Scientific Data Analysis using Neo4j

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Abstract: There is new material regarding Neo4j algorithm questions posed in this report as well as where we did our due diligence research to resolve them. These results often provide details, including inquiries recorded after each monitoring period. Initially, a literature review supported the development of an initial data modeling, which was further provided as experimental analysis. By using Neo4j Graph Database, graph analytics can provide useful analysis.

1 INTRODUCTION

Due to recent innovations in social networks, e-commerce and website tracking technology, data collection and management have become a challenge for data storage and retrieval. Today, we work with data that cannot be stored in a traditional database because it has a huge volume. There is no longer a consensus that Relational Databases (RDBs) are the best solution to data complexity problems and volume growth in terms of scale.

Although RDB designs have shown to be flexible and scalable in complex systems, Graph Databases (GDBS) can be better in these two aspects (Pokorny, 2016). A GDB makes use of nodes, margins, attributes, and graphs for data representation and makes direct use of database objects seem like data elements. Data may be connected to the other without using intermediate folders or data views, and it is possible to retrieve a highly complex query using a single connection process in certain situations. Neo4j is open-source and matches a broad adoption of the ACID (Atomicity, Consistency, Isolation, and Durability) properties is a highly scalable open-source graph database with good interest (Neo4j Graph Database Platform, 2021a). Under the "network-driven" approach (there are said to be nodes with associations and resources in the above), a network with data items is made up of a web of connections, like those in the latter. Relationships 1) have an index annotation, which tells you about all the interactions among the nodes they belong to; and 2) are expressed as items that have indices to their respective contexts. When working with semi-structured data, Neo4j performs as well as it is said to do. Moreover, applications that tend to be hierarchical fit well the project models.

2 BACKGROUND WORK

Disruptive technology represents an innovative method that greatly changes how a customer, an industry, or a company manages. Disruptive technologies would sweep across the industries or conventions it takes the place of due to their demonstrable superiority (Smith, 2020). Automobiles, electrical services, and consumer products could represent different types of disruptive technology in their respective eras. More recently, disruptive industries consist of the Internet of Things, cloud computing, fintech, robotics, and artificial

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intelligence (AI). Neo4j used in this paper is also one of the disruptive technologies and has become a leader in its industry.

Neo4j is disruptive in several ways. First of all, it provides developers and data scientists with state-of-the-art techniques to establish intelligent applications and machine learning workflows in modern society, which turns out available as a completely managed cloud service or self-hosted (Neo4j, 2021). Second, Neo4j is a persistent Java engine and an entirely transactional database, in which structures can be reserved based on graphs rather than tables. Third, Neo4j employs native graph reservation, removing restrictions of administrating and reserving data in a highly regulated way. It is regarded as one of the most prevalent and most used graph databases globally, applied in various fields such as health, government, automotive production, and military. Lastly, most databases currently operate based on a server accessible through a client library. Neo4j can run in server and embedded modes depending on data analysis requirements (Fernandes and Bernardino, 2018).

This paper analyses the dataset with numerous algorithms in neo4j. We can learn how the implementation and mutation work on large-scale data set by these algorithms. The objectives of this paper are as follows:

1) Finding the interconnectivity between nodes and relationships using the Louvain Community Detection Algorithm.
2) Finding the similar sets using the Jaccard Similarity Algorithm.
3) Measuring the nodes and relationships using Betweenness Algorithm.
4) Ranking the nodes and entities using Page Ranking Algorithm.
5) Prioritizing the nodes using the Modularity Detection Algorithm.
6) Node calculations using the Clustering Coefficient Algorithm.
7) Finding the shortest path using the All-Pair Shortest Algorithm.
8) Finding the node embeddings using the Node2Vec Algorithm.
9) Finding the Strongly Connected components between the nodes and relationships.

