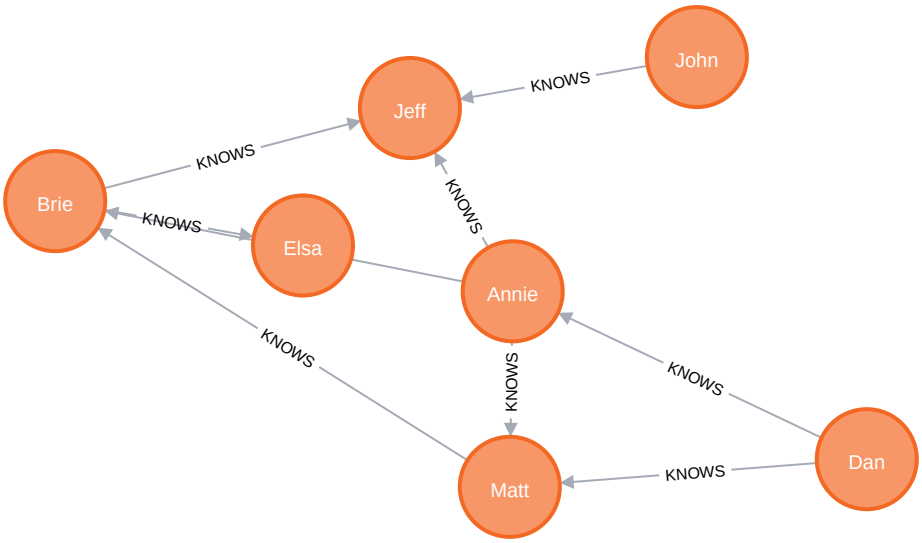
Table 750. Results

Name	Type	Description
nodeCount	Integer	The number of nodes processed.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing data.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the GraphSAGE algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small friends network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  // Persons
  (  dan:Person {name: 'Dan',   age: 20, heightAndWeight: [185, 75]}),
  (annie:Person {name: 'Annie', age: 12, heightAndWeight: [124, 42]}),
  ( matt:Person {name: 'Matt',  age: 67, heightAndWeight: [170, 80]}),
  ( jeff:Person {name: 'Jeff',  age: 45, heightAndWeight: [192, 85]}),
  ( brie:Person {name: 'Brie',  age: 27, heightAndWeight: [176, 57]}),
  ( elsa:Person {name: 'Elsa',  age: 32, heightAndWeight: [158, 55]}),
  ( john:Person {name: 'John',  age: 35, heightAndWeight: [172, 76]}),

  (dan)-[:KNOWS {relWeight: 1.0}]->(annie),
  (dan)-[:KNOWS {relWeight: 1.6}]->(matt),
  (annie)-[:KNOWS {relWeight: 0.1}]->(matt),
  (annie)-[:KNOWS {relWeight: 3.0}]->(jeff),
  (annie)-[:KNOWS {relWeight: 1.2}]->(brie),
  (matt)-[:KNOWS {relWeight: 10.0}]->(brie),
  (brie)-[:KNOWS {relWeight: 1.0}]->(elsa),
  (brie)-[:KNOWS {relWeight: 2.2}]->(jeff),
  (john)-[:KNOWS {relWeight: 5.0}]->(jeff)
```

```
CALL gds.graph.project(
  'persons',
  {
    Person: {
      label: 'Person',
      properties: ['age', 'heightAndWeight']
    }
  }, {
    KNOWS: {
      type: 'KNOWS',
      orientation: 'UNDIRECTED',
      properties: ['relWeight']
    }
})
```

The algorithm is defined for UNDIRECTED graphs.

Train

Before we are able to generate node embeddings we need to train a model and store it in the model catalog. Below is an example of how to do that.

The names specified in the `featureProperties` configuration parameter must exist in the projected graph.

```
CALL gds.beta.graphSage.train(
  'persons',
  {
    modelName: 'exampleTrainModel',
    featureProperties: ['age', 'heightAndWeight'],
    aggregator: 'mean',
    activationFunction: 'sigmoid',
    randomSeed: 1337,
    sampleSizes: [25, 10]
  }
) YIELD modelInfo as info
RETURN
  info.modelName as modelName,
  info.metrics.didConverge as didConverge,
  info.metrics.ranEpochs as ranEpochs,
  info.metrics.epochLosses as epochLosses
```

Table 751. Results

modelName	didConverge	ranEpochs	epochLosses
"exampleTrainModel"	false	1	[186.04946807210226]

Due to the random initialisation of the weight variables the results may vary between different runs.

Looking at the results we can draw the following conclusions, the training converged after a single epoch, the losses are almost identical. Tuning the algorithm parameters, such as trying out different `sampleSizes`, `searchDepth`, `embeddingDimension` or `batchSize` can improve the losses. For different datasets, GraphSAGE may require different train parameters for producing good models.

The trained model is automatically registered in the model catalog.

Train with multiple node labels

In this section we describe how to train on a graph with multiple labels. The different labels may have different sets of properties. To run on such a graph, GraphSAGE is run in *multi-label mode*, in which the feature properties are projected into a common feature space. Therefore, all nodes have feature vectors of the same dimension after the projection.

The projection for a label is linear and given by a matrix of weights. The weights for each label are learned jointly with the other weights of the GraphSAGE model.

In the multi-label mode, the following is applied prior to the usual aggregation layers:

1. A property representing the label is added to the feature properties for that label
2. The feature properties for each label are projected into a feature vector of a shared dimension

The projected feature dimension is configured with `projectedFeatureDimension`, and specifying it enables the multi-label mode.

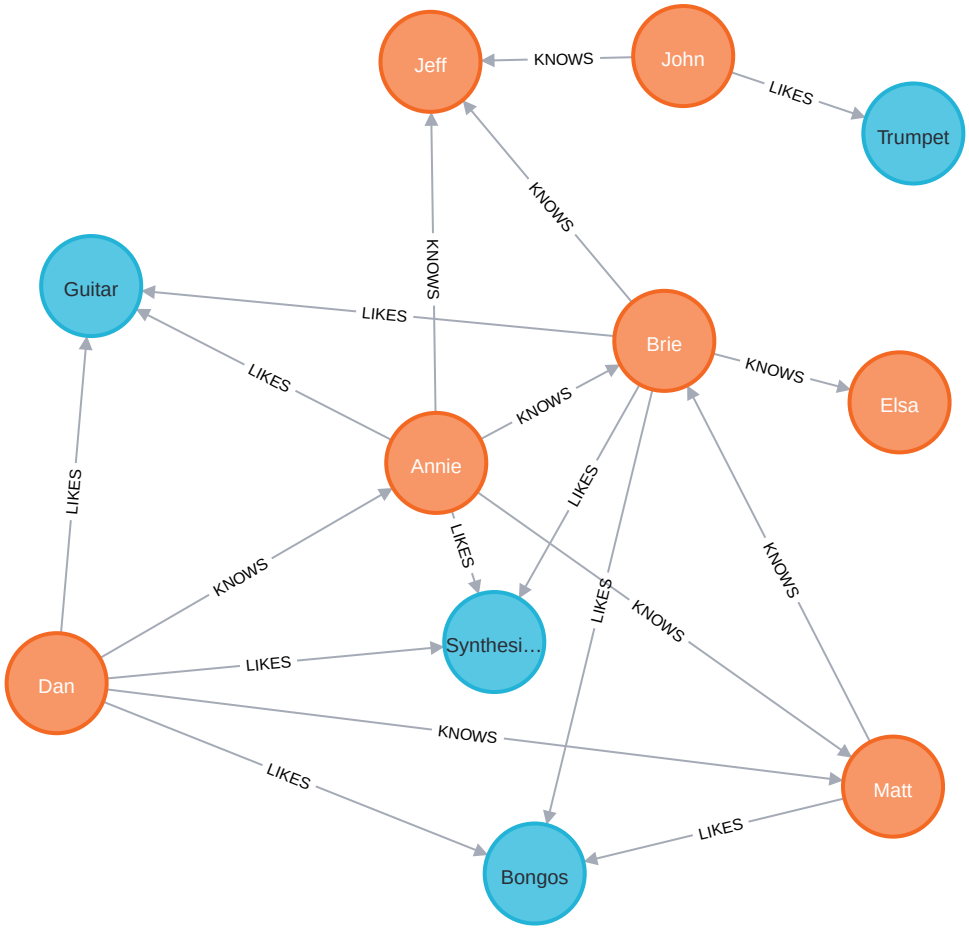
The feature properties used for a label are those present in the `featureProperties` configuration parameter which exist in the graph for that label. In the multi-label mode, it is no longer required that all labels have all the specified properties.

Assumptions

- A requirement for multi-label mode is that each node belongs to exactly one label.
- A GraphSAGE model trained in this mode must be applied on graphs with the same schema with regards to node labels and properties.

Examples

In order to demonstrate GraphSAGE with multiple labels, we add instruments and relationships of type `LIKE` between person and instrument to the example graph.



The following Cypher statement will extend the example graph in the Neo4j database:

```
MATCH
  (dan:Person {name: "Dan"}),
  (annie:Person {name: "Annie"}),
  (matt:Person {name: "Matt"}),
  (brie:Person {name: "Brie"}),
  (john:Person {name: "John"})
CREATE
  (guitar:Instrument {name: 'Guitar', cost: 1337.0}),
  (synth:Instrument {name: 'Synthesizer', cost: 1337.0}),
  (bongos:Instrument {name: 'Bongos', cost: 42.0}),
  (trumpet:Instrument {name: 'Trumpet', cost: 1337.0}),
  (dan)-[:LIKES]->(guitar),
  (dan)-[:LIKES]->(synth),
  (dan)-[:LIKES]->(bongos),
  (annie)-[:LIKES]->(guitar),
  (annie)-[:LIKES]->(synth),
  (matt)-[:LIKES]->(bongos),
  (brie)-[:LIKES]->(guitar),
  (brie)-[:LIKES]->(synth),
  (brie)-[:LIKES]->(bongos),
  (john)-[:LIKES]->(trumpet)
```

```
CALL gds.graph.project(
  'persons_with_instruments',
  {
    Person: {
      label: 'Person',
      properties: ['age', 'heightAndWeight']
    },
    Instrument: {
      label: 'Instrument',
      properties: ['cost']
    }
  }, {
    KNOWS: {
      type: 'KNOWS',
      orientation: 'UNDIRECTED'
    },
    LIKES: {
      type: 'LIKES',
      orientation: 'UNDIRECTED'
    }
})
```

We can now run GraphSAGE in multi-label mode on that graph by specifying the `projectedFeatureDimension` parameter. Multi-label GraphSAGE removes the requirement, that each node in the in-memory graph must have all `featureProperties`. However, the projections are independent per label and even if two labels have the same `featureProperty` they are considered as different features before projection. The `projectedFeatureDimension` equals the maximum length of the feature-array, i.e., `age` and `cost` both are scalar features plus the list feature `heightAndWeight` which has a length of two. For each node its unique labels properties is projected using a label specific projection to vector space of dimension `projectedFeatureDimension`. Note that the `cost` feature is only defined for the instrument nodes, while `age` and `heightAndWeight` are only defined for persons.

```
CALL gds.beta.graphSage.train(
  'persons_with_instruments',
  {
    modelName: 'multiLabelModel',
    featureProperties: ['age', 'heightAndWeight', 'cost'],
    projectedFeatureDimension: 4
  }
)
```

Train with relationship weights

The GraphSAGE implementation supports training using relationship weights. Greater relationship weight between nodes signifies that the nodes should have more similar embedding values.

The following Cypher query trains a GraphSAGE model using relationship weights

```
CALL gds.beta.graphSage.train(
  'persons',
  {
    modelName: 'weightedTrainedModel',
    featureProperties: ['age', 'heightAndWeight'],
    relationshipWeightProperty: 'relWeight',
    nodeLabels: ['Person'],
    relationshipTypes: ['KNOWS']
  }
)
```

Train when there are no node properties present in the graph

In the case when you have a graph that does not have node properties we recommend to use existing algorithm in `mutate` mode to create node properties. Good candidates are Centrality algorithms or Community algorithms.

The following example illustrates calling Degree Centrality in `mutate` mode and then using the mutated property as feature of GraphSAGE training. For the purpose of this example we are going to use the `Persons` graph, but we will not load any properties to the in-memory graph.

Create a graph projection without any node properties

```
CALL gds.graph.project(
  'noPropertiesGraph',
  'Person', {
    KNOWS: {
      type: 'KNOWS',
      orientation: 'UNDIRECTED'
    }
})
```

Run DegreeCentrality mutate to create a new property for each node

```
CALL gds.degree.mutate(
  'noPropertiesGraph',
  {
    mutateProperty: 'degree'
  }
) YIELD nodePropertiesWritten
```

Run GraphSAGE train using the property produced by DegreeCentrality as feature property

```
CALL gds.beta.graphSage.train(
  'noPropertiesGraph',
  {
    modelName: 'myModel',
    featureProperties: ['degree']
  }
)
YIELD trainMillis
RETURN trainMillis
```

`gds.degree.mutate` will create a new node property `degree` for each of the nodes in the in-memory graph, which then can be used as `featureProperty` in the `GraphSAGE.train` mode.

Using separate algorithms to produce featureProperties can also be very useful to capture graph topology properties.

Stream

To generate embeddings and stream them back to the client we can use the stream mode. We must first train a model, which we do using the `gds.beta.graphSage.train` procedure.

```
CALL gds.beta.graphSage.train(
  'persons',
  {
    modelName: 'graphSage',
    featureProperties: ['age', 'heightAndWeight'],
    embeddingDimension: 3,
    randomSeed: 19
  }
)
```

Once we have trained a model (named `'graphSage'`) we can use it to generate and stream the embeddings.

```
CALL gds.beta.graphSage.stream(
  'persons',
  {
    modelName: 'graphSage'
  }
)
YIELD nodeId, embedding
```

Table 752. Results

nodeId	embedding
0	[0.528500243954147, 0.46821819122905217, 0.7081378518617193]
1	[0.5285002439545966, 0.4682181912292858, 0.7081378518612291]
2	[0.5285002439541305, 0.4682181912290437, 0.7081378518617372]
3	[0.528500243952747, 0.46821819122832464, 0.7081378518632452]
4	[0.5285002439970667, 0.46821819125135444, 0.7081378518149409]
5	[0.5285002440594959, 0.46821819128379416, 0.7081378517468996]
6	[0.528500243952941, 0.46821819122842556, 0.7081378518630335]

Due to the random initialisation of the weight variables the results may vary slightly between the runs.

Mutate

The model trained as part of the stream example can be reused to write the results to the in-memory graph using the `mutate` mode of the procedure. Below is an example of how to achieve this.

```
CALL gds.beta.graphSage.mutate(
  'persons',
  {
    mutateProperty: 'inMemoryEmbedding',
    modelName: 'graphSage'
  }
) YIELD
  nodeCount,
  nodePropertiesWritten
```

Table 753. Results

nodeCount	nodePropertiesWritten
7	7

Write

The model trained as part of the stream example can be reused to write the results to Neo4j. Below is an example of how to achieve this.

```
CALL gds.beta.graphSage.write(
  'persons',
  {
    writeProperty: 'embedding',
    modelName: 'graphSage'
  }
) YIELD
  nodeCount,
  nodePropertiesWritten
```

Table 754. Results

nodeCount	nodePropertiesWritten
7	7

6.6.3. Node2Vec Beta

> *This section describes the Node2Vec node embedding algorithm in the Neo4j Graph Data Science library.*

Node2Vec is a node embedding algorithm that computes a vector representation of a node based on random walks in the graph. The neighborhood is sampled through random walks. Using a number of random neighborhood samples, the algorithm trains a single hidden layer neural network. The neural network is trained to predict the likelihood that a node will occur in a walk based on the occurrence of another node.

For more information on this algorithm, see:

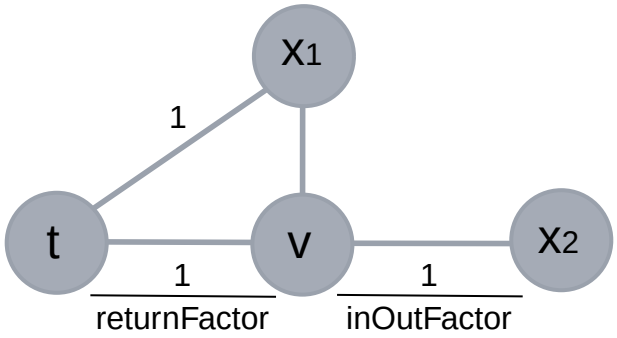
- Grover, Aditya, and Jure Leskovec. "node2vec: Scalable feature learning for networks." Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining. 2016.
- https://snap.stanford.edu/node2vec/

Random Walks

A main concept of the Node2Vec algorithm are the second order random walks. A random walk simulates a traversal of the graph in which the traversed relationships are chosen at random. In a classic random walk, each relationship has the same, possibly weighted, probability of being picked. This probability is not influenced by the previously visited nodes. The concept of second order random walks, however, tries to model the transition probability based on the currently visited node `v`, the node `t` visited before the current

one, and the node `x` which is the target of a candidate relationship. Node2Vec random walks are thus influenced by two parameters: the `returnFactor` and the `inOutFactor`:

- The `returnFactor` is used if `t` equals `x`, i.e., the random walk returns to the previously visited node.
- The `inOutFactor` is used if the distance from `t` to `x` is equal to 2, i.e., the walk traverses further away from the node `t`



The probabilities for traversing a relationship during a random walk can be further influenced by specifying a `relationshipWeightProperty`. A relationship property value greater than 1 will increase the likelihood of a relationship being traversed, a property value between 0 and 1 will decrease that probability.

For every node in the graph Node2Vec generates a series of random walks with the particular node as start node. The number of random walks per node can be influenced by the `walkPerNode` configuration parameters, the walk length is controlled by the `walkLength` parameter.

Syntax

Node2Vec syntax per mode

Run Node2Vec in stream mode on a named graph.

```
CALL gds.beta.node2vec.stream(
  graphName: String,
  configuration: Map
) YIELD
  nodeId: Integer,
  embedding: List of Float
```

Table 755. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 756. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 757. Algorithm specific configuration

Name	Type	Default	Optional	Description
walkLength	Integer	80	yes	The number of steps in a single random walk.
walksPerNode	Integer	10	yes	The number of random walks generated for each node.
inOutFactor	Float	1.0	yes	Tendency of the random walk to stay close to the start node or fan out in the graph. Higher value means stay local.
returnFactor	Float	1.0	yes	Tendency of the random walk to return to the last visited node. A value below 1.0 means a higher tendency.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights to influence the probabilities of the random walks. The weights need to be >= 0. If unspecified, the algorithm runs unweighted.
windowSize	Integer	10	yes	Size of the context window when training the neural network.
negativeSamplingRate	Integer	5	yes	Number of negative samples to produce for each positive sample.

Name	Type	Default	Optional	Description
positiveSamplingFactor	Float	`0.001`	yes	Factor for influencing the distribution for positive samples. A higher value increases the probability that frequent nodes are down-sampled.
negativeSamplingExponent	Float	`0.75`	yes	Exponent applied to the node frequency to obtain the negative sampling distribution. A value of 1.0 samples proportionally to the frequency. A value of 0.0 samples each node equally.
embeddingDimension	Integer	`128`	yes	Size of the computed node embeddings.
iterations	Integer	`1`	yes	Number of training iterations.
initialLearningRate	Float	`0.01`	yes	Learning rate used initially for training the neural network. The learning rate decreases after each training iteration.
minLearningRate	Float	`0.0001`	yes	Lower bound for learning rate as it is decreased during training.
randomSeed	Integer	`random`	yes	Seed value used to generate the random walks, which are used as the training set of the neural network. Note, that the generated embeddings are still nondeterministic.
walkBufferSize	Integer	`1000`	yes	The number of random walks to complete before starting training.

Table 758. Results

Name	Type	Description
`nodeId`	Integer	The Neo4j node ID.
`embedding`	List of Float	The computed node embedding.

Run Node2Vec in mutate mode on a graph stored in the catalog.

```
CALL gds.beta.node2vec.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 759. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 760. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 761. Algorithm specific configuration

Name	Type	Default	Optional	Description
walkLength	Integer	80	yes	The number of steps in a single random walk.
walksPerNode	Integer	10	yes	The number of random walks generated for each node.
inOutFactor	Float	1.0	yes	Tendency of the random walk to stay close to the start node or fan out in the graph. Higher value means stay local.
returnFactor	Float	1.0	yes	Tendency of the random walk to return to the last visited node. A value below 1.0 means a higher tendency.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights to influence the probabilities of the random walks. The weights need to be >= 0. If unspecified, the algorithm runs unweighted.
windowSize	Integer	10	yes	Size of the context window when training the neural network.

Name	Type	Default	Optional	Description
negativeSamplingRate	Integer	5	yes	Number of negative samples to produce for each positive sample.
positiveSamplingFactor	Float	0.001	yes	Factor for influencing the distribution for positive samples. A higher value increases the probability that frequent nodes are down-sampled.
negativeSamplingExponent	Float	0.75	yes	Exponent applied to the node frequency to obtain the negative sampling distribution. A value of 1.0 samples proportionally to the frequency. A value of 0.0 samples each node equally.
embeddingDimension	Integer	128	yes	Size of the computed node embeddings.
iterations	Integer	1	yes	Number of training iterations.
initialLearningRate	Float	0.01	yes	Learning rate used initially for training the neural network. The learning rate decreases after each training iteration.
minLearningRate	Float	0.0001	yes	Lower bound for learning rate as it is decreased during training.
randomSeed	Integer	random	yes	Seed value used to generate the random walks, which are used as the training set of the neural network. Note, that the generated embeddings are still nondeterministic.
walkBufferSize	Integer	1000	yes	The number of random walks to complete before starting training.

Table 762. Results

Name	Type	Description
nodeCount	Integer	The number of nodes processed.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
postProcessingMillis	Integer	Milliseconds for post-processing of the results.
configuration	Map	The configuration used for running the algorithm.

Run Node2Vec in write mode on a graph stored in the catalog.

```
CALL gds.beta.node2vec.write(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 763. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 764. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 765. Algorithm specific configuration

Name	Type	Default	Optional	Description
walkLength	Integer	80	yes	The number of steps in a single random walk.
walksPerNode	Integer	10	yes	The number of random walks generated for each node.
inOutFactor	Float	1.0	yes	Tendency of the random walk to stay close to the start node or fan out in the graph. Higher value means stay local.
returnFactor	Float	1.0	yes	Tendency of the random walk to return to the last visited node. A value below 1.0 means a higher tendency.

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights to influence the probabilities of the random walks. The weights need to be >= 0. If unspecified, the algorithm runs unweighted.
windowSize	Integer	10	yes	Size of the context window when training the neural network.
negativeSamplingRate	Integer	5	yes	Number of negative samples to produce for each positive sample.
positiveSamplingFactor	Float	0.001	yes	Factor for influencing the distribution for positive samples. A higher value increases the probability that frequent nodes are down-sampled.
negativeSamplingExponent	Float	0.75	yes	Exponent applied to the node frequency to obtain the negative sampling distribution. A value of 1.0 samples proportionally to the frequency. A value of 0.0 samples each node equally.
embeddingDimension	Integer	128	yes	Size of the computed node embeddings.
iterations	Integer	1	yes	Number of training iterations.
initialLearningRate	Float	0.01	yes	Learning rate used initially for training the neural network. The learning rate decreases after each training iteration.
minLearningRate	Float	0.0001	yes	Lower bound for learning rate as it is decreased during training.
randomSeed	Integer	random	yes	Seed value used to generate the random walks, which are used as the training set of the neural network. Note, that the generated embeddings are still nondeterministic.
walkBufferSize	Integer	1000	yes	The number of random walks to complete before starting training.

Table 766. Results

Name	Type	Description
nodeCount	Integer	The number of nodes processed.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

Consider the graph created by the following Cypher statement:

```
CREATE (alice:Person {name: 'Alice'})
CREATE (bob:Person {name: 'Bob'})
CREATE (carol:Person {name: 'Carol'})
CREATE (dave:Person {name: 'Dave'})
CREATE (eve:Person {name: 'Eve'})
CREATE (guitar:Instrument {name: 'Guitar'})
CREATE (synth:Instrument {name: 'Synthesizer'})
CREATE (bongos:Instrument {name: 'Bongos'})
CREATE (trumpet:Instrument {name: 'Trumpet'})

CREATE (alice)-[:LIKES]->(guitar)
CREATE (alice)-[:LIKES]->(synth)
CREATE (alice)-[:LIKES]->(bongos)
CREATE (bob)-[:LIKES]->(guitar)
CREATE (bob)-[:LIKES]->(synth)
CREATE (carol)-[:LIKES]->(bongos)
CREATE (dave)-[:LIKES]->(guitar)
CREATE (dave)-[:LIKES]->(synth)
CREATE (dave)-[:LIKES]->(bongos);
```

```
CALL gds.graph.project('myGraph', ['Person', 'Instrument'], 'LIKES');
```

Run the Node2Vec algorithm on `myGraph`

```
CALL gds.beta.node2vec.stream('myGraph', {embeddingDimension: 2})
YIELD nodeId, embedding
RETURN nodeId, embedding
```

Table 767. Results

nodeId	embedding
0	[-0.14295829832553864, 0.08884537220001221]
1	[0.016700705513358116, 0.2253911793231964]
2	[-0.06589698046445847, 0.042405471205711365]
3	[0.05862073227763176, 0.1193704605102539]
4	[0.10888434946537018, -0.18204474449157715]
5	[0.16728264093399048, 0.14098615944385529]
6	[-0.007779224775731564, 0.02114257402718067]
7	[-0.213893860578537, 0.06195802614092827]
8	[0.2479933649301529, -0.137322798371315]

6.7. Topological link prediction

This chapter provides explanations and examples for each of the link prediction algorithms in the Neo4j Graph Data Science library.

Link prediction algorithms help determine the closeness of a pair of nodes using the topology of the graph. The computed scores can then be used to predict new relationships between them.

The following algorithms use only the topology of the graph to make predictions about relationships between nodes. To make predictions also utilizing node properties one can use the machine learning based method Link prediction pipelines.

The Neo4j GDS library includes the following link prediction algorithms, grouped by quality tier:

- Alpha
  - Adamic Adar
  - Common Neighbors
  - Preferential Attachment
  - Resource Allocation
  - Same Community
  - Total Neighbors

6.7.1. Adamic Adar Alpha

This section describes the Adamic Adar algorithm in the Neo4j Graph Data Science library.

Adamic Adar is a measure used to compute the closeness of nodes based on their shared neighbors.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

The Adamic Adar algorithm was introduced in 2003 by Lada Adamic and Eytan Adar to predict links in a social network. It is computed using the following formula:

$$A(x,y) = \sum_{u \in N(x) \cap N(y)} \frac{1}{\log |N(u)|}$$

where `N(u)` is the set of nodes adjacent to `u`.

A value of 0 indicates that two nodes are not close, while higher values indicate nodes are closer.

The library contains a function to calculate closeness between two nodes.

Syntax

The following will run the algorithm and return the result:

```
RETURN gds.alpha.linkprediction.adamicAdar(node1:Node, node2:Node, {
    relationshipQuery:String,
    direction:String
})
```

Table 768. Parameters

Name	Type	Default	Optional	Description
node1	Node	null	no	A node
node2	Node	null	no	Another node
relationshipQuery	String	null	yes	The relationship type used to compute similarity between node1 and node2
direction	String	BOTH	yes	The relationship direction used to compute similarity between node1 and node2. Possible values are OUTGOING, INCOMING and BOTH.

Adamic Adar algorithm sample

The following will create a sample graph:

```
CREATE
 (zhen:Person {name: 'Zhen'}),
 (praveena:Person {name: 'Praveena'}),
 (michael:Person {name: 'Michael'}),
 (arya:Person {name: 'Arya'}),
 (karin:Person {name: 'Karin'}),

 (zhen)-[:FRIENDS]->(arya),
 (zhen)-[:FRIENDS]->(praveena),
 (praveena)-[:WORKS_WITH]->(karin),
 (praveena)-[:FRIENDS]->(michael),
 (michael)-[:WORKS_WITH]->(karin),
 (arya)-[:FRIENDS]->(karin)
```

The following will return the Adamic Adar score for Michael and Karin:

```
 MATCH (p1:Person {name: 'Michael'})
 MATCH (p2:Person {name: 'Karin'})
 RETURN gds.alpha.linkprediction.adamicAdar(p1, p2) AS score
```

Table 769. Results

score
0.9102392266268373

We can also compute the score of a pair of nodes based on a specific relationship type.

The following will return the Adamic Adar score for Michael and Karin based only on the FRIENDS relationships:

```
 MATCH (p1:Person {name: 'Michael'})
 MATCH (p2:Person {name: 'Karin'})
 RETURN gds.alpha.linkprediction.adamicAdar(p1, p2, {relationshipQuery: 'FRIENDS'}) AS score
```

Table 770. Results

score
0.0

6.7.2. Common Neighbors Alpha

> *This section describes the Common Neighbors algorithm in the Neo4j Graph Data Science library.*

Common neighbors captures the idea that two strangers who have a friend in common are more likely to be introduced than those who don't have any friends in common.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

It is computed using the following formula:

$$CN(x, y) = |N(x) \cap N(y)|$$

where `N(x)` is the set of nodes adjacent to node `x`, and `N(y)` is the set of nodes adjacent to node `y`.

A value of 0 indicates that two nodes are not close, while higher values indicate nodes are closer.

The library contains a function to calculate closeness between two nodes.

Syntax

The following will run the algorithm and return the result:

```
RETURN gds.alpha.linkprediction.commonNeighbors(node1:Node, node2:Node, {
    relationshipQuery:String,
    direction:String
})
```

Table 771. Parameters

Name	Type	Default	Optional	Description
`node1`	Node	null	no	A node
`node2`	Node	null	no	Another node
`relationshipQuery`	String	null	yes	The relationship type used to compute similarity between `node1` and `node2`.
`direction`	String	BOTH	yes	The relationship direction used to compute similarity between `node1` and `node2`. Possible values are `OUTGOING`, `INCOMING` and `BOTH`.

Common Neighbors algorithm sample

The following will project a sample graph:

```
CREATE
 (zhen:Person {name: 'Zhen'}),
 (praveena:Person {name: 'Praveena'}),
 (michael:Person {name: 'Michael'}),
 (arya:Person {name: 'Arya'}),
 (karin:Person {name: 'Karin'}),

 (zhen)-[:FRIENDS]->(arya),
 (zhen)-[:FRIENDS]->(praveena),
 (praveena)-[:WORKS_WITH]->(karin),
 (praveena)-[:FRIENDS]->(michael),
 (michael)-[:WORKS_WITH]->(karin),
 (arya)-[:FRIENDS]->(karin)
```

The following will return the number of common neighbors for Michael and Karin:

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Karin'})
RETURN gds.alpha.linkprediction.commonNeighbors(p1, p2) AS score
```

Table 772. Results

score
1.0

We can also compute the score of a pair of nodes based on a specific relationship type.

The following will return the number of common neighbors for Michael and Karin based only on the `FRIENDS` *relationships:*

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Karin'})
RETURN gds.alpha.linkprediction.commonNeighbors(p1, p2, {relationshipQuery: "FRIENDS"}) AS score
```

Table 773. Results

score
0.0

6.7.3. Preferential Attachment Alpha

> *This section describes the Preferential Attachment algorithm in the Neo4j Graph Data Science library.*

Preferential Attachment is a measure used to compute the closeness of nodes, based on their shared neighbors.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

Preferential attachment means that the more connected a node is, the more likely it is to receive new links. This algorithm was popularised by Albert-László Barabási and Réka Albert through their work on scale-free networks. It is computed using the following formula:

$$PA(x, y) = |N(x)| * |N(y)|$$

where `N(u)` is the set of nodes adjacent to `u`.

A value of 0 indicates that two nodes are not close, while higher values indicate that nodes are closer.

The library contains a function to calculate closeness between two nodes.

Syntax

The following will run the algorithm and return the result:

```
RETURN gds.alpha.linkprediction.preferentialAttachment(node1:Node, node2:Node, {
    relationshipQuery:String,
    direction:String
})
```

Table 774. Parameters

Name	Type	Default	Optional	Description
`node1`	Node	null	no	A node
`node2`	Node	null	no	Another node
`relationshipQuery`	String	null	yes	The relationship type used to compute similarity between `node1` and `node2`
`direction`	String	BOTH	yes	The relationship direction used to compute similarity between `node1` and `node2`. Possible values are `OUTGOING`, `INCOMING` and `BOTH`.

Preferential Attachment algorithm sample

The following will create a sample graph:

```
CREATE
 (zhen:Person {name: 'Zhen'}),
 (praveena:Person {name: 'Praveena'}),
 (michael:Person {name: 'Michael'}),
 (arya:Person {name: 'Arya'}),
 (karin:Person {name: 'Karin'}),

 (zhen)-[:FRIENDS]->(arya),
 (zhen)-[:FRIENDS]->(praveena),
 (praveena)-[:WORKS_WITH]->(karin),
 (praveena)-[:FRIENDS]->(michael),
 (michael)-[:WORKS_WITH]->(karin),
 (arya)-[:FRIENDS]->(karin)
```

The following will return the Preferential Attachment score for Michael and Karin:

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Karin'})
RETURN gds.alpha.linkprediction.preferentialAttachment(p1, p2) AS score
```

Table 775. Results

score
6.0

We can also compute the score of a pair of nodes based on a specific relationship type.

The following will return the Preferential Attachment score for Michael and Karin based only on the `FRIENDS` *relationship:*

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Karin'})
RETURN gds.alpha.linkprediction.preferentialAttachment(p1, p2, {relationshipQuery: "FRIENDS"}) AS score
```

Table 776. Results

score
1.0

6.7.4. Resource Allocation Alpha

> *This section describes the Resource Allocation algorithm in the Neo4j Graph Data Science library.*

Resource Allocation is a measure used to compute the closeness of nodes based on their shared neighbors.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

The Resource Allocation algorithm was introduced in 2009 by Tao Zhou, Linyuan Lü, and Yi-Cheng Zhang as part of a study to predict links in various networks. It is computed using the following formula:

$$RA(x,y) = \sum_{u \in N(x) \cap N(y)} \frac{1}{|N(u)|}$$

where `N(u)` is the set of nodes adjacent to `u`.

A value of 0 indicates that two nodes are not close, while higher values indicate nodes are closer.

The library contains a function to calculate closeness between two nodes.

Syntax

The following will run the algorithm and return the result:

```
RETURN gds.alpha.linkprediction.resourceAllocation(node1:Node, node2:Node, {
    relationshipQuery:String,
    direction:String
})
```

Table 777. Parameters

Name	Type	Default	Optional	Description
node1	Node	null	no	A node
node2	Node	null	no	Another node
relationshipQuery	String	null	yes	The relationship type to use to compute similarity between node1 and node2
direction	String	BOTH	yes	The relationship direction used to compute similarity between node1 and node2. Possible values are OUTGOING, INCOMING and BOTH.

Resource Allocation algorithm sample

The following will create a sample graph:

```
CREATE
 (zhen:Person {name: 'Zhen'}),
 (praveena:Person {name: 'Praveena'}),
 (michael:Person {name: 'Michael'}),
 (arya:Person {name: 'Arya'}),
 (karin:Person {name: 'Karin'}),

 (zhen)-[:FRIENDS]->(arya),
 (zhen)-[:FRIENDS]->(praveena),
 (praveena)-[:WORKS_WITH]->(karin),
 (praveena)-[:FRIENDS]->(michael),
 (michael)-[:WORKS_WITH]->(karin),
 (arya)-[:FRIENDS]->(karin)
```

The following will return the Resource Allocation score for Michael and Karin:

```
 MATCH (p1:Person {name: 'Michael'})
 MATCH (p2:Person {name: 'Karin'})
 RETURN gds.alpha.linkprediction.resourceAllocation(p1, p2) AS score
```

Table 778. Results

score
0.3333333333333333

We can also compute the score of a pair of nodes based on a specific relationship type.

The following will return the Resource Allocation score for Michael and Karin based only on the FRIENDS relationships:

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Karin'})
RETURN gds.alpha.linkprediction.resourceAllocation(p1, p2, {relationshipQuery: "FRIENDS"}) AS score
```

Table 779. Results

score
0.0

6.7.5. Same Community Alpha

> *This section describes the Same Community algorithm in the Neo4j Graph Data Science library.*

Same Community is a way of determining whether two nodes belong to the same community. These communities could be computed by using one of the Community detection.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

If two nodes belong to the same community, there is a greater likelihood that there will be a relationship between them in future, if there isn't already.

A value of 0 indicates that two nodes are not in the same community. A value of 1 indicates that two nodes are in the same community.

The library contains a function to calculate closeness between two nodes.

Syntax

The following will run the algorithm and return the result:

```
RETURN gds.alpha.linkprediction.sameCommunity(node1:Node, node2:Node, communityProperty:String)
```

Table 780. Parameters

Name	Type	Default	Optional	Description
node1	Node	null	no	A node
node2	Node	null	no	Another node
communityProperty	String	'community'	yes	The property that contains the community to which nodes belong

Same Community algorithm sample

The following will create a sample graph:

```
CREATE (zhen:Person {name: 'Zhen', community: 1}),
       (praveena:Person {name: 'Praveena', community: 2}),
       (michael:Person {name: 'Michael', community: 1}),
       (arya:Person {name: 'Arya', partition: 5}),
       (karin:Person {name: 'Karin', partition: 5}),
       (jennifer:Person {name: 'Jennifer'})
```

The following will indicate that Michael and Zhen belong to the same community:

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Zhen'})
RETURN gds.alpha.linkprediction.sameCommunity(p1, p2) AS score
```

Table 781. Results

score
1.0

The following will indicate that Michael and Praveena do not belong to the same community:

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Praveena'})
RETURN gds.alpha.linkprediction.sameCommunity(p1, p2) AS score
```

Table 782. Results

score
0.0

If one of the nodes doesn't have a community, this means it doesn't belong to the same community as any other node.

The following will indicate that Michael and Jennifer do not belong to the same community:

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Jennifer'})
RETURN gds.alpha.linkprediction.sameCommunity(p1, p2) AS score
```

Table 783. Results

score
0.0

By default, the community is read from the `community` property, but it is possible to explicitly state which property to read from.

The following will indicate that Arya and Karin belong to the same community, based on the `partition` *property:*

```
MATCH (p1:Person {name: 'Arya'})
MATCH (p2:Person {name: 'Karin'})
RETURN gds.alpha.linkprediction.sameCommunity(p1, p2, 'partition') AS score
```

Table 784. Results

score
1.0

6.7.6. Total Neighbors Alpha

> *This section describes the Total Neighbors algorithm in the Neo4j Graph Data Science library.*

Total Neighbors computes the closeness of nodes, based on the number of unique neighbors that they have. It is based on the idea that the more connected a node is, the more likely it is to receive new links.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

History and explanation

Total Neighbors is computed using the following formula:

$$TN(x, y) = |N(x) \cup N(y)|$$

where `N(x)` is the set of nodes adjacent to `x`, and `N(y)` is the set of nodes adjacent to `y`.

A value of 0 indicates that two nodes are not close, while higher values indicate nodes are closer.

The library contains a function to calculate the closeness between two nodes.

Syntax

The following will run the algorithm and return the result:

```
RETURN gds.alpha.linkprediction.totalNeighbors(node1:Node, node2:Node, {
    relationshipQuery: null,
    direction: "BOTH"
})
```

Table 785. Parameters

Name	Type	Default	Optional	Description
node1	Node	null	no	A node
node2	Node	null	no	Another node

Name	Type	Default	Optional	Description
relationshipQuery	String	null	yes	The relationship type used to compute similarity between node1 and node2
direction	String	BOTH	yes	The relationship direction used to compute similarity between node1 and node2. Possible values are OUTGOING, INCOMING and BOTH.

Total Neighbors algorithm sample

The following will create a sample graph:

```
CREATE (zhen:Person {name: 'Zhen'}),
       (praveena:Person {name: 'Praveena'}),
       (michael:Person {name: 'Michael'}),
       (arya:Person {name: 'Arya'}),
       (karin:Person {name: 'Karin'}),

       (zhen)-[:FRIENDS]->(arya),
       (zhen)-[:FRIENDS]->(praveena),
       (praveena)-[:WORKS_WITH]->(karin),
       (praveena)-[:FRIENDS]->(michael),
       (michael)-[:WORKS_WITH]->(karin),
       (arya)-[:FRIENDS]->(karin)
```

The following will return the Total Neighbors score for Michael and Karin:

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Karin'})
RETURN gds.alpha.linkprediction.totalNeighbors(p1, p2) AS score
```

Table 786. Results

score
4.0

We can also compute the score of a pair of nodes, based on a specific relationship type.

The following will return the Total Neighbors score for Michael and Karin based only on the FRIENDS relationship:

```
MATCH (p1:Person {name: 'Michael'})
MATCH (p2:Person {name: 'Karin'})
RETURN gds.alpha.linkprediction.totalNeighbors(p1, p2, {relationshipQuery: "FRIENDS"}) AS score
```

Table 787. Results

score
2.0

6.8. Auxiliary procedures

This chapter provides explanations and examples for auxiliary procedures in the Neo4j Graph Data Science library.

Auxiliary procedures are extra tools that can be useful in your workflow.
The Neo4j GDS library includes the following auxiliary procedures, grouped by quality tier:

- Beta
  - Graph Generation
- Alpha
  - Collapse Path
  - Scale Properties
  - One Hot Encoding
  - Split Relationships

6.8.1. Graph Generation Beta

This section describes how random graphs can be generated in the Neo4j Graph Data Science library.

In certain use cases it is useful to generate random graphs, for example, for testing or benchmarking purposes. For that reason the Neo4j Graph Algorithm library comes with a set of built-in graph generators. The generator stores the resulting graph in the graph catalog. That graph can be used as input for any algorithm in the library.

This algorithm is in the beta tier. For more information on algorithm tiers, see Graph Algorithms.

It is currently not possible to persist these graphs in Neo4j. Running an algorithm in write mode on a generated graph will lead to unexpected results.

The graph generation is parameterized by three dimensions:

- node count - the number of nodes in the generated graph
- average degree - describes the average out-degree of the generated nodes
- relationship distribution function - the probability distribution method used to connect generated nodes

Syntax

The following describes the API for running the algorithm

```
CALL gds.beta.graph.generate(graphName: String, nodeCount: Integer, averageDegree: Integer, {
  relationshipDistribution: String,
  relationshipProperty: Map
})
YIELD name, nodes, relationships, generateMillis, relationshipSeed, averageDegree,
relationshipDistribution, relationshipProperty
```

Table 788. Parameters

Name	Type	Default	Optional	Description
graphName	String	null	no	The name under which the generated graph is stored.
nodeCount	Integer	null	no	The number of generated nodes.
averageDegree	Integer	null	no	The average out-degree of generated nodes.
configuration	Map	{}	yes	Additional configuration, see below.

Table 789. Configuration

Name	Type	Default	Optional	Description
relationshipDistribution	String	UNIFORM	yes	The probability distribution method used to connect generated nodes. For more information see Relationship Distribution.
relationshipSeed	Integer	null	yes	The seed used for generating relationships.
relationshipProperty	Map	{}	yes	Describes the method used to generate a relationship property. By default no relationship property is generated. For more information see Relationship Property.
aggregation	String	NONE	yes	The relationship aggregation method cf. Relationship Projection.
orientation	String	NATURAL	yes	The method of orienting edges. Allowed values are NATURAL, REVERSE and UNDIRECTED.
allowSelfLoops	Boolean	false	yes	Whether to allow relationships with identical source and target node.

Table 790. Results

Name	Type	Description
name	String	The name under which the stored graph was stored.
nodes	Integer	The number of nodes in the graph.
relationships	Integer	The number of relationships in the graph.
generateMillis	Integer	Milliseconds for generating the graph.
relationshipSeed	Integer	The seed used for generating relationships.
averageDegree	Float	The average out degree of the generated nodes.
relationshipDistribution	String	The probability distribution method used to connect generated nodes.
relationshipProperty	String	The configuration of the generated relationship property.

Relationship Distribution

The relationshipDistribution parameter controls the statistical method used for the generation of new relationships. Currently there are three supported methods:

- UNIFORM - Distributes the outgoing relationships evenly, i.e., every node has exactly the same out

degree (equal to the average degree). The target nodes are selected randomly.

- `RANDOM` - Distributes the outgoing relationships using a normal distribution with an average of `averageDegree` and a standard deviation of `2 * averageDegree`. The target nodes are selected randomly.
- `POWER_LAW` - Distributes the incoming relationships using a power law distribution. The out degree is based on a normal distribution.

Relationship Seed

The `relationshipSeed` parameter allows, to generate graphs with the same relationships, if they have no property. Currently the `relationshipProperty` is not seeded, therefore the generated graphs can differ in their property values. Hence generated graphs based on the same `relationshipSeed` are not identical.

Relationship Property

The graph generator is capable of generating a relationship property. This can be controlled using the `relationshipProperty` parameter which accepts the following parameters:

Table 791. Configuration

Name	Type	Default	Optional	Description
`name`	String	null	no	The name under which the property values are stored.
`type`	String	null	no	The method used to generate property values.
`min`	Float	0.0	yes	Minimal value of the generated property (only supported by `RANDOM`).
`max`	Float	1.0	yes	Maximum value of the generated property (only supported by `RANDOM`).
`value`	Float	null	yes	Fixed value assigned to every relationship (only supported by `FIXED`).

Currently, there are two supported methods to generate relationship properties:

- `FIXED` - Assigns a fixed value to every relationship. The `value` parameter must be set.
- `RANDOM` - Assigns a random value between the lower (`min`) and upper (`max`) bound.

6.8.2. Collapse Path Alpha

This section describes the Collapse Path algorithm in the Neo4j Graph Data Science library.

Introduction

The Collapse Path algorithm is a traversal algorithm capable of creating relationships between the start and end nodes of a traversal. In other words, the path between the start node and the end node is collapsed into a single relationship (a direct path). The algorithm is intended to support the creation of monopartite graphs required by many graph algorithms.

The main input for the algorithm is a list of relationship types. Starting from every node in the specified graph, these relationship types are traversed one after the other using the order specified in the configuration. Only nodes reached after traversing every relationship type specified are used as end nodes. Exactly one directed relationship is created for every pair of nodes for which at least one path from start to end node exists.

Syntax

Collapse *Path syntax per mode*

Run Collapse Path in mutate mode on a named graph.

```
CALL gds.alpha.collapsePath.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  relationshipsWritten: Integer,
  configuration: Map
```

Table 792. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 793. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 794. Algorithm specific configuration

Name	Type	Default	Optional	Description
relationshipTypes	List of String	n/a	no	Ordered list of relationship types used for the traversal. The same relationship type can be added multiple times, in order to traverse them as indicated.
mutateRelationshipType	String	n/a	no	Relationship type of the newly created relationships.
allowSelfLoops	Boolean	false	yes	Indicates whether it is possible to create self referencing relationships, i.e. relationships where the start and end node are identical.

Table 795. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
relationshipsWritten	Integer	The number of relationships created by the algorithm.

Name	Type	Description
configuration	Map	The configuration used for running the algorithm.

Examples

Consider the graph created by the following Cypher statement:

```
CREATE
  (Dan:Person),
  (Annie:Person),
  (Matt:Person),
  (Jeff:Person),

  (Guitar:Instrument),
  (Flute:Instrument),

  (Dan)-[:PLAYS]->(Guitar),
  (Annie)-[:PLAYS]->(Guitar),

  (Matt)-[:PLAYS]->(Flute),
  (Jeff)-[:PLAYS]->(Flute)
```

In this example we want to create a relationship, called `PLAYS_SAME_INSTRUMENT`, between `Person` nodes that play the same instrument. To achieve that we have to traverse a path specified by the following Cypher pattern:

```
(p1:Person)-[:PLAYS]->(:Instrument)-[:PLAYED_BY]->(p2:Person)
```

In our source graph only the `PLAYS` relationship type exists. The `PLAYED_BY` relationship type can be created by loading the `PLAYS` relationship type in `REVERSE` direction. The following query will project such a graph:

```
CALL gds.graph.project(
  'persons',
  ['Person', 'Instrument'],
  {
    PLAYS: {
      type: 'PLAYS',
      orientation: 'NATURAL'
    },
    PLAYED_BY: {
      type: 'PLAYS',
      orientation: 'REVERSE'
    }
})
```

Now we can run the algorithm by specifying the traversal `PLAYS, PLAYED_BY` in the `relationshipTypes` option.

```
CALL gds.alpha.collapsePath.mutate(
  'persons',
  {
    relationshipTypes: ['PLAYS', 'PLAYED_BY'],
    allowSelfLoops: false,
    mutateRelationshipType: 'PLAYS_SAME_INSTRUMENT'
  }
) YIELD relationshipsWritten
```

Table 796. Results

relationshipsWritten
4

The mutated graph will look like the following graph when filtered by the `PLAYS_SAME_INSTRUMENT` *relationship*

```
CREATE
  (Dan:Person),
  (Annie:Person),
  (Matt:Person),
  (Jeff:Person),

  (Guitar:Instrument),
  (Flute:Instrument),

  (Dan)-[:PLAYS_SAME_INSTRUMENT]->(Annie),
  (Annie)-[:PLAYS_SAME_INSTRUMENT]->(Dan),

  (Matt)-[:PLAYS_SAME_INSTRUMENT]->(Jeff),
  (Jeff)-[:PLAYS_SAME_INSTRUMENT]->(Matt)
```

6.8.3. Scale Properties Alpha

This section describes the Scale Properties algorithm in the Neo4j Graph Data Science library.

Introduction

The Scale Properties algorithm is a utility algorithm that is used to pre-process node properties for model training or post-process algorithm results such as PageRank scores. It scales the node properties based on the specified scaler. Multiple properties can be scaled at once and are returned in a list property.

The input properties must be numbers or lists of numbers. The lists must all have the same size. The output property will always be a list. The size of the output list is equal to the sum of length of the input properties. That is, if the input properties are two scalar numeric properties and one list property of length three, the output list will have a total length of five.

There are a number of supported scalers for the Scale Properties algorithm. These can be configured using the `scaler` configuration parameter.

List properties are scaled index-by-index. See the list example for more details.

In the following equations, p denotes the vector containing all property values for a single property across all nodes in the graph.

Min-max scaler

Scales all property values into the range `[0, 1]` where the minimum value(s) get the scaled value `0` and the maximum value(s) get the scaled value `1`, according to this formula:

$$p_{scaled} = \frac{p - min(p)}{max(p) - min(p)}$$

Max scaler

Scales all property values into the range `[-1, 1]` where the absolute maximum value(s) get the scaled value `1`, according to this formula:

$$p_{scaled} = \frac{p}{|max(p)|}$$

Mean scaler

Scales all property values into the range `[-1, 1]` where the average value(s) get the scaled value `0`.

$$p_{scaled} = \frac{p - avg(p)}{max(p) - min(p)}$$

Log scaler

Transforms all property values using the natural logarithm.

$$p_{scaled} = ln(p)$$

Standard Score

Scales all property values using the Standard Score (Wikipedia).

$$p_{scaled} = \frac{p - avg(p)}{std(p)}$$

L1 Norm

Scales all property values into the range `[0.0, 1.0]`.

$$p_{sc\ \ e} = \frac{p}{|p|_1}$$

L2 Norm

Scales all property values using the L2 Norm (Wikipedia).

$$p_{scaled} = \frac{p}{||p||}$$

Syntax

This section covers the syntax used to execute the Scale Properties algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Scale Properties syntax per mode

Run Scale Properties in stream mode on a named graph.

```
CALL gds.alpha.scaleProperties.stream(
  graphName: String,
  configuration: Map
) YIELD
  nodeId: Integer,
  scaledProperty: List of Float
```

Table 797. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 798. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 799. Algorithm specific configuration

Name	Type	Default	Optional	Description
nodeProperties	List of String	n/a	no	The names of the node properties that are to be scaled. All property names must exist in the projected graph.
scaler	String	n/a	no	The name of the scaler applied for the properties. Supported values are `MinMax`, `Max`, `Mean`, `Log`, `L1Norm`, `L2Norm` and `StdScore`.

Table 800. Results

Name	Type	Description
nodeId	Integer	Node ID.
scaledProperty	List of Float	Scaled values for each input node property.

Run Scale Properties in mutate mode on a named graph.

```
CALL gds.alpha.scaleProperties.mutate(
  graphName: String,
  configuration: Map
) YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  postProcessingMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 801. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 802. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 803. Algorithm specific configuration

Name	Type	Default	Optional	Description
nodeProperties	List of String	n/a	no	The names of the node properties that are to be scaled. All property names must exist in the projected graph.
scaler	String	n/a	no	The name of the scaler applied for the properties. Supported values are `MinMax`, `Max`, `Mean`, `Log`, `L1Norm`, `L2Norm` and `StdScore`.

Table 804. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
postProcessingMillis	Integer	Unused.

Name	Type	Description
nodePropertiesWritten	Integer	Number of node properties written.
configuration	Map	Configuration used for running the algorithm.

Examples

In this section we will show examples of running the Scale Properties algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small hotel graph of a handful nodes connected in a particular pattern. The example graph looks like this:

The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (:Hotel {avgReview: 4.2, buildYear: 1978, storyCapacity: [32, 32, 0], name: 'East'}),
  (:Hotel {avgReview: 8.1, buildYear: 1958, storyCapacity: [18, 20, 0], name: 'Plaza'}),
  (:Hotel {avgReview: 19.0, buildYear: 1999, storyCapacity: [100, 100, 70], name: 'Central'}),
  (:Hotel {avgReview: -4.12, buildYear: 2005, storyCapacity: [250, 250, 250], name: 'West'}),
  (:Hotel {avgReview: 0.01, buildYear: 2020, storyCapacity: [1250, 1250, 900], name: 'Polar'}),
  (:Hotel {avgReview: 3.3, buildYear: 1981, storyCapacity: [240, 240, 0], name: 'Beach'}),
  (:Hotel {avgReview: 6.7, buildYear: 1984, storyCapacity: [80, 0, 0], name: 'Mountain'}),
  (:Hotel {avgReview: -1.2, buildYear: 2010, storyCapacity: [55, 20, 0], name: 'Forest'})
```

With the graph in Neo4j we can now project it into the graph catalog to prepare it for algorithm execution. We do this using a native projection targeting the `Hotel` nodes, including their properties. Note that no relationships are necessary to scale the node properties. Thus we use a star projection ('*') for relationships.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  'Hotel',
  '*',
  { nodeProperties: ['avgReview', 'buildYear', 'storyCapacity'] }
)
```

In the following examples we will demonstrate how to scale the node properties of this graph.

Stream

In the `stream` execution mode, the algorithm returns the scaled properties for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm in `stream` mode:

```
CALL gds.alpha.scaleProperties.stream('myGraph', {
  nodeProperties: ['buildYear', 'avgReview'],
  scaler: 'MinMax'
}) YIELD nodeId, scaledProperty
RETURN gds.util.asNode(nodeId).name AS name, scaledProperty
  ORDER BY name ASC
```

Table 805. Results

name	scaledProperty
"Beach"	[0.3709677419354839, 0.3209342560553633]
"Central"	[0.6612903225806451, 1.0]
"East"	[0.3225806451612903, 0.35986159169550175]
"Forest"	[0.8387096774193549, 0.12629757785467127]
"Mountain"	[0.41935483870967744, 0.4679930795847751]
"Plaza"	[0.0, 0.5285467128027681]
"Polar"	[1.0, 0.17863321799307957]
"West"	[0.7580645161290323, 0.0]

In the results we can observe that the first element in the resulting `scaledProperty` we get the min-max-scaled values for `buildYear`, where the `Plaza` hotel has the minimum value and is scaled to zero, while the `Polar` hotel has the maximum value and is scaled to one. This can be verified with the example graph. The second value in the `scaledProperty` result are the scaled values of the `avgReview` property.

Mutate

The `mutate` execution mode enables updating the named graph with a new node property containing the scaled properties for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row containing metrics from the computation. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

In this example we will scale the two hotel properties of `buildYear` and `avgReview` using the Mean scaler. The output is a list property which we will call `hotelFeatures`, imagining that we will use this as input for a machine learning model later on.

The following will run the algorithm in `mutate` mode:

```
CALL gds.alpha.scaleProperties.mutate('myGraph', {
  nodeProperties: ['buildYear', 'avgReview'],
  scaler: 'Mean',
  mutateProperty: 'hotelFeatures'
}) YIELD nodePropertiesWritten
```

Table 806. Results

nodePropertiesWritten
8

The result shows that there are now eight new node properties in the in-memory graph. These contain the scaled values from the input properties, where the scaled `buildYear` values are in the first list position and scaled `avgReview` values are in the second position. To find out how to inspect the new schema of the in-memory graph, see Listing graphs in the catalog.

List properties

The `storyCapacity` property models the amount of rooms on each story of the hotel. The property is normalized so that hotels with fewer stories have a zero value. This is because the Scale Properties algorithm requires that all values for the same property have the same length. In this example we will show how to scale the values in these lists using the Scale Properties algorithm. We imagine using the output as feature vector to input in a machine learning algorithm. Additionally, we will include the `avgReview` property in our feature vector.

The following will run the algorithm in `mutate` mode:

```
CALL gds.alpha.scaleProperties.stream('myGraph', {
  nodeProperties: ['avgReview', 'storyCapacity'],
  scaler: 'StdScore'
}) YIELD nodeId, scaledProperty
RETURN gds.util.asNode(nodeId).name AS name, scaledProperty AS features
  ORDER BY name ASC
```

Table 807. Results

name	features
"Beach"	[-0.17956547594003253, -0.03401933556831381, 0.00254261210704973, -0.5187592498702616]
"Central"	[2.172199255871029, -0.3968922482969945, -0.3534230828799124, -0.2806402499298136]
"East"	[-0.0447509371737933, -0.5731448059080679, -0.526320706159294, -0.5187592498702616]
"Forest"	[-0.8536381697712284, -0.513529970245499, -0.5568320514438908, -0.5187592498702616]
"Mountain"	[0.32973389273242665, -0.4487312358296632, -0.6076842935848854, -0.5187592498702616]
"Plaza"	[0.5394453974799097, -0.609432097180936, -0.5568320514438908, -0.5187592498702616]
"Polar"	[-0.672387512096618, 2.583849534831454, 2.5705808402272767, 2.542770749364069]
"West"	[-1.2910364511016934, -0.00809984180197948, 0.027968733177547028, 0.3316657499170525]

The resulting feature vector contains the standard-score scaled value for the `avgReview` property in the first list position. We can see that some values are negative and that the maximum value sticks out for the `Central` hotel.

The other three list positions are the scaled values for the `storyCapacity` list property. Note that each list item is scaled only with respect to the corresponding item in the other lists. Thus, the `Polar` hotel has the greatest scaled value in all list positions.

6.8.4. One Hot Encoding Alpha

> *This section describes the One Hot Encoding function in the Neo4j Graph Data Science library.*

The One Hot Encoding function is used to convert categorical data into a numerical format that can be used by Machine Learning libraries.

This algorithm is in the alpha tier. For more information on algorithm tiers, see Graph Algorithms.

One Hot Encoding sample

One hot encoding will return a list equal to the length of the `available values`. In the list, `selected values` are represented by `1`, and `unselected values` are represented by `0`.

The following will run the algorithm on hardcoded lists:

```
RETURN gds.alpha.ml.oneHotEncoding(['Chinese', 'Indian', 'Italian'], ['Italian']) AS embedding
```

Table 808. Results

embedding
[0,0,1]

The following will create a sample graph:

```
CREATE (french:Cuisine {name:'French'}),
       (italian:Cuisine {name:'Italian'}),
       (indian:Cuisine {name:'Indian'}),

       (zhen:Person {name: "Zhen"}),
       (praveena:Person {name: "Praveena"}),
       (michael:Person {name: "Michael"}),
       (arya:Person {name: "Arya"}),

       (praveena)-[:LIKES]->(indian),
       (zhen)-[:LIKES]->(french),
       (michael)-[:LIKES]->(french),
       (michael)-[:LIKES]->(italian)
```

The following will return a one hot encoding for each user and the types of cuisine that they like:

```
MATCH (cuisine:Cuisine)
WITH cuisine
  ORDER BY cuisine.name
WITH collect(cuisine) AS cuisines
MATCH (p:Person)
RETURN p.name AS name, gds.alpha.ml.oneHotEncoding(cuisines, [(p)-[:LIKES]->(cuisine) | cuisine]) AS
embedding
  ORDER BY name
```

Table 809. Results

name	embedding
Arya	[0,0,0]
Michael	[1,0,1]
Praveena	[0,1,0]
Zhen	[1,0,0]

Table 810. Parameters

Name	Type	Default	Optional	Description
availableValues	list	null	yes	The available values. If null, the function will return an empty list.
selectedValues	list	null	yes	The selected values. If null, the function will return a list of all 0's.

Table 811. Results

Type	Description
list	One hot encoding of the selected values.

6.8.5. Split Relationships Alpha

This section describes the Split Relationships algorithm in the Neo4j Graph Data Science library.

Introduction

The Split relationships algorithm is a utility algorithm that is used to pre-process a graph for model training. It splits the relationships into a holdout set and a remaining set. The holdout set is divided into two classes: positive, i.e., existing relationships, and negative, i.e., non-existing relationships. The class is indicated by a `label` property on the relationships. This enables the holdout set to be used for training or testing a machine learning model. Both, the holdout and the remaining relationships are added to the projected graph.

If the configuration option `relationshipWeightProperty` is specified, then the corresponding relationship property is preserved on the remaining set of relationships. Note however that the holdout set only has the `label` property; it is not possible to induce relationship weights on the holdout set as it also contains negative samples.

Syntax

This section covers the syntax used to execute the Split Relationships algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

Split Relationships syntax per mode

Run Split Relationships in mutate mode on a named graph.

```
CALL gds.alpha.ml.splitRelationships.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  relationshipsWritten: Integer,
  configuration: Map
```

Table 812. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 813. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 814. Algorithm specific configuration

Name	Type	Default	Optional	Description
holdoutFraction	Float	n/a	no	The fraction of all relationships being used as holdout set.
negativeSamplingRatio	Float	n/a	no	The desired ratio of negative to positive samples in holdout set.
holdoutRelationshipType	String	n/a	no	Relationship type used for the holdout set. Each relationship has a property `label` indicating whether it is a positive or negative sample.
remainingRelationshipType	String	n/a	no	Relationship type used for the remaining set.
nonNegativeRelationshipTypes	List of String	n/a	yes	Additional relationship types that are used for negative sampling.
relationshipWeightProperty	String	null	yes	Name of the relationship property that is inherited by the `remainingRelationshipType`.

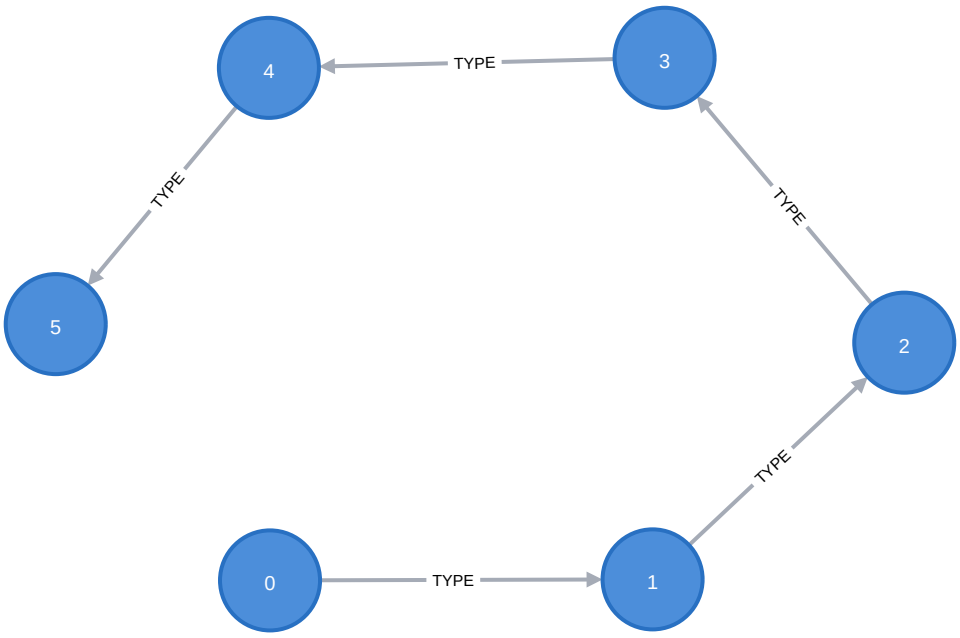
Name	Type	Default	Optional	Description
randomSeed	Integer	n/a	yes	An optional seed value for the random selection of relationships.

Table 815. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
relationshipsWritten	Integer	The number of relationships created by the algorithm.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the Split Relationships algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small graph of a handful nodes connected in a particular pattern. The example graph looks like this:



Consider the graph created by the following Cypher statement:

```
CREATE
    (n0:Label),
    (n1:Label),
    (n2:Label),
    (n3:Label),
    (n4:Label),
    (n5:Label),

    (n0)-[:TYPE { prop: 0} ]->(n1),
    (n1)-[:TYPE { prop: 1} ]->(n2),
    (n2)-[:TYPE { prop: 4} ]->(n3),
    (n3)-[:TYPE { prop: 9} ]->(n4),
    (n4)-[:TYPE { prop: 16} ]->(n5)
```

Given the above graph, we want to use 20% of the relationships as holdout set. The holdout set will be split into two same-sized classes: positive and negative. Positive relationships will be randomly selected from the existing relationships and marked with a property `label: 1`. Negative relationships will be randomly generated, i.e., they do not exist in the input graph, and are marked with a property `label: 0`.

```
CALL gds.graph.project(
    'graph',
    'Label',
    { TYPE: { orientation: 'UNDIRECTED' } }
)
```

Now we can run the algorithm by specifying the appropriate ratio and the output relationship types. We use a random seed value in order to produce deterministic results.

```
CALL gds.alpha.ml.splitRelationships.mutate('graph', {
    holdoutRelationshipType: 'TYPE_HOLDOUT',
    remainingRelationshipType: 'TYPE_REMAINING',
    holdoutFraction: 0.2,
    negativeSamplingRatio: 1.0,
    randomSeed: 1337
}) YIELD relationshipsWritten
```

Table 816. Results

relationshipsWritten
10

The input graph consists of 5 relationships. We use 20% (1 relationship) of the relationships to create the 'TYPE_HOLDOUT' relationship type (holdout set). This creates 1 relationship with positive label. Because of the `negativeSamplingRatio`, one relationship with negative label is also created. Finally, the `TYPE_REMAINING` relationship type is formed with the remaining 80% (4 relationships). These are written as orientation `UNDIRECTED` which counts as writing 8 relationships.

The mutated graph will look like the following graph when filtered by the `TEST` and `TRAIN` relationship.

```
CREATE
    (n0:Label),
    (n1:Label),
    (n2:Label),
    (n3:Label),
    (n4:Label),
    (n5:Label),

    (n2)-[:TYPE_HOLDOUT { label: 0 } ]->(n5), // negative, non-existing
    (n3)-[:TYPE_HOLDOUT { label: 1 } ]->(n2), // positive, existing

    (n0)<-[:TYPE_REMAINING { prop: 0} ]-(n1),
    (n1)<-[:TYPE_REMAINING { prop: 1} ]-(n2),
    (n3)<-[:TYPE_REMAINING { prop: 9} ]-(n4),
    (n4)<-[:TYPE_REMAINING { prop: 16} ]-(n5),
    (n0)-[:TYPE_REMAINING { prop: 0} ]->(n1),
    (n1)-[:TYPE_REMAINING { prop: 1} ]->(n2),
    (n3)-[:TYPE_REMAINING { prop: 9} ]->(n4),
    (n4)-[:TYPE_REMAINING { prop: 16} ]->(n5)
```

6.9. Pregel API

This chapter provides documentation for the Pregel API in the Neo4j Graph Data Science library.

6.9.1. Introduction

Pregel is a vertex-centric computation model to define your own algorithms via a user-defined compute function. Node values can be updated within the compute function and represent the algorithm result. The input graph contains default node values or node values from a graph projection.

The compute function is executed in multiple iterations, also called supersteps. In each superstep, the compute function runs for each node in the graph. Within that function, a node can receive messages from other nodes, typically its neighbors. Based on the received messages and its currently stored value, a node can compute a new value. A node can also send messages to other nodes, typically its neighbors, which are received in the next superstep. The algorithm terminates after a fixed number of supersteps or if no messages are being sent between nodes.

A Pregel computation is executed in parallel. Each thread executes the compute function for a batch of nodes.

For more information about Pregel, have a look at https://kowshik.github.io/JPregel/pregel_paper.pdf.

To implement your own Pregel algorithm, the Graph Data Science library provides a Java API, which is described below.

The introduction of a new Pregel algorithm can be separated in two main steps. First, we need to implement the algorithm using the Pregel Java API. Second, we need to expose the algorithm via a Cypher procedure to make use of it.

For an example on how to expose a custom Pregel computation via a Neo4j procedure, have a look at the Pregel examples.

6.9.2. Pregel Java API

The Pregel Java API allows us to easily build our own algorithm by implementing several interfaces.

Computation

The first step is to implement the `org.neo4j.gds.beta.pregel.PregelComputation` interface. It is the main interface to express user-defined logic using the Pregel framework.

The Pregel computation

```
public interface PregelComputation<C extends PregelConfig> {
    // The schema describes the node property layout.
    PregelSchema schema();
    // Called in the first superstep and allows initializing node state.
    default void init(PregelContext.InitContext<C> context) {}
    // Called in each superstep for each node and contains the main logic.
    void compute(PregelContext.ComputeContext<C> context, Pregel.Messages messages);
    // Called exactly once at the end of each superstep by a single thread.
    default void masterCompute(MasterComputeContext<C> context) {}
    // Used to combine all messages sent to a node to a single value.
    default Optional<Reducer> reducer() {
        return Optional.empty();
    }
    // Used to apply a relationship weight on a message.
    default double applyRelationshipWeight(double message, double relationshipWeight);
}
```

Pregel node values are composite values. The `schema` describes the layout of that composite value. Each element of the schema can represent either a primitive long or double value as well as arrays of those. The element is uniquely identified by a key, which is used to access the value during the computation. Details on schema declaration can be found in the dedicated section.

The `init` method is called in the beginning of the first superstep of the Pregel computation and allows initializing node values. The interface defines an abstract `compute` method, which is called for each node in every superstep. Algorithm-specific logic is expressed within the `compute` method. The context parameter provides access to node properties of the projected graph and the algorithm configuration.

The `compute` method is called individually for each node in every superstep as long as the node receives messages or has not voted to halt yet. Since an implementation of `PregelComputation` is stateless, a node can only communicate with other nodes via messages. In each superstep, a node receives `messages` and can send new messages via the `context` parameter. Messages can be sent to neighbor nodes or any node if its identifier is known.

The `masterCompute` method is called exactly once at the end of each superstep. It is executed by a single thread and can be used to modify a global state based on the current computation state. Details on using a master computation can be found in the dedicated section.

An optional `reducer` can be used to define a function that is being applied on messages sent to a single node. It takes two arguments, the current value and a message value, and produces a new value. The function is called repeatedly, once for each message that is sent to a node. Eventually, only one message will be received by the node in the next superstep. By defining a reducer, memory consumption and computation runtime can be improved significantly. Check the dedicated section for more details.

The `applyRelationshipWeight` method can be used to modify the message based on a relationship

property. If the input graph has no relationship properties, i.e. is unweighted, the method is skipped.

Pregel schema

In Pregel, each node is associated with a value which can be accessed from within the `compute` method. The value is typically used to represent intermediate computation state and eventually the computation result. To represent complex state, the node value is a composite type which consists of one or more named values. From the perspective of the `compute` function, each of these values can be accessed by its name.

When implementing a `PregelComputation`, one must override the `schema()` method. The following example shows the simplest possible example:

```
PregelSchema schema() {
    return PregelSchema.Builder().add("foobar", ValueType.LONG).build();
}
```

The node value consists of a single value named `foobar` which is of type `long`. A node value can be of any GDS-supported type, i.e. `long`, `double`, `long[]`, `double[]` and `float[]`.

We can add an arbitrary number of values to the schema:

```
PregelSchema schema() {
    return PregelSchema.Builder()
        .add("foobar", ValueType.LONG)
        .add("baz", ValueType.DOUBLE)
        .build();
}
```

Note, that each property consumes additional memory when executing the algorithm, which typically amounts to the number of nodes multiplied by the size of a single value (e.g. 64 Bit for a `long` or `double`).

The `add` method on the builder takes a third argument: `Visibility`. There are two possible values: `PUBLIC` (default) and `PRIVATE`. The visibility is considered during procedure code generation to indicate if the value is part of the Pregel result or not. Any value that has visibility `PUBLIC` will be part of the computation result and included in the result of the procedure, e.g., streamed to the caller, mutated to the in-memory graph or written to the database.

The following shows a schema where one value is used as result and a second value is only used during computation:

```
PregelSchema schema() {
    return PregelSchema.Builder()
        .add("result", ValueType.LONG, Visiblity.PUBLIC)
        .add("tempValue", ValueType.DOUBLE, Visiblity.PRIVATE)
        .build();
}
```

Init context and compute context

The main purpose of the two context objects is to enable the computation to communicate with the Pregel framework. A context is stateful, and all its methods are subject to the current superstep and the currently

processed node. Both context objects share a set of methods, e.g., to access the config and node state. Additionally, each context adds context-specific methods.

The `org.neo4j.gds.beta.pregel.PregelContext.InitContext` is available in the `init` method of a Pregel computation. It provides access to node properties stored in the in-memory graph. We can set the initial node state to a fixed value, e.g. the node id, or use graph properties and the user-defined configuration to initialize a context-dependent state.

The InitContext

```
public final class InitContext {
    // The currently processed node id.
    public long nodeId();
    // User-defined Pregel configuration
    public PregelConfig config();
    // Sets a double node value for the given schema key.
    public void setNodeValue(String key, double value);
    // Sets a long node value for the given schema key.
    public void setNodeValue(String key, long value);
    // Sets a double array node value for the given schema key.
    public void setNodeValue(String key, double[] value);
    // Sets a long array node value for the given schema key.
    public void setNodeValue(String key, long[] value);
    // Number of nodes in the input graph.
    public long nodeCount();
    // Number of relationships in the input graph.
    public long relationshipCount();
    // Number of relationships of the current node.
    public int degree();
    // Available node property keys in the input graph.
    public Set<String> nodePropertyKeys();
    // Node properties stored in the input graph.
    public NodeProperties nodeProperties(String key);
}
```

In contrast, `org.neo4j.gds.beta.pregel.PregelContext.ComputeContext` can be accessed inside the `compute` method. The context provides methods to access the computation state, e.g. the current superstep, and to send messages to other nodes in the graph.

The ComputeContext

```
public final class ComputeContext {
    // The currently processed node id.
    public long nodeId();
    // User-defined Pregel configuration
    public PregelConfig config();
    // Sets a double node value for the given schema key.
    public void setNodeValue(String key, double value);
    // Sets a long node value for the given schema key.
    public void setNodeValue(String key, long value);
    // Number of nodes in the input graph.
    public long nodeCount();
    // Number of relationships in the input graph.
    public long relationshipCount();
    // Indicates whether the input graph is a multi-graph.
    public boolean isMultiGraph();
    // Number of relationships of the current node.
    public int degree();
    // Double value for the given node schema key.
    public double doubleNodeValue(String key);
    // Double value for the given node schema key.
    public long longNodeValue(String key);
    // Double array value for the given node schema key.
    public double[] doubleArrayNodeValue(String key);
    // Long array value for the given node schema key.
    public long[] longArrayNodeValue(String key);
    // Notify the framework that the node intends to stop its computation.
    public void voteToHalt();
    // Indicates whether this is superstep 0.
    public boolean isInitialSuperstep();
    // 0-based superstep identifier.
    public int superstep();
    // Sends the given message to all neighbors of the node.
    public void sendToNeighbors(double message);
    // Sends the given message to the target node.
    public void sendTo(long targetNodeId, double message);
    // Stream of neighbor ids of the current node.
    public LongStream getNeighbours();
}
```

Master Computation

Some Pregel programs may require logic that is executed after all threads have finished the current superstep, for example, to reset or evaluate a global data structure. This can be achieved by overriding the `org.neo4j.gds.beta.pregel.PregelComputation.masterCompute` function of the `PregelComputation`. This function will be called at the end of each superstep after all compute threads have finished. The master compute function will be called by a single thread.

The `masterCompute` function has access to the `org.neo4j.gds.beta.pregel.PregelContext.MasterComputeContext`. That context is similar to the `ComputeContext` but is not tied to a specific node and does not allow sending messages. Furthermore, the `MasterComputeContext` allows to run a function for every node in the graph and has access to the computation state of all nodes.

The MasterComputeContext

```
public final class MasterComputeContext {
    // User-defined Pregel configuration
    public PregelConfig config();
    // Number of nodes in the input graph.
    public long nodeCount();
    // Number of relationships in the input graph.
    public long relationshipCount();
    // Indicates whether the input graph is a multi-graph.
    public boolean isMultiGraph();
    // Run the given consumer for every node in the graph.
    public void forEachNode(LongPredicate consumer);
    // Double value for the given node schema key.
    public double doubleNodeValue(long nodeId, String key);
    // Double value for the given node schema key.
    public long longNodeValue(long nodeId, String key);
    // Double array value for the given node schema key.
    public double[] doubleArrayNodeValue(long nodeId, String key);
    // Long array value for the given node schema key.
    public long[] longArrayNodeValue(long nodeId, String key);
    // Sets a double node value for the given schema key.
    public void setNodeValue(long nodeId, String key, double value);
    // Sets a long node value for the given schema key.
    public void setNodeValue(long nodeId, String key, long value);
    // Sets a double array node value for the given schema key.
    public void setNodeValue(long nodeId, String key, double[] value);
    // Sets a long array node value for the given schema key.
    public void setNodeValue(long nodeId, String key, long[] value);
    // Indicates whether this is superstep 0.
    public boolean isInitialSuperstep();
    // 0-based superstep identifier.
    public int superstep();
}
```

Message reducer

Many Pregel computations rely on computing a single value from all messages being sent to a node. For example, the page rank algorithm computes the sum of all messages being sent to a single node. In those cases, a reducer can be used to combine all messages to a single value. If applicable, this optimization improves memory consumption and computation runtime.

By default, a Pregel computation does not make use of a reducer. All messages sent to a node are stored in a queue and received in the next superstep. To enable message reduction, one needs to implement the `reducer` method and provide either a custom or a pre-defined reducer.

The Reducer interface that needs to be implemented.

```
public interface Reducer {
    // The identity element is used as the initial value.
    double identity();
    // Computes a new value based on the current value and the message.
    double reduce(double current, double message);
}
```

The identity value is used as the initial value for the `current` argument in the `reduce` function. All subsequent calls use the result of the previous call as `current` value.

The framework already provides implementations for computing the minimum, maximum, sum and count of messages. The default implementations are part of the `Reducer` interface and can be applied as follows:

Applying the sum reducer in a custom computation.