3 DATA MODELLING AND EXTRACTION

The model involves depicting a disconnected network of entities and their various attributes and relationships on a general level, allowing users to define general and complex structures. According to its rules, a Graph database query is shaped to address questions about Neo4j is written to meet the needs and solve commercial and technological challenges in the context of both technical and organizational issues (Haojun et al., 2020).

To better understand the process of designing a graph data model, let us take a small set of data from the healthcare domain and walk through each step of creating a graph data model. The data this paper used is Safeguarding Adults.

Let us extract our graph database schema visualization. As shown in Figure 1, this schema contains nodes and relationships directed to each node, where the region node and council node act as constraints. The region node is directed to the council node, which has a relationship of HAS_COUNCIL. Suppose we want to find out which council in the database can query between the region and council nodes to find out the council sub-nodes. Each sub-node is then followed by the relationship, respectively.

The file loaded with headers and created nodes with labels and properties can also create a graph entity from a map. All the key/value pairs in the map will be set as properties on the created relationship of a node.

4 EXPERIMENTAL ANALYSIS

4.1 Louvain Community Detection

The Louvain community detection algorithm was proposed in 2008 as a tool for communities that sped up the analysis of complex networks. It has two distinct stages: Local Moving Nodes and Aggregation of the network.

The algorithm begins with a network of N nodes connected by equal-weighted links (Hu et al., 2016). During the first loop, the algorithm's operations, the connections to all the networks are each given a group to reside in their own nodes. Each node looks at the neighboring nodes and judges if the one to be "expanded" has a positive or negative effect on the node-size community by looking for ways to reduce the size of the existing node connections (Ryu and

Kim, 2016). If the increase in group benefit outweighs the costs and individual gains, the node would be added to the community. Otherwise, it will stay in the same place. Any single instance of this method is carried out on its own on all nodes before no more change is observed (Ghosh et al., 2018). The first iteration of the Louvain algorithm has reached a local maximum as it finds the global maximum expansion set of elements. If the initial network has been created, in the first step, the algorithm expands it by treating communities in the initial network as nodes. When the second step is over, the algorithm can then expand the result of the first phase to the new network. These procedures are performed several times before the network has no further connections and optimum modularity has been achieved.

At the same time, the Louvain algorithm locator tries to identify groups when expanding. It is most often used because it is easy to use and fast.

As we stated, the Louvain approach is a community discovery algorithm that detects populations in networks. It maximizes each community's modularity score. In contrast, modularity quantifies the consistency of a node's assignment to a group.

The output is visualized in Figure 1 below.

4.2 Jaccard Similarity Algorithm

The Jaccard Similarity, a concept introduced by Paul Jaccard, refers to the measure of relationships between sets. The formula for Jaccard similarity is notated below.

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

The input for this algorithm is a bipartite, disconnected graph comprising two disconnected sets of nodes. Each partnership begins with first node instances and finishes with instances of second-node or subtypes.

The Node Similarity algorithm compares each node that has outgoing relationships with another node of the same kind (Neo4j Graph Database Platform, 2021c). We collect the outgoing neighborhood N(n) of each node n, that is, all nodes m that have a connection from n to m. The algorithm computes a similarity for each pair n, m, which is the Jaccard similarity of N(n) and N(m) (m). The algorithm strips away ambiguity by ignoring nodes that are no longer in contact and a function of numerical difficulty (Bie et al., 2020).

The algorithm generates new relationships between pairs of the first node-set. Relationship properties are used to express similarity ratings.