```
public class CustomComputation implements PregelComputation<PregelConfig> {

    @Override
    public void compute(PregelContext.ComputeContext<CustomConfig> context, Pregel.Messages messages) {
        // ...
        for (var message : messages) {
            // ...
        }
    }

    @Override
    public Optional<Reducer> reducer() {
        return Optional.of(new Reducer.Sum());
    }
}
```

The implementation of the compute method does not need to be adapted. If a reducer is present, the `messages` iterator contains either zero or one message. Note, that defining a reducer precludes running the computation with asynchronous messaging. The `isAsynchronous` flag at the config is ignored in that case.

Configuration

To configure the execution of a custom Pregel computation, the framework requires a configuration. The `org.neo4j.gds.beta.pregel.PregelConfig` provides the minimum set of options to execute a computation. The configuration options also map to the parameters that can later be set via a custom procedure. This is equivalent to all the other algorithms within the GDS library.

Table 817. Pregel Configuration

Name	Type	Default Value	Description
maxIterations	Integer	-	Maximum number of supersteps after which the computation will terminate.
isAsynchronous	Boolean	false	Flag indicating if messages can be sent and received in the same superstep.
partitioning	String	"range"	Selects the partitioning of the input graph, can be either "range", "degree" or "auto".
relationshipWeightProperty	String	null	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
concurrency	Integer	4	Concurrency used when executing the Pregel computation.
writeConcurrency	Integer	concurrency	Concurrency used when writing computation results to Neo4j.
writeProperty	String	"pregel_"	Prefix string that is prepended to node schema keys in write mode.
mutateProperty	String	"pregel_"	Prefix string that is prepended to node schema keys in mutate mode.

For some algorithms, we want to specify additional configuration options.

Typically, these options are algorithm specific arguments, such as thresholds. Another reason for a custom config relates to the initialization phase of the computation. If we want to init the node state based on a graph property, we need to access that property via its key. Since those keys are dynamic properties of the graph, we need to provide them to the computation. We can achieve that by declaring an option to set that key in a custom configuration.

If a user-defined Pregel computation requires custom options a custom configuration can be created by extending the `PregelConfig`.

A custom configuration and how it can be used in the init phase.

```
@ValueClass
@Configuration
public interface CustomConfig extends PregelConfig {
    // A property key that refers to a seed property.
    String seedProperty();
    // An algorithm specific parameter.
    int minDegree();
}

public class CustomComputation implements PregelComputation<CustomConfig> {

    @Override
    public void init(PregelContext.InitContext<CustomConfig> context) {
        // Use the custom config key to access a graph property.
        var seedProperties = context.nodeProperties(context.config().seedProperty());
        // Init the node state with the graph property for that node.
        context.setNodeValue("state", seedProperties.doubleValue(context.nodeId()));
    }

    @Override
    public void compute(PregelContext.ComputeContext<CustomConfig> context, Pregel.Messages messages) {
        if (context.degree() >= context.config().minDegree()) {
            // ...
        }
    }

    // ...
}
```

Logging

The following methods are available for all contexts (`InitContext`, `ComputeContext`, `MasterComputeContext`) to inject custom messages into the progress log of the algorithm execution.

The log methods can be used in Pregel contexts

```
// All contexts inherit from PregelContext
public abstract class PregelContext<CONFIG extends PregelConfig> {

    // Log a debug message to the Neo4j log.
    public void logDebug(String message) {
        progressTracker.logDebug(message);
    }

    // Log a warning message to the Neo4j log.
    public void logWarning(String message) {
        progressTracker.logWarning(message);
    }

    // Log a info message to the Neo4j log
    public void logMessage(String message) {
        progressTracker.logMessage(message);
    }

}
```

6.9.3. Run Pregel via Cypher

To make a custom Pregel computation accessible via Cypher, it needs to be exposed via the procedure API. The Pregel framework in GDS provides an easy way to generate procedures for all the default modes.

Procedure generation

To generate procedures for a computation, it needs to be annotated with the `@org.neo4j.gds.beta.pregel.annotation.PregelProcedure` annotation. In addition, the config parameter of the custom computation must be a subtype of `org.neo4j.gds.beta.pregel.PregelProcedureConfig`.

Using the `@PregelProcedure` annotation to configure code generation.

```
@PregelProcedure(
    name = "custom.pregel.proc",
    modes = {GDSMode.STREAM, GDSMode.WRITE},
    description = "My custom Pregel algorithm"
)
public class CustomComputation implements PregelComputation<PregelProcedureConfig> {
    // ...
}
```

The annotation provides a number of configuration options for the code generation.

Table 818. Configuration

Name	Type	Default Value	Description
name	String	-	The prefix of the generated procedure name. It is appended by the mode.
modes	List	`[STREAM, WRITE, MUTATE, STATS]`	A procedure is generated for each of the specified modes.
description	String	`""`	Procedure description that is printed in `dbms.listProcedures()`.

For the above Code snippet, we generate four procedures:

- `custom.pregel.proc.stream`
- `custom.pregel.proc.stream.estimate`
- `custom.pregel.proc.write`
- `custom.pregel.proc.write.estimate`

Note that by default, all values specified in the `PregelSchema` are included in the procedure results. To change that behaviour, we can change the visibility for individual parts of the schema. For more details, please refer to the dedicated documentation section.

Building and installing a Neo4j plugin

In order to use a Pregel algorithm in Neo4j via a procedure, we need to package it as Neo4j plugin. The pregel-bootstrap project is a good starting point. The `build.gradle` file within the project contains all the dependencies necessary to implement a Pregel algorithm and to generate corresponding procedures.

Make sure to change the `gdsVersion` and `neo4jVersion` according to your setup. GDS and Neo4j are runtime dependencies. Therefore, GDS needs to be installed as a plugin on the Neo4j server.

To build the project and create a plugin jar, just run:

```
./gradlew shadowJar
```

You can find the `pregel-bootstrap.jar` in `build/libs`. The jar needs to be placed in the `plugins` directory within your Neo4j installation alongside a GDS plugin jar. In order to have access to the procedure in Cypher, its namespace potentially needs to be added to the `neo4j.conf` file.

Enabling an example procedure in `neo4j.conf`

```
dbms.security.procedures.unrestricted=custom.pregel.proc.*
dbms.security.procedures.allowlist=custom.pregel.proc.*
```

Before `Neo4j 4.2`, the configuration setting is called `dbms.security.procedures.whitelist`

6.9.4. Examples

The pregel-examples module contains a set of examples for Pregel algorithms. The algorithm implementations demonstrate the usage of the Pregel API. Along with each example, we provide test classes that can be used as a guideline on how to write tests for custom algorithms. To play around, we recommend copying one of the algorithms into the `pregel-bootstrap` project, build it and setup the plugin in Neo4j.

Chapter 7. Machine learning

This chapter provides explanations and examples for the supervised machine learning in the Neo4j Graph Data Science library.

In GDS, our pipelines offer an end-to-end workflow, from feature extraction to training and applying machine learning models. Pipelines can be inspected through the Pipeline catalog. The trained models can then be accessed via the Model catalog and used to make predictions about your graph.

To help with building the ML models, there are additional guides for pre-processing and hyperparameter tuning available in:

- Pre-processing
- Training methods

The Neo4j GDS library includes the following pipelines to train and apply machine learning models, grouped by quality tier:

- Beta
  - Node Classification Pipelines
  - Link Prediction Pipelines

7.1. Pre-processing

In most machine learning scenarios, several pre-processing steps are applied to produce data that is amenable to machine learning algorithms. This is also true for graph data. The goal of pre-processing is to provide good features for the learning algorithm. As part of our pipelines we offer adding such pre-procesing steps as node property steps (see Node Classification or Link Prediction).

In GDS some options include:

- Node embeddings
- Centrality algorithms
- Auxiliary algorithms
  - Of special interest is Scale Properties

7.2. Node embeddings

This chapter provides explanations and examples for the node embedding algorithms in the Neo4j Graph Data Science library.

Node embedding algorithms compute low-dimensional vector representations of nodes in a graph. These vectors, also called embeddings, can be used for machine learning. The Neo4j Graph Data Science library

contains the following node embedding algorithms:

- Production-quality
  - FastRP
- Beta
  - GraphSAGE
  - Node2Vec

7.2.1. Fast Random Projection

This section describes the Fast Random Projection (FastRP) node embedding algorithm in the Neo4j Graph Data Science library.

Supported algorithm traits:

Directed

Undirected

Homogeneous

Heterogeneous

Weighted

Introduction

Fast Random Projection, or FastRP for short, is a node embedding algorithm in the family of random projection algorithms. These algorithms are theoretically backed by the Johnsson-Lindenstrauss lemma according to which one can project *n* vectors of *arbitrary* dimension into *O(log(n))* dimensions and still approximately preserve pairwise distances among the points. In fact, a linear projection chosen in a random way satisfies this property.

Such techniques therefore allow for aggressive dimensionality reduction while preserving most of the distance information. The FastRP algorithm operates on graphs, in which case we care about preserving similarity between nodes and their neighbors. This means that two nodes that have similar neighborhoods should be assigned similar embedding vectors. Conversely, two nodes that are not similar should be not be assigned similar embedding vectors.

The FastRP algorithm initially assigns random vectors to all nodes using a technique called *very sparse random projection*, see (Achlioptas, 2003) below. Moreover, in GDS it is possible to use node properties for the creation of these *initial random vectors* in a way described below. We will also use *projection of a node* synonymously with the initial random vector of a node.

Starting with these random vectors and iteratively averaging over node neighborhoods, the algorithm constructs a sequence of *intermediate embeddings* e_n^i for each node *n*. More precisely,

$$e_n^i = \mathrm{avg}(e_m^{i-1}),$$

where *m* ranges over neighbors of *n* and e_n^0 is the node's initial random vector.

The embedding e_n of node *n*, which is the output of the algorithm, is a combination of the vectors and embeddings defined above:

$$e_n = w_0 \cdot \text{normalize}(r_n) + \sum_{i=1}^{i=k} w_i \cdot \text{normalize}(e_n^i),$$

where `normalize` is the function which divides a vector with its L2 norm, the value of `nodeSelfInfluence` is w_0, and the values of `iterationWeights` are $[w_1, w_2, \ldots, w_k]$. We will return to Node Self Influence later on.

Therefore, each node's embedding depends on a neighborhood of radius equal to the number of iterations. This way FastRP exploits higher-order relationships in the graph while still being highly scalable.

The present implementation extends the original algorithm to support weighted graphs, which computes weighted averages of neighboring embeddings using the relationship weights. In order to make use of this, the `relationshipWeightProperty` parameter should be set to an existing relationship property.

The original algorithm is intended only for undirected graphs. We support running on both on directed graphs and undirected graph. For directed graphs we consider only the outgoing neighbors when computing the intermediate embeddings for a node. Therefore, using the orientations `NATURAL`, `REVERSE` or `UNDIRECTED` will all give different embeddings. In general, it is recommended to first use `UNDIRECTED` as this is what the original algorithm was evaluated on.

For more information on this algorithm see:

- H. Chen, S.F. Sultan, Y. Tian, M. Chen, S. Skiena: Fast and Accurate Network Embeddings via Very Sparse Random Projection, 2019.
- Dimitris Achlioptas. Database-friendly random projections: Johnson-Lindenstrauss with binary coins. Journal of Computer and System Sciences, 66(4):671–687, 2003.

Node properties

Most real-world graphs contain node properties which store information about the nodes and what they represent. The FastRP algorithm in the GDS library extends the original FastRP algorithm with a capability to take node properties into account. The resulting embeddings can therefore represent the graph more accurately.

The node property aware aspect of the algorithm is configured via the parameters `featureProperties` and `propertyRatio`. Each node property in `featureProperties` is associated with a randomly generated vector of dimension `propertyDimension`, where `propertyDimension = embeddingDimension * propertyRatio`. Each node is then initialized with a vector of size `embeddingDimension` formed by concatenation of two parts:

1. The first part is formed like in the standard FastRP algorithm,
2. The second one is a linear combination of the property vectors, using the property values of the node as weights.

The algorithm then proceeds with the same logic as the FastRP algorithm. Therefore, the algorithm will

output arrays of size `embeddingDimension`. The last `propertyDimension` coordinates in the embedding captures information about property values of nearby nodes (the "property part" below), and the remaining coordinates (`embeddingDimension` - `propertyDimension` of them; "topology part") captures information about nearby presence of nodes.

```
[0, 1, ...        | ...,   N - 1, N]
 ^^^^^^^^^^^^^^^^ | ^^^^^^^^^^^^^^^
  topology part   |  property part
                  ^
           property ratio
```

Tuning algorithm parameters

In order to improve the embedding quality using FastRP on one of your graphs, it is possible to tune the algorithm parameters. This process of finding the best parameters for your specific use case and graph is typically referred to as hyperparameter tuning. We will go through each of the configuration parameters and explain how they behave.

For statistically sound results, it is a good idea to reserve a test set excluded from parameter tuning. After selecting a set of parameter values, the embedding quality can be evaluated using a downstream machine learning task on the test set. By varying the parameter values and studying the precision of the machine learning task, it is possible to deduce the parameter values that best fit the concrete dataset and use case. To construct such a set you may want to use a dedicated node label in the graph to denote a subgraph without the test data.

Embedding dimension

The embedding dimension is the length of the produced vectors. A greater dimension offers a greater precision, but is more costly to operate over.

The optimal embedding dimension depends on the number of nodes in the graph. Since the amount of information the embedding can encode is limited by its dimension, a larger graph will tend to require a greater embedding dimension. A typical value is a power of two in the range 128 - 1024. A value of at least 256 gives good results on graphs in the order of 10^5 nodes, but in general increasing the dimension improves results. Increasing embedding dimension will however increase memory requirements and runtime linearly.

Normalization strength

The normalization strength is used to control how node degrees influence the embedding. Using a negative value will downplay the importance of high degree neighbors, while a positive value will instead increase their importance. The optimal normalization strength depends on the graph and on the task that the embeddings will be used for. In the original paper, hyperparameter tuning was done in the range of `[-1,0]` (no positive values), but we have found cases where a positive normalization strengths gives better results.

Iteration weights

The iteration weights parameter control two aspects: the number of iterations, and their relative impact on the final node embedding. The parameter is a list of numbers, indicating one iteration per number where the number is the weight applied to that iteration.

In each iteration, the algorithm will expand across all relationships in the graph. This has some implications:

- With a single iteration, only direct neighbors will be considered for each node embedding.
- With two iterations, direct neighbors and second-degree neighbors will be considered for each node embedding.
- With three iterations, direct neighbors, second-degree neighbors, and third-degree neighbors will be considered for each node embedding. Direct neighbors may be reached twice, in different iterations.
- In general, the embedding corresponding to the `i`:th iteration contains features depending on nodes reachable with paths of length `i`. If the graph is undirected, then a node reachable with a path of length `L` can also be reached with length `L+2k`, for any integer `k`.
- In particular, a node may reach back to itself on each even iteration (depending on the direction in the graph).

It is good to have at least one non-zero weight in an even and in an odd position. Typically, using at least a few iterations, for example three, is recommended. However, a too high value will consider nodes far away and may not be informative or even be detrimental. The intuition here is that as the projections reach further away from the node, the less specific the neighborhood becomes. Of course, a greater number of iterations will also take more time to complete.

Node Self Influence

Node Self Influence is a variation of the original FastRP algorithm.

How much a node's embedding is affected by the intermediate embedding at iteration *i* is controlled by the *i*'th element of `iterationWeights`. This can also be seen as how much the initial random vectors, or projections, of nodes that can be reached in *i* hops from a node affect the embedding of the node. Similarly, `nodeSelfInfluence` behaves like an iteration weight for a 0 th iteration, or the amount of influence the projection of a node has on the embedding of the same node.

A reason for setting this parameter to a non-zero value is if your graph has low connectivity or a significant amount of isolated nodes. Isolated nodes combined with using `propertyRatio = 0.0` leads to embeddings that contain all zeros. However using node properties along with node self influence can thus produce more meaningful embeddings for such nodes. This can be seen as producing fallback features when graph structure is (locally) missing. Moreover, sometimes a node's own properties are simply informative features and are good to include even if connectivity is high. Finally, node self influence can be used for pure dimensionality reduction to compress node properties used for node classification.

If node properties are not used, using `nodeSelfInfluence` may also have a positive effect, depending on other settings and on the problem.

Orientation

Choosing the right orientation when creating the graph may have the single greatest impact. The FastRP algorithm is designed to work with undirected graphs, and we expect this to be the best in most cases. If you expect only outgoing or incoming relationships to be informative for a prediction task, then you may want to try using the orientations `NATURAL` or `REVERSE` respectively.

Syntax

This section covers the syntax used to execute the FastRP algorithm in each of its execution modes. We are describing the named graph variant of the syntax. To learn more about general syntax variants, see Syntax overview.

FastRP syntax per mode

Run FastRP in stream mode on a named graph.

```
CALL gds.fastRP.stream(
  graphName: String,
  configuration: Map
) YIELD
  nodeId: Integer,
  embedding: List of Float
```

Table 819. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 820. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 821. Algorithm specific configuration

Name	Type	Default	Optional	Description
propertyRatio	Float	0.0	yes	The desired ratio of the property embedding dimension to the total `embeddingDimension`. A positive value requires `featureProperties` to be non-empty.
featureProperties	List of String	[]	yes	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	n/a	no	The dimension of the computed node embeddings. Minimum value is 1.
iterationWeights	List of Float	[0.0, 1.0, 1.0]	yes	Contains a weight for each iteration. The weight controls how much the intermediate embedding from the iteration contributes to the final embedding.
nodeSelfInfluence	Float	0.0	yes	Controls for each node how much its initial random vector contributes to its final embedding.
normalizationStrength	Float	0.0	yes	The initial random vector for each node is scaled by its degree to the power of `normalizationStrength`.
randomSeed	Integer	n/a	yes	A random seed which is used for all randomness in computing the embeddings.

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use for weighted random projection. If unspecified, the algorithm runs unweighted.
The number of iterations is equal to the length of `iterationWeights`.				
It is required that `iterationWeights` is non-empty or `nodeSelfInfluence` is non-zero.				

Table 822. Results

Name	Type	Description
nodeId	Integer	Node ID.
embedding	List of Float	FastRP node embedding.

Run FastRP in stats mode on a named graph.

```
CALL gds.fastRP.stats(
  graphName: String,
  configuration: Map
) YIELD
  nodeCount: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  configuration: Map
```

Table 823. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 824. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 825. Algorithm specific configuration

Name	Type	Default	Optional	Description
propertyRatio	Float	0.0	yes	The desired ratio of the property embedding dimension to the total `embeddingDimension`. A positive value requires `featureProperties` to be non-empty.
featureProperties	List of String	[]	yes	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	n/a	no	The dimension of the computed node embeddings. Minimum value is 1.
iterationWeights	List of Float	[0.0, 1.0, 1.0]	yes	Contains a weight for each iteration. The weight controls how much the intermediate embedding from the iteration contributes to the final embedding.
nodeSelfInfluence	Float	0.0	yes	Controls for each node how much its initial random vector contributes to its final embedding.
normalizationStrength	Float	0.0	yes	The initial random vector for each node is scaled by its degree to the power of `normalizationStrength`.
randomSeed	Integer	n/a	yes	A random seed which is used for all randomness in computing the embeddings.

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use for weighted random projection. If unspecified, the algorithm runs unweighted.
The number of iterations is equal to the length of `iterationWeights`.				
It is required that `iterationWeights` is non-empty or `nodeSelfInfluence` is non-zero.				

Table 826. Results

Name	Type	Description
nodeCount	Integer	Number of nodes processed.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
configuration	Map	Configuration used for running the algorithm.

Run FastRP in mutate mode on a named graph.

```
CALL gds.fastRP.mutate(
  graphName: String,
  configuration: Map
) YIELD
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 827. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 828. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm.

Table 829. Algorithm specific configuration

Name	Type	Default	Optional	Description
propertyRatio	Float	`0.0`	yes	The desired ratio of the property embedding dimension to the total `embeddingDimension`. A positive value requires `featureProperties` to be non-empty.
featureProperties	List of String	`[]`	yes	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	`n/a`	no	The dimension of the computed node embeddings. Minimum value is 1.
iterationWeights	List of Float	`[0.0, 1.0, 1.0]`	yes	Contains a weight for each iteration. The weight controls how much the intermediate embedding from the iteration contributes to the final embedding.
nodeSelfInfluence	Float	`0.0`	yes	Controls for each node how much its initial random vector contributes to its final embedding.
normalizationStrength	Float	`0.0`	yes	The initial random vector for each node is scaled by its degree to the power of `normalizationStrength`.

Name	Type	Default	Optional	Description
randomSeed	Integer	`n/a`	yes	A random seed which is used for all randomness in computing the embeddings.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use for weighted random projection. If unspecified, the algorithm runs unweighted.
The number of iterations is equal to the length of `iterationWeights`.				
It is required that `iterationWeights` is non-empty or `nodeSelfInfluence` is non-zero.				

Table 830. Results

Name	Type	Description
nodeCount	Integer	Number of nodes processed.
nodePropertiesWritten	Integer	Number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the in-memory graph.
configuration	Map	Configuration used for running the algorithm.

Run FastRP in write mode on a named graph.

```
CALL gds.fastRP.write(
  graphName: String,
  configuration: Map
) YIELD
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 831. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 832. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 833. Algorithm specific configuration

Name	Type	Default	Optional	Description
propertyRatio	Float	`0.0`	yes	The desired ratio of the property embedding dimension to the total `embeddingDimension`. A positive value requires `featureProperties` to be non-empty.
featureProperties	List of String	`[]`	yes	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	`n/a`	no	The dimension of the computed node embeddings. Minimum value is 1.
iterationWeights	List of Float	`[0.0, 1.0, 1.0]`	yes	Contains a weight for each iteration. The weight controls how much the intermediate embedding from the iteration contributes to the final embedding.
nodeSelfInfluence	Float	`0.0`	yes	Controls for each node how much its initial random vector contributes to its final embedding.

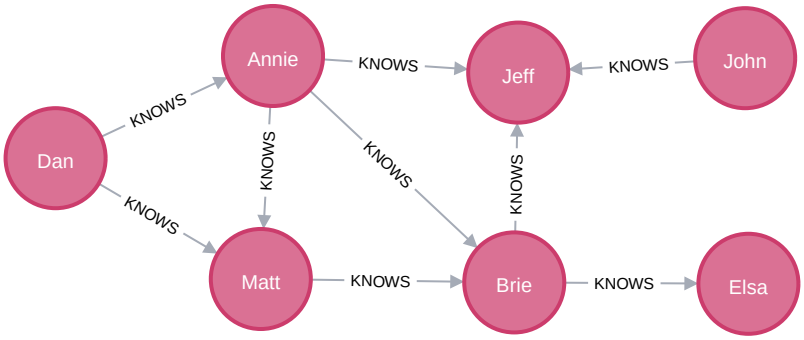
Name	Type	Default	Optional	Description
normalizationStrength	Float	`0.0`	yes	The initial random vector for each node is scaled by its degree to the power of `normalizationStrength`.
randomSeed	Integer	`n/a`	yes	A random seed which is used for all randomness in computing the embeddings.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use for weighted random projection. If unspecified, the algorithm runs unweighted.
The number of iterations is equal to the length of `iterationWeights`.				
It is required that `iterationWeights` is non-empty or `nodeSelfInfluence` is non-zero.				

Table 834. Results

Name	Type	Description
nodeCount	Integer	Number of nodes processed.
nodePropertiesWritten	Integer	Number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
configuration	Map	Configuration used for running the algorithm.

Examples

In this section we will show examples of running the FastRP node embedding algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small social network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (dan:Person {name: 'Dan', age: 18}),
  (annie:Person {name: 'Annie', age: 12}),
  (matt:Person {name: 'Matt', age: 22}),
  (jeff:Person {name: 'Jeff', age: 51}),
  (brie:Person {name: 'Brie', age: 45}),
  (elsa:Person {name: 'Elsa', age: 65}),
  (john:Person {name: 'John', age: 64}),

  (dan)-[:KNOWS {weight: 1.0}]->(annie),
  (dan)-[:KNOWS {weight: 1.0}]->(matt),
  (annie)-[:KNOWS {weight: 1.0}]->(matt),
  (annie)-[:KNOWS {weight: 1.0}]->(jeff),
  (annie)-[:KNOWS {weight: 1.0}]->(brie),
  (matt)-[:KNOWS {weight: 3.5}]->(brie),
  (brie)-[:KNOWS {weight: 1.0}]->(elsa),
  (brie)-[:KNOWS {weight: 2.0}]->(jeff),
  (john)-[:KNOWS {weight: 1.0}]->(jeff);
```

This graph represents seven people who know one another. A relationship property `weight` denotes the strength of the knowledge between two persons.

With the graph in Neo4j we can now project it into the graph catalog to prepare it for algorithm execution. We do this using a native projection targeting the `Person` nodes and the `KNOWS` relationships. For the relationships we will use the `UNDIRECTED` orientation. This is because the FastRP algorithm has been measured to compute more predictive node embeddings in undirected graphs. We will also add the `weight` relationship property which we will make use of when running the weighted version of FastRP.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'persons'.

```
CALL gds.graph.project(
  'persons',
  'Person',
  {
    KNOWS: {
      orientation: 'UNDIRECTED',
      properties: 'weight'
    }
  },
  { nodeProperties: ['age'] }
)
```

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `stream` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm:

```
CALL gds.fastRP.stream.estimate('persons', {embeddingDimension: 128})
YIELD nodeCount, relationshipCount, bytesMin, bytesMax, requiredMemory
```

Table 835. Results

nodeCount	relationshipCount	bytesMin	bytesMax	requiredMemory
7	18	11424	11424	"11424 Bytes"

Stream

In the `stream` execution mode, the algorithm returns the embedding for each node. This allows us to inspect the results directly or post-process them in Cypher without any side effects.

For more details on the `stream` mode in general, see Stream.

The following will run the algorithm, and stream results:

```
CALL gds.fastRP.stream('persons',
  {
    embeddingDimension: 4,
    randomSeed: 42
  }
)
YIELD nodeId, embedding
```

Table 836. Results

nodeId	embedding
0	[0.4774002134799957, -0.6602408289909363, -0.36686956882476807, -1.7089111804962158]
1	[0.7989360094070435, -0.4918718934059143, -0.41281944513320923, -1.6314401626586914]
2	[0.47275322675704956, -0.49587157368659973, -0.3340468406677246, -1.7141895294189453]
3	[0.8290714025497437, -0.3260476291179657, -0.3317275643348694, -1.4370529651641846]
4	[0.7749264240264893, -0.4773247539997101, 0.0675133764743805, -1.5248265266418457]
5	[0.8408374190330505, -0.37151476740837097, 0.12121132016181946, -1.530960202217102]
6	[1.0, -0.11054422706365585, -0.3697933852672577, -0.9225144982337952]

The results of the algorithm are not very intuitively interpretable, as the node embedding format is a mathematical abstraction of the node within its neighborhood, designed for machine learning programs. What we can see is that the embeddings have four elements (as configured using `embeddingDimension`) and that the numbers are relatively small (they all fit in the range of `[-2, 2]`). The magnitude of the

numbers is controlled by the `embeddingDimension`, the number of nodes in the graph, and by the fact that FastRP performs euclidean normalization on the intermediate embedding vectors.

Due to the random nature of the algorithm the results will vary between the runs. However, this does not necessarily mean that the pairwise distances of two node embeddings vary as much.

Stats

In the `stats` execution mode, the algorithm returns a single row containing a summary of the algorithm result. This execution mode does not have any side effects. It can be useful for evaluating algorithm performance by inspecting the `computeMillis` return item. In the examples below we will omit returning the timings. The full signature of the procedure can be found in the syntax section.

For more details on the `stats` mode in general, see Stats.

The following will run the algorithm and returns the result in form of statistical and measurement values

```
CALL gds.fastRP.stats('persons', { embeddingDimension: 8 })
YIELD nodeCount
```

Table 837. Results

nodeCount
7

The `stats` mode does not currently offer any statistical results for the embeddings themselves. We can however see that the algorithm has successfully processed all seven nodes in our example graph.

Mutate

The `mutate` execution mode extends the `stats` mode with an important side effect: updating the named graph with a new node property containing the embedding for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

The following will run the algorithm in `mutate` mode:

```
CALL gds.fastRP.mutate(
  'persons',
  {
    embeddingDimension: 8,
    mutateProperty: 'fastrp-embedding'
  }
)
YIELD nodePropertiesWritten
```

Table 838. Results

nodePropertiesWritten
7

The returned result is similar to the `stats` example. Additionally, the graph 'persons' now has a node property `fastrp-embedding` which stores the node embedding for each node. To find out how to inspect the new schema of the in-memory graph, see Listing graphs.

Write

The `write` execution mode extends the `stats` mode with an important side effect: writing the embedding for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row, similar to `stats`, but with some additional metrics. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

The following will run the algorithm in `write` mode:

```
CALL gds.fastRP.write(
  'persons',
  {
    embeddingDimension: 8,
    writeProperty: 'fastrp-embedding'
  }
)
YIELD nodePropertiesWritten
```

Table 839. Results

nodePropertiesWritten
7

The returned result is similar to the `stats` example. Additionally, each of the seven nodes now has a new property `fastrp-embedding` in the Neo4j database, containing the node embedding for that node.

Weighted

By default, the algorithm is considering the relationships of the graph to be unweighted. To change this behaviour we can use configuration parameter called `relationshipWeightProperty`. Below is an example of running the weighted variant of algorithm.

The following will run the algorithm, and stream results:

```
CALL gds.fastRP.stream(
  'persons',
  {
    embeddingDimension: 4,
    randomSeed: 42,
    relationshipWeightProperty: 'weight'
  }
)
YIELD nodeId, embedding
```

Table 840. Results

nodeId	embedding
0	[0.10945529490709305, -0.5032674074172974, 0.464673787355423, -1.7539862394332886]
1	[0.3639600872993469, -0.39210301637649536, 0.46271592378616333, -1.829423427581787]
2	[0.12314096093177795, -0.3213110864162445, 0.40100979804992676, -1.471055269241333]
3	[0.30704641342163086, -0.24944794178009033, 0.3947891891002655, -1.3463698625564575]
4	[0.23112300038337708, -0.30148714780807495, 0.584831714630127, -1.2822188138961792]
5	[0.14497177302837372, -0.2312137484550476, 0.5552002191543579, -1.2605633735656738]
6	[0.5139184594154358, -0.07954332232475281, 0.3690345287322998, -0.9176374077796936]

Since the initial state of the algorithm is randomised, it isn't possible to intuitively analyse the effect of the relationship weights.

Using node properties as features

To explain the novel initialization using node properties, let us consider an example where `embeddingDimension` is 10, `propertyRatio` is 0.2. The dimension of the embedded properties, `propertyDimension` is thus 2. Assume we have a property `f1` of scalar type, and a property `f2` storing arrays of length 2. This means that there are 3 features which we order like `f1` followed by the two values of `f2`. For each of these three features we sample a two dimensional random vector. Let's say these are `p1=[0.0, 2.4]`, `p2=[-2.4, 0.0]` and `p3=[2.4, 0.0]`. Consider now a node `(n {f1: 0.5, f2: [1.0, -1.0]})`. The linear combination mentioned above, is in concrete terms `0.5 * p1 + 1.0 * p2 - 1.0 * p3 = [-4.8, 1.2]`. The initial random vector for the node `n` contains first 8 values sampled as in the original FastRP paper, and then our computed values `-4.8` and `1.2`, totalling 10 entries.

In the example below, we again set the embedding dimension to 2, but we set `propertyRatio` to 1, which means the embedding is computed from node properties only.

The following will run FastRP with feature properties:

```
CALL gds.fastRP.stream('persons', {
    randomSeed: 42,
    embeddingDimension: 2,
    propertyRatio: 1.0,
    featureProperties: ['age'],
    iterationWeights: [1.0]
}) YIELD nodeId, embedding
```

Table 841. Results

nodeId	embedding
0	[0.0, -1.0]
1	[0.0, -1.0]
2	[0.0, -0.9999999403953552]
3	[0.0, -1.0]
4	[0.0, -0.9999999403953552]
5	[0.0, -1.0]
6	[0.0, -1.0]

In this example, the embeddings are based on the age property. Because of L2 normalization which is applied to each iteration (here only one iteration), all nodes have the same embedding despite having different age values (apart from rounding errors).

7.2.2. GraphSAGE Beta

> *This section describes the GraphSAGE node embedding algorithm in the Neo4j Graph Data Science library.*

GraphSAGE is an *inductive* algorithm for computing node embeddings. GraphSAGE is using node feature information to generate node embeddings on unseen nodes or graphs. Instead of training individual embeddings for each node, the algorithm learns a function that generates embeddings by sampling and aggregating features from a node's local neighborhood.

The algorithm is defined for UNDIRECTED graphs.

For more information on this algorithm see:

- William L. Hamilton, Rex Ying, and Jure Leskovec. "Inductive Representation Learning on Large Graphs." 2018.
- Amit Pande, Kai Ni and Venkataramani Kini. "SWAG: Item Recommendations using Convolutions on Weighted Graphs." 2019.

Considerations

If you are embedding a graph that has an isolated node, the aggregation step in GraphSAGE can only draw information from the node itself. When all the properties of that node are `0.0`, and the activation function is ReLU, this leads to an all-zero vector for that node. However, since GraphSAGE normalizes node embeddings using the L2-norm, and a zero vector cannot be normalized, we assign all-zero embeddings to such nodes under these special circumstances. In scenarios where you generate all-zero embeddings for orphan nodes, that may have impacts on downstream tasks such as nearest neighbor or other similarity algorithms. It may be more appropriate to filter out these disconnected nodes prior to running GraphSAGE.

When doing memory estimation of the training, the feature dimension is computed as if each feature property is scalar.

Syntax

GraphSAGE syntax per mode

Run GraphSAGE in train mode on a named graph.

```
CALL gds.beta.graphSage.train(
  graphName: String,
  configuration: Map
) YIELD
  modelInfo: Map,
  configuration: Map,
  trainMillis: Integer
```

Table 842. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 843. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 844. Algorithm specific configuration

Name	Type	Default	Optional	Description
modelName	String	n/a	no	The name of the model to train, must not exist in the Model Catalog.
featureProperties	List of String	n/a	no	The names of the node properties that should be used as input features. All property names must exist in the projected graph and be of type Float or List of Float.
embeddingDimension	Integer	64	yes	The dimension of the generated node embeddings as well as their hidden layer representations.
aggregator	String	"mean"	yes	The aggregator to be used by the layers. Supported values are "mean" and "pool".
activationFunction	String	"sigmoid"	yes	The activation function to be used in the model architecture. Supported values are "sigmoid" and "relu".
sampleSizes	List of Integer	[25, 10]	yes	A list of Integer values, the size of the list determines the number of layers and the values determine how many nodes will be sampled by the layers.

Name	Type	Default	Optional	Description
projectedFeatureDimension	Integer	`n/a`	yes	The dimension of the projected `featureProperties`. This enables multi-label GraphSage, where each label can have a subset of the `featureProperties`.
batchSize	Integer	`100`	yes	The number of nodes per batch.
tolerance	Float	`1e-4`	yes	Tolerance used for the early convergence of an epoch.
learningRate	Float	`0.1`	yes	The learning rate determines the step size at each iteration while moving toward a minimum of a loss function.
epochs	Integer	`1`	yes	Number of times to traverse the graph.
maxIterations	Integer	`10`	yes	Maximum number of weight updates per batch. Batches can also converge early based on `tolerance`.
searchDepth	Integer	`5`	yes	Maximum depth of the RandomWalks to sample nearby nodes for the training.
negativeSampleWeight	Integer	`20`	yes	The weight of the negative samples. Higher values increase the impact of negative samples in the loss.
relationshipWeightProperty	String	`null`	yes	Name of the relationship property to use as weights. If unspecified, the algorithm runs unweighted.
randomSeed	Integer	`random`	yes	A random seed which is used to control the randomness in computing the embeddings.

Table 845. Results

Name	Type	Description
`modelInfo`	Map	Details of the trained model.
`configuration`	Map	The configuration used to run the procedure.
`trainMillis`	Integer	Milliseconds to train the model.

Table 846. Details on `modelInfo`

Name	Type	Description
`name`	String	The name of the trained model.
`type`	String	The type of the trained model. Always `graphSage`.
`metrics`	Map	Metrics related to running the training, details in the table below.

Table 847. Metrics collected during training

Name	Type	Description
ranEpochs	Integer	The number of ran epochs during training.
epochLosses	List	Ordered list of the losses after each epoch.
didConverge	Boolean	Indicates if the training has converged.

Run GraphSAGE in stream mode on a named graph.

```
CALL gds.beta.graphSage.stream(
  graphName: String,
  configuration: Map
) YIELD
  nodeId: Integer,
  embedding: List
```

Table 848. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 849. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 850. Algorithm specific configuration

Name	Type	Default	Optional	Description
batchSize	Integer	100	yes	The number of nodes per batch.

Table 851. Results

Name	Type	Description
nodeId	Integer	The Neo4j node ID.
embedding	List of Float	The computed node embedding.

Run GraphSAGE in mutate mode on a graph stored in the catalog.

```
CALL gds.beta.graphSage.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  mutateMillis: Integer,
  configuration: Map
```

Table 852. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 853. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 854. Algorithm specific configuration

Name	Type	Default	Optional	Description
batchSize	Integer	100	yes	The number of nodes per batch.

Table 855. Results

Name	Type	Description
nodeCount	Integer	The number of nodes processed.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for writing result data back to the projected graph.
configuration	Map	The configuration used for running the algorithm.

Run GraphSAGE in write mode on a graph stored in the catalog.

```
CALL gds.beta.graphSage.write(
  graphName: String,
  configuration: Map
)
YIELD
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  configuration: Map
```

Table 856. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 857. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 858. Algorithm specific configuration

Name	Type	Default	Optional	Description
batchSize	Integer	100	yes	The number of nodes per batch.

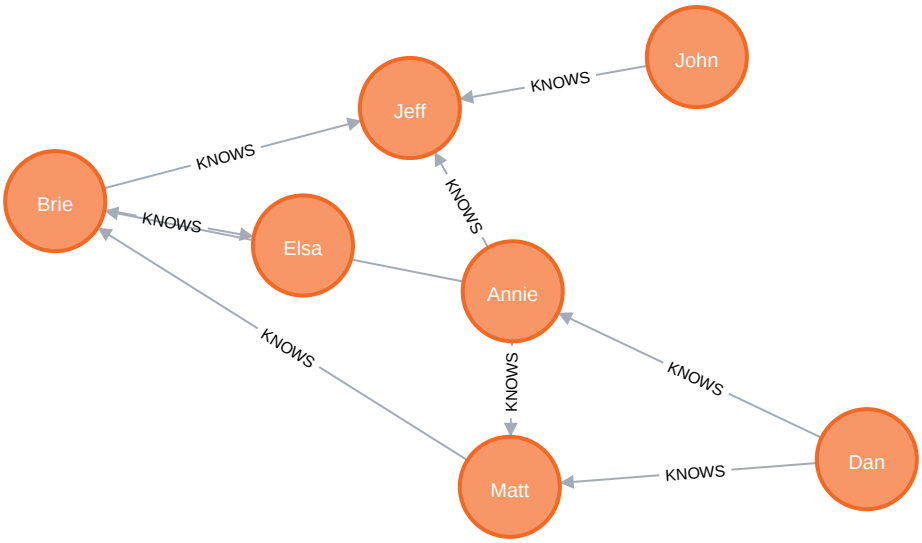
Table 859. Results

Name	Type	Description
nodeCount	Integer	The number of nodes processed.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing data.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

In this section we will show examples of running the GraphSAGE algorithm on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the algorithm in a real setting. We will do this on a small friends network graph of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  // Persons
  (  dan:Person {name: 'Dan',   age: 20, heightAndWeight: [185, 75]}),
  (annie:Person {name: 'Annie', age: 12, heightAndWeight: [124, 42]}),
  ( matt:Person {name: 'Matt',  age: 67, heightAndWeight: [170, 80]}),
  ( jeff:Person {name: 'Jeff',  age: 45, heightAndWeight: [192, 85]}),
  ( brie:Person {name: 'Brie',  age: 27, heightAndWeight: [176, 57]}),
  ( elsa:Person {name: 'Elsa',  age: 32, heightAndWeight: [158, 55]}),
  ( john:Person {name: 'John',  age: 35, heightAndWeight: [172, 76]}),

  (dan)-[:KNOWS {relWeight: 1.0}]->(annie),
  (dan)-[:KNOWS {relWeight: 1.6}]->(matt),
  (annie)-[:KNOWS {relWeight: 0.1}]->(matt),
  (annie)-[:KNOWS {relWeight: 3.0}]->(jeff),
  (annie)-[:KNOWS {relWeight: 1.2}]->(brie),
  (matt)-[:KNOWS {relWeight: 10.0}]->(brie),
  (brie)-[:KNOWS {relWeight: 1.0}]->(elsa),
  (brie)-[:KNOWS {relWeight: 2.2}]->(jeff),
  (john)-[:KNOWS {relWeight: 5.0}]->(jeff)
```

```
CALL gds.graph.project(
  'persons',
  {
    Person: {
      label: 'Person',
      properties: ['age', 'heightAndWeight']
    }
  }, {
    KNOWS: {
      type: 'KNOWS',
      orientation: 'UNDIRECTED',
      properties: ['relWeight']
    }
})
```

The algorithm is defined for UNDIRECTED graphs.

Train

Before we are able to generate node embeddings we need to train a model and store it in the model catalog. Below is an example of how to do that.

The names specified in the `featureProperties` configuration parameter must exist in the projected graph.

```
CALL gds.beta.graphSage.train(
  'persons',
  {
    modelName: 'exampleTrainModel',
    featureProperties: ['age', 'heightAndWeight'],
    aggregator: 'mean',
    activationFunction: 'sigmoid',
    randomSeed: 1337,
    sampleSizes: [25, 10]
  }
) YIELD modelInfo as info
RETURN
  info.modelName as modelName,
  info.metrics.didConverge as didConverge,
  info.metrics.ranEpochs as ranEpochs,
  info.metrics.epochLosses as epochLosses
```

Table 860. Results

modelName	didConverge	ranEpochs	epochLosses
"exampleTrainModel"	false	1	[186.04946807210226]

Due to the random initialisation of the weight variables the results may vary between different runs.

Looking at the results we can draw the following conclusions, the training converged after a single epoch, the losses are almost identical. Tuning the algorithm parameters, such as trying out different `sampleSizes`, `searchDepth`, `embeddingDimension` or `batchSize` can improve the losses. For different datasets, GraphSAGE may require different train parameters for producing good models.

The trained model is automatically registered in the model catalog.

Train with multiple node labels

In this section we describe how to train on a graph with multiple labels. The different labels may have different sets of properties. To run on such a graph, GraphSAGE is run in *multi-label mode*, in which the feature properties are projected into a common feature space. Therefore, all nodes have feature vectors of the same dimension after the projection.

The projection for a label is linear and given by a matrix of weights. The weights for each label are learned jointly with the other weights of the GraphSAGE model.

In the multi-label mode, the following is applied prior to the usual aggregation layers:

1. A property representing the label is added to the feature properties for that label
2. The feature properties for each label are projected into a feature vector of a shared dimension

The projected feature dimension is configured with `projectedFeatureDimension`, and specifying it enables the multi-label mode.

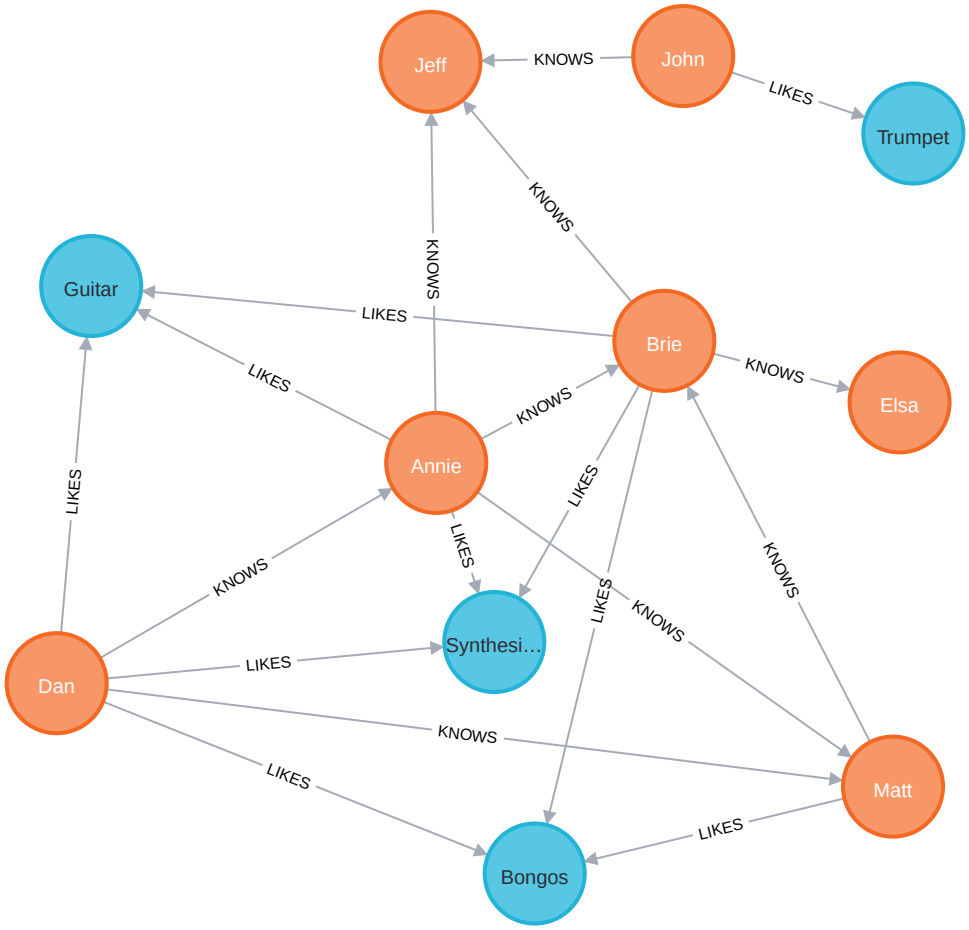
The feature properties used for a label are those present in the `featureProperties` configuration parameter which exist in the graph for that label. In the multi-label mode, it is no longer required that all labels have all the specified properties.

Assumptions

- A requirement for multi-label mode is that each node belongs to exactly one label.
- A GraphSAGE model trained in this mode must be applied on graphs with the same schema with regards to node labels and properties.

Examples

In order to demonstrate GraphSAGE with multiple labels, we add instruments and relationships of type `LIKE` between person and instrument to the example graph.



The following Cypher statement will extend the example graph in the Neo4j database:

```
MATCH
  (dan:Person {name: "Dan"}),
  (annie:Person {name: "Annie"}),
  (matt:Person {name: "Matt"}),
  (brie:Person {name: "Brie"}),
  (john:Person {name: "John"})
CREATE
  (guitar:Instrument {name: 'Guitar', cost: 1337.0}),
  (synth:Instrument {name: 'Synthesizer', cost: 1337.0}),
  (bongos:Instrument {name: 'Bongos', cost: 42.0}),
  (trumpet:Instrument {name: 'Trumpet', cost: 1337.0}),
  (dan)-[:LIKES]->(guitar),
  (dan)-[:LIKES]->(synth),
  (dan)-[:LIKES]->(bongos),
  (annie)-[:LIKES]->(guitar),
  (annie)-[:LIKES]->(synth),
  (matt)-[:LIKES]->(bongos),
  (brie)-[:LIKES]->(guitar),
  (brie)-[:LIKES]->(synth),
  (brie)-[:LIKES]->(bongos),
  (john)-[:LIKES]->(trumpet)
```

```
CALL gds.graph.project(
  'persons_with_instruments',
  {
    Person: {
      label: 'Person',
      properties: ['age', 'heightAndWeight']
    },
    Instrument: {
      label: 'Instrument',
      properties: ['cost']
    }
  }, {
    KNOWS: {
      type: 'KNOWS',
      orientation: 'UNDIRECTED'
    },
    LIKES: {
      type: 'LIKES',
      orientation: 'UNDIRECTED'
    }
})
```

We can now run GraphSAGE in multi-label mode on that graph by specifying the `projectedFeatureDimension` parameter. Multi-label GraphSAGE removes the requirement, that each node in the in-memory graph must have all `featureProperties`. However, the projections are independent per label and even if two labels have the same `featureProperty` they are considered as different features before projection. The `projectedFeatureDimension` equals the maximum length of the feature-array, i.e., `age` and `cost` both are scalar features plus the list feature `heightAndWeight` which has a length of two. For each node its unique labels properties is projected using a label specific projection to vector space of dimension `projectedFeatureDimension`. Note that the `cost` feature is only defined for the instrument nodes, while `age` and `heightAndWeight` are only defined for persons.

```
CALL gds.beta.graphSage.train(
  'persons_with_instruments',
  {
    modelName: 'multiLabelModel',
    featureProperties: ['age', 'heightAndWeight', 'cost'],
    projectedFeatureDimension: 4
  }
)
```

Train with relationship weights

The GraphSAGE implementation supports training using relationship weights. Greater relationship weight between nodes signifies that the nodes should have more similar embedding values.

The following Cypher query trains a GraphSAGE model using relationship weights

```
CALL gds.beta.graphSage.train(
  'persons',
  {
    modelName: 'weightedTrainedModel',
    featureProperties: ['age', 'heightAndWeight'],
    relationshipWeightProperty: 'relWeight',
    nodeLabels: ['Person'],
    relationshipTypes: ['KNOWS']
  }
)
```

Train when there are no node properties present in the graph

In the case when you have a graph that does not have node properties we recommend to use existing algorithm in `mutate` mode to create node properties. Good candidates are Centrality algorithms or Community algorithms.

The following example illustrates calling Degree Centrality in `mutate` mode and then using the mutated property as feature of GraphSAGE training. For the purpose of this example we are going to use the `Persons` graph, but we will not load any properties to the in-memory graph.

Create a graph projection without any node properties

```
CALL gds.graph.project(
  'noPropertiesGraph',
  'Person', {
    KNOWS: {
      type: 'KNOWS',
      orientation: 'UNDIRECTED'
    }
})
```

Run DegreeCentrality mutate to create a new property for each node

```
CALL gds.degree.mutate(
  'noPropertiesGraph',
  {
    mutateProperty: 'degree'
  }
) YIELD nodePropertiesWritten
```

Run GraphSAGE train using the property produced by DegreeCentrality as feature property

```
CALL gds.beta.graphSage.train(
  'noPropertiesGraph',
  {
    modelName: 'myModel',
    featureProperties: ['degree']
  }
)
YIELD trainMillis
RETURN trainMillis
```

`gds.degree.mutate` will create a new node property `degree` for each of the nodes in the in-memory graph, which then can be used as `featureProperty` in the `GraphSAGE.train` mode.

Using separate algorithms to produce featureProperties can also be very useful to capture graph topology properties.

Stream

To generate embeddings and stream them back to the client we can use the stream mode. We must first train a model, which we do using the `gds.beta.graphSage.train` procedure.

```
CALL gds.beta.graphSage.train(
  'persons',
  {
    modelName: 'graphSage',
    featureProperties: ['age', 'heightAndWeight'],
    embeddingDimension: 3,
    randomSeed: 19
  }
)
```

Once we have trained a model (named `'graphSage'`) we can use it to generate and stream the embeddings.

```
CALL gds.beta.graphSage.stream(
  'persons',
  {
    modelName: 'graphSage'
  }
)
YIELD nodeId, embedding
```

Table 861. Results

nodeId	embedding
0	[0.528500243954147, 0.46821819122905217, 0.7081378518617193]
1	[0.5285002439545966, 0.4682181912292858, 0.7081378518612291]
2	[0.5285002439541305, 0.4682181912290437, 0.7081378518617372]
3	[0.528500243952747, 0.46821819122832464, 0.7081378518632452]
4	[0.5285002439970667, 0.46821819125135444, 0.7081378518149409]
5	[0.5285002440594959, 0.46821819128379416, 0.7081378517468996]
6	[0.528500243952941, 0.46821819122842556, 0.7081378518630335]

Due to the random initialisation of the weight variables the results may vary slightly between the runs.

Mutate

The model trained as part of the stream example can be reused to write the results to the in-memory graph using the `mutate` mode of the procedure. Below is an example of how to achieve this.

```
CALL gds.beta.graphSage.mutate(
  'persons',
  {
    mutateProperty: 'inMemoryEmbedding',
    modelName: 'graphSage'
  }
) YIELD
  nodeCount,
  nodePropertiesWritten
```

Table 862. Results

nodeCount	nodePropertiesWritten
7	7

Write

The model trained as part of the stream example can be reused to write the results to Neo4j. Below is an example of how to achieve this.

```
CALL gds.beta.graphSage.write(
  'persons',
  {
    writeProperty: 'embedding',
    modelName: 'graphSage'
  }
) YIELD
  nodeCount,
  nodePropertiesWritten
```

Table 863. Results

nodeCount	nodePropertiesWritten
7	7

7.2.3. Node2Vec Beta

> *This section describes the Node2Vec node embedding algorithm in the Neo4j Graph Data Science library.*

Node2Vec is a node embedding algorithm that computes a vector representation of a node based on random walks in the graph. The neighborhood is sampled through random walks. Using a number of random neighborhood samples, the algorithm trains a single hidden layer neural network. The neural network is trained to predict the likelihood that a node will occur in a walk based on the occurrence of another node.

For more information on this algorithm, see:

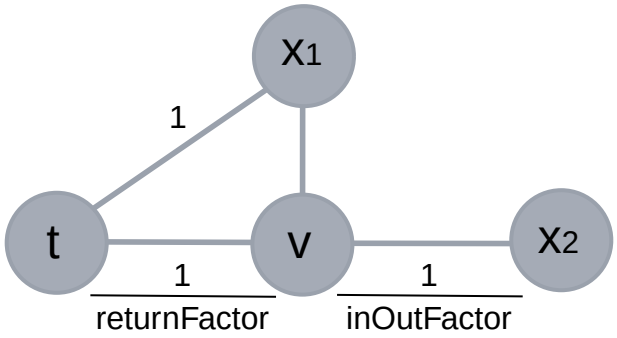
- Grover, Aditya, and Jure Leskovec. "node2vec: Scalable feature learning for networks." Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining. 2016.
- https://snap.stanford.edu/node2vec/

Random Walks

A main concept of the Node2Vec algorithm are the second order random walks. A random walk simulates a traversal of the graph in which the traversed relationships are chosen at random. In a classic random walk, each relationship has the same, possibly weighted, probability of being picked. This probability is not influenced by the previously visited nodes. The concept of second order random walks, however, tries to model the transition probability based on the currently visited node `v`, the node `t` visited before the current

one, and the node `x` which is the target of a candidate relationship. Node2Vec random walks are thus influenced by two parameters: the `returnFactor` and the `inOutFactor`:

- The `returnFactor` is used if `t` equals `x`, i.e., the random walk returns to the previously visited node.
- The `inOutFactor` is used if the distance from `t` to `x` is equal to 2, i.e., the walk traverses further away from the node `t`



The probabilities for traversing a relationship during a random walk can be further influenced by specifying a `relationshipWeightProperty`. A relationship property value greater than 1 will increase the likelihood of a relationship being traversed, a property value between 0 and 1 will decrease that probability.

For every node in the graph Node2Vec generates a series of random walks with the particular node as start node. The number of random walks per node can be influenced by the `walkPerNode` configuration parameters, the walk length is controlled by the `walkLength` parameter.

Syntax

Node2Vec syntax per mode

Run Node2Vec in stream mode on a named graph.

```
CALL gds.beta.node2vec.stream(
  graphName: String,
  configuration: Map
) YIELD
  nodeId: Integer,
  embedding: List of Float
```

Table 864. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 865. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 866. Algorithm specific configuration

Name	Type	Default	Optional	Description
walkLength	Integer	80	yes	The number of steps in a single random walk.
walksPerNode	Integer	10	yes	The number of random walks generated for each node.
inOutFactor	Float	1.0	yes	Tendency of the random walk to stay close to the start node or fan out in the graph. Higher value means stay local.
returnFactor	Float	1.0	yes	Tendency of the random walk to return to the last visited node. A value below 1.0 means a higher tendency.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights to influence the probabilities of the random walks. The weights need to be >= 0. If unspecified, the algorithm runs unweighted.
windowSize	Integer	10	yes	Size of the context window when training the neural network.
negativeSamplingRate	Integer	5	yes	Number of negative samples to produce for each positive sample.

Name	Type	Default	Optional	Description
positiveSamplingFactor	Float	`0.001`	yes	Factor for influencing the distribution for positive samples. A higher value increases the probability that frequent nodes are down-sampled.
negativeSamplingExponent	Float	`0.75`	yes	Exponent applied to the node frequency to obtain the negative sampling distribution. A value of 1.0 samples proportionally to the frequency. A value of 0.0 samples each node equally.
embeddingDimension	Integer	`128`	yes	Size of the computed node embeddings.
iterations	Integer	`1`	yes	Number of training iterations.
initialLearningRate	Float	`0.01`	yes	Learning rate used initially for training the neural network. The learning rate decreases after each training iteration.
minLearningRate	Float	`0.0001`	yes	Lower bound for learning rate as it is decreased during training.
randomSeed	Integer	`random`	yes	Seed value used to generate the random walks, which are used as the training set of the neural network. Note, that the generated embeddings are still nondeterministic.
walkBufferSize	Integer	`1000`	yes	The number of random walks to complete before starting training.

Table 867. Results

Name	Type	Description
`nodeId`	Integer	The Neo4j node ID.
`embedding`	List of Float	The computed node embedding.

Run Node2Vec in mutate mode on a graph stored in the catalog.

```
CALL gds.beta.node2vec.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 868. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 869. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 870. Algorithm specific configuration

Name	Type	Default	Optional	Description
walkLength	Integer	80	yes	The number of steps in a single random walk.
walksPerNode	Integer	10	yes	The number of random walks generated for each node.
inOutFactor	Float	1.0	yes	Tendency of the random walk to stay close to the start node or fan out in the graph. Higher value means stay local.
returnFactor	Float	1.0	yes	Tendency of the random walk to return to the last visited node. A value below 1.0 means a higher tendency.
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights to influence the probabilities of the random walks. The weights need to be >= 0. If unspecified, the algorithm runs unweighted.
windowSize	Integer	10	yes	Size of the context window when training the neural network.

Name	Type	Default	Optional	Description
negativeSamplingRate	Integer	`5`	yes	Number of negative samples to produce for each positive sample.
positiveSamplingFactor	Float	`0.001`	yes	Factor for influencing the distribution for positive samples. A higher value increases the probability that frequent nodes are down-sampled.
negativeSamplingExponent	Float	`0.75`	yes	Exponent applied to the node frequency to obtain the negative sampling distribution. A value of 1.0 samples proportionally to the frequency. A value of 0.0 samples each node equally.
embeddingDimension	Integer	`128`	yes	Size of the computed node embeddings.
iterations	Integer	`1`	yes	Number of training iterations.
initialLearningRate	Float	`0.01`	yes	Learning rate used initially for training the neural network. The learning rate decreases after each training iteration.
minLearningRate	Float	`0.0001`	yes	Lower bound for learning rate as it is decreased during training.
randomSeed	Integer	`random`	yes	Seed value used to generate the random walks, which are used as the training set of the neural network. Note, that the generated embeddings are still nondeterministic.
walkBufferSize	Integer	`1000`	yes	The number of random walks to complete before starting training.

Table 871. Results

Name	Type	Description
nodeCount	Integer	The number of nodes processed.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
postProcessingMillis	Integer	Milliseconds for post-processing of the results.
configuration	Map	The configuration used for running the algorithm.

Run Node2Vec in write mode on a graph stored in the catalog.

```
CALL gds.beta.node2vec.write(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  writeMillis: Integer,
  nodeCount: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 872. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 873. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	value of 'concurrency'	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 874. Algorithm specific configuration

Name	Type	Default	Optional	Description
walkLength	Integer	80	yes	The number of steps in a single random walk.
walksPerNode	Integer	10	yes	The number of random walks generated for each node.
inOutFactor	Float	1.0	yes	Tendency of the random walk to stay close to the start node or fan out in the graph. Higher value means stay local.
returnFactor	Float	1.0	yes	Tendency of the random walk to return to the last visited node. A value below 1.0 means a higher tendency.

Name	Type	Default	Optional	Description
relationshipWeightProperty	String	null	yes	Name of the relationship property to use as weights to influence the probabilities of the random walks. The weights need to be >= 0. If unspecified, the algorithm runs unweighted.
windowSize	Integer	10	yes	Size of the context window when training the neural network.
negativeSamplingRate	Integer	5	yes	Number of negative samples to produce for each positive sample.
positiveSamplingFactor	Float	0.001	yes	Factor for influencing the distribution for positive samples. A higher value increases the probability that frequent nodes are down-sampled.
negativeSamplingExponent	Float	0.75	yes	Exponent applied to the node frequency to obtain the negative sampling distribution. A value of 1.0 samples proportionally to the frequency. A value of 0.0 samples each node equally.
embeddingDimension	Integer	128	yes	Size of the computed node embeddings.
iterations	Integer	1	yes	Number of training iterations.
initialLearningRate	Float	0.01	yes	Learning rate used initially for training the neural network. The learning rate decreases after each training iteration.
minLearningRate	Float	0.0001	yes	Lower bound for learning rate as it is decreased during training.
randomSeed	Integer	random	yes	Seed value used to generate the random walks, which are used as the training set of the neural network. Note, that the generated embeddings are still nondeterministic.
walkBufferSize	Integer	1000	yes	The number of random walks to complete before starting training.

Table 875. Results

Name	Type	Description
nodeCount	Integer	The number of nodes processed.
nodePropertiesWritten	Integer	The number of node properties written.
preProcessingMillis	Integer	Milliseconds for preprocessing the data.
computeMillis	Integer	Milliseconds for running the algorithm.
writeMillis	Integer	Milliseconds for writing result data back to Neo4j.
configuration	Map	The configuration used for running the algorithm.

Examples

Consider the graph created by the following Cypher statement:

```
CREATE (alice:Person {name: 'Alice'})
CREATE (bob:Person {name: 'Bob'})
CREATE (carol:Person {name: 'Carol'})
CREATE (dave:Person {name: 'Dave'})
CREATE (eve:Person {name: 'Eve'})
CREATE (guitar:Instrument {name: 'Guitar'})
CREATE (synth:Instrument {name: 'Synthesizer'})
CREATE (bongos:Instrument {name: 'Bongos'})
CREATE (trumpet:Instrument {name: 'Trumpet'})

CREATE (alice)-[:LIKES]->(guitar)
CREATE (alice)-[:LIKES]->(synth)
CREATE (alice)-[:LIKES]->(bongos)
CREATE (bob)-[:LIKES]->(guitar)
CREATE (bob)-[:LIKES]->(synth)
CREATE (carol)-[:LIKES]->(bongos)
CREATE (dave)-[:LIKES]->(guitar)
CREATE (dave)-[:LIKES]->(synth)
CREATE (dave)-[:LIKES]->(bongos);
```

```
CALL gds.graph.project('myGraph', ['Person', 'Instrument'], 'LIKES');
```

Run the Node2Vec algorithm on `myGraph`

```
CALL gds.beta.node2vec.stream('myGraph', {embeddingDimension: 2})
YIELD nodeId, embedding
RETURN nodeId, embedding
```

Table 876. Results

nodeId	embedding
0	[-0.14295829832553864, 0.08884537220001221]
1	[0.016700705513358116, 0.2253911793231964]
2	[-0.06589698046445847, 0.042405471205711365]
3	[0.05862073227763176, 0.1193704605102539]
4	[0.10888434946537018, -0.18204474449157715]
5	[0.16728264093399048, 0.14098615944385529]
6	[-0.007779224775731564, 0.02114257402718067]
7	[-0.213893860578537, 0.06195802614092827]
8	[0.2479933649301529, -0.137322798371315]

7.3. Node classification pipelines

This section describes Node classification pipelines in the Neo4j Graph Data Science library.

7.3.1. Introduction

Node Classification is a common machine learning task applied to graphs: training models to classify nodes. Concretely, Node Classification models are used to predict the classes of unlabeled nodes as a node properties based on other node properties. During training, the property representing the class of the node is referred to as the target property. GDS supports both binary and multi-class node classification.

In GDS, we have Node Classification pipelines which offer an end-to-end workflow, from feature extraction to node classification. The training pipelines reside in the pipeline catalog. When a training pipeline is executed, a classification model is created and stored in the model catalog.

A training pipeline is a sequence of two phases:

I. The graph is augmented with new node properties in a series of steps.

II. The augmented graph is used for training a node classification model.

One can configure which steps should be included above. The steps execute GDS algorithms that create new node properties. After configuring the node property steps, one can select a subset of node properties to be used as features. The training phase (II) trains multiple model candidates using cross-validation, selects the best one, and reports relevant performance metrics.

After training the pipeline, a classification model is created. This model includes the node property steps and feature configuration from the training pipeline and uses them to generate the relevant features for classifying unlabeled nodes. The classification model can be applied to predict the class of previously unseen nodes. In addition to the predicted class for each node, the predicted probability for each class may also be retained on the nodes. The order of the probabilities matches the order of the classes registered in the model.

Classification can only be done with a classification model (not with a training pipeline).

The rest of this page is divided as follows:

- Creating a pipeline
- Adding node properties
- Adding features
- Configuring the node splits
- Configuring the model parameter space
- Training the pipeline
- Applying a classification model to make predictions

7.3.2. Creating a pipeline

The first step of building a new pipeline is to create one using `gds.beta.pipeline.nodeClassification.create`. This stores a trainable pipeline object in the pipeline catalog of type `Node classification training pipeline`. This represents a configurable pipeline that can later be invoked for training, which in turn creates a classification model. The latter is also a model which is

stored in the catalog with type `NodeClassification`.

Syntax

Create pipeline syntax

```
CALL gds.beta.pipeline.nodeClassification.create(
  pipelineName: String
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureProperties: List of String,
  splitConfig: Map,
  parameterSpace: List of Map
```

Table 877. Parameters

Name	Type	Description
pipelineName	String	The name of the created pipeline.

Table 878. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureProperties	List of String	List of node properties to be used as features.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Example

The following will create a pipeline:

```
CALL gds.beta.pipeline.nodeClassification.create('pipe')
```

Table 879. Results

name	nodePropertySteps	featureProperties	splitConfig	parameterSpace
"pipe"	[]	[]	{testFraction=0.3, validationFolds=3}	{RandomForest=[], LogisticRegression=[]}

This shows that the newly created pipeline does not contain any steps yet, and has defaults for the split and train parameters.

7.3.3. Adding node properties

A node classification pipeline can execute one or several GDS algorithms in mutate mode that create node properties in the in-memory graph. Such steps producing node properties can be chained one after another and created properties can later be used as features. Moreover, the node property steps that are added to the training pipeline will be executed both when training a model and when the classification pipeline is applied for classification.

The name of the procedure that should be added can be a fully qualified GDS procedure name ending with `.mutate`. The ending `.mutate` may be omitted and one may also use shorthand forms such as `node2vec` instead of `gds.beta.node2vec.mutate`.

For example, pre-processing algorithms can be used as node property steps.

Syntax

Add node property syntax

```
CALL gds.beta.pipeline.nodeClassification.addNodeProperty(
  pipelineName: String,
  procedureName: String,
  procedureConfiguration: Map
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureProperties: List of String,
  splitConfig: Map,
  parameterSpace: List of Map
```

Table 880. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
procedureName	String	The name of the procedure to be added to the pipeline.
procedureConfiguration	Map	The configuration of the procedure, excluding `graphName`, `nodeLabels` and `relationshipTypes`.

Table 881. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureProperties	List of String	List of node properties to be used as features.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Example

The following will add a node property step to the pipeline. Here we assume that the input graph contains a property `sizePerStory`.

```
CALL gds.beta.pipeline.nodeClassification.addNodeProperty('pipe', 'alpha.scaleProperties', {
  nodeProperties: 'sizePerStory',
  scaler: 'L1Norm',
  mutateProperty:'scaledSizes'
})
YIELD name, nodePropertySteps
```

Table 882. Results

name	nodePropertySteps
"pipe"	[{name=gds.alpha.scaleProperties.mutate, config={scaler=L1Norm, mutateProperty=scaledSizes, nodeProperties=sizePerStory}}]

The `scaledSizes` property can be later used as a feature.

7.3.4. Adding features

A Node Classification Pipeline allows you to select a subset of the available node properties to be used as features for the machine learning model. When executing the pipeline, the selected `nodeProperties` must be either present in the input graph, or created by a previous node property step. For example, the `embedding` property could be created by the previous example, and we expect `numberOfPosts` to already be present in the in-memory graph used as input, at train and predict time.

Syntax

Adding a feature to a pipeline syntax

```
CALL gds.beta.pipeline.nodeClassification.selectFeatures(
  pipelineName: String,
  nodeProperties: List or String
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureProperties: List of String,
  splitConfig: Map,
  parameterSpace: List of Map
```

Table 883. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
nodeProperties	List or String	Configuration for splitting the relationships.

Table 884. Results

Name	Type	Description
name	String	Name of the pipeline.

Name	Type	Description
nodePropertySteps	List of Map	List of configurations for node property steps.
featureProperties	List of String	List of node properties to be used as features.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Example

The following will select features for the pipeline. Here we assume that the input graph contains a property `sizePerStory` and `scaledSizes` was created in a `nodePropertyStep`.

```
CALL gds.beta.pipeline.nodeClassification.selectFeatures('pipe', ['scaledSizes', 'sizePerStory'])
YIELD name, featureProperties
```

Table 885. Results

name	featureProperties
"pipe"	[scaledSizes, sizePerStory]

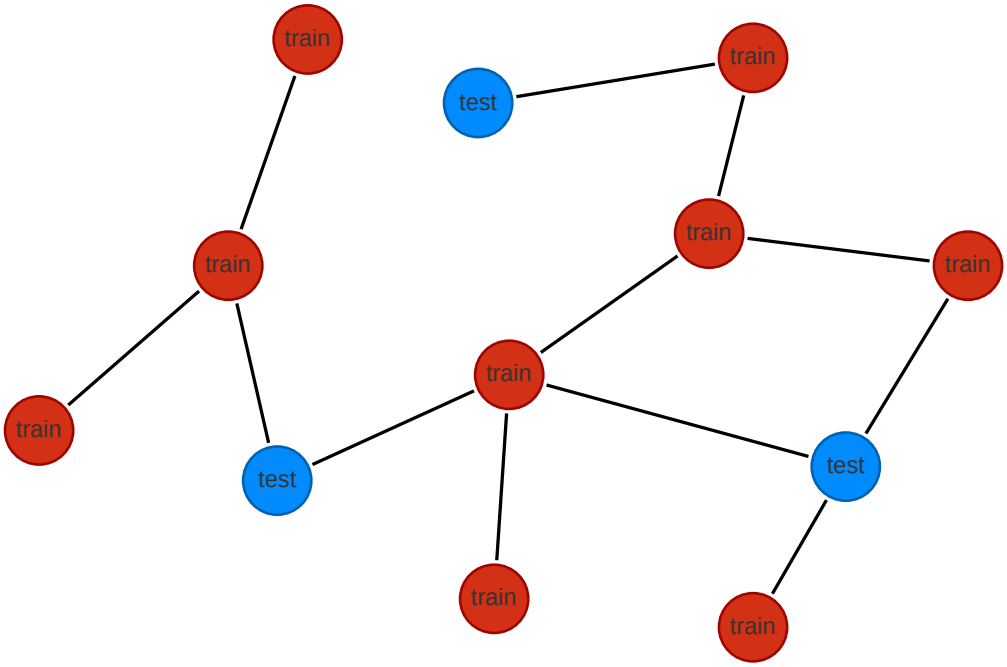
7.3.5. Configuring the node splits

Node Classification Pipelines manage splitting the nodes into several sets for training, testing and validating the models defined in the parameter space. Configuring the splitting is optional, and if omitted, splitting will be done using default settings. The splitting configuration of a pipeline can be inspected by using `gds.beta.model.list` and possibly only yielding `splitConfig`.

The node splits are used in the training process as follows:

1. The input graph is split into two parts: the train graph and the test graph. See the example below.
2. The train graph is further divided into a number of validation folds, each consisting of a train part and a validation part. See the animation below.
3. Each model candidate is trained on each train part and evaluated on the respective validation part.
4. The model with the highest average score according to the primary metric will win the training.
5. The winning model will then be retrained on the entire train graph.
6. The winning model is evaluated on the train graph as well as the test graph.
7. The winning model is retrained on the entire original graph.

Below we illustrate an example for a graph with 12 nodes. First we use a `holdoutFraction` of 0.25 to split into train and test subgraphs.



Then we carry out three validation folds, where we first split the train subgraph into 3 disjoint subsets (s1, s2 and s3), and then alternate which subset is used for validation. For each fold, all candidate models are trained in the red nodes, and validated in the green nodes.

[validation-folds-image] | *train-test-splitting/validation-folds-node-classification.gif*

Syntax

Configure the node split syntax

```
CALL gds.beta.pipeline.nodeClassification.configureSplit(
  pipelineName: String,
  configuration: Map
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureProperties: List of Strings,
  splitConfig: Map,
  parameterSpace: List of Map
```

Table 886. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
configuration	Map	Configuration for splitting the relationships.

Table 887. Configuration

Name	Type	Default	Description
validationFolds	Integer	3	Number of divisions of the training graph used during model selection.
testFraction	Double	0.3	Fraction of the graph reserved for testing. Must be in the range (0, 1). The fraction used for the training is `1 - testFraction`.

Table 888. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureProperties	List of String	List of node properties to be used as features.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Example

The following will configure the splitting of the pipeline:

```
CALL gds.beta.pipeline.nodeClassification.configureSplit('pipe', {
 testFraction: 0.2,
  validationFolds: 5
})
YIELD splitConfig
```

Table 889. Results

splitConfig
{testFraction=0.2, validationFolds=5}

We now reconfigured the splitting of the pipeline, which will be applied during training.

7.3.6. Adding model candidates

A pipeline contains a collection of configurations for model candidates which is initially empty. This collection is called the *parameter space*. One or more model configurations must be added to the *parameter space* of the training pipeline, using one of the following procedures:

- `gds.beta.pipeline.nodeClassification.addLogisticRegression`
- `gds.alpha.pipeline.nodeClassification.addRandomForest`

For information about the available training methods in GDS, logistic regression and random forest, see Training methods.

In Training the pipeline, we explain further how the configured model candidates are trained, evaluated and compared.

The parameter space of a pipeline can be inspected using `gds.beta.model.list` and optionally yielding only `parameterSpace`.

At least one model candidate must be added to the pipeline before training it.

Syntax

Configure the train parameters syntax

```
CALL gds.beta.pipeline.nodeClassification.addLogisticRegression(
  pipelineName: String,
  config: Map
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureProperties: List of String,
  splitConfig: Map,
  parameterSpace: Map
```

Table 890. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
config	Map	The logistic regression config for a potential model. The allowed parameters for a model are defined in the next table.

Table 891. Logistic regression configuration

Name	Type	Default	Optional	Description
penalty	Float	0.0	yes	Penalty used for the logistic regression. By default, no penalty is applied.
batchSize	Integer	100	yes	Number of nodes per batch.
minEpochs	Integer	1	yes	Minimum number of training epochs.
maxEpochs	Integer	100	yes	Maximum number of training epochs.
patience	Integer	1	yes	Maximum number of unproductive consecutive epochs.
tolerance	Float	0.001	yes	The minimal improvement of the loss to be considered productive.

Table 892. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureProperties	List of String	List of node properties to be used as features.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Configure the train parameters syntax

```
CALL gds.alpha.pipeline.nodeClassification.addRandomForest(
  pipelineName: String,
  config: Map
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureProperties: List of String,
  splitConfig: Map,
  parameterSpace: Map
```

Table 893. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
config	Map	The random forest config for a potential model. The allowed parameters for a model are defined in the next table.

Table 894. Random Forest configuration

Name	Type	Default	Optional	Description
maxFeaturesRatio	Float	`1 / sqrt(|features|)`	yes	The ratio of features to consider when looking for the best split
numberOfSamplesRatio	Float	`1.0`	yes	The ratio of samples to consider per decision tree. We use sampling with replacement. A value of `0` indicates using every training example (no sampling).
numberOfDecisionTrees	Integer	`100`	yes	The number of decision trees.
maxDepth	Integer	`No max depth`	yes	The maximum depth of a decision tree.
minSplitSize	Integer	`2`	yes	The minimum number of samples required to split an internal node.

Table 895. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureProperties	List of String	List of node properties to be used as features.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Example

We can add multiple model candidates to our pipeline.

The following will add a logistic regression model:

```
CALL gds.beta.pipeline.nodeClassification.addLogisticRegression('pipe', {penalty: 0.0625})
YIELD parameterSpace
```

The following will add a random forest model:

```
CALL gds.alpha.pipeline.nodeClassification.addRandomForest('pipe', {numberOfDecisionTrees: 5})
YIELD parameterSpace
```

The following will add another logistic regression model:

```
CALL gds.beta.pipeline.nodeClassification.addLogisticRegression('pipe', {maxEpochs: 500})
YIELD parameterSpace
RETURN parameterSpace.RandomForest AS randomForestSpace, parameterSpace.LogisticRegression AS
logisticRegressionSpace
```

Table 896. Results

randomForestSpace	logisticRegressionSpace
[{maxDepth=2147483647, minSplitSize=2, numberOfDecisionTrees=5, methodName=RandomForest, numberOfSamplesRatio=1.0}]	[{maxEpochs=100, minEpochs=1, penalty=0.0625, patience=1, methodName=LogisticRegression, batchSize=100, tolerance=0.001}, {maxEpochs=500, minEpochs=1, penalty=0.0, patience=1, methodName=LogisticRegression, batchSize=100, tolerance=0.001}]

The `parameterSpace` in the pipeline now contains the three different model candidates, expanded with the default values. Each specified model candidate will be tried out during the model selection in training.

These are somewhat naive examples of how to add and configure model candidates. Please see Training methods for more information on how to tune the configuration parameters of each method.

7.3.7. Training the pipeline

The train mode, `gds.beta.pipeline.nodeClassification.train`, is responsible for splitting data, feature extraction, model selection, training and storing a model for future use. Running this mode results in a classification model of type `NodeClassification`, which is then stored in the model catalog. The classification model can be applied to a possibly different graph which classifies nodes.

More precisely, the training proceeds as follows:

1. Apply `nodeLabels` and `relationshipType` filters to the graph.
2. Apply the node property steps, added according to Adding node properties, on the whole graph.
3. Select node properties to be used as features, as specified in Adding features.

4. Split the input graph into two parts: the train graph and the test graph. This is described in Configuring the node splits. These graphs are internally managed and exist only for the duration of the training.
5. Split the nodes in the train graph using stratified k-fold cross-validation. The number of folds k can be configured as described in Configuring the node splits.
6. Each model candidate defined in the parameter space is trained on each train set and evaluated on the respective validation set for every fold. The evaluation uses the specified primary metric.
7. Choose the best performing model according to the highest average score for the primary metric.
8. Retrain the winning model on the entire train graph.
9. Evaluate the performance of the winning model on the whole train graph as well as the test graph.
10. Retrain the winning model on the entire original graph.
11. Register the winning model in the Model Catalog.

The above steps describe what the procedure does logically. The actual steps as well as their ordering in the implementation may differ.

A step can only use node properties that are already present in the input graph or produced by steps, which were added before.

Metrics

The Node Classification model in the Neo4j GDS library supports the following evaluation metrics:

- Global metrics
  - `F1_WEIGHTED`
  - `F1_MACRO`
  - `ACCURACY`
- Per-class metrics
  - `F1(class=<number>)` or `F1(class=*)`
  - `PRECISION(class=<number>)` or `PRECISION(class=*)`
  - `RECALL(class=<number>)` or `RECALL(class=*)`
  - `ACCURACY(class=<number>)` or `ACCURACY(class=*)`

The `*` is syntactic sugar for reporting the metric for each class in the graph. When using a per-class metric, the reported metrics contain keys like for example `ACCURACY_class_1`.

More than one metric can be specified during training but only the first specified — the `primary` one — is used for evaluation, the results of all are present in the train results. The primary metric may not be a `*` expansion due to the ambiguity of which of the expanded metrics should be the `primary` one.

Syntax

Run Node Classification in train mode on a named graph:

```
CALL gds.beta.pipeline.nodeClassification.train(
  graphName: String,
  configuration: Map
) YIELD
  trainMillis: Integer,
  modelInfo: Map,
  modelSelectionStats: Map,
  configuration: Map
```

Table 897. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 898. Configuration

Name	Type	Default	Optional	Description
pipeline	String	n/a	no	The name of the pipeline to execute.
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.
targetProperty	String	n/a	no	The class of the node. Must be of type Integer.
metrics	List of String	n/a	no	Metrics used to evaluate the models.
randomSeed	Integer	n/a	yes	Seed for the random number generator used during training.
modelName	String	n/a	no	The name of the model to train, must not exist in the Model Catalog.

Table 899. Results

Name	Type	Description
trainMillis	Integer	Milliseconds used for training.
modelInfo	Map	Information about the training and the winning model.
modelSelectionStats	Map	Statistics about evaluated metrics for all model candidates.
configuration	Map	Configuration used for the train procedure.

The `modelInfo` can also be retrieved at a later time by using the Model List Procedure. The `modelInfo` return field has the following algorithm-specific subfields:

Table 900. Model info fields

Name	Type	Description
classes	List of Integer	Sorted list of class ids which are the distinct values of `targetProperty` over the entire graph.
bestParameters	Map	The model parameters which performed best on average on validation folds according to the primary metric.
metrics	Map	Map from metric description to evaluated metrics for the winning model over the subsets of the data, see below.
trainingPipeline	Map	The pipeline used for the training.

The structure of `modelInfo` is:

```
{
    bestParameters: Map,          ①
    trainingPipeline: Map         ②
    classes: List of Integer,     ③
    metrics: {                    ④
        <METRIC_NAME>: {          ⑤
            test: Float,          ⑥
            outerTrain: Float,    ⑦
            train: {              ⑧
                avg: Float,
                max: Float,
                min: Float,
            },
            validation: {         ⑨
                avg: Float,
                max: Float,
                min: Float,
                params: Map
            }
        }
    }
}
```

① The best scoring model candidate configuration.

② The pipeline used for the training.

③ Sorted list of class ids which are the distinct values of `targetProperty` over the entire graph.

④ The `metrics` map contains an entry for each metric description, and the corresponding results for that metric.

⑤ A metric name specified in the configuration of the procedure, e.g., `F1_MACRO` or `RECALL(class=4)`.

⑥ Numeric value for the evaluation of the winning model on the test set.

⑦ Numeric value for the evaluation of the winning model on the outer train set.

⑧ The `train` entry summarizes the metric results over the `train` set.

⑨ The `validation` entry summarizes the metric results over the `validation` set.

Example

In this section we will show examples of running a Node Classification training pipeline on a concrete graph. The intention is to illustrate what the results look like and to provide a guide in how to make use of the model in a real setting. We will do this on a small graph of a handful of nodes representing houses. This is an example of Multi-class classification, the `class` node property distinct values determine the

number of classes, in this case three (0, 1 and 2). The example graph looks like this:

The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (:House {color: 'Gold', sizePerStory: [15.5, 23.6, 33.1], class: 0}),
  (:House {color: 'Red', sizePerStory: [15.5, 23.6, 100.0], class: 0}),
  (:House {color: 'Blue', sizePerStory: [11.3, 35.1, 22.0], class: 0}),
  (:House {color: 'Green', sizePerStory: [23.2, 55.1, 0.0], class: 1}),
  (:House {color: 'Gray', sizePerStory: [34.3, 24.0, 0.0],  class: 1}),
  (:House {color: 'Black', sizePerStory: [71.66, 55.0, 0.0], class: 1}),
  (:House {color: 'White', sizePerStory: [11.1, 111.0, 0.0], class: 1}),
  (:House {color: 'Teal', sizePerStory: [80.8, 0.0, 0.0], class: 2}),
  (:House {color: 'Beige', sizePerStory: [106.2, 0.0, 0.0], class: 2}),
  (:House {color: 'Magenta', sizePerStory: [99.9, 0.0, 0.0], class: 2}),
  (:House {color: 'Purple', sizePerStory: [56.5, 0.0, 0.0], class: 2}),
  (:UnknownHouse {color: 'Pink', sizePerStory: [23.2, 55.1, 56.1]}),
  (:UnknownHouse {color: 'Tan', sizePerStory: [22.32, 102.0, 0.0]}),
  (:UnknownHouse {color: 'Yellow', sizePerStory: [39.0, 0.0, 0.0]});
```

With the graph in Neo4j we can now project it into the graph catalog to prepare it for the pipeline execution. We do this using a native projection targeting the `House` and `UnknownHouse` labels. We will also project the `sizeOfStory` property to use as a model feature, and the `class` property to use as a target feature.