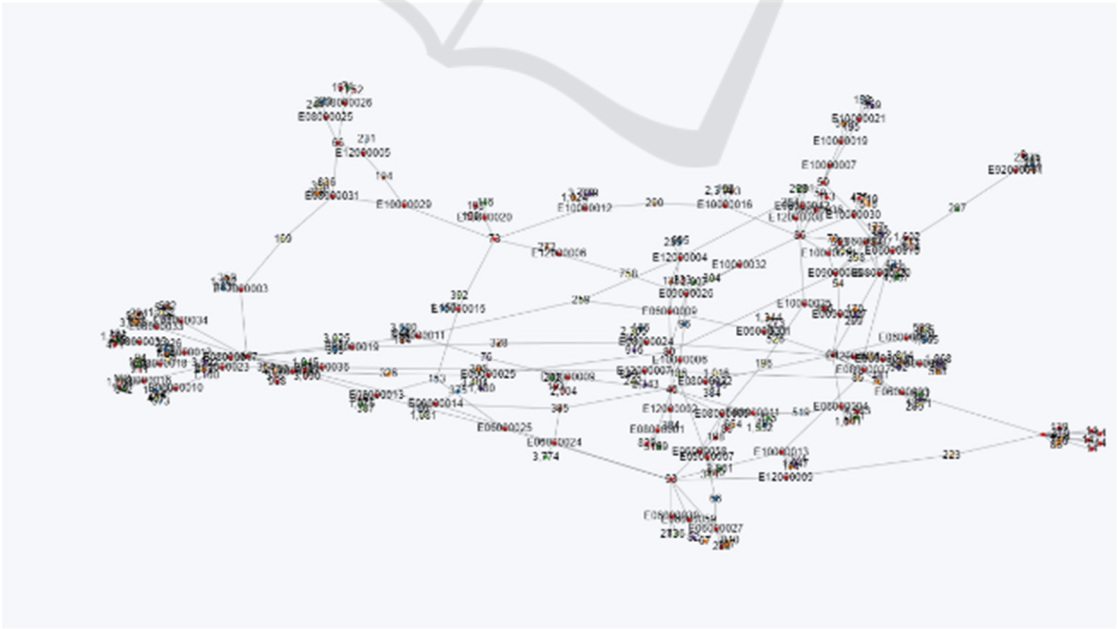


Figure 1: Community Detection graph.

The table below shows the results from two nodes with properties where each node has a similarity of 0.6.

Table 1: The score of each node respective to their labels and properties.

From Labels	From Properties	To Labels	To Properties	Similarity
REGION	County	REGION	Outer London	0.6
REGION	County	REGION	Unitary Authority	0.6
REGION	County	REGION	Metropolitan District	0.6
REGION	Inner London	REGION	Outer London	0.6
REGION	Metropolitan District	REGION	Unitary Authority	0.6
REGION	Outer London	REGION	Inner London	0.6
REGION	Unitary Authority	REGION	Metropolitan District	0.6

4.3 Betweenness Centrality

Betweenness centrality measures how much power a node has on the flow of knowledge in a graph. It is often used to locate nodes that link two parts of a graph (Chen et al., 2017).

Brandes' estimated algorithm for unweighted graphs serves as the foundation for the GDS implementation. The algorithm finds the unweighted shortest path between two nodes in a graph (Vu and Potika, 2020; Petersen et al., 2016). A score is assigned to each node depending on the amount of shortest paths that pass through it. Higher betweenness centrality scores would be assigned to nodes that often lie on the shortest paths between other nodes (Roditty and Shapira, 2011; Jha and Sunitha, 2017). The implementation takes up O(n + m) space and runs in O(n * m) time, where n is the number of nodes in the graph and m is the number of relationships.

Vertices with a strong betweenness greatly impact a graph due to their power over transferring knowledge between multiple vertices (Chehreghani, 2014; Xu et al., 2019). This also suggests that eliminating them from the network would create the most disturbance of the network's knowledge flow.

The output is visualized in Figure 2. We can see the betweenness for each node with a higher rate of 29758.671120 and a lower rate of 17825.790736, which has multiple connections between every node. So, the shorted path of the node has a betweenness of 17825.790736.

Figure 2: Betweenness Centrality Graph.

4.4 Page Ranking Algorithm

This post proposes using a random walk algorithm based on Personalized PageRank (PPR) to disambiguate NEs. Firstly, a network graph with all vertices connected was built (Tian, 2010). We run the PPR algorithm on this graph, with the restriction that only the highest-scoring candidate should become the start point of a hop and efficiently filter out potential noise. Since all candidates but the correct ones are incorrect and most definitely wrong, limiting the random walk (Altman and Tennenholtz, 2005).