In the examples below we will use named graphs and native projections as the norm. However, Cypher projections can also be used.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project('myGraph', {
    House: { properties: ['sizePerStory', 'class'] },
    UnknownHouse: { properties: 'sizePerStory' }
  },
  '*'
)
```

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `train` mode in this example. Estimating the algorithm is useful

to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in train mode:

```
CALL gds.beta.pipeline.nodeClassification.train.estimate('myGraph', {
  pipeline: 'pipe',
  nodeLabels: ['House'],
  modelName: 'nc-model',
  targetProperty: 'class',
  randomSeed: 2,
  metrics: [ 'F1_WEIGHTED' ]
})
YIELD bytesMin, bytesMax, requiredMemory
```

Table 901. Results

bytesMin	bytesMax	requiredMemory
66787480	66862560	"[63 MiB ... 63 MiB]"

If a node property step does not have an estimation implemented, the step will be ignored in the estimation.

Train

In the following examples we will demonstrate running the Node Classification training pipeline on this graph. We will train a model to predict the class in which a house belongs, based on its `sizePerStory` property.

The following will train a model using a pipeline:

```
CALL gds.beta.pipeline.nodeClassification.train('myGraph', {
  pipeline: 'pipe',
  nodeLabels: ['House'],
  modelName: 'nc-pipeline-model',
  targetProperty: 'class',
  randomSeed: 42,
  concurrency:1,
  metrics: ['F1_WEIGHTED']
}) YIELD modelInfo
RETURN
  modelInfo.bestParameters AS winningModel,
  modelInfo.metrics.F1_WEIGHTED.train.avg AS avgTrainScore,
  modelInfo.metrics.F1_WEIGHTED.outerTrain AS outerTrainScore,
  modelInfo.metrics.F1_WEIGHTED.test AS testScore
```

Table 902. Results

winningModel	avgTrainScore	outerTrainScore	testScore
{maxEpochs=100, minEpochs=1, penalty=0.0625, patience=1, methodName=LogisticRegression, batchSize=100, tolerance=0.001}	0.999999989939394	0.9999999912121211	0.9999999850000002

Here we can observe that the model candidate with penalty `0.0625` performed the best in the training phase, with an `F1_WEIGHTED` score nearing 1 over the train graph as well as on the test graph. This indicates that the model reacted very well to the train graph, and was able to generalize fairly well to unseen data. Notice that this is just a toy example on a very small graph. In order to achieve a higher test score, we may need to use better features, a larger graph, or different model configuration.

7.3.8. Applying a trained model for prediction

In the previous sections we have seen how to build up a Node Classification training pipeline and train it to produce a classification pipeline. After training, the runnable model is of type `NodeClassification` and resides in the model catalog.

The classification model can be executed with a graph in the graph catalog to predict the class of previously unseen nodes. In addition to the predicted class for each node, the predicted probability for each class may also be retained on the nodes. The order of the probabilities matches the order of the classes registered in the model.

Since the model has been trained on features which are created using the feature pipeline, the same feature pipeline is stored within the model and executed at prediction time. As during training, intermediate node properties created by the node property steps in the feature pipeline are transient and not visible after execution.

The predict graph must contain the properties that the pipeline requires and the used array properties must have the same dimensions as in the train graph. If the predict and train graphs are distinct, it is also beneficial that they have similar origins and semantics, so that the model is able to generalize well.

Syntax

Node Classification syntax per mode

Run Node Classification in stream mode on a named graph:

```
CALL gds.beta.pipeline.nodeClassification.predict.stream(
  graphName: String,
  configuration: Map
)
YIELD
  nodeId: Integer,
  predictedClass: Integer,
  predictedProbabilities: List of Float
```

Table 903. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 904. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 905. Algorithm specific configuration

Name	Type	Default	Optional	Description
includePredictedProbabilities	Boolean	false	yes	Whether to return the probability for each class. If `false` then `null` is returned in `predictedProbabilites`. The order of the classes can be inspected in the `modelInfo` of the classification model (see listing models).

Table 906. Results

Name	Type	Description
nodeId	Integer	Node ID.
predictedClass	Integer	Predicted class for this node.
predictedProbabilities	List of Float	Probabilities for all classes, for this node.

Run Node Classification in mutate mode on a named graph:

```
CALL gds.beta.pipeline.nodeClassification.predict.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 907. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 908. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 909. Algorithm specific configuration

Name	Type	Default	Optional	Description
predictedProbabilityProperty	String	n/a	yes	The node property in which the class probability list is stored. If omitted, the probability list is discarded. The order of the classes can be inspected in the `modelInfo` of the classification model (see listing models).

Table 910. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the global metrics.
mutateMillis	Integer	Milliseconds for adding properties to the in-memory graph.

Name	Type	Description
nodePropertiesWritten	Integer	Number of node properties written.
configuration	Map	Configuration used for running the algorithm.

Run Node Classification in write mode on a named graph:

```
CALL gds.beta.pipeline.nodeClassification.predict.write(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  writeMillis: Integer,
  nodePropertiesWritten: Integer,
  configuration: Map
```

Table 911. Parameters

Name	Type	Default	Optional	Description
graphName	String	`n/a`	no	The name of a graph stored in the catalog.
configuration	Map	`{}`	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 912. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	`['*']`	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	`['*']`	yes	Filter the named graph using the given relationship types.
concurrency	Integer	`4`	yes	The number of concurrent threads used for running the algorithm. Also provides the default value for 'writeConcurrency'.
writeConcurrency	Integer	`value of 'concurrency'`	yes	The number of concurrent threads used for writing the result to Neo4j.

Table 913. Algorithm specific configuration

Name	Type	Default	Optional	Description
predictedProbabilityProperty	String	`n/a`	yes	The node property in which the class probability list is stored. If omitted, the probability list is discarded. The order of the classes can be inspected in the `modelInfo` of the classification model (see listing models).

Table 914. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.

Name	Type	Description
postProcessingMillis	Integer	Milliseconds for computing the global metrics.
writeMillis	Integer	Milliseconds for writing result back to Neo4j.
nodePropertiesWritten	Integer	Number of node properties written.
configuration	Map	Configuration used for running the algorithm.

Example

In the following examples we will show how to use a classification model to predict the class of a node in your in-memory graph. In addition to the predicted class, we will also produce the probability for each class in another node property. In order to do this, we must first have an already trained model registered in the Model Catalog. We will use the model which we trained in the train example which we gave the name `'nc-pipeline-model'`.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `stream` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations, the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for running the algorithm in stream mode:

```
CALL gds.beta.pipeline.nodeClassification.predict.stream.estimate('myGraph', {
  modelName: 'nc-pipeline-model',
  includePredictedProbabilities: true,
  nodeLabels: ['UnknownHouse']
})
YIELD bytesMin, bytesMax, requiredMemory
```

Table 915. Results

bytesMin	bytesMax	requiredMemory
10200	10200	"10200 Bytes"

If a node property step does not have an estimation implemented, the step will be ignored in the estimation.

Stream

```
CALL gds.beta.pipeline.nodeClassification.predict.stream('myGraph', {
  modelName: 'nc-pipeline-model',
  includePredictedProbabilities: true,
  nodeLabels: ['UnknownHouse']
})
 YIELD nodeId, predictedClass, predictedProbabilities
WITH gds.util.asNode(nodeId) AS houseNode, predictedClass, predictedProbabilities
RETURN
  houseNode.color AS classifiedHouse,
  predictedClass,
  floor(predictedProbabilities[predictedClass] * 100) AS confidence
  ORDER BY classifiedHouse
```

Table 916. Results

classifiedHouse	predictedClass	confidence
"Pink"	0	98.0
"Tan"	1	98.0
"Yellow"	2	79.0

As we can see, the model was able to predict the pink house into class 0, tan house into class 1, and yellow house into class 2. This makes sense, as all houses in class 0 had three stories, class 1 two stories and class 2 one story, and the same is true of the pink, tan and yellow houses, respectively. Additionally, we see that the model is confident in these predictions, as the confidence is >=79% in all cases.

The indices in the `predictedProbabilities` correspond to the order of the classes in the classification model. To inspect the order of the classes, we can look at its `modelInfo` (see listing models).

Mutate

The `mutate` execution mode updates the named graph with a new node property containing the predicted class for that node. The name of the new property is specified using the mandatory configuration parameter `mutateProperty`. The result is a single summary row including information about timings and how many properties were written. The `mutate` mode is especially useful when multiple algorithms are used in conjunction.

For more details on the `mutate` mode in general, see Mutate.

```
CALL gds.beta.pipeline.nodeClassification.predict.mutate('myGraph', {
  nodeLabels: ['UnknownHouse'],
  modelName: 'nc-pipeline-model',
  mutateProperty: 'predictedClass',
  predictedProbabilityProperty: 'predictedProbabilities'
}) YIELD nodePropertiesWritten
```

Table 917. Results

nodePropertiesWritten
6

Since we specified also the `predictedProbabilityProperty` we are writing two properties for each of the 3 `UnknownHouse` nodes.

Write

The `write` execution mode writes the predicted property for each node as a property to the Neo4j database. The name of the new property is specified using the mandatory configuration parameter `writeProperty`. The result is a single summary row including information about timings and how many properties were written. The `write` mode enables directly persisting the results to the database.

For more details on the `write` mode in general, see Write.

```
CALL gds.beta.pipeline.nodeClassification.predict.write('myGraph', {
  nodeLabels: ['UnknownHouse'],
  modelName: 'nc-pipeline-model',
  writeProperty: 'predictedClass',
  predictedProbabilityProperty: 'predictedProbabilities'
}) YIELD nodePropertiesWritten
```

Table 918. Results

nodePropertiesWritten
6

Since we specified also the `predictedProbabilityProperty` we are writing two properties for each of the 3 `UnknownHouse` nodes.

7.4. Link prediction pipelines

This section describes Link prediction pipelines in the Neo4j Graph Data Science library.

7.4.1. Introduction

Link prediction is a common machine learning task applied to graphs: training a model to learn, between pairs of nodes in a graph, where relationships should exist. More precisely, the input to the machine learning model are *examples* of node pairs. During training, the node pairs are labeled as adjacent or not adjacent.

In GDS, we have Link prediction pipelines which offer an end-to-end workflow, from feature extraction to link prediction. The training pipelines reside in the pipeline catalog. When a training pipeline is executed, a prediction model is created and stored in the model catalog.

A training pipeline is a sequence of three phases:

I. From the graph three sets of node pairs are derived: feature set, training set, test set. The latter two are labeled.

II. The nodes in the graph are augmented with new properties by running a series of steps on the graph with only relationships from the feature set.

III. The train and test sets are used for training a link prediction pipeline. Link features are derived by combining node properties of node pairs.

For the training and test sets, positive examples are selected from the relationships in the graph. The negative examples are sampled from non-adjacent nodes.

One can configure which steps should be included above. The steps execute GDS algorithms that create new node properties. After configuring the node property steps, one can define how to combine node properties of node pairs into link features. The training phase (III) trains multiple model candidates using cross-validation, selects the best one, and reports relevant performance metrics.

After training the pipeline, a prediction model is created. This model includes the node property steps and link feature steps from the training pipeline and uses them to generate the relevant features for predicting new relationships. The prediction model can be applied to infer the probability of the existence of a relationship between two non-adjacent nodes.

Prediction can only be done with a prediction model (not with a training pipeline).

The rest of this page is divided as follows:

- Creating a pipeline
- Adding node properties
- Adding link features
- Configuring the relationship splits
- Configuring the model parameter space
- Training the pipeline
- Applying a trained model for prediction

7.4.2. Creating a pipeline

The first step of building a new pipeline is to create one using `gds.beta.pipeline.linkPrediction.create`. This stores a trainable pipeline object in the pipeline catalog of type `Link prediction training pipeline`. This represents a configurable pipeline that can later be invoked for training, which in turn creates a trained pipeline. The latter is also a model which is stored in the catalog with type `LinkPrediction`.

Syntax

Create pipeline syntax

```
CALL gds.beta.pipeline.linkPrediction.create(
  pipelineName: String
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureSteps: List of Map,
  splitConfig: Map,
  parameterSpace: List of Map
```

Table 919. Parameters

Name	Type	Description
pipelineName	String	The name of the created pipeline.

Table 920. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureSteps	List of Map	List of configurations for feature steps.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Example

The following will create a pipeline:

```
CALL gds.beta.pipeline.linkPrediction.create('pipe')
```

Table 921. Results

name	nodePropertySteps	featureSteps	splitConfig	parameterSpace
"pipe"	[]	[]	{negativeSamplingRatio=1.0, testFraction=0.1, validationFolds=3, trainFraction=0.1}	{RandomForest=[], LogisticRegression=[]}

This shows that the newly created pipeline does not contain any steps yet, and has defaults for the split and train parameters.

7.4.3. Adding node properties

A link prediction pipeline can execute one or several GDS algorithms in mutate mode that create node properties in the projected graph. Such steps producing node properties can be chained one after another and created properties can also be used to add features. Moreover, the node property steps that are added to the pipeline will be executed both when training a pipeline and when the trained model is applied for prediction.

The name of the procedure that should be added can be a fully qualified GDS procedure name ending with `.mutate`. The ending `.mutate` may be omitted and one may also use shorthand forms such as `node2vec` instead of `gds.beta.node2vec.mutate`.

For example, pre-processing algorithms can be used as node property steps.

Syntax

Add node property syntax

```
CALL gds.beta.pipeline.linkPrediction.addNodeProperty(
  pipelineName: String,
  procedureName: String,
  procedureConfiguration: Map
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureSteps: List of Map,
  splitConfig: Map,
  parameterSpace: List of Map
```

Table 922. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
procedureName	String	The name of the procedure to be added to the pipeline.
procedureConfiguration	Map	The configuration of the procedure, excluding `graphName`, `nodeLabels` and `relationshipTypes`.

Table 923. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureSteps	List of Map	List of configurations for feature steps.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Example

The following will add a node property step to the pipeline:

```
CALL gds.beta.pipeline.linkPrediction.addNodeProperty('pipe', 'fastRP', {
  mutateProperty: 'embedding',
  embeddingDimension: 256,
  randomSeed: 42
})
```

Table 924. Results

name	nodePropertySteps	featureSteps	splitConfig	parameterSpace
"pipe"	[{name=gds.fastRP.mutate, config={randomSeed=42, embeddingDimension=256, mutateProperty=embedding}}]	[]	{negativeSamplingRatio=1.0, testFraction=0.1, validationFolds=3, trainFraction=0.1}	{RandomForest=[], LogisticRegression=[]}

The pipeline will now execute the fastRP algorithm in mutate mode both before training a model, and when the trained model is applied for prediction. This ensures the `embedding` property can be used as an input for link features.

7.4.4. Adding link features

A Link Prediction pipeline executes a sequence of steps to compute the features used by a machine learning model. A feature step computes a vector of features for given node pairs. For each node pair, the results are concatenated into a single *link feature vector*. The order of the features in the link feature vector follows the order of the feature steps. Like with node property steps, the feature steps are also executed both at training and prediction time. The supported methods for obtaining features are described below.

Syntax

Adding a link feature to a pipeline syntax

```
CALL gds.beta.pipeline.linkPrediction.addFeature(
  pipelineName: String,
  featureType: String,
  configuration: Map
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureSteps: List of Map,
  splitConfig: Map,
  parameterSpace: List of Map
```

Table 925. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
featureType	String	The featureType determines the method used for computing the link feature. See supported types.
configuration	Map	Configuration for splitting the relationships.

Table 926. Configuration

Name	Type	Default	Description
nodeProperties	List of String	no	The names of the node properties that should be used as input.

Table 927. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureSteps	List of Map	List of configurations for feature steps.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Supported feature types

A feature step can use node properties that exist in the input graph or are added by the pipeline. For each node in each potential link, the values of `nodeProperties` are concatenated, in the configured order, into a vector *f*. That is, for each potential link the feature vector for the source node, $s = [s_1, s_2, \ldots, s_d]$, is combined with the one for the target node, $t = [t_1, t_2, \ldots, t_d]$, into a single feature vector *f*.

The supported types of features can then be described as follows:

Table 928. Supported feature types

Feature Type	Formula / Description
L2	$f = [(s_1 - t_1)^2, (s_2 - t_2)^2, ..., (s_d - t_d)^2]$
HADAMARD	$f = [s_1 * t_1, s_2 * t_2, ..., s_d * t_d]$
COSINE	$f = \frac{\sum_{i=1}^{d} s_i t_i}{\sqrt{\sum_{i=1}^{d} s_i^2}\sqrt{\sum_{i=1}^{d} t_i^2}}$

Example

The following will add a feature step to the pipeline:

```
CALL gds.beta.pipeline.linkPrediction.addFeature('pipe', 'hadamard', {
  nodeProperties: ['embedding', 'numberOfPosts']
}) YIELD featureSteps
```

Table 929. Results

featureSteps
[{name=HADAMARD, config={nodeProperties=[embedding, numberOfPosts]}}]

When executing the pipeline, the `nodeProperties` must be either present in the input graph, or created by a previous node property step. For example, the `embedding` property could be created by the previous example, and we expect `numberOfPosts` to already be present in the in-memory graph used as input, at train and predict time.

7.4.5. Configuring the relationship splits

Link Prediction training pipelines manage splitting the relationships into several sets and add sampled negative relationships to some of these sets. Configuring the splitting is optional, and if omitted, splitting will be done using default settings.

The splitting configuration of a pipeline can be inspected by using `gds.beta.model.list` and possibly only yielding `splitConfig`.

The splitting of relationships proceeds internally in the following steps:

1. The graph is filtered according to specified `nodeLabels` and `relationshipTypes`, which are configured at train time.
2. The relationships remaining after filtering we call *positive*, and they are split into a `test` set and remaining relationships which we refer to as `test-complement` set.
    - The `test` set contains a `testFraction` fraction of the positive relationships.
    - Random negative relationships are added to the `test` set. The number of negative relationships is the number of positive ones multiplied by the `negativeSamplingRatio`.
    - The negative relationships do not coincide with positive relationships.
3. The relationships in the `test-complement` set are split into a `train` set and a `feature-input` set.
    - The `train` set contains a `trainFraction` fraction of the `test-complement` set.
    - The `feature-input` set contains `(1-trainFraction)` fraction of the `test-complement` set.
    - Random negative relationships are added to the `train` set. The number of negative relationships is the number of positive ones multiplied by the `negativeSamplingRatio`.
    - The negative relationships do not coincide with positive relationships, nor with test relationships.

The sampled positive and negative relationships are given relationship weights of `1.0` and `0.0` respectively so that they can be distinguished.

The `feature-input` graph is used, both in training and testing, for computing node properties and therefore also features which depend on node properties.

The `train` and `test` relationship sets are used for:

- determining the label (positive or negative) for each training or test example
- identifying the node pair for which link features are to be computed

However, they are not used by the algorithms run in the node property steps. The reason for this is that otherwise the model would use the prediction target (existence of a relationship) as a feature.

Syntax

Configure the relationship split syntax

```
CALL gds.beta.pipeline.linkPrediction.configureSplit(
  pipelineName: String,
  configuration: Map
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureSteps: List of Map,
  splitConfig: Map,
  parameterSpace: List of Map
```

Table 930. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
configuration	Map	Configuration for splitting the relationships.

Table 931. Configuration

Name	Type	Default	Description
validationFolds	Integer	3	Number of divisions of the training graph used during model selection.
testFraction	Double	0.1	Fraction of the graph reserved for testing. Must be in the range (0, 1).
trainFraction	Double	0.1	Fraction of the test-complement set reserved for training. Must be in the range (0, 1).
negativeSamplingRatio	Double	1.0	The desired ratio of negative to positive samples in the test and train set. More details here.

Table 932. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureSteps	List of Map	List of configurations for feature steps.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Example

The following will configure the splitting of the pipeline:

```
CALL gds.beta.pipeline.linkPrediction.configureSplit('pipe', {
  testFraction: 0.25,
  trainFraction: 0.6,
  validationFolds: 3
})
YIELD splitConfig
```

Table 933. Results

splitConfig
{negativeSamplingRatio=1.0, testFraction=0.25, validationFolds=3, trainFraction=0.6}

We now reconfigured the splitting of the pipeline, which will be applied during training.

7.4.6. Adding model candidates

A pipeline contains a collection of configurations for model candidates which is initially empty. This collection is called the *parameter space*. One or more model configurations must be added to the *parameter space* of the training pipeline, using one of the following procedures:

- `gds.beta.pipeline.linkPrediction.addLogisticRegression`
- `gds.alpha.pipeline.linkPrediction.addRandomForest`

For information about the available training methods in GDS, logistic regression and random forest, see Training methods.

In Training the pipeline, we explain further how the configured model candidates are trained, evaluated and compared.

The parameter space of a pipeline can be inspected using `gds.beta.model.list` and optionally yielding only `parameterSpace`.

At least one model candidate must be added to the pipeline before training it.

Syntax

Configure the train parameters syntax

```
CALL gds.beta.pipeline.linkPrediction.addLogisticRegression(
  pipelineName: String,
  config: Map
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureSteps: List of Map,
  splitConfig: Map,
  parameterSpace: Map
```

Table 934. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
config	Map	The logistic regression config for a model candidate. The allowed parameters for a model are defined in the next table.

Table 935. Logistic regression configuration

Name	Type	Default	Optional	Description
penalty	Float	0.0	yes	Penalty used for the logistic regression. By default, no penalty is applied.
batchSize	Integer	100	yes	Number of nodes per batch.
minEpochs	Integer	1	yes	Minimum number of training epochs.
maxEpochs	Integer	100	yes	Maximum number of training epochs.
patience	Integer	1	yes	Maximum number of unproductive consecutive epochs.
tolerance	Float	0.001	yes	The minimal improvement of the loss to be considered productive.

Table 936. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureSteps	List of Map	List of configurations for feature steps.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Configure the train parameters syntax

```
CALL gds.alpha.pipeline.linkPrediction.addRandomForest(
  pipelineName: String,
  config: Map
)
YIELD
  name: String,
  nodePropertySteps: List of Map,
  featureSteps: List of Map,
  splitConfig: Map,
  parameterSpace: Map
```

Table 937. Parameters

Name	Type	Description
pipelineName	String	The name of the pipeline.
config	Map	The random forest config for a model candidate. The allowed parameters for a model are defined in the next table.

Table 938. Random Forest configuration

Name	Type	Default	Optional	Description
maxFeaturesRatio	Float	`1 / sqrt(|features|)`	yes	The ratio of features to consider when looking for the best split
numberOfSamplesRatio	Float	`1.0`	yes	The ratio of samples to consider per decision tree. We use sampling with replacement. A value of `0` indicates using every training example (no sampling).
numberOfDecisionTrees	Integer	`100`	yes	The number of decision trees.
maxDepth	Integer	`No max depth`	yes	The maximum depth of a decision tree.
minSplitSize	Integer	`2`	yes	The minimum number of samples required to split an internal node.

Table 939. Results

Name	Type	Description
name	String	Name of the pipeline.
nodePropertySteps	List of Map	List of configurations for node property steps.
featureSteps	List of Map	List of configurations for feature steps.
splitConfig	Map	Configuration to define the split before the model training.
parameterSpace	List of Map	List of parameter configurations for models which the train mode uses for model selection.

Example

We can add multiple model candidates to our pipeline.

The following will add a logistic regression model:

```
CALL gds.beta.pipeline.linkPrediction.addLogisticRegression('pipe', {penalty: 0.0625})
YIELD parameterSpace
```

The following will add a random forest model:

```
CALL gds.alpha.pipeline.linkPrediction.addRandomForest('pipe', {numberOfDecisionTrees: 5})
YIELD parameterSpace
```

The following will add another logistic regression model:

```
CALL gds.beta.pipeline.linkPrediction.addLogisticRegression('pipe', {maxEpochs: 500})
YIELD parameterSpace
RETURN parameterSpace.RandomForest AS randomForestSpace, parameterSpace.LogisticRegression AS
logisticRegressionSpace
```

Table 940. Results

randomForestSpace	logisticRegressionSpace
[{maxDepth=2147483647, minSplitSize=2, numberOfDecisionTrees=5, methodName=RandomForest, numberOfSamplesRatio=1.0}]	[{maxEpochs=100, minEpochs=1, penalty=0.0625, patience=1, methodName=LogisticRegression, batchSize=100, tolerance=0.001}, {maxEpochs=500, minEpochs=1, penalty=0.0, patience=1, methodName=LogisticRegression, batchSize=100, tolerance=0.001}]

The `parameterSpace` in the pipeline now contains the three different model candidates, expanded with the default values. Each specified model candidate will be tried out during the model selection in training.

These are somewhat naive examples of how to add and configure model candidates. Please see Training methods for more information on how to tune the configuration parameters of each method.

7.4.7. Training the pipeline

The train mode, `gds.beta.pipeline.linkPrediction.train`, is responsible for splitting data, feature extraction, model selection, training and storing a model for future use. Running this mode results in a prediction model of type `LinkPrediction` being stored in the model catalog along with metrics collected during training. The model can be applied to a possibly different graph which produces a relationship type of predicted links, each having a predicted probability stored as a property.

More precisely, the procedure will in order:

1. Apply `nodeLabels` and `relationshipType` filters to the graph. All subsequent graphs have the same node set.
2. Create a relationship split of the graph into `test`, `train` and `feature-input` sets as described in

Configuring the relationship splits. These graphs are internally managed and exist only for the duration of the training.

3. Apply the node property steps, added according to Adding node properties, on the `feature-input` graph.
4. Apply the feature steps, added according to Adding link features, to the `train` graph, which yields for each `train` relationship an *instance*, that is, a feature vector and a binary label.
5. Split the training instances using stratified k-fold cross-validation. The number of folds `k` can be configured using `validationFolds` in `gds.beta.pipeline.linkPrediction.configureSplit`.
6. Train each model candidate given by the parameter space for each of the folds and evaluate the model on the respective validation set. The evaluation uses the AUCPR metric.
7. Declare as winner the model with the highest average metric across the folds.
8. Re-train the winning model on the whole training set and evaluate it on both the `train` and `test` sets. In order to evaluate on the `test` set, the feature pipeline is first applied again as for the `train` set.
9. Register the winning model in the Model Catalog.

The above steps describe what the procedure does logically. The actual steps as well as their ordering in the implementation may differ.

A step can only use node properties that are already present in the input graph or produced by steps, which were added before.

Syntax

Run Link Prediction in train mode on a named graph:

```
CALL gds.beta.pipeline.linkPrediction.train(
  graphName: String,
  configuration: Map
) YIELD
  trainMillis: Integer,
  modelInfo: Map,
  modelSelectionStats: Map,
  configuration: Map
```

Table 941. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 942. Configuration

Name	Type	Default	Optional	Description
modelName	String	n/a	no	The name of the model to train, must not exist in the Model Catalog.
pipeline	String	n/a	no	The name of the pipeline to execute.

Name	Type	Default	Optional	Description
negativeClassWeight	Float	1.0	yes	Weight of negative examples in model evaluation. Positive examples have weight 1. More details here.
randomSeed	Integer	n/a	yes	Seed for the random number generator used during training.
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 943. Results

Name	Type	Description
trainMillis	Integer	Milliseconds used for training.
modelInfo	Map	Information about the training and the winning model.
modelSelectionStats	Map	Statistics about evaluated metrics for all model candidates.
configuration	Map	Configuration used for the train procedure.

The `modelInfo` can also be retrieved at a later time by using the Model List Procedure. The `modelInfo` return field has the following algorithm-specific subfields:

Table 944. Model info fields

Name	Type	Description
bestParameters	Map	The model parameters which performed best on average on validation folds according to the primary metric.
metrics	Map	Map from metric description to evaluated metrics for the winning model over the subsets of the data, see below.
trainingPipeline	Map	The pipeline used for the training.

The structure of `modelInfo` is:

```
{
    bestParameters: Map,          ①
    trainingPipeline: Map         ②
    metrics: {                    ③
        AUCPR: {
            test: Float,          ④
            outerTrain: Float,    ⑤
            train: {              ⑥
                avg: Float,
                max: Float,
                min: Float,
            },
            validation: {         ⑦
                avg: Float,
                max: Float,
                min: Float
            }
        }
    }
}
```

① The best scoring model candidate configuration.

② The pipeline used for the training.

③ The `metrics` map contains an entry for each metric description (currently only `AUCPR`) and the corresponding results for that metric.

④ Numeric value for the evaluation of the best model on the test set.

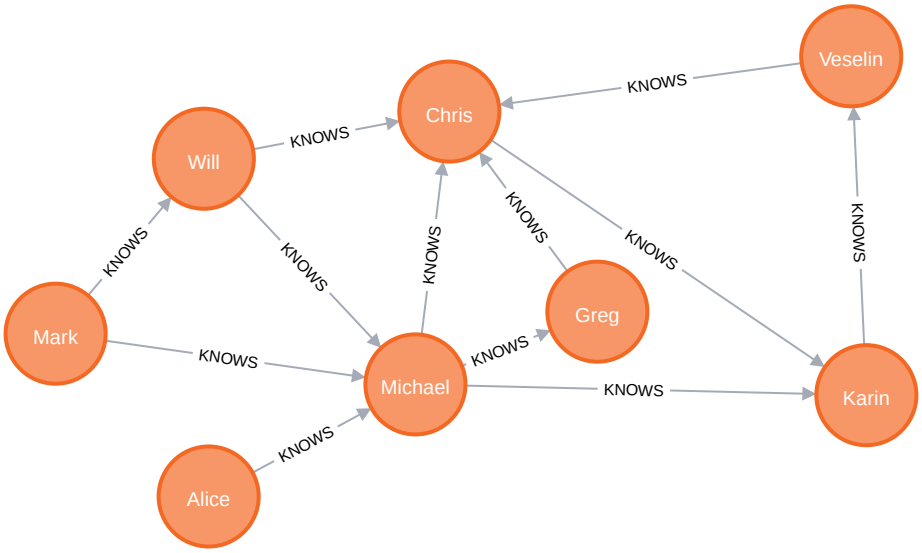
⑤ Numeric value for the evaluation of the best model on the outer train set.

⑥ The `train` entry summarizes the metric results over the `train` set.

⑦ The `validation` entry summarizes the metric results over the `validation` set.

Example

In this example we will create a small graph and use the training pipeline we have built up thus far. The graph consists of a handful nodes connected in a particular pattern. The example graph looks like this:



The following Cypher statement will create the example graph in the Neo4j database:

```
CREATE
  (alice:Person {name: 'Alice', numberOfPosts: 38}),
  (michael:Person {name: 'Michael', numberOfPosts: 67}),
  (karin:Person {name: 'Karin', numberOfPosts: 30}),
  (chris:Person {name: 'Chris', numberOfPosts: 132}),
  (will:Person {name: 'Will', numberOfPosts: 6}),
  (mark:Person {name: 'Mark', numberOfPosts: 32}),
  (greg:Person {name: 'Greg', numberOfPosts: 29}),
  (veselin:Person {name: 'Veselin', numberOfPosts: 3}),

  (alice)-[:KNOWS]->(michael),
  (michael)-[:KNOWS]->(karin),
  (michael)-[:KNOWS]->(chris),
  (michael)-[:KNOWS]->(greg),
  (will)-[:KNOWS]->(michael),
  (will)-[:KNOWS]->(chris),
  (mark)-[:KNOWS]->(michael),
  (mark)-[:KNOWS]->(will),
  (greg)-[:KNOWS]->(chris),
  (veselin)-[:KNOWS]->(chris),
  (karin)-[:KNOWS]->(veselin),
  (chris)-[:KNOWS]->(karin);
```

With the graph in Neo4j we can now project it into the graph catalog. We do this using a native projection targeting the `Person` nodes and the `KNOWS` relationships. We will also project the `numberOfPosts` property, so it can be used when creating link features. For the relationships we must use the `UNDIRECTED` orientation. This is because the Link Prediction pipelines are defined only for undirected graphs.

The following statement will project a graph using a native projection and store it in the graph catalog under the name 'myGraph'.

```
CALL gds.graph.project(
  'myGraph',
  {
    Person: {
      properties: ['numberOfPosts']
    }
  },
  {
    KNOWS: {
      orientation: 'UNDIRECTED'
    }
  }
)
```

The Link Prediction model requires the graph to be created using the `UNDIRECTED` orientation for relationships.

Memory Estimation

First off, we will estimate the cost of training the pipeline by using the `estimate` procedure. Estimation is useful to understand the memory impact that training the pipeline on your graph will have. When actually training the pipeline the system will perform an estimation and prohibit the execution if the estimation shows there is a very high probability of the execution running out of memory. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for training the pipeline:

```
CALL gds.beta.pipeline.linkPrediction.train.estimate('myGraph', {
  pipeline: 'pipe',
  modelName: 'lp-pipeline-model'
})
YIELD requiredMemory
```

Table 945. Results

requiredMemory
"[58 KiB ... 1807 KiB]"

Training

The following will train a model using a pipeline:

```
CALL gds.beta.pipeline.linkPrediction.train('myGraph', {
  pipeline: 'pipe',
  modelName: 'lp-pipeline-model',
  randomSeed: 42
}) YIELD modelInfo
RETURN
  modelInfo.bestParameters AS winningModel,
  modelInfo.metrics.AUCPR.train.avg AS avgTrainScore,
  modelInfo.metrics.AUCPR.outerTrain AS outerTrainScore,
  modelInfo.metrics.AUCPR.test AS testScore
```

Table 946. Results

winningModel	avgTrainScore	outerTrainScore	testScore
{maxDepth=2147483647, minSplitSize=2, numberOfDecisionTrees=5, methodName=RandomForest, numberOfSamplesRatio=1.0}	0.904365079365079	0.971428571428572	0.583333333333333

We can see the RandomForest model configuration with `numberOfDecisionTrees = 5` (and defaults filled for remaining parameters) was selected, and has a score of `0.58` on the test set. The score computed as the AUCPR metric, which is in the range [0, 1]. A model which gives higher score to all links than non-links will have a score of 1.0, and a model that assigns random scores will on average have a score of 0.5.

7.4.8. Applying a trained model for prediction

In the previous sections we have seen how to build up a Link Prediction training pipeline and train it to produce a predictive model. After training, the runnable model is of type `LinkPrediction` and resides in the model catalog.

The trained model can then be applied to a graph in the graph catalog to create a new relationship type containing the predicted links. The relationships also have a property which stores the predicted probability of the link, which can be seen as a relative measure of the model's prediction confidence.

Since the model has been trained on features which are created using the feature pipeline, the same feature pipeline is stored within the model and executed at prediction time. As during training, intermediate node properties created by the node property steps in the feature pipeline are transient and

not visible after execution.

When using the model for prediction, the relationships of the input graph are used in two ways. First, the input graph is fed into the feature pipeline and therefore influences predictions if there is at least one step in the pipeline which uses the input relationships (typically any node property step does). Second, predictions are carried out on each node pair that is not connected in the input graph.

The predicted links are sorted by score before the ones having score below the configured `threshold` are discarded. Finally, the configured `topN` predictions are stored back to the projected graph.

It is necessary that the predict graph contains the properties that the pipeline requires and that the used array properties have the same dimensions as in the train graph. If the predict and train graphs are distinct, it is also beneficial that they have similar origins and semantics, so that the model is able to generalize well.