The following characteristics are shared by our system: 1) Our solution does not have training model parameters since it is focused on a random walk algorithm; 2) our process can better utilize the local similarities between a region node and a council node, and we customize the PPR algorithm to only concentrate on one region node. Each graph node - (m,c) is a pair of an entity mention m and a candidate c; each node is given an initial normalized score for all nodes for the same entity. If the data entry referring to one of the two nodes includes a path to the other node, we insert an edge between them. Assuming that this relationship is bidirectional, we conclude that this edge is undirected.

PageRank is a more sophisticated method of calculating the value or significance of nodes than merely counting the number of relationships that refer to it (Scarselli et al., 2005). If a backlink comes from a relevant node, it is assigned a higher weighting than backlinks from unimportant nodes. A simple relation from one node to another can be interpreted as a ballot. However, not only is the number of votes received by a page deemed significant but so is the significance or validity of those who cast these votes.

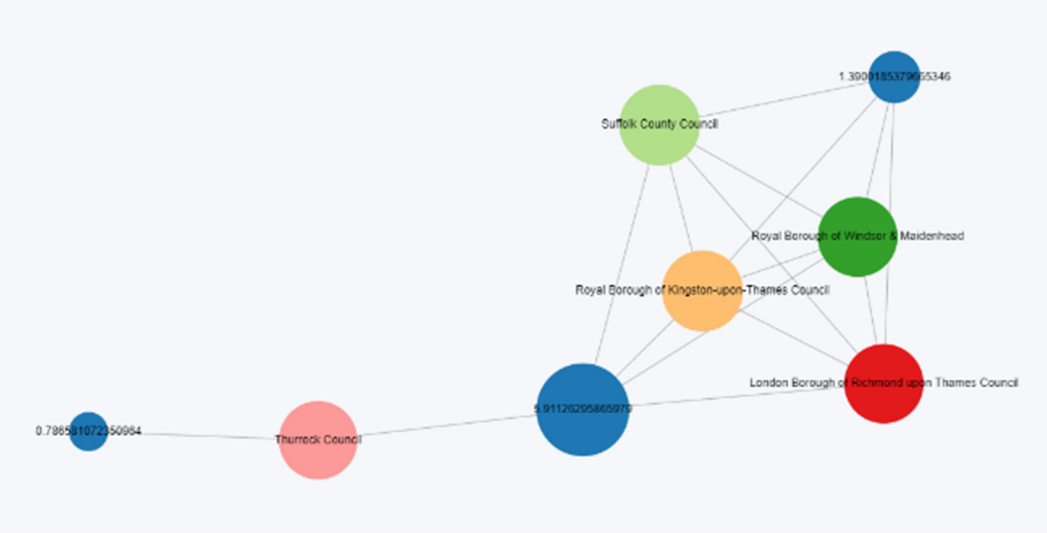


Figure 3: Graph showing the nodes connected with the page ranking.

Table 2 explains the page ranking and score with the nodes where node(-) with the page rank of 19.633 has the highest score of 0.76244 and the lowest score of 0.20486 from node 153, page rank of 0.803131.

Table 2: Results showing page ranking on each node.