Syntax

Link Prediction syntax per mode

Run Link Prediction in mutate mode on a named graph:

```
CALL gds.beta.pipeline.linkPrediction.predict.mutate(
  graphName: String,
  configuration: Map
)
YIELD
  preProcessingMillis: Integer,
  computeMillis: Integer,
  postProcessingMillis: Integer,
  mutateMillis: Integer,
  relationshipsWritten: Integer,
  probabilityDistribution: Integer,
  samplingStats: Map,
  configuration: Map
```

Table 947. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 948. Configuration

Name	Type	Default	Optional	Description
modelName	String	n/a	no	The name of a Link Prediction model in the model catalog.
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.
mutateRelationshipType	String	n/a	no	The relationship type used for the new relationships written to the projected graph.
mutateProperty	String	'probability'	yes	The relationship property in the GDS graph to which the result is written.

Table 949. Algorithm specific configuration

Name	Type	Default	Optional	Description
sampleRate	Float	n/a	no	Sample rate to determine how many links are considered for each node. If set to 1, all possible links are considered, i.e., exhaustive search. Otherwise, a kNN-based approximate search will be used. Value must be between 0 (exclusive) and 1 (inclusive).
topN [4]	Integer	n/a	no	Limit on predicted relationships to output.

Name	Type	Default	Optional	Description
threshold [4]	Float	`0.0`	yes	Minimum predicted probability on relationships to output.
topK [5]	Integer	`10`	yes	Limit on number of predicted relationships to output for each node. This value cannot be lower than 1.
deltaThreshold [5]	Float	`0.001`	yes	Value as a percentage to determine when to stop early. If fewer updates than the configured value happen, the algorithm stops. Value must be between 0 (exclusive) and 1 (inclusive).
maxIterations [5]	Integer	`100`	yes	Hard limit to stop the algorithm after that many iterations.
randomJoins [5]	Integer	`10`	yes	Between every iteration, how many attempts are being made to connect new node neighbors based on random selection.
initialSampler [5]	String	`"uniform"`	yes	The method used to sample the first `k` random neighbors for each node. "uniform" and "randomWalk", both case-insensitive, are valid inputs.
randomSeed [5]	Integer	`n/a`	yes	The seed value to control the randomness of the algorithm. Note that `concurrency` must be set to 1 when setting this parameter.

Table 950. Results

Name	Type	Description
preProcessingMillis	Integer	Milliseconds for preprocessing the graph.
computeMillis	Integer	Milliseconds for running the algorithm.
postProcessingMillis	Integer	Milliseconds for computing the global metrics.
mutateMillis	Integer	Milliseconds for adding properties to the projected graph.
relationshipsWritten	Integer	Number of relationships created.
probabilityDistribution	Map	Description of distribution of predicted probabilities.
samplingStats	Map	Description of how predictions were sampled.
configuration	Map	Configuration used for running the algorithm.

Run Link Prediction in stream mode on a named graph:

```
CALL gds.beta.pipeline.linkPrediction.predict.stream(
  graphName: String,
  configuration: Map
)
YIELD
  node1: Integer,
  node2: Integer,
  probability: Float
```

Table 951. Parameters

Name	Type	Default	Optional	Description
graphName	String	n/a	no	The name of a graph stored in the catalog.
configuration	Map	{}	yes	Configuration for algorithm-specifics and/or graph filtering.

Table 952. General configuration for algorithm execution on a named graph.

Name	Type	Default	Optional	Description
nodeLabels	List of String	['*']	yes	Filter the named graph using the given node labels.
relationshipTypes	List of String	['*']	yes	Filter the named graph using the given relationship types.
concurrency	Integer	4	yes	The number of concurrent threads used for running the algorithm.

Table 953. Algorithm specific configuration

Name	Type	Default	Optional	Description
sampleRate	Float	n/a	no	Sample rate to determine how many links are considered for each node. If set to 1, all possible links are considered, i.e., exhaustive search. Otherwise, a kNN-based approximate search will be used. Value must be between 0 (exclusive) and 1 (inclusive).
topN [6]	Integer	n/a	no	Limit on predicted relationships to output.
threshold [4]	Float	0.0	yes	Minimum predicted probability on relationships to output.
topK [7]	Integer	10	yes	Limit on number of predicted relationships to output for each node. This value cannot be lower than 1.
deltaThreshold [5]	Float	0.001	yes	Value as a percentage to determine when to stop early. If fewer updates than the configured value happen, the algorithm stops. Value must be between 0 (exclusive) and 1 (inclusive).
maxIterations [5]	Integer	100	yes	Hard limit to stop the algorithm after that many iterations.

Name	Type	Default	Optional	Description
randomJoins [5]	Integer	`10`	yes	Between every iteration, how many attempts are being made to connect new node neighbors based on random selection.
initialSampler [5]	String	`"uniform"`	yes	The method used to sample the first `k` random neighbors for each node. "uniform" and "randomWalk", both case-insensitive, are valid inputs.
randomSeed [5]	Integer	`n/a`	yes	The seed value to control the randomness of the algorithm. Note that `concurrency` must be set to 1 when setting this parameter.

Table 954. Results

Name	Type	Description
node1	Integer	Node ID of the first node.
node2	Integer	Node ID of the second node.
probability	Float	Predicted probability of a link between the nodes.

Example

In this example we will show how to use a trained model to predict new relationships in your projected graph. In order to do this, we must first have an already trained model registered in the Model Catalog. We will use the model which we trained in the train example which we gave the name `lp-pipeline-model`. The algorithm excludes predictions for existing relationships in the graph as well as self-loops.

There are two different strategies for choosing which node pairs to consider when predicting new links, exhaustive search and approximate search. Whereas the former considers all possible new links, the latter will use a randomized strategy that only considers a subset of them in order to run faster. We will explain each individually with examples in the mutate examples below.

The relationships that are produced by the write and mutate procedures are undirected, just like the input. However, no parallel relationships are produced. So for example if when doing approximate search, `a − b` are among the top predictions for `a`, and `b − a` are among the top predictions for `b`, then there will still only be one undirected relationship `a − b` produced. The stream procedure will yield a node pair only once.

Memory Estimation

First off, we will estimate the cost of running the algorithm using the `estimate` procedure. This can be done with any execution mode. We will use the `stream` mode in this example. Estimating the algorithm is useful to understand the memory impact that running the algorithm on your graph will have. When you later actually run the algorithm in one of the execution modes the system will perform an estimation. If the estimation shows that there is a very high probability of the execution going over its memory limitations,

the execution is prohibited. To read more about this, see Automatic estimation and execution blocking.

For more details on `estimate` in general, see Memory Estimation.

The following will estimate the memory requirements for applying the model:

```
CALL gds.beta.pipeline.linkPrediction.predict.stream.estimate('myGraph', {
  modelName: 'lp-pipeline-model',
  topN: 5,
  threshold: 0.45
})
YIELD requiredMemory
```

Table 955. Results

requiredMemory
"24 KiB"

Stream

```
CALL gds.beta.pipeline.linkPrediction.predict.stream('myGraph', {
  modelName: 'lp-pipeline-model',
  topN: 5,
  threshold: 0.45
})
 YIELD node1, node2, probability
 RETURN gds.util.asNode(node1).name AS person1, gds.util.asNode(node2).name AS person2, probability
 ORDER BY probability DESC, person1
```

We specified `threshold` to filter out predictions with probability less than 45%, and `topN` to further limit output to the top 5 relationships.

Table 956. Results

person1	person2	probability
"Michael"	"Veselin"	0.8
"Alice"	"Mark"	0.6
"Alice"	"Will"	0.6
"Greg"	"Veselin"	0.6
"Karin"	"Greg"	0.6

We can see, that our model predicts the most likely link is between Michael and Veselin.

Mutate

In these examples we will show how to write the predictions to your projected graph. We will use the model `lp-pipeline-model`, that we trained in the train example.

Exhaustive search

The exhaustive search will simply run through all possible new links, that is, check all node pairs that are not already connected by a relationship. For each such node pair the model we trained will be used to predict whether there they should be connected be a link or not.

```
CALL gds.beta.pipeline.linkPrediction.predict.mutate('myGraph', {
  modelName: 'lp-pipeline-model',
  relationshipTypes: ['KNOWS'],
  mutateRelationshipType: 'KNOWS_EXHAUSTIVE_PREDICTED',
  topN: 5,
  threshold: 0.45
}) YIELD relationshipsWritten, samplingStats
```

We specify `threshold` to filter out predictions with probability less than 45%, and `topN` to further limit output to the top 5 relationships. Note that we omit setting the `sampleRate` in our configuration as it defaults to 1 implying that the exhaustive search strategy is used. Because we are using the `UNDIRECTED` orientation, we will write twice as many relationships to the in-memory graph.

Table 957. Results

relationshipsWritten	samplingStats
10	{linksConsidered=16, strategy=exhaustive}

As we can see in the `samplingStats`, we use the exhaustive search strategy and check 16 possible links during the prediction. Indeed, since there are a total of `8 * (8 - 1) / 2 = 28` possible links in the graph and we already have 12, that means we check all possible new links. Although 16 links were considered, we only mutate the best five (since `topN = 5`) that are above our threshold.

If our graph is very large there may be a lot of possible new links. As such it may take a very long time to run the predictions. It may therefore be a more viable option to use a search strategy that only looks at a subset of all possible new links.

Approximate search

To avoid possibly having to run for a very long time considering all possible new links (due to the inherent quadratic complexity over node count) we can use an approximate search strategy.

The approximate search strategy lets us leverage the K-Nearest Neighbors algorithm with our model's prediction function as its similarity measure to trade off lower runtime for accuracy. Accuracy in this context refers to how close we are in finding the very best actual new possible links according to our models predictions, i.e. the best predictions that would be made by exhaustive search.

The initial set of considered links for each node is picked at random and then refined in multiple iterations based of previously predicted links. The number of iterations is limited by the configuration parameter `maxIterations`, and we also limit the number of random links considered between kNN iterations using `randomJoins`. The algorithm may stop earlier if the link predictions per node only change by a small amount, which can be controlled by the configuration parameter `deltaThreshold`. See the K-Nearest Neighbors documentation for more details on how the search works.

```
CALL gds.beta.pipeline.linkPrediction.predict.mutate('myGraph', {
  modelName: 'lp-pipeline-model',
  relationshipTypes: ['KNOWS'],
  mutateRelationshipType: 'KNOWS_APPROX_PREDICTED',
  sampleRate: 0.5,
  topK: 1,
  randomJoins: 2,
  maxIterations: 3,
  // necessary for deterministic results
  concurrency: 1,
  randomSeed: 42
})
 YIELD relationshipsWritten, samplingStats
```

In order to use the approximate strategy we make sure to set the `sampleRate` explicitly to a value `< 1.0`. In this small example we set `topK = 1` to only get one link predicted for each node. Because we are using the `UNDIRECTED` orientation, we will write twice as many relationships to the in-memory graph.

Table 958. Results

relationshipsWritten	samplingStats
16	{linksConsidered=49, didConverge=true, strategy=approximate, ranIterations=3}

As we can see in the `samplingStats`, we use the approximate search strategy and check 44 possible links during the prediction. Though in this small example we actually consider more links that in the exhaustive case, this will typically not be the case for larger graphs. Since the relationships we write are undirected, reported `relationshipsWritten` is 16 when we search for the best (`topK = 1`) prediction for each node.

7.4.9. Appendix

This section details some theoretical concepts related to how link prediction is performed in GDS. It's not strictly required reading but can be helpful in improving understanding.

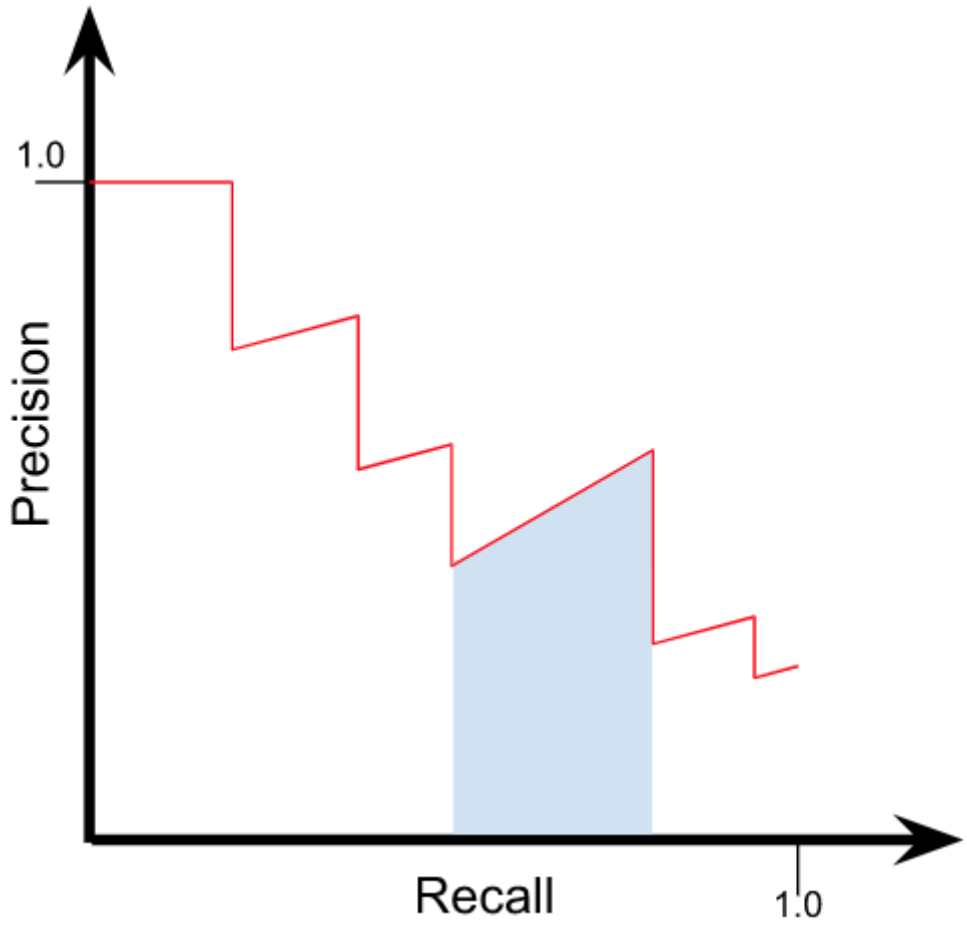
Metrics

The Link Prediction pipeline in the Neo4j GDS library supports only the Area Under the Precision-Recall Curve metric, abbreviated as AUCPR. In order to compute precision and recall we require a set of examples, each of which has a positive or negative label. For each example we have also a predicted label. Given the true and predicted labels, we can compute precision and recall (for reference, see f.e. Wikipedia).

Then, to compute the AUCPR, we construct the precision-recall curve, as follows:

- Each prediction is associated with a prediction strength. We sort the examples in descending order of prediction strength.
- For all prediction strengths that occur, we use that strength as a threshold and consider all examples of that strength or higher to be positively labeled.
- We now compute precision `p` and recall `r` and consider the tuple `(r, p)` as a point on a curve, the precision-recall curve.
- Finally, the curve is linearly interpolated and the area is computed as a union of trapezoids with corners on the points.

The curve will have a shape that looks something like this:



Note here the blue area which shows one trapezoid under the curve.

The area under the Precision-Recall curve can also be interpreted as an average precision where the average is over different classification thresholds.

Class imbalance

Most graphs have far more non-adjacent node pairs than adjacent ones (e.g. sparse graphs). Thus, typically we have an issue with *class imbalance*. There are multiple strategies to account for imbalanced data. In pipeline training procedure, the AUCPR metric is used. It is considered more suitable than the commonly used AUROC (Area Under the Receiver Operating Characteristic) metric for imbalanced data. For the metric to appropriately reflect both positive (adjacent node pairs) and negative (non-adjacent node pairs) examples, we provide the ability to both control the ratio of sampling between the classes, and to control the relative weight of classes via `negativeClassWeight`. The former is configured by the configuration parameter `negativeSamplingRatio` in configureSplits when using that procedure to generate the train and test sets. Tuning the `negativeClassWeight`, which is explained below, means weighting up or down the false positives when computing precision.

The recommended value for `negativeSamplingRatio` is the *true class ratio* of the graph, in other words, not applying *undersampling*. However, the higher the value, the bigger the test set and thus the time to evaluate. The ratio of total probability mass of negative versus positive examples in the test set is approximately `negativeSamplingRatio * negativeClassWeight`. Thus, both of these parameters can be

adjusted in tandem to trade off evaluation accuracy with speed.

The true class ratio is computed as `(q - r) / r`, where `q = n(n-1)/2` is the number of possible undirected relationships, and `r` is the number of actual undirected relationships. Please note that the `relationshipCount` reported by the graph list procedure is the *directed* count of relationships summed over all existing relationship types. Thus, we recommend using Cypher to obtain `r` on the source Neo4j graph. For example, this query will count the number of relationships of type `T` or `R`:

```
MATCH (a)-[rel:T | R]-(b)
WHERE a < b
RETURN count(rel) AS r
```

When choosing a value for `negativeClassWeight`, two factors should be considered. First, the desired ratio of total probability mass of negative versus positive examples in the test set. Second, what the ratio of sampled negative examples to positive examples was in the test set. To be consistent with *traditional* evaluation, one should choose parameters so that `negativeSamplingRatio * negativeClassWeight = 1.0`, for example by setting the values to the true class ratio and its reciprocal, or both values to `1.0`.

Alternatively, one can aim for the ratio of total probability weight between the classes to be close to the true class ratio. That is, making sure `negativeSamplingRatio * negativeClassWeight` is close to the true class ratio. The reported metric (AUCPR) then better reflects the expected precision on unseen highly imbalanced data. With this type of evaluation one has to adjust expectations as the metric value then becomes much smaller.

7.5. Pipeline catalog

> *This section details the pipeline catalog operations available to manage named training pipelines within the Neo4j Graph Data Science library.*

In GDS, we have machine learning pipelines which offer an end-to-end workflow, from graph feature extraction to model training. This includes the following:

- Node Classification pipelines
- Link Prediction pipelines

The pipeline catalog is a concept within the GDS library that allows managing multiple training pipelines by name.

This chapter explains the available pipeline catalog operations.

7.5.1. Listing pipelines

Information about pipelines in the catalog can be retrieved using the `gds.beta.pipeline.list()` procedure.

Syntax

List pipelines from the catalog:

```
CALL gds.beta.pipeline.list(pipelineName: String)
YIELD
    pipelineName: String,
    pipelineType: String,
    creationTime: DateTime,
    pipelineInfo: Map
```

Table 959. Parameters

Name	Type	Default	Optional	Description
pipelineName	String	n/a	yes	The name of a pipeline. If not specified, all pipelines in the catalog are listed.

Table 960. Results

Name	Type	Description
pipelineName	String	The name of the pipeline.
pipelineType	String	The type of the pipeline.
creationTime	Datetime	Time when the pipeline was created.
pipelineInfo	Map	Detailed information about this particular training pipeline, such as about intermediate steps in the pipeline.

Examples

Once we have created training pipelines in the catalog we can see information about either all of them or a single model using its name.

To exemplify listing pipelines, we create a node classification pipeline and a link prediction pipeline so that we have something to list.

Creating a link prediction training pipelines:

```
CALL gds.beta.pipeline.linkPrediction.create('lpPipe')
```

Creating node classification training pipelines:

```
CALL gds.beta.pipeline.nodeClassification.create('ncPipe')
```

Listing all pipelines

Listing detailed information about all pipelines:

```
CALL gds.beta.pipeline.list()
YIELD pipelineName, pipelineType
```

Table 961. Results

pipelineName	pipelineType
"lpPipe"	"Link prediction training pipeline"
"ncPipe"	"Node classification training pipeline"

Listing a specific pipeline

Listing detailed information about specific pipeline:

```
CALL gds.beta.pipeline.list('lpPipe')
YIELD pipelineName, pipelineType
```

Table 962. Results

pipelineName	pipelineType
"lpPipe"	"Link prediction training pipeline"

7.5.2. Checking if a pipeline exists

We can check if a pipeline is available in the catalog by looking up its name.

Syntax

Check if a pipeline exists in the catalog:

```
CALL gds.beta.pipeline.exists(pipelineName: String)
YIELD
    pipelineName: String,
    pipelineType: String,
    exists: Boolean
```

Table 963. Parameters

Name	Type	Default	Optional	Description
pipelineName	String	n/a	no	The name of a pipeline.

Table 964. Results

Name	Type	Description
pipelineName	String	The name of a pipeline.
pipelineType	String	The type of the pipeline.
exists	Boolean	True, if the pipeline exists in the pipeline catalog.

Example

In this section we are going to demonstrate the usage of `gds.beta.pipeline.exists`. To exemplify this, we create a node classification pipeline and check for its existence.

Creating a link prediction training pipelines:

```
CALL gds.beta.pipeline.nodeClassification.create('pipe')
```

Check if a pipeline exists in the catalog:

```
CALL gds.beta.pipeline.exists('pipe')
```

Table 965. Results

pipelineName	pipelineType	exists
"pipe"	"Node classification training pipeline"	true

7.5.3. Removing pipelines

If we no longer need a training pipeline, we can remove it from the catalog.

Syntax

Remove a pipeline from the catalog:

```
CALL gds.beta.pipeline.drop(pipelineName: String, failIfMissing: Boolean)
YIELD
    pipelineName: String,
    pipelineType: String,
    creationTime: DateTime,
    pipelineInfo: Map
```

Table 966. Parameters

Name	Type	Default	Optional	Description
pipelineName	String	`n/a`	yes	The name of a pipeline. If not specified, all pipelines in the catalog are listed.
failIfMissing	Boolean	`true`	yes	By default, the library will raise an error when trying to remove a non-existing pipeline. When set to `false`, the procedure returns an empty result.

Table 967. Results

Name	Type	Description
pipelineName	String	The name of the pipeline.
pipelineType	String	The type of the pipeline.
creationTime	Datetime	Time when the pipeline was created.
pipelineInfo	Map	Detailed information about this particular training pipeline, such as about intermediate steps in the pipeline.

Example

In this section we are going to demonstrate the usage of `gds.beta.pipeline.drop`. To exemplify this, we

first create a link prediction pipeline.

Creating a link prediction training pipelines:

```
CALL gds.beta.pipeline.linkPrediction.create('pipe')
```

Remove a pipeline from the catalog:

```
CALL gds.beta.pipeline.drop('pipe')
YIELD pipelineName, pipelineType
```

Table 968. Results

pipelineName	pipelineType
"pipe"	"Link prediction training pipeline"

Since the `failIfMissing` flag defaults to `true`, if the pipeline name does not exist, an error will be raised.

7.6. Model catalog

This section details the model catalog operations available to manage named trained models within the Neo4j Graph Data Science library.

Machine learning algorithms which support the `train` mode produce trained models which are stored in the Model Catalog. Similarly, `predict` procedures can use such trained models to produce predictions. A model is generally a mathematical formula representing real-world or fictitious entities. Each algorithm requiring a trained model provides the formulation and means to compute this model.

The model catalog is a concept within the GDS library that allows storing and managing multiple trained models by name.

This chapter explains the available model catalog operations.

Name	Description
`gds.beta.model.list`	Prints information about models that are currently available in the catalog.
`gds.beta.model.exists`	Checks if a named model is available in the catalog.
`gds.beta.model.drop`	Drops a named model from the catalog.
`gds.alpha.model.store`	Stores a names model from the catalog on disk.
`gds.alpha.model.load`	Loads a named and stored model from disk.
`gds.alpha.model.delete`	Removes a named and stored model from disk.
`gds.alpha.model.publish`	Makes a model accessible to all users.

Training models is a responsibility of the corresponding algorithm and is provided by a procedure mode - `train`. Training, using, listing, and dropping named models are management operations bound to a Neo4j user. Models trained by a different Neo4j user are not accessible at any time.

7.6.1. Listing models

Information about models in the catalog can be retrieved using the `gds.beta.model.list()` procedure.

Syntax

List models from the catalog:

```
CALL gds.beta.model.list(modelName: String)
YIELD
    modelInfo: Map,
    trainConfig: Map,
    graphSchema: Map,
    loaded: Boolean,
    stored: Boolean,
    creationTime: DateTime,
    shared: Boolean
```

Table 969. Parameters

Name	Type	Default	Optional	Description
modelName	String	n/a	yes	The name of a model. If not specified, all models in the catalog are listed.

Table 970. Results

Name	Type	Description
modelInfo	Map	Detailed information about the trained model. Always includes the `modelName` and `modelType`, e.g., GraphSAGE. Dependent on the model type, there are additional fields.
trainConfig	Map	The configuration used for training the model.
graphSchema	Map	The schema of the graph on which the model was trained.
loaded	Boolean	True, if the model is loaded in the in-memory model catalog.
stored	Boolean	True, if the model is stored on disk.
creationTime	Datetime	Time when the model was created.
shared	Boolean	True, if the model is shared between users.

Examples

Once we have trained models in the catalog we can see information about either all of them or a single model using its name

Listing all models

Listing detailed information about all models:

```
CALL gds.beta.model.list()
YIELD modelInfo, loaded, shared, stored
RETURN modelInfo.modelName AS modelName, loaded, shared, stored
```

Table 971. Results

modelName	loaded	shared	stored
"my-model"	true	false	false

Listing a specific model

Listing detailed information about specific model:

```
CALL gds.beta.model.list('my-model')
YIELD modelInfo, loaded, shared, stored
RETURN modelInfo.modelName AS modelName, loaded, shared, stored
```

Table 972. Results

modelName	loaded	shared	stored
"my-model"	true	false	false

7.6.2. Checking if a model exists

We can check if a model is available in the catalog by looking up its name.

Syntax

Check if a model exists in the catalog:

```
CALL gds.beta.model.exists(modelName: String)
YIELD
    modelName: String,
    modelType: String,
    exists: Boolean
```

Table 973. Parameters

Name	Type	Default	Optional	Description
modelName	String	n/a	no	The name of a model.

Table 974. Results

Name	Type	Description
modelName	String	The name of a model.
modelType	String	The type of the model.

Name	Type	Description
exists	Boolean	True, if the model exists in the model catalog.

Example

In this section we are going to demonstrate the usage of `gds.beta.model.exists`. Assume we trained a model by running `train` on one of our Machine learning algorithms.

Check if a model exists in the catalog:

```
CALL gds.beta.model.exists('my-model');
```

Table 975. Results

modelName	modelType	exists
"my-model"	"graphSage"	true

7.6.3. Removing models

If we no longer need a trained model and want to free up memory, we can remove the model from the catalog.

Syntax

Remove a model from the catalog:

```
CALL gds.beta.model.drop(modelName: String, failIfMissing: Boolean)
YIELD
    modelInfo: Map,
    trainConfig: Map,
    graphSchema: Map,
    loaded: Boolean,
    stored: Boolean,
    creationTime: DateTime,
    shared: Boolean
```

Table 976. Parameters

Name	Type	Default	Optional	Description
modelName	String	`n/a`	no	The name of a model stored in the catalog.
failIfMissing	Boolean	`true`	yes	By default, the library will raise an error when trying to remove a non-existing model. When set to `false`, the procedure returns an empty result.

Table 977. Results

Name	Type	Description
modelInfo	Map	Detailed information about the trained model. Always includes the `modelName` and `modelType`, e.g., GraphSAGE. Dependent on the model type, there are additional fields.

Name	Type	Description
trainConfig	Map	The configuration used for training the model.
graphSchema	Map	The schema of the graph on which the model was trained.
loaded	Boolean	True, if the model is loaded in the in-memory model catalog.
stored	Boolean	True, if the model is stored on disk.
creationTime	Datetime	Time when the model was created.
shared	Boolean	True, if the model is shared between users.

Example

In this section we are going to demonstrate the usage of `gds.beta.model.drop`. Assume we trained a model by running `train` on one of our Machine learning algorithms.

Remove a model from the catalog:

```
CALL gds.beta.model.drop('my-model')
YIELD modelInfo, loaded, shared, stored
RETURN modelInfo.modelName AS modelName, loaded, shared, stored
```

Table 978. Results

modelName	loaded	shared	stored
"my-model"	true	false	false

In this example, the removed `my-model` was of the imaginary type `some-model-type`. The model was loaded in-memory, but neither stored on disk nor published.

If the model name does not exist, an error will be raised.

7.6.4. Storing models on disk

The model store feature is in the alpha tier.

The model catalog exists as long as the Neo4j instance is running. When Neo4j is restarted, models are no longer available in the catalog and need to be trained again. This can be prevented by storing a model on disk.

The location of the stored models can be configured via the configuration parameter `gds.model.store_location` in the `neo4j.conf`. The location must be a directory and writable by the Neo4j process.

The `gds.model.store_location` parameter must be configured for this feature.

Storing models from the catalog on disk Alpha

Models that can be stored

- GraphSAGE model
- Node Classification model
- Link Prediction model

For Node Classification and Link Prediction, storing a model is only supported for a subset of trainer-methods. The trainer method of a model can be inspected in the `modelInfo` under `bestParameters`.

Currently, we only support Logistic Regression.

Syntax

Remove a model from the catalog:

```
CALL gds.alpha.model.store(
    modelName: String,
    failIfUnsupportedType: Boolean
)
YIELD
    modelName: String,
    storeMillis: Integer
```

Table 979. Parameters

Name	Type	Default	Optional	Description
modelName	String	n/a	no	The name of a model.
failIfUnsupportedType	Boolean	true	yes	By default, the library will raise an error when trying to store a non-supported model. When set to `false`, the procedure returns an empty result.

Table 980. Results

Name	Type	Description
modelName	String	The name of the stored model.
storeMillis	Integer	The number of milliseconds it took to store the model.

Example

Store a model on disk:

```
CALL gds.alpha.model.store('my-model')
YIELD
  modelName,
  storeMillis
```

Loading models from disk Alpha

GDS will discover available models from the configured store location upon database startup. During discovery, only model metadata is loaded, not the actual model data. In order to use a stored model, it has to be explicitly loaded.

Syntax

Remove a model from the catalog:

```
CALL gds.alpha.model.load(modelName: String)
YIELD
    modelName: String,
    loadMillis: Integer
```

Table 981. Parameters

Name	Type	Default	Optional	Description
modelName	String	n/a	no	The name of a model.

Table 982. Results

Name	Type	Description
modelName	String	The name of the loaded model.
loadMillis	Integer	The number of milliseconds it took to load the model.

Example

Store a model on disk:

```
CALL gds.alpha.model.load('my-model')
YIELD
  modelName,
  loadMillis
```

To verify if a model is loaded, we can use the `gds.beta.model.list` procedure. The procedure returns flags to indicate if the model is stored and if the model is loaded into memory. The operation is idempotent, and skips loading if the model is already loaded.

Deleting models from disk Alpha

To remove a stored model from disk, it has to be deleted. This is different from dropping a model. Dropping a model will remove it from the in-memory model catalog, but not from disk. Deleting a model will remove it from disk, but keep it in the in-memory model catalog if it was already loaded.

Syntax

Remove a model from the catalog:

```
CALL gds.alpha.model.delete(modelName: String)
YIELD
    modelName: String,
    deleteMillis: Integer
```

Table 983. Parameters

Name	Type	Default	Optional	Description
modelName	String	n/a	no	The name of a model.

Table 984. Results

Name	Type	Description
modelName	String	The name of the loaded model.
deleteMillis	Integer	The number of milliseconds it took to delete the model.

Example

Store a model on disk:

```
CALL gds.alpha.model.delete('my-model')
YIELD
  modelName,
  deleteMillis
```

7.6.5. Publishing models

Publishing models is an alpha tier feature.

By default, a trained model is visible to the user that created it. Making a model accessible to other users can be achieved by publishing it.

Syntax

Publish a model from the catalog:

```
CALL gds.alpha.model.publish(modelName: String)
YIELD
    modelInfo: Map,
    trainConfig: Map,
    graphSchema: Map,
    loaded: Boolean,
    stored: Boolean,
    creationTime: DateTime,
    shared: Boolean
```

Table 985. Parameters

Name	Type	Default	Optional	Description
modelName	String	n/a	no	The name of a model stored in the catalog.

Table 986. Results

Name	Type	Description
modelInfo	Map	Detailed information about the trained model. Always includes the `modelName` and `modelType`, e.g., GraphSAGE. Dependent on the model type, there are additional fields.

Name	Type	Description
trainConfig	Map	The configuration used for training the model.
graphSchema	Map	The schema of the graph on which the model was trained.
loaded	Boolean	True, if the model is loaded in the in-memory model catalog.
stored	Boolean	True, if the model is stored on disk.
creationTime	Datetime	Time when the model was created.
shared	Boolean	True, if the model is shared between users.

Examples

Publishing trained model:

```
CALL gds.alpha.model.publish('my-model')
YIELD modelInfo, loaded, shared, stored
RETURN modelInfo.modelName AS modelName, shared
```

Table 987. Results

modelName	shared
"my-model_public"	true

We can see that the model is now shared. The shared model has the `_public` suffix.

7.7. Training methods

> *This section describes supervised machine learning methods for training pipelines in the Neo4j Graph Data Science library.*

Node Classification Pipelines and Link Prediction Pipelines are trained using supervised machine learning methods. Currently, GDS supports two such methods, namely Logistic regression and Random forest. Each of these methods have several hyperparameters that one can set to influence the training. The objective of this page is to give a brief overview of logistic regression and random forest, as well as advice on how to tune their hyperparameters.

Configuring and training model candidates using these methods is supported for Node Classification and Link Prediction pipelines.

7.7.1. Logistic regression Beta

Logistic regression is a fundamental supervised machine learning classification method. This trains a model by minimizing a loss function which depends on a weight matrix and on the training data. The loss can be minimized for example using gradient descent. In GDS we use the Adam optimizer which is a gradient descent type algorithm.

The weights are in the form of a `[c,d]` sized matrix `W` and a bias vector `b` of length `c`, where `d` is the feature

dimension and `c` is equal to the number of classes. The loss function is then defined as:

```
CE(softmax(Wx + b))
```

where `CE` is the cross entropy loss, `softmax` is the softmax function, and `x` is a feature vector training sample of length `d`.

To avoid overfitting one may also add a regularization term to the loss. In GDS, this we provide the option of adding `l2` regularization.

Tuning the hyperparameters

The parameters `maxEpochs`, `tolerance` and `patience` control for how long the training will run until termination. These parameters give ways to limit a computational budget. In general, higher `maxEpochs` and `patience` and lower `tolerance` lead to longer training but higher quality models. It is however well-known that restricting the computational budget can serve the purpose of regularization and mitigate overfitting.

When faced with a heavy training task, a strategy to perform hyperparameter optimization faster, is to initially use lower values for the budget related parameters while exploring better ranges for other general or algorithm specific parameters.

More precisely, `maxEpochs` is the maximum number of epochs trained until termination. Whether the training exhausted the maximum number of epochs or converged prior is reported in the neo4j debug log.

As for `patience` and `tolerance`, the former is the maximum number of consecutive epochs that do not improve the training loss at least by a `tolerance` fraction of the current loss. After `patience` such unproductive epochs, the training is terminated. In our experience, reasonable values for `patience` are in the range `1` to `3`.

It is also possible, via `minEpochs`, to control a minimum number of epochs before the above termination criteria enter into play.

The training algorithm applied to the above algorithms is gradient descent. The gradients are computed concurrently on batches of `batchSize` samples using `concurrency` many threads. At the end of an epoch the gradients are summed and scaled before updating the weights. Therefore `batchSize` and `concurrency` do not affect model quality, but are very useful to tune for training speed.

7.7.2. Random forest Alpha

Random forest is a popular supervised machine learning method for classification (and regression) that consists of using several decision trees, and combining the trees' predictions into an overall prediction. To train the random forest is to train each of its decision trees independently. Each decision tree is typically trained on a slightly different part of the training set, and may look at different features for its node splits.

Random forest predictions are made by simply taking the majority votes of its decision trees. The idea is that the difference in how each decision tree is trained will help avoid overfitting which is not uncommon when just training a single decision tree on the entire training set.

The approach of combining several predictors (in this case decision trees) is also known as *ensemble learning*, and using different parts of the training set for each predictor is often referred to as *bootstrap*

aggregating or *bagging*.

The loss used by the decision trees in GDS is the Gini impurity.

Tuning the hyperparameters

In order to balance matters such as bias vs variance of the model, and speed vs memory consumption of the training, GDS exposes several hyperparameters that one can tune. Each of these are described below.

Number of decision trees

This parameter sets the number of decision trees that will be part of the random forest.

Having a too small number of trees could mean that the model will overfit to some parts of the dataset.

A larger number of trees will in general mean that the training takes longer, and the memory consumption will be higher.

Max features ratio

For each node split in a decision tree, a set of features of the feature vectors are considered. The number of such features considered is the `maxFeaturesRatio` multiplied by the total number of features. If the number of features to be considered are fewer than the total number of features, a subset of all features are sampled (without replacement). This is sometimes referred to as *feature bagging*.

A high (close to 1.0) max features ratio means that the training will take longer as there are more options for how to split nodes in the decision trees. It will also mean that each decision tree will be better at predictions over the training set. While this is positive in some sense, it might also mean that each decision tree will overfit on the training set.

Max depth

This parameter sets the maximum depth of the decision trees in the random forest.

A high maximum depth means that the training might take longer, as more node splits might need to be considered. The memory footprint of the produced prediction model might also be higher since the trees simply may be larger (deeper).

A deeper decision tree may be able to better fit to the training set, but that may also mean that it overfits.

Min split size

This parameter sets the minimum number of training samples required to be present in a node of a decision tree in order for it to be split during training. To split a node means to continue the tree construction process to add further children below the node.

A large split size means less specialization on the training set, and thus possibly worse performance on the training set, but possibly avoiding overfitting. It will likely also mean that the training will be faster as probably fewer node splits will be considered.

Number of samples ratio

Each decision tree in the random forest is trained using a subset of the training set. This subset is sampled with replacement, meaning that a feature vector of the training may be sampled several times for a single decision tree. The number of training samples for each decision tree is the `numberOfSamplesRatio` multiplied by the total number of samples in the training set.

A high ratio will likely imply better generalization for each decision tree, but not necessarily so for the random forest overall. Training will also take longer as more feature vectors will need to be considered in each node split of each decision tree.

The special value of 0.0 is used to indicate no sampling. In this case all feature vectors of the training set will be used for training by every decision tree in the random forest.

[4] Only applicable in the exhaustive search.
[5] Only applicable in the approximate strategy. For more details look at the syntax section of kNN
[6] Only applicable in the exhaustive search.
[7] Only applicable in the approximate strategy. For more details look at the syntax section of kNN

Chapter 8. End-to-end examples

For each algorithm in the Algorithms pages we have small examples of limited scope that demonstrate the usage of that particular algorithm, typically only using that one algorithm. The purpose of this section is show how the algorithms in GDS can be used to solve fairly realistic use cases end-to-end, typically using several algorithms in each example.

- Product recommendation engine using FastRP and kNN

8.1. FastRP and kNN example

In this example we consider a graph of products and customers, and we want to find new products to recommend for each customer. We want to use the K-Nearest Neighbors algorithm (kNN) to identify similar customers and base our product recommendations on that. In order to be able to leverage topological information about the graph in kNN, we will first create node embeddings using FastRP. These embeddings will then be the input to the kNN algorithm.

For each pair of similar customers we can then recommend products that have been purchased by one of the customers but not the other, using a simple cypher query.