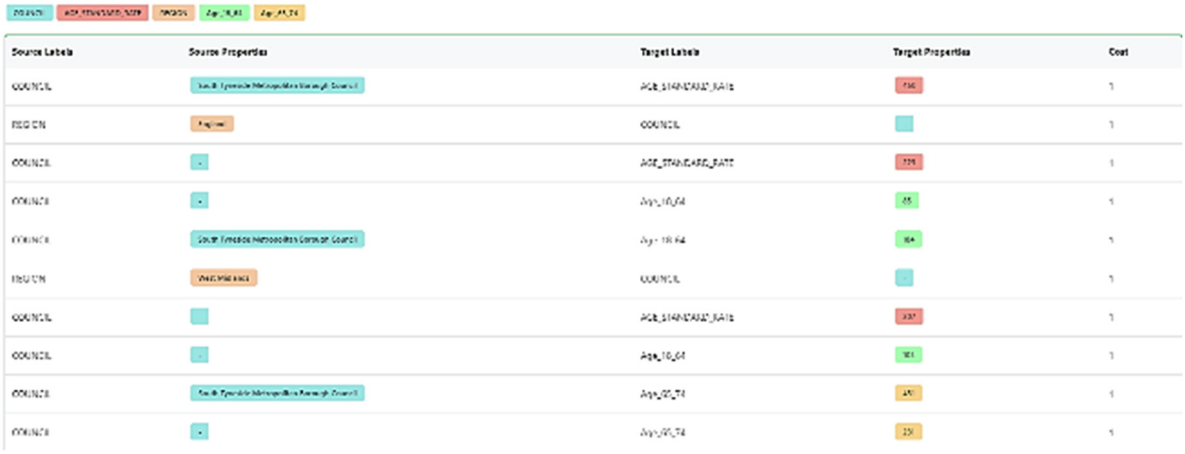
Node	Score
-, 19.633746216818693	0.7624459417182045
5, 1.0142337696277537	0.22313292682520117
76, 0.9820994517707731	0.22233425780285856
15, 1.0167618133593352	0.2222280314700857
85, 1.0115520314662718	0.22214709760622778
10, 0.9114799050759756	0.21350007391301917
153,0.8031313558603869	0.20486719490208813

As shown in Figure 3, the node with a page rank of 1.390185 is connected to the multiple council nodes with a higher page rank compared with other nodes. The edge of the node is the node with a page rank of 0.7858102, following with the council Thurrock.

4.5 Modularity Detection Algorithm

When we consider vertices in a neighborhood to be densely connected, the combination of these vertices is often referred to as modules or groups. Moreover, all the members of the same subgroup are like each other. The challenge of community exploration is to separate the network into clusters of vertices with several edges inside clusters and little connections within them. When evaluating the community structure of a network, broad usage of modularity is developed (Sun et al., 2020). This is particularly true for the connectivity of groups and the extensibility of modules. Node similarity and community similarity are used for group identification. Most of the studies so far are on locating some two connected nodes based on local knowledge. It means that, while the similarity of the community's calculation ignores the non-to-ness of local structure, it also analyses the shared components pertinent to global communication. However, the nature of two nodes' interconnectedness is a key feature in network expansion, and the extent of their interconnectedness should be gauged to make it reliable. Currently, there is nothing to be found in the literature about such an approach.

There are also two different approaches to be considered for finding new similarities between nodes to expand this capacity to include global and local communication (Meng et al., 2016). By utilizing this general networking modularity, the conventional modularity is established at a hierarchical scale, and it unrolls each node's network to quantify the degree of their relationship. Such actions quantify the level of interconnectedness between the nodes and subsequently create a group. The proposed similarity-based generalized modularity measure is simplified to the traditional one when the similarity matrix is replaced by an adjacency matrix. It provides a numerical weight to any partition of a network's nodes following their communal characteristics. See Figure 4.



Source Labels	Source Properties	Target Labels	Target Properties	Cost
COUNCIL				1
REGION		COUNCIL		1
COUNCIL				1
COUNCIL				1
COUNCIL				1
REGION		COUNCIL		1
COUNCIL				1
COUNCIL				1
COUNCIL				1
COUNCIL				1

Figure 4: Result showing the modularity optimization on various nodes.