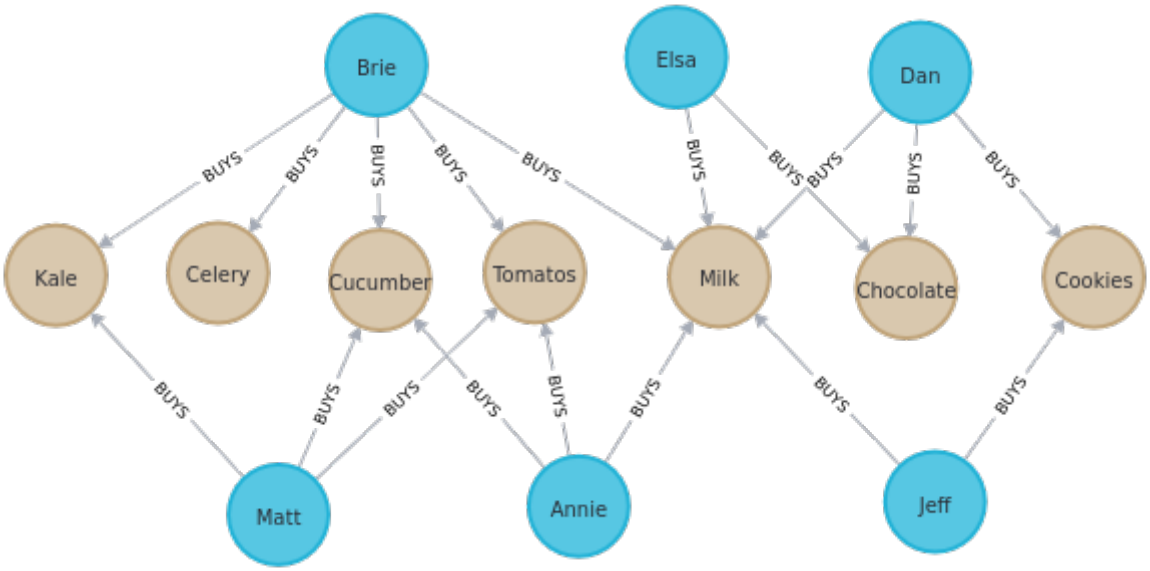
8.1.1. Graph creation

We will start by creating our graph of products and customers in the database. The `amount` relationship property represents the average weekly amount of money spent by a customer on a given product.

Consider the graph created by the following Cypher statement:

```
CREATE
 (dan:Person {name: 'Dan'}),
 (annie:Person {name: 'Annie'}),
 (matt:Person {name: 'Matt'}),
 (jeff:Person {name: 'Jeff'}),
 (brie:Person {name: 'Brie'}),
 (elsa:Person {name: 'Elsa'}),

 (cookies:Product {name: 'Cookies'}),
 (tomatoes:Product {name: 'Tomatoes'}),
 (cucumber:Product {name: 'Cucumber'}),
 (celery:Product {name: 'Celery'}),
 (kale:Product {name: 'Kale'}),
 (milk:Product {name: 'Milk'}),
 (chocolate:Product {name: 'Chocolate'}),

 (dan)-[:BUYS {amount: 1.2}]->(cookies),
 (dan)-[:BUYS {amount: 3.2}]->(milk),
 (dan)-[:BUYS {amount: 2.2}]->(chocolate),

 (annie)-[:BUYS {amount: 1.2}]->(cucumber),
 (annie)-[:BUYS {amount: 3.2}]->(milk),
 (annie)-[:BUYS {amount: 3.2}]->(tomatoes),

 (matt)-[:BUYS {amount: 3}]->(tomatoes),
 (matt)-[:BUYS {amount: 2}]->(kale),
 (matt)-[:BUYS {amount: 1}]->(cucumber),

 (jeff)-[:BUYS {amount: 3}]->(cookies),
 (jeff)-[:BUYS {amount: 2}]->(milk),

 (brie)-[:BUYS {amount: 1}]->(tomatoes),
 (brie)-[:BUYS {amount: 2}]->(milk),
 (brie)-[:BUYS {amount: 2}]->(kale),
 (brie)-[:BUYS {amount: 3}]->(cucumber),
 (brie)-[:BUYS {amount: 0.3}]->(celery),

 (elsa)-[:BUYS {amount: 3}]->(chocolate),
 (elsa)-[:BUYS {amount: 3}]->(milk);
```

The graph can be visualized in the following way:



Now we can proceed to project a graph which we can run the algorithms on.

Project a graph called 'purchases' and store it in the graph catalog:

```
CALL gds.graph.project(
  'purchases',
  ['Person','Product'],
  {
    BUYS: {
      orientation: 'UNDIRECTED',
      properties: 'amount'
    }
  }
)
```

8.1.2. FastRP embedding

Now we run the FastRP algorithm to generate node embeddings that capture topological information from the graph. We choose to work with `embeddingDimension` set to 4 which is sufficient since our example graph is very small. The `iterationWeights` are chosen empirically to yield sensible results. Please see the syntax section of the FastRP documentation for more information on these parameters. Since we want to use the embeddings as input when we run kNN later we use FastRP's `mutate` mode.

Create node embeddings using FastRP:

```
CALL gds.fastRP.mutate('purchases',
  {
    embeddingDimension: 4,
    randomSeed: 42,
    mutateProperty: 'embedding',
    relationshipWeightProperty: 'amount',
    iterationWeights: [0.8, 1, 1, 1]
  }
)
YIELD nodePropertiesWritten
```

Table 988. Results

nodePropertiesWritten
13

8.1.3. Similarities with kNN

Now we can run kNN to identify similar nodes by using the node embeddings that we generated with FastRP as `nodeProperties`. Since we are working with a small graph, we can set `sampleRate` to 1 and `deltaThreshold` to 0 without having to worry about long computation times. The `concurrency` parameter is set to 1 (along with the fixed `randomSeed`) in order to get a deterministic result. Please see the syntax section of the kNN documentation for more information on these parameters. Note that we use the algorithm's `write` mode to write the properties and relationships back to our database, so that we can analyze them later using Cypher.

Run kNN with FastRP node embeddings as input:

```
CALL gds.knn.write('purchases', {
    topK: 2,
    nodeProperties: ['embedding'],
    randomSeed: 42,
    concurrency: 1,
    sampleRate: 1.0,
    deltaThreshold: 0.0,
    writeRelationshipType: "SIMILAR",
    writeProperty: "score"
})
YIELD nodesCompared, relationshipsWritten, similarityDistribution
RETURN nodesCompared, relationshipsWritten, similarityDistribution.mean as meanSimilarity
```

Table 989. Results

nodesCompared	relationshipsWritten	meanSimilarity
13	26	0.917060998769907

As we can see the mean similarity between nodes is quite high. This is due to the fact that we have a small example where there are no long paths between nodes leading to many similar FastRP node embeddings.

8.1.4. Results exploration

Let us now inspect the results of our kNN call by using Cypher. We can use the `SIMILARITY` relationship type to filter out the relationships we are interested in. And since we just care about similarities between people for our product recommendation engine, we make sure to only match nodes with the `Person` label.

List pairs of people that are similar:

```
MATCH (n:Person)-[r:SIMILAR]->(m:Person)
RETURN n.name as person1, m.name as person2, r.score as similarity
ORDER BY similarity DESCENDING, person1, person2
```

Table 990. Results

person1	person2	similarity
"Annie"	"Matt"	0.983087003231049
"Matt"	"Annie"	0.983087003231049
"Dan"	"Elsa"	0.980300545692444
"Elsa"	"Dan"	0.980300545692444
"Jeff"	"Annie"	0.815471172332764

Our kNN results indicate among other things that the `Person` nodes named "Annie" and "Matt" are very similar. Looking at the `BUYS` relationships for these two nodes we can see that such a conclusion makes sense. They both buy three products, two of which are the same (`Product` nodes named "Cucumber" and "Tomatoes") for both people and with similar amounts. We therefore have high confidence in our approach.

8.1.5. Making recommendations

Using the information we derived that the `Person` nodes named "Annie" and "Matt" are similar, we can make product recommendations for each of them. Since they are similar, we can assume that products purchased by only one of the people may be of interest to buy also for the other person not already buying the product. By this principle we can derive product recommendations for the `Person` named "Matt" using a simple Cypher query.

Product recommendations for `Person` node with name "Matt":

```
MATCH (:Person {name: "Annie"})-->(p1:Product)
WITH collect(p1) as products
MATCH (:Person {name: "Matt"})-->(p2:Product)
WHERE not p2 in products
RETURN p2.name as recommendation
```

Table 991. Results

recommendation
"Kale"

Indeed, "Kale" is the one product that the `Person` named "Annie" buys that is also not purchased by the `Person` named "Matt".

8.1.6. Conclusion

Using two GDS algorithms and some basic Cypher we were easily able to derive some sensible product recommendations for a customer in our small example.

To make sure to get similarities to other customers for every customer in our graph with kNN, we could play around with increasing the `topK` parameter.

Chapter 9. Production deployment

This chapter explains advanced details with regards to common Neo4j components.

This chapter is divided into the following sections:

9.1. Transaction Handling

This section describes the usage of transactions during the execution of an algorithm. When an algorithm procedure is called from Cypher, the procedure call is executed within the same transaction as the Cypher statement.

9.1.1. During graph projection

During graph projection, new transactions are used that do not inherit the transaction state of the Cypher transaction. This means that changes from the Cypher transaction state are not visible to the graph projection transactions.

For example, the following statement will only project an empty graph (assuming the `MyLabel` label was not already present in the Neo4j database):

```
CREATE (n:MyLabel) // the new node is part of Cypher transaction state
WITH *
CALL gds.graph.project('myGraph', 'MyLabel', '*')
YIELD nodeCount
RETURN nodeCount
```

Table 992. Results

nodeCount
0

9.1.2. During results writing

Results from algorithms (node properties, for example) are written to the graph in new transactions. The number of transactions used depends on the size of the results and the `writeConcurrency` configuration parameter (for more details, please refer to sections Write and Common Configuration parameters). These transactions are committed independently from the Cypher transaction. This means, if the Cypher transaction is terminated (either by the user or by the database system), already committed write

transactions will *not* be rolled back.

Transaction writing examples

The code in this section is for illustrative purposes. The goal is to demonstrate correct usage of the GDS library write functionality with Cypher Shell and Java API.

Cypher Shell

Example for incorrect use.

```
:BEGIN

// Project a graph
CALL gds.graph.project.cypher(
  'test',
  'MATCH (n) WHERE n:Artist OR n:Genre RETURN id(n) AS id',
  'MATCH (a:Artist)<-[:RELEASED_BY]-(:Album)-[:HAS_GENRE]->(g:Genre)
   RETURN id(g) AS source, id(a) AS target, "IS_ASSOCIATED_WITH" AS type'
);

// Delete the old stuff
MATCH ()-[r:SIMILAR_TO]->() DELETE r;

// Run the algorithm
CALL gds.nodeSimilarity.write(
  'test', {
    writeRelationshipType: 'SIMILAR_TO',
    writeProperty: 'score'
  }
);

:COMMIT
```

The issue with the above statement is that all the queries run in the same transaction.

A correct handling of the above statement would be to run each statement in its own transaction, which is shown below. Notice the reordering of the statements, this ensures that the in-memory graph will have the most recent changes after the removal of the relationships.

First remove the unwanted relationships.

```
:BEGIN

MATCH ()-[r:SIMILAR_TO]->() DELETE r;

:COMMIT
```

Project a graph.

```
:BEGIN

CALL gds.graph.project.cypher(
  'test',
  'MATCH (n) WHERE n:Artist OR n:Genre RETURN id(n) AS id',
  'MATCH (a:Artist)<-[:RELEASED_BY]-(:Album)-[:HAS_GENRE]->(g:Genre)
   RETURN id(g) AS source, id(a) AS target, "IS_ASSOCIATED_WITH" AS type'
);

:COMMIT
```

Run the algorithm.

```
:BEGIN

CALL gds.nodeSimilarity.write(
  'test', {
    writeRelationshipType: 'SIMILAR_TO',
    writeProperty: 'score'
  }
);

:COMMIT
```

Java API

The same issue can be seen using the Java API, the examples are below.

Constants used throughout the examples below:

```
// Removes the in-memory graph (if exists) from the graph catalog
static final String CYPHER_DROP_GDS_GRAPH_IF_EXISTS =
    "CALL gds.graph.drop('test', false)";

// Projects a graph
static final String CYPHER_PROJECT_GDS_GRAPH_ARTIST_GENRE =
    "CALL gds.graph.project.cypher(" +
    "    'test', " +
    "    'MATCH (n) WHERE n:Artist OR n:Genre RETURN id(n) AS id', " +
    "    'MATCH (a:Artist)<-[:RELEASED_BY]-(:Album)-[:HAS_GENRE]->(g:Genre) " +
    "       RETURN id(g) AS source, id(a) AS target, \"IS_ASSOCIATED_WITH\" AS type'" +
    ")";

// Runs NodeSimilarity in `write` mode over the in-memory graph
static final String CYPHER_WRITE_SIMILAR_TO =
    "CALL gds.nodeSimilarity.write(" +
    "   'test', {" +
    "       writeRelationshipType: 'SIMILAR_TO'," +
    "       writeProperty: 'score'"+
    "   }"
    ");";
```

Incorrect use:

```
try (var session = driver.session()) {
    var params = Map.<String, Object>of("graphName", "genre-related-to-artist");
    session.writeTransaction(tx -> {
        tx.run(CYPHER_DROP_GDS_GRAPH_IF_EXISTS, params).consume();
        tx.run(CYPHER_PROJECT_GDS_GRAPH_ARTIST_GENRE, params).consume();
        tx.run("MATCH ()-[r:SIMILAR_TO]->() DELETE r").consume();
        return tx.run(CYPHER_WRITE_SIMILAR_TO, params).consume();
    });
}
```

Here we are facing the same issue with running everything in the same transaction. This can be written correctly by splitting each statement in its own transaction.

Correct handling of the statements:

```
try (var session = driver.session()) {

    // First run the remove statement
    session.writeTransaction(tx -> {
        return tx.run("MATCH ()-[r:SIMILAR_TO]->() DELETE r").consume();
    });

    // Project a graph
    var params = Map.<String, Object>of("graphName", "genre-related-to-artist");
    session.writeTransaction(tx -> {
        tx.run(CYPHER_DROP_GDS_GRAPH_IF_EXISTS, params).consume();
        return tx.run(CYPHER_PROJECT_GDS_GRAPH_ARTIST_GENRE, params).consume();
    });

    // Run the algorithm
    session.writeTransaction(tx -> {
        return tx.run(CYPHER_WRITE_SIMILAR_TO, params).consume();
    });
}
```

Chapter 10. Transaction termination

The Cypher transaction can be terminated by either the user or the database system. This will eventually terminate all transactions that have been opened during graph projection, algorithm execution, or results writing. It is not immediately visible and can take a moment for the transactions to recognize that the Cypher transaction has been terminated.

10.1. Using GDS and Fabric

This section describes how the Neo4j Graph Data Science library can be used in a Neo4j Fabric deployment.

This feature is not available in AuraDS

Neo4j Fabric is a way to store and retrieve data in multiple databases, whether they are on the same Neo4j DBMS or in multiple DBMSs, using a single Cypher query. For more information about Fabric itself, please visit the documentation.

A typical Neo4j Fabric setup consists of two components: one or more shards that hold the data and one or more Fabric proxies that coordinate the distributed queries. Currently, the way of running the Neo4j Graph Data Science library in a Fabric deployment is to run GDS on the shards. Executing GDS on a Fabric proxy is currently not supported.

10.1.1. Running GDS on the Shards

In this mode of using GDS in a Fabric environment, the GDS operations are executed on the shards. The graph projections and algorithms are then executed on each shard individually, and the results can be combined via the Fabric proxy. This scenario is useful, if the graph is partitioned into disjoint subgraphs across shards, i.e. there is no logical relationship between nodes on different shards. Another use case is to replicate the graph's topology across multiple shards, where some shards act as operational and others as analytical databases.

Setup

In this scenario we need to set up the shards to run the Neo4j Graph Data Science library.

Every shard that will run the Graph Data Science library should be configured just as a standalone GDS database would be, for more information see Installation.

The Fabric proxy nodes do not require any special configuration, i.e., the GDS library plugin does not need to be installed. However, the proxy nodes should be configured to handle the amount of data received from the shards.

Examples

Let's assume we have a Fabric setup with two shards. One shard functions as the operational database and holds a graph with the schema `(Person)-[KNOWS]→(Person)`. Every `Person` node also stores an identifying property `id` and the persons `name` and possibly other properties.

The other shard, the analytical database, stores a graph with the same data, except that the only property is the unique identifier.

First we need to project a named graph on the analytical database shard.

```
CALL {
  USE FABRIC_DB_NAME.ANALYTICS_DB
  CALL gds.graph.project('graph', 'Person', 'KNOWS')
  YIELD graphName
  RETURN graphName
}
RETURN graphName
```

Using Fabric, we can now calculate the PageRank score for each Person and join the results with the name of that Person.

```
CALL {
  USE FABRIC_DB_NAME.ANALYTICS_DB
  CALL gds.pagerank.stream('graph', {})
  YIELD nodeId, score AS pageRank
  RETURN gds.util.asNode(nodeId).id AS personId, pageRank
}
CALL {
  USE FABRIC_DB_NAME.OPERATIONAL_DB
  WITH personId
  MATCH (p {id: personId})
  RETURN p.name AS name
}
RETURN name, personId, pageRank
```

The query first connects to the analytical database where the PageRank algorithm computes the rank for each node of an anonymous graph. The algorithm results are streamed to the proxy, together with the unique node id. For every row returned by the first subquery, the operational database is then queried for the persons name, again using the unique node id to identify the `Person` node across the shards.

Limitations

- It is not possible to run algorithms across shards.

10.2. GDS with Neo4j Causal Cluster

> *This section describes how the Neo4j Graph Data Science library can be used in a Neo4j Causal Cluster deployment.*

This feature is not available in AuraDS

It is possible to run GDS as part of Neo4j Causal Cluster deployment. Since GDS performs large

computations with the full resources of the system it is not suitable to run as part of the cluster's core. We make use of a *Read Replica* instance to deploy the GDS library and process analytical workloads. Calls to GDS `write` procedures are internally directed to the cluster `LEADER` instance via *server-side routing*.

10.2.1. Deployment

- The cluster must contain at least one *Read Replica* instance
  - single *Core member* and a *Read Replica* is a valid scenario.
  - GDS workloads are not load-balanced if there are more than one *Read Replica* instances.
- Cluster should be configured to use *server-side routing*.
- GDS plugin deployed on the *Read Replica*.
  - A valid GDS Enterprise Edition license must be installed and configured on the *Read Replica*.
  - The driver connection to operated GDS should be made using the `bolt://` protocol, or *server-policy routed* to the *Read Replica* instance.

For more information on setting up, configuring and managing a Neo4j Causal Clustering, please refer to the documentation.

10.2.2. GDS Configuration

The following optional settings can be used to control transaction size.

Property	Default Value
`gds.cluster.tx.min.size`	10000
`gds.cluster.tx.max.size`	100000

The batch size for writing node properties is computed using both values along with the configured concurrency and total node count. The batch size for writing relationship is using the lower value of the two settings. There are some procedures that support batch size configuration which takes precedence if present in procedure call parameters.

10.3. GDS Feature Toggles

This section describes the available feature toggles in the Neo4j Graph Data Science library.

Feature toggles are not considered part of the public API and can be removed or changed between minor releases of the GDS Library.

10.3.1. BitIdMap Feature Toggle Enterprise edition

GDS Enterprise Edition uses a different in-memory graph implementation that is consuming less memory compared to the GDS Community Edition. This in-memory graph implementation performance depends on the underlying graph size and topology. It can be slower for write procedures and graph creation of

smaller graphs. To switch to the more memory intensive implementation used in GDS Community Edition you can disable this feature by using the following procedure call.

```
CALL gds.features.useBitIdMap(false)
```

10.3.2. Uncompressed Adjacency List Toggle

The in-memory graph for GDS is based on the Compressed Sparse Row (CSR) layout and uses compressed adjacency lists by default. The compression lowers the memory usage for a graph but requires additional computation time to decompress during algorithm execution. Using an uncompressed adjacency list will result in higher memory consumption in order to provide faster traversals. It can also have negative performance impacts due to the increased resident memory size. Using more memory requires a higher memory bandwidth to read the same adjacency list. Whether compressed or uncompressed is better heavily depends on the topology of the graph and the algorithm. Algorithms that are traversal heavy, such as triangle counting, have a higher chance of benefiting from an uncompressed adjacency list. Very dense nodes in graphs with a very skewed degree distribution ("power law") often achieve a higher compression ratio. Using the uncompressed adjacency list on those graphs has a higher chance of running into memory bandwidth limitations.

To switch to uncompressed adjacency lists, use the following procedure call.

```
CALL gds.features.useUncompressedAdjacencyList(true)
```

To switch to compressed adjacency lists, use the following procedure call.

```
CALL gds.features.useUncompressedAdjacencyList(false)
```

To reset the setting to the default value, use the following procedure call.

```
CALL gds.features.useUncompressedAdjacencyList.reset() YIELD enabled
```

10.3.3. Reordered Adjacency List Toggle

The in-memory graph for GDS writes adjacency lists out of order due to the way the data is read from the underlying store. This feature toggle will add a step during graph creation in which the adjacency lists will be reordered to follow the internal node ids. That reordering results in a CSR representation that is closer to the textbook layout, where the adjacency lists are written in node id order. Reordering can have benefits for some graphs and some algorithms because adjacency lists that will be traversed by the same thread are more likely to be stored close together in memory (caches). The order depends on the GDS internal node ids that are assigned in the in-memory graph and not on the node ids loaded from the underlying Neo4j store.

To enable reordering, use the following procedure call.

```
CALL gds.features.useReorderedAdjacencyList(true)
```

To disable reordering, use the following procedure call.

```
CALL gds.features.useReorderedAdjacencyList(false)
```

To reset the setting to the default value, use the following procedure call.

```
CALL gds.features.useReorderedAdjacencyList.reset() YIELD enabled
```

Chapter 11. Python client

This chapter documents how to use the dedicated Python Client for Neo4j Graph Data Science.

To help users of GDS who work with Python as their primary language and environment, there is an official GDS client package called `graphdatascience`. It enables users to write pure Python code to project graphs, run algorithms, and define and use machine learning pipelines in GDS. To avoid naming confusion with the server-side GDS library, we will here refer to the Neo4j Graph Data Science client as the *Python client*.

The Python client API is designed to mimic the GDS Cypher procedure API in Python code. It wraps and abstracts the necessary operations of the Neo4j Python driver to offer a simpler surface. Except for those listed in Known limitations, every operation of the GDS Cypher API should be represented in the Python client API. For a high level explanation of how the Cypher API maps to the Python client API please see Mapping between Cypher and Python.

This chapter is divided into the following sections:

11.1. Installation

To install the latest deployed version of the Python client, run:

```
pip install graphdatascience
```

11.1.1. System requirements

The GDS Python client depends on Python, the Neo4j Python Driver, and a server-side installation of the GDS library (see Installation). The Python client supports the following versions of the other three components:

Python Client	GDS version	Python version	Neo4j Python Driver version
1.0.0	2.0	3.6+	4.4.2+

11.1.2. Versioning

To make things easy for users of the Python client, our aim is that running `pip install --upgrade graphdatascience` should give you a version of the client that supports all currently supported GDS library versions, starting with 2.0.

The Python client follows semantic versioning.

Python client versions do not map identically to versions of the GDS library. Eg. Python client version X.0 must not necessarily be compatible with GDS library version X.0. Instead, the Python client may be released independently and one has to consult System requirements above to figure out whether one's client version is compatible with the GDS library on the server.

11.2. Getting started

The design philosophy of the Python client is to mimic the GDS Cypher API in Python code. The Python client will translate the Python code written by the user to a corresponding Cypher query which it will then run on the Neo4j server using a Neo4j Python driver connection.

The Python client attempts to be as pythonic as possible to maximize convenience for users accustomed to and experienced with Python environments. As such standard Python and pandas types are used as much as possible. However, to be consistent with the Cypher surface the general return value of calling a method corresponding to a Cypher procedure will be in the form of a table (a pandas `DataFrame` in Python). Read more about this in Mapping between Cypher and Python.

The root component of the Python client is the `GraphDataScience` object. Once instantiated it forms the entrypoint to interacting with the GDS library. That includes projecting graphs, running algorithms, and defining and using machine learning pipelines in GDS. As a convention we recommend always calling the instantiated `GraphDataScience` object `gds` as using it will then most resemble using the Cypher API directly.

11.2.1. Import and setup

The simplest way to instantiate the `GraphDataScience` object is from a Neo4j server URI and corresponding credentials:

```
from graphdatascience import GraphDataScience

# Use Neo4j URI and credentials according to your setup
gds = GraphDataScience("bolt://localhost:7687", auth=None)

print(gds.version())
```

Results:

```
"2.0.0-alpha01"
```

Alternatively, for use cases where direct access and control of the Neo4j driver is required, one can use the method `GraphDataScience.from_neo4j_driver` for instantiating the gds object.

If we don't want to use the default database of our DBMS, we can specify which one to use:

```
gds.set_database("my-db")
```

AuraDS

If you are connecting the client to an AuraDS instance, you can get recommended non-default configuration settings of the Python Driver applied automatically. To achieve this, set the constructor argument `aura_ds=True`:

```
from graphdatascience import GraphDataScience

# Configures the driver with AuraDS-recommended settings
gds = GraphDataScience(
    "neo4j+s://my-aura-ds.databases.neo4j.io:7687",
    auth=("neo4j", "my-password"),
    aura_ds=True
)
```

11.2.2. Minimal example

In the following example we illustrate the Python client to run a Cypher query, project a graph into GDS, run an algorithm and inspect the result via the client-side graph object.

```
from graphdatascience import GraphDataScience

# We follow the convention to name our `GraphDataScience` object `gds`
gds = GraphDataScience("bolt://my-server.neo4j.io:7687", auth=("neo4j", "my-password"))

# Create a minimal example graph
gds.run_cypher(
  """
  CREATE
  (m: City {name: "Malmö"}),
  (l: City {name: "London"}),
  (s: City {name: "San Mateo"}),
  (m)-[:FLY_TO]->(l),
  (l)-[:FLY_TO]->(m),
  (l)-[:FLY_TO]->(s),
  (s)-[:FLY_TO]->(l)
  """
)

# Project the graph into the GDS Graph Catalog
# We call the object representing the projected graph `G_office`
G_office, _ = gds.graph.project("neo4j-offices", "City", "FLY_TO")

# Run the mutate mode of the PageRank algorithm
_ = gds.pageRank.mutate(G_office, tolerance=0.5, mutateProperty="rank")

# We can inspect the node properties of our projected graph directly
# via the graph object and see that indeed the new property exists
print(G_office.node_properties("City"))
```

Results:

```
["rank"]
```

11.2.3. Mapping between Cypher and Python

There are some general principles for how the Cypher API maps to the Python client API:

- Method calls corresponding to Cypher procedures (preceded by `CALL` in the docs) return:
  - A table as a pandas `DataFrame`, if the procedure returns several rows (eg. stream mode algorithm calls).
  - A row as a pandas `Series`, if the procedure returns exactly one row (eg. stats mode algorithm calls).

  Some notable exceptions to this are:
  - Procedures instantiating graph objects and model objects have two return values: a graph or model object, and a row of metadata (typically a pandas `Series`) from the underlying procedure call.
  - Any methods on pipeline, graph or model objects (native to the Python client) mapping to Cypher procedures.
  - `gds.version()` which returns a string.
- Method calls corresponding to Cypher functions (preceded by `RETURN` in the docs) will simply return the value the function returns.
- The Python client also contains specific functionality for inspecting graphs from the GDS Graph Catalog, using a client-side graph object. Similarly, models from the GDS Model Catalog can be inspected using a client-side model object.
- Cypher functions and procedures of GDS that take references to graphs and/or models as strings for input typically instead take graph objects and/or model objects as input in the Python client API.
- To configure and use machine learning pipelines in GDS, specific pipeline objects are used in the Python client.

11.3. The graph object

In order to utilize most the functionality in GDS, you must first project a graph into the GDS Graph Catalog. When projecting a graph with the Python client, a client-side reference to the projected graph is returned. We call these references `Graph` objects.

Once created, the `Graph` objects can be passed as arguments to other methods in the Python client, for example for running algorithms or training machine learning models. Additionally, the `Graph` objects have convenience methods allowing for inspection of the projected graph represented without explicitly involving the graph catalog.

In the examples below we assume that we have an instantiated `GraphDataScience` object called `gds`. Read more about this in Getting started.

11.3.1. Constructing a graph object

There are several ways of constructing a graph object. The simplest way is to do a native projection:

```
G, res = gds.graph.project(
    "my-graph",                 #  Graph name
    ["MyLabel", "YourLabel"],   #  Node projection
    "MY_REL_TYPE",              #  Relationship projection
    readConcurrency=4               #  Configuration parameters
)
```

where `G` is a `Graph` object, and `res` is a pandas `Series` containing metadata from the underlying procedure call.

Note that all projection syntax variants are supported by way of specifying a Python `dict` or `list` for the node and relationship projection arguments. To specify configuration parameters corresponding to the keys of the procedure's `configuration` map, we give named keyword arguments, like for `concurrency=4` above. Read more about this in Syntax.

Similarly to Cypher there's also a corresponding `gds.graph.project.estimate` method that can be called in an analogous way.

To get a graph object that represents a graph that has already been projected into the graph catalog, one can call the client-side only `get` method and passing it a name:

```
G = gds.graph.get("my-graph")
```

In addition to those aforementioned there are three more methods that construct graph objects:

- `gds.graph.project.cypher`
- `gds.beta.graph.subgraph`
- `gds.beta.graph.generate`

Their Cypher signatures map to Python in much the same way as `gds.graph.project` above.

11.3.2. Inspecting a graph object

There are convenience methods on the graph object that let us extract information about our projected graph.

Table 993. Graph object methods

Name	Arguments	Return type	Description
`name`	`-`	`str`	The name of the projected graph.
`node_count`	`-`	`int`	The node count of the projected graph.
`relationship_count`	`-`	`int`	The relationship count of the projected graph.
`node_properties`	`label: str`	`list[str]`	A list of the node properties present on the nodes with the node label provided as input.
`relationship_properties`	`type: str`	`list[str]`	A list of the relationship properties present on the relationships with the relationship type provided as input.

Name	Arguments	Return type	Description
degree_distribution	-	Series	The average out-degree of generated nodes.
density	-	float	Density of the graph.
size_in_bytes	-	int	Number of bytes used in the Java heap to store the graph.
memory_usage	-	str	Human-readable description of size_in_bytes.
exists	-	bool	Returns True if the graph exists in the GDS Graph Catalog, otherwise False.
drop	-	None	Removes the graph from the GDS Graph Catalog.

For example, to get the node count and node properties of a graph G, we would do the following:

```
n = G.node_count()
props = G.node_properties("MyLabel")
```

11.3.3. Using a graph object

The primary use case for a graph object is to pass it to algorithms. The syntax for doing that follows the standard Cypher API, where the graph is the first parameter passed to the algorithm.

Syntax composition:

```
result = gds[.<tier>].<algorithm>.<execution-mode>[.<estimate>](
  G: Graph,
  **configuration: dict[str, any]
)
```

For example, to run the WCC on a graph G, and then drop the graph, do the following:

```
G, _ = gds.graph.project(...)

res = gds.wcc.stream(G)

gds.graph.drop(G)  # same as G.drop()
```

In most Cypher operations where a graph name is required, the graph object is used in the Python client instead. In some cases where this does not make sense, such as for gds.graph.exist(), where a graph name string is used instead.

11.4. Running algorithms

In the examples below we assume that we have an instantiated GraphDataScience object called gds. Read more about this in Getting started.

11.4.1. Introduction

Running most algorithms with the Python client is structurally similar to using the Cypher API:

Syntax composition:

```
result = gds[.<tier>].<algorithm>.<execution-mode>[.<estimate>](
  G: Graph,
  **configuration: dict[str, any]
)
```

Here we can note a few key differences:

- Instead of a graph name string as first argument, we have a graph object as first positional argument.
- Instead of a configuration map, we have named keyword arguments.

The result of running a procedure is returned as either a pandas `DataFrame` or a pandas `Series` depending on the execution mode.

For example, to run the WCC and FastRP algorithms on a graph `G`, we could do the following:

```
G, _ = gds.graph.project(...)

wcc_res = gds.wcc.mutate(
    G,                          #  Graph object
    threshold=0.8,              #  Configuration parameters
    mutateProperty="wcc"
)
assert wcc_res["componentCount"] > 0

fastrp_res = gds.fastRP.write(
    G,                          #  Graph object
    featureProperties=["wcc"],  #  Configuration parameters
    embeddingDimension=256,
    propertyRatio=0.3,
    writeProperty="embedding"
)
assert fastrp_res["nodePropertiesWritten"] == G.node_count()
```

Some algorithms deviate from the standard syntactic structure. We describe how to use them in the Python client in the sections below.

11.4.2. Execution modes

Algorithms return results in a format that is controlled by its execution mode. These modes are explained in some detail in Running algorithms. In the Python client, the `stats`, `mutate` and `write` modes return a pandas `Series` containing the summary result of running the algorithm. The same applies to `estimate` procedures.

Stream

The `stream` mode is a bit different as this mode does not retain the result in any form on the server side. Instead, the result is streamed back to the Python client, as a pandas `DataFrame`. The result is materialized on the client side immediately once the computation is finished. Streaming results back in this way can be resource-intensive, as the result can be large. Typically, the result size will be in the same order of magnitude as the graph. Some algorithms produce particularly sizeable results, for example node embeddings.

Train

The `train` mode is used for algorithms that produce a machine learning model into the GDS Model Catalog. The Python client has special support for working with such models, which we describe in The model object.

11.4.3. Algorithms that require node matching

Some algorithms take (database) node ids as inputs. These node ids must be matched directly from the Neo4j database. This is straight-forward when working in Cypher. In the Python client there is a convenience method `gds.find_node_id` to retrieve a node id based on node labels and property key-value pairs.

For example, to find a source and target node of a graph `G` with cities to run Dijkstra Source-Target Shortest Path on, we could do the following:

```
source_id = gds.find_node_id(["City"], {"name": "New York"})
target_id = gds.find_node_id(["City"], {"name": "Philadelphia"})

res = gds.shortestPath.dijkstra.stream(G, sourceNode=source_id, targetNode=target_id)
assert res["totalCost"][0] == 100
```

`gds.find_node_id` takes a list of node labels and a dictionary of node property key-value pairs. The nodes found are those that have all labels specified and fully match all property key-value pairs given. Note that exactly one node per method call must be matched, otherwise an error will be raised.

Cypher mapping

The Python call:

```
gds.find_node_id(["A", "B"], {"p1": 1, "p2": "foo"})
```

is exactly equivalent to the Cypher statement:

```
MATCH (n:A:B {p1: 1, p2: 'foo'})
RETURN id(n) AS id
```

To do more advanced matching beyond the capabilities of `find_node_id()` we recommend using Cypher's `MATCH` via `gds.run_cypher`.

11.4.4. Topological link prediction

The methods for doing Topological link prediction are a bit different. Just like in the GDS procedure API they do not take a graph as an argument, but rather two node references as positional arguments. And they simply return the similarity score of the prediction just made as a float - not any kind of pandas data structure.

For example, to run the Adamic Adar algorithm, we can use the following:

```
node1 = gds.find_node_id(["User"], {"name": "Mats"})
node2 = gds.find_node_id(["User"], {"name": "Adam"})

score = gds.alpha.linkprediction.adamicAdar(node1, node2)
assert score >= 0
```

11.5. Machine learning pipelines

The Python client has special support for Link prediction pipelines and Node classification pipelines. The GDS pipelines are represented as pipeline objects.

The Python method calls to create the pipelines match their Cypher counterparts exactly. However, the rest of the pipeline functionality is deferred to methods on the pipeline objects themselves. Once created, the `TrainingPipeline` can be passed as arguments to methods in the Python client, such as the pipeline catalog operations. Additionally, the `TrainingPipeline` has convenience methods allowing for inspection of the pipeline represented without explicitly involving the pipeline catalog.

In the examples below we assume that we have an instantiated `GraphDataScience` object called `gds`. Read more about this in Getting started.

11.5.1. Node classification

This section outlines how to use the Python client to build, configure and train a node classification pipeline, as well as how to use the model that training produces for predictions.

Pipeline

The creation of the node classification pipeline is very similar to how it's done in Cypher. To create a new node classification pipeline one would make the following call:

```
pipe, res = gds.beta.pipeline.nodeClassification.create("my-pipe")
```

where `pipe` is a pipeline object, and `res` is a pandas `Series` containing metadata from the underlying procedure call.

To then go on to build, configure and train the pipeline we would call methods directly on the node classification pipeline object. Below is a description of the methods on such objects:

Table 994. Node classification pipeline methods

Name	Arguments	Return type	Description
`addNodeProperty`	`procedure_name: str, config: **kwargs`	`Series`	Add an algorithm that produces a node property to the pipeline, with optional algorithm-specific configuration.
`selectFeatures`	`node_properties: Union[str, list[str]]`	`Series`	Select node properties to be used as features.
`configureSplit`	`config: **kwargs`	`Series`	Configure the train-test dataset split.

Name	Arguments	Return type	Description
addLogisticRegression	parameter_space: dict[str, any]	Series	Add a logistic regression model configuration to train as a candidate in the model selection phase.
addRandomForest	parameter_space: dict[str, any]	Series	Add a random forest model configuration to train as a candidate in the model selection phase.
train	G: Graph, config: **kwargs	NCPredictionPipeline, Series	Train the pipeline on the given input graph using given keyword arguments.
train_estimate	G: Graph, config: **kwargs	Series	Estimate training the pipeline on the given input graph using given keyword arguments.
node_property_steps	-	DataFrame	Returns the node property steps of the pipeline.
feature_properties	-	Series	Returns a list of the selected feature properties for the pipeline.
split_config	-	Series	Returns the configuration set up for train-test splitting of the dataset.
parameter_space	-	Series	Returns the model parameter space set up for model selection when training.
name	-	str	The name of the pipeline as it appears in the pipeline catalog.
type	-	str	The type of pipeline.
creation_time	-	neo4j.time.Datetime	Time when the pipeline was created.
drop	-	None	Removes the model from the GDS Pipeline Catalog.
exists	-	bool	True if the model exists in the GDS Pipeline Catalog, False otherwise.

There are two main differences when comparing the methods above that map to procedures of the Cypher API:

- As the Python methods are called on the pipeline object, one does not need to provide a name when calling them.
- Configuration parameters in the Cypher calls are represented by named keyword arguments in the Python method calls.

Another difference is that the `train` Python call takes a graph object instead of a graph name, and returns a `NCModel` model object that we can run predictions with as well as a pandas `Series` with the metadata from the training.

Please consult the node classification Cypher documentation for information about what kind of input the methods expect.

Example

Below is a small example of how one could configure and train a very basic node classification pipeline. Note that we don't configure splits explicitly, but rather use the default. We suppose that the graph `G` we train on has a node property "my-class" which will be the target of our classification training.

```
pipe, _ = gds.beta.pipeline.nodeClassification.create("my-pipe")

# Add Degree centrality as a property step producing "rank" node properties
pipe.addNodeProperty("degree", mutateProperty="rank")

# Select our "rank" property as a feature for the model training
pipe.selectFeatures("rank")

# Verify that the features to be used in model training are what we expect
steps = pipe.feature_properties()
assert len(steps) == 1
assert steps[0]["feature"] == "rank"

# Configure the model training do to 2-fold cross-validation over tolerance
pipe.addLogisticRegression({"tolerance": 0.01})
pipe.addLogisticRegression({"tolerance": 0.001})

# Train the pipeline targeting node property "my-class" as label and "ACCURACY" as only metric
trained_pipe_model, res = pipe.train(G, modelName="my-model", targetProperty="my-class", metrics=
["ACCURACY"])
assert res["trainMillis"] >= 0
```

A model referred to as "my-model" in the GDS Model Catalog is produced. In the next section we will go over how to use that model to make predictions.

Model

As we saw in the previous section, node classification models are created when training a node classification pipeline. In addition to inheriting the methods common to all model objects, node classification models have the following methods:

Table 995. Node classification model methods

Name	Arguments	Return type	Description
`predict_mutate`	`G: Graph, config: **kwargs`	`Series`	Predict classes for nodes of the input graph and mutate graph with predictions.
`predict_mutate_estimate`	`G: Graph, config: **kwargs`	`Series`	Estimate predicting classes for nodes of the input graph and mutating graph with predictions.
`predict_stream`	`G: Graph, config: **kwargs`	`DataFrame`	Predict classes for nodes of the input graph and stream the results.
`predict_stream_estimate`	`G: Graph, config: **kwargs`	`Series`	Estimate predicting classes for nodes of the input graph and streaming the results.
`predict_write`	`G: Graph, config: **kwargs`	`Series`	Predict classes for nodes of the input graph and write results back to the database.
`predict_write_estimate`	`G: Graph, config: **kwargs`	`Series`	Estimate predicting classes for nodes of the input graph and writing the results back to the database.
`metrics`	`-`	`Series`	Returns values for the metrics specified when training, for this particular model.