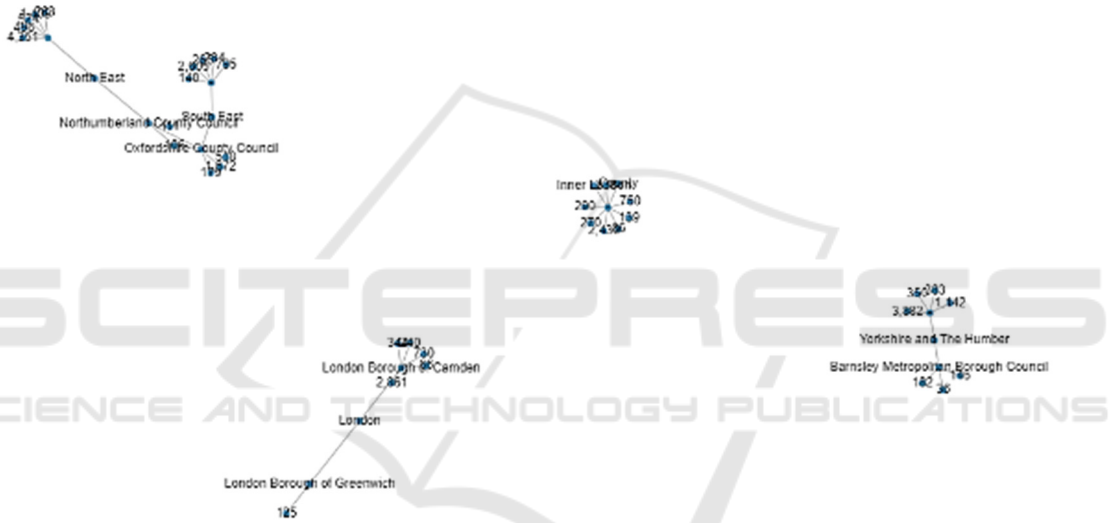


Figure 5: Graph showing the node optimized to respective modularity score.

The above table shows the modularity optimization of nodes with source labels and properties targeting other node labels. We can see that the cost of all nodes was equal to 1. See Figure 5.

4.6 Clustering Coefficient Algorithm

The LCC (or Local Clustering algorithm) computes the local clustering coefficients for each node in the graph. The measure of the relatedness between nodes denoted by the "Cn" of a given node defines the probability that the nodes' "n" neighbors are also associated. If we were calculating Cn, we could count the number of triangles a node is involved in and the degree of the node, and we have to do n node calculations. To obtain the local clustering coefficient, simply calculate the formula for cluster ID as follows (Liao and Yang, 2017).

$$C_n = \frac{2T_n}{d_n(d_n - 1)}$$

Furthermore, the algorithm will obtain the graph's whole clustering coefficient of magnitude, not just the isolated values. This is the root mean a square number of the square of the local coefficients (Zhang et al., 2014; Wang and Xu, 2019).

This can be done by declaring the gds local clustering coefficient stream function and configuring the parameters with node projection and relationship projection (Qiu et al., 2006; Zhou, 2011). In the next step, we yield the nodeId as coefficient with utils of nodeId as node and coefficient ordering them in the descending order to the integer limit.

Table 3: Results showing the clustering coefficient.

	name	localClusteringCoefficient
1	"County"	1.0
2	"Inner London"	1.0
3	"Metropolitan District"	1.0
4	"Outer London"	1.0
5	"Unitary Authority"	1.0

Now we are finding the average clustering coefficient and node count by running the stats on configuration, with the gds local clustering coefficient function shown in Figure 6.

In the above, we declare the gds local clustering coefficient function to determine the average clustering and node count based on the configuration.

Table 4: Showing the average clustering on node count.

averageClusteringCoefficient	nodeCount
0.02160838019616753	1408

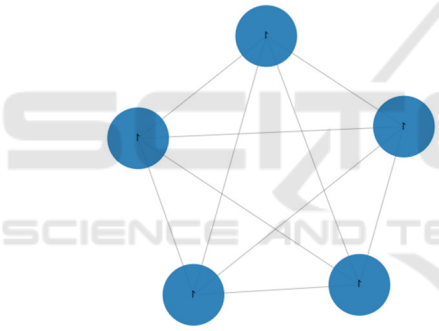


Figure 6: Results showing the mapping between the clustering coefficients.