One can note that the predict methods are indeed very similar to their Cypher counterparts. The three main differences are that:

- They take a graph object instead of a graph name.
- They have Python keyword arguments representing the keys of the configuration map.
- One does not have to provide a "modelName" since the model object used itself have this information.

Example (continued)

We now continue the example above using the node classification model `trained_pipe_model` we trained there. Suppose that we have a new graph `H` that we want to run predictions on.

```
# Make sure our model performed well enough on the test set
metrics = trained_pipe_model.metrics()
assert metrics["ACCURACY"]["test"] >= 0.85

# Predict on `H` and stream the results with a specific concurrency of 8
result = trained_pipe_model.predict_stream(H, concurrency=8)
assert len(results) == H.node_count()
```

11.5.2. Link prediction

This section outlines how to use the Python client to build, configure and train a link prediction pipeline, as well as how to use the model that training produces for predictions.

Pipeline

The creation of the link prediction pipeline is very similar to how it's done in Cypher. To create a new link prediction pipeline one would make the following call:

```
pipe, res = gds.beta.pipeline.linkPrediction.create("my-pipe")
```

where `pipe` is a pipeline object, and `res` is a pandas `Series` containing metadata from the underlying procedure call.

To then go on to build, configure and train the pipeline we would call methods directly on the link prediction pipeline object. Below is a description of the methods on such objects:

Table 996. Link prediction pipeline methods

Name	Arguments	Return type	Description
`addNodeProperty`	`procedure_name: str, config: **kwargs`	`Series`	Add an algorithm that produces a node property to the pipeline, with optional algorithm-specific configuration.
`addFeature`	`feature_type: str, config: **kwargs`	`Series`	Add a link feature for model training based on node properties and a feature combiner.

Name	Arguments	Return type	Description
`configureSplit`	`config: **kwargs`	`Series`	Configure the feature-train-test dataset split.
`addLogisticRegression`	`parameter_space: dict[str, any]`	`Series`	Add a logistic regression model configuration to train as a candidate in the model selection phase.
`addRandomForest`	`parameter_space: dict[str, any]`	`Series`	Add a random forest model configuration to train as a candidate in the model selection phase.
`train`	`G: Graph, config: **kwargs`	`LPPredictionPipeline, Series`	Train the model on the given input graph using given keyword arguments.
`train_estimate`	`G: Graph, config: **kwargs`	`Series`	Estimate training the pipeline on the given input graph using given keyword arguments.
`node_property_steps`	-	`DataFrame`	Returns the node property steps of the pipeline.
`feature_steps`	-	`DataFrame`	Returns a list of the selected feature steps for the pipeline.
`split_config`	-	`Series`	Returns the configuration set up for feature-train-test splitting of the dataset.
`parameter_space`	-	`Series`	Returns the model parameter space set up for model selection when training.
`name`	-	`str`	The name of the pipeline as it appears in the pipeline catalog.
`type`	-	`str`	The type of pipeline.
`creation_time`	-	`neo4j.time.Datetime`	Time when the pipeline was created.
`drop`	-	`None`	Removes the model from the GDS Pipeline Catalog.
`exists`	-	`bool`	`True` if the model exists in the GDS Pipeline Catalog, `False` otherwise.

There are two main differences when comparing the methods above that map to procedures of the Cypher API:

- As the Python methods are called on the pipeline object, one does not need to provide a name when calling them.
- Configuration parameters in the Cypher calls are represented by named keyword arguments in the Python method calls.

Another difference is that the `train` Python call takes a graph object instead of a graph name, and returns a `LPModel` model object that we can run predictions with as well as a pandas `Series` with the metadata from the training.

Please consult the link prediction Cypher documentation for information about what kind of input the methods expect.

Example

Below is a small example of how one could configure and train a very basic link prediction pipeline. Note that we don't configure training parameters explicitly, but rather use the default. Suppose we have a graph `G` that we want to train our pipeline on.

```
pipe, _ = gds.beta.pipeline.linkPrediction.create("my-pipe")

# Add FastRP as a property step producing "embedding" node properties
pipe.addNodeProperty("fastRP", embeddingDimension=128, mutateProperty="embedding")

# Combine our "embedding" node properties with Hadamard to create link features for training
pipe.addFeature("hadamard", nodeProperties=["embedding"])

# Verify that the features to be used in model training are what we expect
steps = pipe.feature_steps()
assert len(steps) == 1
assert steps[0]["name"] == "HADAMARD"

# Specify the fractions we want for our dataset split
pipe.configureSplit(trainFraction=0.2, testFraction=0.1)

# Add a random forest model with default configuration
pipe.addRandomForest()

# Train the pipeline and produce a model named "my-model"
trained_pipe_model, res = pipe.train(G, modelName="my-model")
assert res["trainMillis"] >= 0
```

A model referred to as "my-model" in the GDS Model Catalog is produced. In the next section we will go over how to use that model to make predictions.

Model

As we saw in the previous section, link prediction models are created when training a link prediction pipeline. In addition to inheriting the methods common to all model objects, link prediction models have the following methods:

Table 997. Link prediction model methods

Name	Arguments	Return type	Description
`predict_mutate`	`G: Graph, config: **kwargs`	`Series`	Predict links between non-neighboring nodes of the input graph and mutate graph with predictions.
`predict_mutate_estimate`	`G: Graph, config: **kwargs`	`Series`	Estimate predicting links between non-neighboring nodes of the input graph and mutating graph with predictions.
`predict_stream`	`G: Graph, config: **kwargs`	`DataFrame`	Predict links between non-neighboring nodes of the input graph and stream the results.
`predict_stream_estimate`	`G: Graph, config: **kwargs`	`Series`	Estimate predicting links between non-neighboring nodes of the input graph and streaming the results.

Name	Arguments	Return type	Description
`metrics`	-	`Series`	Returns values for the metrics used when training, for this particular model.

One can note that the predict methods are indeed very similar to their Cypher counterparts. The three main differences are that:

- They take a graph object instead of a graph name.
- They have Python keyword arguments representing the keys of the configuration map.
- One does not have to provide a "modelName" since the model object used itself have this information.

Example (continued)

We now continue the example above using the link prediction model `trained_pipe_model` we trained there. Suppose that we have a new graph `H` that we want to run predictions on.

```
# Make sure our model performed well enough on the test set
metrics = trained_pipe_model.metrics()
assert metrics["AUCPR"]["test"] >= 0.85

# Predict on `H` and mutate it with the relationship predictions
results = trained_pipe_model.predict_mutate(H, topN=5, mutateRelationshipType="PRED_REL")
assert result["relationshipsWritten"] == 5 * 2  # Undirected relationships
```

11.5.3. The pipeline catalog

The primary way to use pipeline objects is for training models. Additionally, pipeline objects can be used as input to GDS Pipeline Catalog operations. For instance, supposing we have a pipeline object `pipe`, we could:

```
catalog_contains_pipe = gds.beta.pipeline.exists(pipe)

gds.beta.model.drop(pipe)  # same as pipe.drop()
```

11.6. The model object

Models of the GDS Model Catalog are represented as `Model` objects in the Python client, similar to how there are graph objects. `Model` objects are typically constructed from training a pipeline or a GraphSAGE model, in which case a reference to the trained model in the form of a `Model` object is returned.

Once created, the `Model` objects can be passed as arguments to methods in the Python client, such as the model catalog operations. Additionally, the `Model` objects have convenience methods allowing for inspection of the models represented without explicitly involving the model catalog.

In the examples below we assume that we have an instantiated `GraphDataScience` object called `gds`. Read more about this in Getting started.

11.6.1. Constructing a model object

There are several ways of constructing a model object. One of the simplest is to train a GraphSAGE model. Supposing we have a graph `G` that have an integer node property "price", we could do the following:

```
model, res = gds.beta.graphSage.train(G, modelName="my-model", featureProperties=["price"])
```

where `model` is the model object, and `res` is a pandas `Series` containing metadata from the underlying procedure call.

Similarly, we can also get model objects from training machine learning pipelines.

To get a model object that represents a model that has already been trained and is present in the model catalog, one can call the client-side only `get` method and passing it a name:

```
model = gds.model.get("my-model")
```

11.6.2. Inspecting a model object

There are convenience methods on all model objects that let us extract information about the represented model.

Table 998. Model object methods

Name	Arguments	Return type	Description
`name`	-	`str`	The name of the model as it appears in the model catalog.
`type`	-	`str`	The type of model it is, eg. "graphSage".
`train_config`	-	`Series`	The configuration used for training the model.
`graph_schema`	-	`Series`	The schema of the graph on which the model was trained.
`loaded`	-	`bool`	`True` if the model is loaded in the in-memory model catalog, `False` otherwise.
`stored`	-	`bool`	`True` if the model is stored on disk, `False` otherwise.
`creation_time`	-	`neo4j.time.Datetime`	Time when the model was created.
`shared`	-	`bool`	`True` if the model is shared between users, `False` otherwise.
`exists`	-	`bool`	`True` if the model exists in the GDS Model Catalog, `False` otherwise.
`drop`	-	`None`	Removes the model from the GDS Model Catalog.

For example, to get the train configuration of a model object `model`, we would do the following:

```
train_config = model.train_config()
```

11.6.3. Using a model object

The primary way to use model objects is for prediction. How to do so for GraphSAGE is described below, and on the Machine learning pipelines page for pipelines.

Additionally, model objects can be used as input to GDS Model Catalog operations. For instance, supposing we have a model object `model`, we could:

```
# Store the model on disk (GDS Enterprise Edition)
_ = gds.alpha.model.store(model)

gds.beta.model.drop(model)  # same as model.drop()
```

GraphSAGE

As exemplified above in Constructing a model object, training a GraphSAGE model with the Python client is analogous to its Cypher counterpart.

Once trained, in addition to the methods above, the GraphSAGE model object will have the following methods.

Table 999. GraphSAGE model methods

Name	Arguments	Return type	Description
`predict_mutate`	`G: Graph, config: **kwargs`	`Series`	Predict embeddings for nodes of the input graph and mutate graph with predictions.
`predict_stream`	`G: Graph, config: **kwargs`	`DataFrame`	Predict embeddings for nodes of the input graph and stream the results.
`predict_write`	`G: Graph, config: **kwargs`	`Series`	Predict embeddings for nodes of the input graph and write the results back to the database.
`metrics`	`-`	`Series`	Returns values for the metrics computed when training.

Suppose then that we have a trained GraphSAGE model `gs_model` and a graph `H` for which we would like to derive node embeddings. Then we could do the following:

```
# Make sure our training actually converged
metrics = gs_model.metrics()
assert metrics["didConverge"]

# Predict on `H` and write embedding node properties back to the database
results = gs_model.predict_write(H, writeProperty="embedding")
assert result["nodePropertiesWritten"] == H.node_count()
```

11.7. Known limitations

Operations known to not work with the Python client are:

- Numeric utility functions (will never be supported)
- Cypher on GDS (might be supported in the future)

Appendix A: Operations reference

This chapter contains a reference of all the procedures and functions in the Neo4j Graph Data Science library.

The operations in the Graph Data Science library can be divided into the following categories:

- Graph Catalog
- Pipeline Catalog
- Model Catalog
- Graph Algorithms
- Additional Operations

11.A.1. Graph Catalog

Production-quality tier

Table 1000. List of all production-quality graph operations in the GDS library. Functions are written in italic.

Description	Operation
Project Graph	`gds.graph.project`
	`gds.graph.project.estimate`
	`gds.graph.project.cypher`
	`gds.graph.project.cypher.estimate`
	`gds.alpha.graph.project`
Check if a graph exists	`gds.graph.exists`
	`gds.graph.exists`
List graphs	`gds.graph.list`
Remove node properties from a named graph	`gds.graph.removeNodeProperties`
Delete relationships from a named graph	`gds.graph.deleteRelationships`
Remove a named graph from memory	`gds.graph.drop`
Stream a single node property to the procedure caller	`gds.graph.streamNodeProperty`
Stream node properties to the procedure caller	`gds.graph.streamNodeProperties`
Stream a single relationship property to the procedure caller	`gds.graph.streamRelationshipProperty`
Stream relationship properties to the procedure caller	`gds.graph.streamRelationshipProperties`
Write node properties to Neo4j	`gds.graph.writeNodeProperties`
Write relationships to Neo4j	`gds.graph.writeRelationship`
Graph Export	`gds.graph.export`

Beta Tier

Table 1001. List of all beta graph operations in the GDS library. Functions are written in italic.

Description	Operation
Project a graph from a graph in the catalog	`gds.beta.graph.project.subgraph`
Generate Random Graph	`gds.beta.graph.generate`
CSV Export	`gds.beta.graph.export.csv`
	`gds.beta.graph.export.csv.estimate`

11.A.2. Pipeline Catalog

Beta Tier

Table 1002. List of all beta pipeline catalog operations in the GDS library.

Description	Operation
Check if a pipeline exists	`gds.beta.pipeline.exists`
Remove a pipeline from memory	`gds.beta.pipeline.drop`
List pipelines	`gds.beta.pipeline.list`

11.A.3. Model Catalog

Beta Tier

Table 1003. List of all beta model catalog operations in the GDS library. Functions are written in italic.

Description	Operation
Check if a model exists	`gds.beta.model.exists`
Remove a model from memory	`gds.beta.model.drop`
List models	`gds.beta.model.list`

Alpha Tier

Table 1004. List of all alpha model catalog operations in the GDS library. Functions are written in italic.

Description	Operation
Store a model	`gds.alpha.model.store`
Load a stored model	`gds.alpha.model.load`
Delete a stored model	`gds.alpha.model.delete`
Publish a model	`gds.alpha.model.publish`

11.A.4. Graph Algorithms

Algorithms exist in one of three tiers of maturity:

- Production-quality
  - Indicates that the algorithm has been tested with regards to stability and scalability.
  - Algorithms in this tier are prefixed with `gds.<algorithm>`.
- Beta
  - Indicates that the algorithm is a candidate for the production-quality tier.
  - Algorithms in this tier are prefixed with `gds.beta.<algorithm>`.
- Alpha
  - Indicates that the algorithm is experimental and might be changed or removed at any time.
  - Algorithms in this tier are prefixed with `gds.alpha.<algorithm>`.

Production-quality tier

Table 1005. List of all production-quality algorithms in the GDS library. Functions are written in italic.

Algorithm name	Operation
Label Propagation	`gds.labelPropagation.mutate`
	`gds.labelPropagation.mutate.estimate`
	`gds.labelPropagation.write`
	`gds.labelPropagation.write.estimate`
	`gds.labelPropagation.stream`
	`gds.labelPropagation.stream.estimate`
	`gds.labelPropagation.stats`
	`gds.labelPropagation.stats.estimate`
Louvain	`gds.louvain.mutate`
	`gds.louvain.mutate.estimate`
	`gds.louvain.write`
	`gds.louvain.write.estimate`
	`gds.louvain.stream`
	`gds.louvain.stream.estimate`
	`gds.louvain.stats`
	`gds.louvain.stats.estimate`

Algorithm name	Operation
Node Similarity	gds.nodeSimilarity.mutate
	gds.nodeSimilarity.mutate.estimate
	gds.nodeSimilarity.write
	gds.nodeSimilarity.write.estimate
	gds.nodeSimilarity.stream
	gds.nodeSimilarity.stream.estimate
	gds.nodeSimilarity.stats
	gds.nodeSimilarity.stats.estimate
PageRank	gds.pageRank.mutate
	gds.pageRank.mutate.estimate
	gds.pageRank.write
	gds.pageRank.write.estimate
	gds.pageRank.stream
	gds.pageRank.stream.estimate
	gds.pageRank.stats
	gds.pageRank.stats.estimate
Weakly Connected Components	gds.wcc.mutate
	gds.wcc.mutate.estimate
	gds.wcc.write
	gds.wcc.write.estimate
	gds.wcc.stream
	gds.wcc.stream.estimate
	gds.wcc.stats
	gds.wcc.stats.estimate
Triangle Count	gds.triangleCount.stream
	gds.triangleCount.stream.estimate
	gds.triangleCount.stats
	gds.triangleCount.stats.estimate
	gds.triangleCount.write
	gds.triangleCount.write.estimate
	gds.triangleCount.mutate
	gds.triangleCount.mutate.estimate

Algorithm name	Operation
Local Clustering Coefficient	gds.localClusteringCoefficient.stream
	gds.localClusteringCoefficient.stream.estimate
	gds.localClusteringCoefficient.stats
	gds.localClusteringCoefficient.stats.estimate
	gds.localClusteringCoefficient.write
	gds.localClusteringCoefficient.write.estimate
	gds.localClusteringCoefficient.mutate
	gds.localClusteringCoefficient.mutate.estimate
Betweenness Centrality	gds.betweenness.stream
	gds.betweenness.stream.estimate
	gds.betweenness.stats
	gds.betweenness.stats.estimate
	gds.betweenness.mutate
	gds.betweenness.mutate.estimate
	gds.betweenness.write
	gds.betweenness.write.estimate
Fast Random Projection	gds.fastRP.mutate
	gds.fastRP.mutate.estimate
	gds.fastRP.stats
	gds.fastRP.stats.estimate
	gds.fastRP.stream
	gds.fastRP.stream.estimate
	gds.fastRP.write
	gds.fastRP.write.estimate
Degree Centrality	gds.degree.mutate
	gds.degree.mutate.estimate
	gds.degree.stats
	gds.degree.stats.estimate
	gds.degree.stream
	gds.degree.stream.estimate
	gds.degree.write
	gds.degree.write.estimate

Algorithm name	Operation
ArticleRank	gds.articleRank.mutate
	gds.articleRank.mutate.estimate
	gds.articleRank.write
	gds.articleRank.write.estimate
	gds.articleRank.stream
	gds.articleRank.stream.estimate
	gds.articleRank.stats
	gds.articleRank.stats.estimate
Eigenvector	gds.eigenvector.mutate
	gds.eigenvector.mutate.estimate
	gds.eigenvector.write
	gds.eigenvector.write.estimate
	gds.eigenvector.stream
	gds.eigenvector.stream.estimate
	gds.eigenvector.stats
	gds.eigenvector.stats.estimate
All Shortest Paths Delta-Stepping	gds.allShortestPaths.delta.stream
	gds.allShortestPaths.delta.stream.estimate
	gds.allShortestPaths.delta.write
	gds.allShortestPaths.delta.write.estimate
	gds.allShortestPaths.delta.mutate
	gds.allShortestPaths.delta.mutate.estimate
Shortest Path Dijkstra	gds.shortestPath.dijkstra.stream
	gds.shortestPath.dijkstra.stream.estimate
	gds.shortestPath.dijkstra.write
	gds.shortestPath.dijkstra.write.estimate
	gds.shortestPath.dijkstra.mutate
	gds.shortestPath.dijkstra.mutate.estimate
All Shortest Paths Dijkstra	gds.allShortestPaths.dijkstra.stream
	gds.allShortestPaths.dijkstra.stream.estimate
	gds.allShortestPaths.dijkstra.write
	gds.allShortestPaths.dijkstra.write.estimate
	gds.allShortestPaths.dijkstra.mutate
	gds.allShortestPaths.dijkstra.mutate.estimate

Algorithm name	Operation
Shortest Paths Yens	gds.shortestPath.yens.stream
	gds.shortestPath.yens.stream.estimate
	gds.shortestPath.yens.write
	gds.shortestPath.yens.write.estimate
	gds.shortestPath.yens.mutate
	gds.shortestPath.yens.mutate.estimate
Shortest Path AStar	gds.shortestPath.astar.stream
	gds.shortestPath.astar.stream.estimate
	gds.shortestPath.astar.write
	gds.shortestPath.astar.write.estimate
	gds.shortestPath.astar.mutate
	gds.shortestPath.astar.mutate.estimate
Similarity functions	gds.similarity.cosine
	gds.similarity.euclidean
	gds.similarity.euclideanDistance
	gds.similarity.jaccard
	gds.similarity.overlap
	gds.similarity.pearson
K-Nearest Neighbors	gds.knn.mutate
	gds.knn.mutate.estimate
	gds.knn.stats
	gds.knn.stats.estimate
	gds.knn.stream
	gds.knn.stream.estimate
	gds.knn.write
	gds.knn.write.estimate
BFS	gds.bfs.mutate
	gds.bfs.mutate.estimate
	gds.bfs.stream
	gds.bfs.stream.estimate
Depth First Search	gds.dfs.mutate
	gds.dfs.mutate.estimate
	gds.dfs.stream
	gds.dfs.stream.estimate

Beta tier

Table 1006. List of all beta algorithms in the GDS library. Functions are written in italic.

Algorithm name	Operation
Closeness Centrality	gds.beta.closeness.mutate
	gds.beta.closeness.stats
	gds.beta.closeness.stream
	gds.beta.closeness.write
GraphSAGE	gds.beta.graphSage.stream
	gds.beta.graphSage.stream.estimate
	gds.beta.graphSage.mutate
	gds.beta.graphSage.mutate.estimate
	gds.beta.graphSage.write
	gds.beta.graphSage.write.estimate
	gds.beta.graphSage.train
	gds.beta.graphSage.train.estimate
K1Coloring	gds.beta.k1coloring.mutate
	gds.beta.k1coloring.mutate.estimate
	gds.beta.k1coloring.stats
	gds.beta.k1coloring.stats.estimate
	gds.beta.k1coloring.stream
	gds.beta.k1coloring.stream.estimate
	gds.beta.k1coloring.write
	gds.beta.k1coloring.write.estimate
Link Prediction Pipeline	gds.beta.pipeline.linkPrediction.create
	gds.beta.pipeline.linkPrediction.addNodeProperty
	gds.beta.pipeline.linkPrediction.addFeature
	gds.beta.pipeline.linkPrediction.addLogisticRegression
	gds.beta.pipeline.linkPrediction.configureSplit
	gds.beta.pipeline.linkPrediction.train
	gds.beta.pipeline.linkPrediction.train.estimate
	gds.beta.pipeline.linkPrediction.predict.mutate
	gds.beta.pipeline.linkPrediction.predict.mutate.estimate
	gds.beta.pipeline.linkPrediction.predict.stream
	gds.beta.pipeline.linkPrediction.predict.stream.estimate

Algorithm name	Operation
Node Classification Pipeline	gds.beta.pipeline.nodeClassification.create
	gds.beta.pipeline.nodeClassification.addNodeProperty
	gds.beta.pipeline.nodeClassification.selectFeatures
	gds.beta.pipeline.nodeClassification.addLogisticRegression
	gds.beta.pipeline.nodeClassification.configureSplit
	gds.beta.pipeline.nodeClassification.train
	gds.beta.pipeline.nodeClassification.train.estimate
	gds.beta.pipeline.nodeClassification.predict.mutate
	gds.beta.pipeline.nodeClassification.predict.mutate.estimate
	gds.beta.pipeline.nodeClassification.predict.stream
	gds.beta.pipeline.nodeClassification.predict.stream.estimate
	gds.beta.pipeline.nodeClassification.predict.write
	gds.beta.pipeline.nodeClassification.predict.write.estimate
Modularity Optimization	gds.beta.modularityOptimization.mutate
	gds.beta.modularityOptimization.mutate.estimate
	gds.beta.modularityOptimization.stream
	gds.beta.modularityOptimization.stream.estimate
	gds.beta.modularityOptimization.write
	gds.beta.modularityOptimization.write.estimate
Node2Vec	gds.beta.node2vec.mutate
	gds.beta.node2vec.mutate.estimate
	gds.beta.node2vec.stream
	gds.beta.node2vec.stream.estimate
	gds.beta.node2vec.write
	gds.beta.node2vec.write.estimate
Random Walk	gds.beta.randomWalk.stream
	gds.beta.randomWalk.stream.estimate

Alpha tier

Table 1007. List of all alpha algorithms in the GDS library. Functions are written in italic.

Algorithm name	Operation
All Shortest Paths	gds.alpha.allShortestPaths.stream
Approximate Maximum k-cut	gds.alpha.maxkcut.mutate
	gds.alpha.maxkcut.mutate.estimate
	gds.alpha.maxkcut.stream
	gds.alpha.maxkcut.stream.estimate

Algorithm name	Operation
Harmonic Centrality	gds.alpha.closeness.harmonic.stream
	gds.alpha.closeness.harmonic.write
Collapse Path	gds.alpha.collapsePath.mutate
HITS	gds.alpha.hits.mutate
	gds.alpha.hits.mutate.estimate
	gds.alpha.hits.stats
	gds.alpha.hits.stats.estimate
	gds.alpha.hits.stream
	gds.alpha.hits.stream.estimate
	gds.alpha.hits.write
	gds.alpha.hits.write.estimate
Strongly Connected Components	gds.alpha.scc.stream
	gds.alpha.scc.write
Scale Properties	gds.alpha.scaleProperties.mutate
	gds.alpha.scaleProperties.stream
Speaker-Listener Label Propagation	gds.alpha.sllpa.mutate
	gds.alpha.sllpa.mutate.estimate
	gds.alpha.sllpa.stats
	gds.alpha.sllpa.stats.estimate
	gds.alpha.sllpa.stream
	gds.alpha.sllpa.stream.estimate
	gds.alpha.sllpa.write
	gds.alpha.sllpa.write.estimate
Spanning Tree	gds.alpha.spanningTree.write
	gds.alpha.spanningTree.kmax.write
	gds.alpha.spanningTree.kmin.write
	gds.alpha.spanningTree.maximum.write
	gds.alpha.spanningTree.minimum.write
Link Prediction Pipeline	gds.alpha.pipeline.linkPrediction.addRandomForest
Node Classification Pipeline	gds.alpha.pipeline.nodeClassification.addRandomForest
Adamic Adar	gds.alpha.linkprediction.adamicAdar
Common Neighbors	gds.alpha.linkprediction.commonNeighbors
Preferential Attachment	gds.alpha.linkprediction.preferentialAttachment
Preferential Attachment	gds.alpha.linkprediction.resourceAllocation
Same Community	gds.alpha.linkprediction.sameCommunity
Total Neighbors	gds.alpha.linkprediction.totalNeighbors

Algorithm name	Operation
Split Relationships	`gds.alpha.ml.splitRelationships.mutate`
Triangle Listing	`gds.alpha.triangles`
Influence Maximization - Greedy	`gds.alpha.influenceMaximization.greedy.stream`
Influence Maximization - CELF	`gds.alpha.influenceMaximization.celf.stream`
Conductance	`gds.alpha.conductance.stream`

11.A.5. Additional Operations

Table 1008. List of all additional operations. Functions are written in italic.

Description	Operation
List all operations in GDS	`gds.list`
List logged progress	`gds.beta.listProgress`
List warnings	`gds.alpha.userLog`
The version of the installed GDS	`gds.version`
Node id functions	`gds.util.asNode`
	`gds.util.asNodes`
Numeric Functions	`gds.util.NaN`
	`gds.util.infinity`
	`gds.util.isFinite`
	`gds.util.isInfinite`
Accessing a node property in a named graph	`gds.util.nodeProperty`
One Hot Encoding	`gds.alpha.ml.oneHotEncoding`
Status of the system	`gds.debug.sysInfo`
Create an impermanent database backed by a projected graph	`gds.alpha.create.cypherdb`
Get an overview of the system's workload and available resources	`gds.alpha.systemMonitor`
Back-up graphs and models to disk	`gds.alpha.backup`
Restore persisted graphs and models to memory	`gds.alpha.restore`

Appendix B: Migration from Graph Data Science library Version 1.x

If you have previously used Graph Data Science library version 1.x, you can find the information you will need to migrate to using version 2.x in this section.

11.B.1. Who should read this guide

This documentation is intended for users who are familiar with the Graph Data Science library. We assume that most of the mentioned operations and concepts can be understood with little explanation. Thus we are intentionally brief in the examples and comparisons. Please see the dedicated chapters in this manual for details on all the features in the Graph Data Science library.

11.B.2. Syntax Changes

In this section we will focus on side-by-side examples of operations using the syntax of versions 1.x and 2.x, respectively.

This section is divided into the following sub-sections:

- Common Changes
- Graph Projection
- Graph Listing
- Graph Drop
- Memory Estimation
- Algorithms
- Machine Learning

11.B.3. Common changes

This section describes changes between version 1.x and 2.x that are common to all procedures.

Table 1009. Changes in algorithm configuration parameter map

1.x	2.x
nodeProjection	removed, due to removal of anonymous graph loading
relationshipProjection	removed, due to removal of anonymous graph loading
readConcurrency	removed, due to removal of anonymous graph loading

Table 1010. Changes in algorithm YIELD fields

1.x	2.x
createMillis	preProcessingMillis

11.B.4. Graph projection

Table 1011. Changes in the YIELD fields

1.x	2.x
`createMillis`	`projectMillis`

1.x	2.x
-	`configuration`
`nodeProjection`	`configuration.nodeProjection`
`relationshipProjection`	`configuration.relationshipProjection`
`nodeQuery`	`configuration.nodeQuery`
`relationshipQuery`	`configuration.relationshipQuery`
`nodeFilter`	`configuration.nodeFilter`
`relationshipFilter`	`configuration.relationshipFilter`

Table 1012. Projecting a graph

1.x	2.x
Native Projection:	
`CALL gds.graph.create( 'myGraph', NODE_PROJECTION, RELATIONSHIP_PROJECTION, ADDITIONAL_CONFIGURATION )`	`CALL gds.graph.project( 'myGraph', NODE_PROJECTION, RELATIONSHIP_PROJECTION, ADDITIONAL_CONFIGURATION )`
Cypher Projection:	
`CALL gds.graph.create.cypher( 'myGraph', NODE_QUERY, RELATIONSHIP_QUERY ADDITIONAL_CONFIGURATION )`	`CALL gds.graph.project.cypher( 'myGraph', NODE_QUERY, RELATIONSHIP_QUERY ADDITIONAL_CONFIGURATION )`
Projecting subgraphs:	
`CALL gds.graph.create.subgraph( 'myGraph', NODE_QUERY, RELATIONSHIP_QUERY ADDITIONAL_CONFIGURATION )`	`CALL gds.graph.project.cypher( 'myGraph', NODE_QUERY, RELATIONSHIP_QUERY ADDITIONAL_CONFIGURATION )`

11.B.5. Graph listing

Table 1013. Changes in the YIELD fields

1.x	2.x
-	`configuration`
`nodeProjection`	`configuration.nodeProjection`

1.x	2.x
`relationshipProjection`	`configuration.relationshipProjection`
`nodeQuery`	`configuration.nodeQuery`
`relationshipQuery`	`configuration.relationshipQuery`
`nodeFilter`	`configuration.nodeFilter`
`relationshipFilter`	`configuration.relationshipFilter`

11.B.6. Graph drop

Table 1014. Changes in the YIELD fields

1.x	2.x
-	`configuration`
`nodeProjection`	`configuration.nodeProjection`
`relationshipProjection`	`configuration.relationshipProjection`
`nodeQuery`	`configuration.nodeQuery`
`relationshipQuery`	`configuration.relationshipQuery`
`nodeFilter`	`configuration.nodeFilter`
`relationshipFilter`	`configuration.relationshipFilter`

11.B.7. Memory estimation

Table 1015. Estimating memory for algorithms without loading the graph:

1.x	2.x
Algorithm estimation on anonymous graphs:	
`CALL gds.ALGO_NAME.estimate( { nodeProjection: NODE_PROJECTION, relationshipProjection: REL_PROJECTION, // algorithm specific configuration } )`	`CALL gds.ALGO_NAME.estimate( { nodeProjection: NODE_PROJECTION, relationshipProjection: REL_PROJECTION }, ALGORIGHM_CONFIGURATION_MAP )`
Algorithm estimation on fictive graphs	
`CALL gds.ALGO_NAME.estimate( { nodeCount: NODE_COUNT, relationshipCount: RELATIONSHIP_COUNT, [ nodeProjection: NODE_PROJECTION, ] [ relationshipProjection: REL_PROJECTION, ] // algorithm specific configuration } )`	`CALL gds.ALGO_NAME.estimate( { nodeCount: NODE_COUNT, relationshipCount: RELATIONSHIP_COUNT, [ nodeProjection: NODE_PROJECTION, ] [ relationshipProjection: REL_PROJECTION, ] }, ALGORIGHM_CONFIGURATION_MAP )`

11.B.8. Algorithms

This section covers migration for all algorithms in the Neo4j Graph Data Science library.

Betweenness Centrality

Table 1016. Changes in YIELD fields

1.x	2.x
`minimumScore`	Use `centralityDistribution.min`
`maximumScore`	Use `centralityDistribution.max`
`scoreSum`	No direct equivalent. For mean, use `centralityDistribution.mean`.

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Table 1017. Changes in configuration

1.x	2.x
String `relationshipWeightProperty`	Removed
`startNodeId`	`sourceNode`

Table 1018. Changes in YIELD fields

1.x	2.x
`startNodeId`	`sourceNode`

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Table 1019. Changes in algorithm configuration parameter map

1.x	2.x
`improve`	`useWassermanFaust`

Table 1020. Changes in `stream` mode YIELD fields

1.x	2.x
`centrality`	`score`

Table 1021. Changes in `write` mode YIELD fields

1.x	2.x
`nodes`	`nodePropertiesWritten`
-	`configuration`

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Table 1022. Changes in configuration

1.x	2.x
String `relationshipWeightProperty`	Removed
`startNodeId`	`sourceNode`

Table 1023. Changes in YIELD fields

1.x	2.x
`startNodeId`	`sourceNode`

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Table 1024. Changes in configuration

1.x	2.x
String `nodeWeightProperty`	String or Map or List of Strings / Maps `nodeProperties`

Chapter 16. Alpha similarity algorithms

The alpha similarity procedures have been removed. Use KNN or Node Similarity instead. The similarity metrics for these can now be configured.

Knn

Cosine, Euclidean, Jaccard, Overlap, Pearson

Node Similarity

Jaccard, Overlap

The alpha similarity functions have been promoted to product tier.

1.x	2.x
`gds.alpha.similarity.cosine`	`gds.similarity.cosine`
`gds.alpha.similarity.euclidean`	`gds.similarity.euclidean`
`gds.alpha.similarity.euclideanDistance`	`gds.similarity.euclideanDistance`
`gds.alpha.similarity.jaccard`	`gds.similarity.jaccard`
`gds.alpha.similarity.overlap`	`gds.similarity.overlap`
`gds.alpha.similarity.pearson`	`gds.similarity.pearson`

16.1. Machine Learning

This section covers migration for Machine Learning algorithms in the Neo4j Graph Data Science library.

Node Classification

The original alpha version of node classification has been completely removed and incorporated into node classification pipelines. Before training a node classification model, you must create and configure a training pipeline.

Train

Some parts of the training are now configured in specific configuration procedures for the training pipeline. These must precede calling the `train` procedure in order to be effective. The remaining parts are moved to the pipeline train procedure. Please see the table below.

Table 1025. Changes in configuration for train

1.x	2.x
`modelName`	This parameter is now only configured in `gds.beta.pipeline.nodeClassification.train`.

1.x	2.x
`featuresProperties`	This parameter is replaced by `gds.beta.pipeline.nodeClassification.selectFeatures`. There is now also a procedure `gds.beta.pipeline.nodeClassification.addNodeProperty` to compute node properties for the input graph in the training pipeline and produced classification model.
`targetProperty`	This parameter is now only configured in `gds.beta.pipeline.nodeClassification.train`.
`holdoutFraction`	This parameter is now named `testFraction` and configured in `gds.beta.pipeline.nodeClassification.configureSplit`.
`validationFolds`	This parameter is now only configured in `gds.beta.pipeline.nodeClassification.configureSplit`.
`metrics`	This parameter is now only configured in `gds.beta.pipeline.nodeClassification.train`.
`params`	This parameter is replaced by `gds.beta.pipeline.nodeClassification.addLogisticRegression`, allowing configuration for a single model candidate. The procedure can be called several times to add several model candidates. There is also a new option for using random forest as a model candidate with `gds.alpha.pipeline.nodeClassification.addRandomForest`.
`randomSeed`	This parameter is now only configured in `gds.beta.pipeline.nodeClassification.train`.

Table 1026. Changes in configuration for the pipeline

1.x	2.x
`gds.beta.pipeline.nodeClassification.configureParams`	

Predict

Apart from the parameters listed below, the API for node classification prediction is the same as before but with different procedures. These procedures are `gds.beta.pipeline.nodeClassification.predict.[mutate,stream,write]`.

Table 1027. Changes in configuration for predict

1.x	2.x
`batchSize`	Batch size is optimized internally and no longer user-configurable.

Table 1028. Prediction procedure replacements:

1.x	2.x
`gds.alpha.ml.nodeClassification.predict.stream`	`gds.beta.pipeline.nodeClassification.predict.stream`

1.x	2.x
gds.alpha.ml.nodeClassification.predict.mutate	gds.beta.pipeline.nodeClassification.predict.mutate
gds.alpha.ml.nodeClassification.predict.write	gds.beta.pipeline.nodeClassification.predict.write

Chapter 17. Link Prediction

The original alpha version of link prediction has been completely removed and incorporated into link prediction pipelines. Before training a link prediction model, you must create and configure a training pipeline.

17.1. Train

Some parts of the training are now configured in specific configuration procedures for the training pipeline. These must precede calling the `train` procedure in order to be effective. The remaining parts are moved to the pipeline train procedure. Please see the table below.

Table 1029. Changes in configuration for train

1.x	2.x
`modelName`	This parameter is now only configured in `gds.beta.pipeline.linkPrediction.train`.
`featuresProperties`	Replaced by `nodeProperties` in `gds.beta.pipeline.linkPrediction.addFeature`. There is also a procedure `gds.beta.pipeline.linkPrediction.addNodeProperty` to compute node properties for the input graph in the training pipeline and produced classification model.
`linkFeatureCombiner`	Replaced by the second positional argument to `gds.beta.pipeline.linkPrediction.addFeature`, called `featureType`.
`trainRelationshipType` and `testRelationshipType`	These parameters are removed. Use `gds.beta.pipeline.linkPrediction.configureSplit` to set up the dataset split.
`validationFolds`	This parameter is now only configured in `gds.beta.pipeline.linkPrediction.configureSplit`.
`negativeClassWeight`	This parameter is now only configured in `gds.beta.pipeline.linkPrediction.train`.
`params`	This parameter is replaced by `gds.beta.pipeline.linkPrediction.addLogisticRegression`, allowing configuration for a single model candidate. The procedure can be called several times to add several model candidates. There is also a new option for using random forest as a model candidate with `gds.alpha.pipeline.linkPrediction.addRandomForest`.
`randomSeed`	This parameter is now only configured in `gds.beta.pipeline.linkPrediction.train`.

Table 1030. Changes in configuration for the pipeline

1.x	2.x
`gds.beta.pipeline.linkPrediction.configureParams`	This procedure, which is no longer present, added logistic regression model candidates. Adding logistic regression candidates, can instead be done by calling `gds.beta.pipeline.linkPrediction.addLogisticRegression` one or multiple times.

17.2. Predict

The API for link prediction classification is the same as before, but with different procedures. These procedures are `gds.beta.pipeline.linkPrediction.predict.[mutate,stream]`. However, there's no longer a `write` mode for link prediction classification, but it's still possible to emulate this behavior using the `mutate` mode followed by `gds.graph.writeRelationships`.

Table 1031. Prediction procedure replacements:

1.x	2.x
`gds.alpha.ml.linkPrediction.predict.stream`	`gds.beta.pipeline.linkPrediction.predict.stream`
`gds.alpha.ml.linkPrediction.predict.mutate`	`gds.beta.pipeline.linkPrediction.predict.mutate`
`gds.alpha.ml.linkPrediction.predict.write`	-

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