4.7 All Pair Shortest Path

The All-Pairs Shortest Path (APSP) considers all of the pair weights about the total weight. The runtime complexity of this algorithm is less than that of using the Single Source Shortest Path algorithm for a pair of nodes in the graph (1).

In the scenario, certain nodes are unreachable, and this means that no shortest path exists between certain pairs of nodes. Since these nodes represent distinct natural numbers, the algorithm would return the value of Infinity, therefore, between them. The expandable in plain text property does not allow text filtering, so a value with a word whose text is Infinity (for example, gds.util.Finite) was implemented to improve.

Use-cases of All Pair Shortest Path:

1) Usage of the All-Pairs Shortest Path includes providing services (which also involves placement of facilities) and certain urban issues, which would like to identify the shortest path connecting different locations, separate sets of locations.
2) Per pair of endpoints in the REWIRE's shortest route has an active role in REWIR's network architecture, resulting in the full bandwidth and minimum delay network design.

Using the Neo4j database, we are loading our all-shortest pair algorithm to configure the data with node projection and relationship projection. The parameters are limited to 10 nodes and relation type with default and orientation directed as Natural. All the nodes were checked while processing with empty properties—declaring the start node and end node null because we must find the shortest distance between all nodes in the graph in Figure 7.

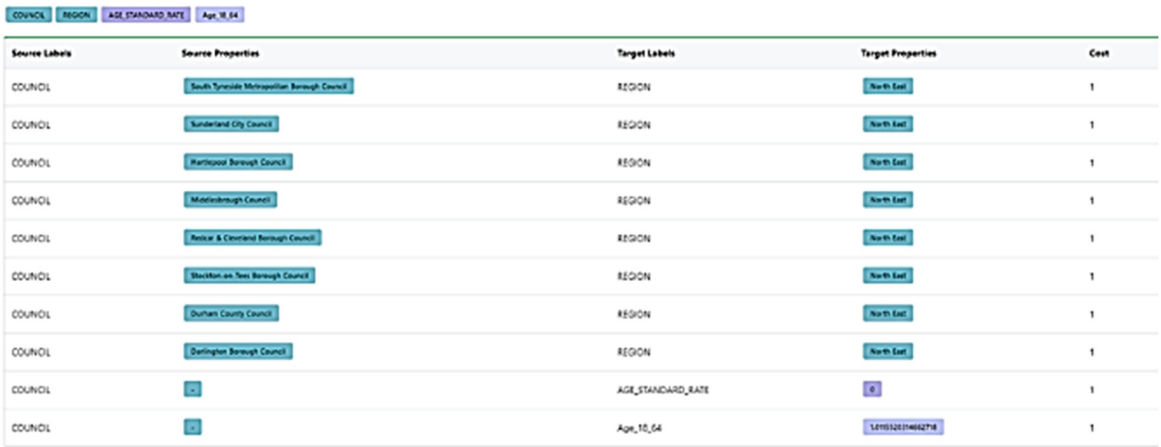


Figure 7: Results showing the score of the shortest pair with nodes and properties.

4.8 Node Embeddings / Node2Vec

The graph is modeled using random walks in the algorithm Node2V, a node embedding method that computes a vector representation of each node in turn (Moon et al., 2019). Walking through the community in an unplanned sequence is conducted to provide information on the general attributes of the place. Randomly picking out a large number of neighborhoods and iterating over their activation patterns (neighborhood vectors) is used to train a single hidden layer neural network. To help build a neural network better understand the probability that a certain node is walking, they are programmed to look for the possibility of doing so.

The data set we have taken to produce some dimensional analysis from node to vector. Scaling a large amount of data can be done in seconds to visualize the graph. It is useful to embed the nodes with weight properties and iterations. For each iteration, the time complexity may be different from the result of the graph.

4.9 Strongly Connected Components

The Strongly Linked Components (SCC) algorithm seeks the maximum number of connected nodes in a guided network. If there is a guided path between each pair of nodes in a set, it is called a strongly linked part. It is often used early in the graph analysis phase to help us understand how our graph is organized (Neo4j Graph Database Platform, 2021b).

Tarjan described the first linear-time algorithm in 1972, and SCC is one of the earliest graph algorithms. The depth-first search algorithm is commonly used to decompose a guided graph into its closely linked components (Hong et al., 2013).

In our implementation, we only used dynamic graph data structures with associated lists for the adjacency array. The graph generator class ensures that each vertex is stored in a sequential position in the adjacency list.

The guided graph interface specifies several approaches to enforce that each node represents a special data member of a generic form and two nodes cannot be connected to the graph if they reflect the same node (Xie and Beerel, 2000; Li et al., 2017). The second attempt would simply be overlooked, and several edges between two nodes are not permitted. An abstract class node, which often acts as an interface for the vertex of a guided graph, keeps a record of its descendants and predecessors.

We need to call the gds scc stream function to configure the node projections and relationship projections, and we have to yield the node and community where we collect all nodes and community returning with the size and community node limit. See Figure 8.

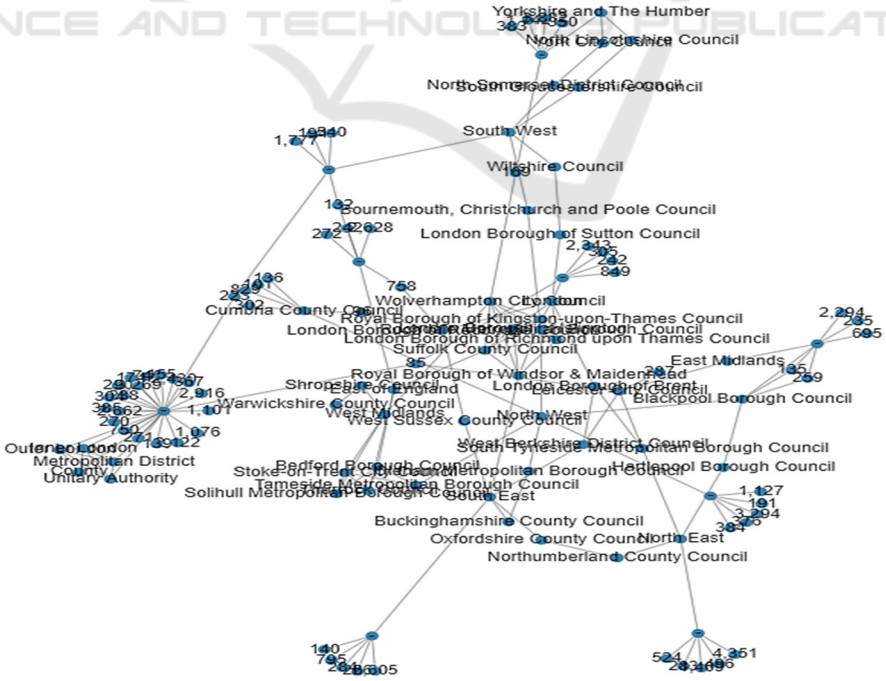


Figure 8: Strongly connected components Graph.

5 CONCLUSIONS

Everyone would be able to consider, model, and forecast complex phenomena such as the distribution of capital or knowledge, the mechanisms through which contagions or network failures propagate, and the impacts on and resiliency of groups using Neo4j graph algorithms. Since Neo4j combines analytics and transaction operations in a native graph platform, you will be able to explore the inner nature of real-world processes for new discoveries and design and execute graph-based applications quicker and with simplified workflows. That is the strength of a well-planned strategy.

The universe revolves around relationships. Neo4j graph analytics shows the significance of such relations using realistic, streamlined graph algorithms like those described above.

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