Big Graph-based Data Visualization Experiences
The WordNet Case Study

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Abstract: In the Big Data era, the visualization of large data sets is becoming an increasingly relevant task due to the great impact that data have from a human perspective. Since visualization is the closer phase to the users within the data life cycle's phases, there is no doubt that an effective, efficient and impressive representation of the analyzed data may result as important as the analytic process itself. This paper presents an experience for importing, querying and visualizing graph database and in particular, we describe as a case study the WordNet database using Neo4J and Cytoscape. We will describe each step in this study focusing on the used strategies for overcoming the different problems mainly due to the intricate nature of the case study. Finally, an attempt to define some criteria to simplify the large-scale visualization of WordNet will be made, providing some examples and considerations which have arisen.

1 INTRODUCTION

Nowadays Data or Information Visualization have become an interesting and wide research field. If the main goal of Data Visualization is to communicate information clearly and efficiently to users, involving the creation and study of the visual representation of data – i.e., "information that has been abstracted in some schematic form, including attributes or variables for the units of information" (Friendly and Denis, 2001) – the Information Visualization main task is the study of (interactive) visual representations of abstract data to reinforce human cognition. The abstract data may include both numerical and non-numerical data, such as text and geographic information. According to (Munzner, 2008), it is possible to distinguish Information Visualization (InfoVis), when the spatial representation is chosen, from Scientific Visualization (SciVis) when the spatial representation is given due to the intrinsic spatial layout of data (e.g., a flow simulation in 3D space). The study presented in this work belongs to the first category because the data we represent do not correspond to physical entities and has no pre-defined spatialization (such as, for example, in the case of maps or geographic informative systems). The field of information visualization has emerged "from research in human-computer interaction, computer science, graphics, visual design, psychology, and business methods. It is increasingly applied as a critical component in scientific research, digital libraries, data mining, financial data analysis, market studies, manufacturing production control, and drug discovery" (Bederson and Shneiderman, 2003). Furthermore, the challenges that the Big Data imperative (Caldarola et al., 2015; Caldarola et al., 2014) imposes to data management severely impact on data visualization. The "bigness" of large data sets and their complexity in term of heterogeneity contribute to complicate the representation of data, making the drawing algorithms quite complex: just to make an example, let us consider the popular social network Facebook, in which the nodes represent people and the links represent interpersonal connections; we note that nodes may be accompanied by information such as age, gender, and identity, and links may also have different types, such as colleague relationships, classmate relationships, and family relationships. The effective representation of all the information at the same time is really challenging. The most common solution is to use visual cues, such as color, shape, or transparency to encode different attributes (Rinaldi, 2012). At the same time, the availability of large data coming from human activities, exploration and experiments, together with the investigations of

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new and efficiently ways of visualizing them, open new perspectives from which to view the world we live in and to make business. The *Infographics* become *Infonomic*, a composite term between the term *Information* and *Economics* that wield information as a real asset, a real opportunity to make business and to discover the world. Various techniques have been proposed for graph visualization for the last two decades and they will be presented in the next section. As far as we can say here, the principled representation methodology we agree on is the Visual Information Seeking Mantra presented by Scheiderman in (Bederson and Shneiderman, 2003). It can be summarized as follows: “overview first, zoom and filter, then details-on-demand”.

The reminder of the paper is organized as follows. After a literature review on the Graph Visualization techniques and methodologies, contained in section 2, a description of the proposed WordNet meta-model is provided in section 3. Afterward, starting from a description of the approach used for the WordNet importing procedure within Neo4j, in section 4, the attempts made in querying and visualizing WordNet are described in section 5 and 6. Finally, section 7 draws the conclusion summarizing the major findings and outlining future investigations

2 RELATED WORKS

Since the study conducted in this paper consists in the visual representation of WordNet inside the Neo4j graph DB, this section focuses mainly on a literature review in *Graph Visualization,* referring to other well-known works in the literature for a complete review of the techniques and theories in Information Visualization (Spence, 2001; Mazza, 2009; Fayyad et al., 2002; Ware, 2012). Graphs are traditional and powerful tools that visually represent sets of data and the relations among them. In the most common sense of the term, a graph is an ordered pair $\boldsymbol{G=(V,E)}$ comprising a set $\boldsymbol{V}$ of vertices or nodes together with a set $\boldsymbol{E}$ of edges or lines, which are 2-element subsets of V (i.e., an edge is related with two vertices, and the relation is represented as an unordered pair of the vertices with respect to the particular edge). Graph visualization usually refers to representation of interconnected nodes arranged in space and navigation through a visual representation to help users understand the global or local original data structures (Cui and Qu, 2007). Graphs are represented visually by drawing a dot or circle for every vertex, and drawing an arc between two vertices if they are connected by an edge. If the graph is directed, the direction is indicated by drawing an arrow. The pioneering work of W. T. Tutte (Tutte, 1963) was very influential in the subject of graph drawing, in particular he introduced the use of linear algebraic methods to obtain graph drawings. The basic graph layout problem is very simple: given a set of nodes with a set of edges, it only needs to calculate the positions of the nodes and draw each edge as curve. Despite the simplicity of the problem, to make graphical layouts understandable and useful is very hard. Basically there are generally accepted aesthetic rules (Purchase, 1997; Purchase et al., 1996), which include: distribute nodes and edges evenly, avoid edge crossing, display isomorphic substructures in the same manner, minimize the bends along the edges. However, since it is quite impossible to meet all rules at the same time, some of them conflict with each other or they are very computationally expensive, practical graphical layouts are usually the results of compromise among the aesthetics.

Below is a brief overview of graph layouts and visualization techniques grouped by categories:

- Node-link layouts.
  - Tree Layout. It uses links between nodes to indicate the parent-child relationships. A very satisfactory solution for node-link layout comes from Reingold et al. (Reingold and Tilford, 1981). Their classical algorithm is simple, fast, predictable, and produces aesthetically pleasing trees on the plane. However, it makes use of screen space in a very inefficient way. In order to overcome this limitation, some compact tree layout algorithms have been developed to obtain more dense tree, while keeping the classical tree looks (Beaudoin et al., 1996). Eades (Huang et al., 2007) proposes another node-link layout called radial layout that recursively positions children of a sub-tree into a circular wedge shape according to their depths in the tree. Generally, radial views, including its variations (Wills, 1997), share a common characteristic: the focus node is always placed at the center of the layout, and the other nodes radiate outward on separated circles. Balloon layout (Carriere and Kazman, 1995) is similar to radial layout and are formed where siblings of sub-trees are placed in circles around their father node. This can be obtained by projecting cone tree onto the plane.
  - Tree Plus Layout. Since large graphs are much more difficult to handle than trees, tree visualization is often used to help users understand graph structures. A straightforward way to visualize graphs is to directly layout span-

ning trees for them. Munzner (Munzner, 1997) finds a particular set of graphs called quasi-hierarchical graphs, which are very suitable to be visualized as minimum spanning trees. However, for most graphs, all links are important. It could be very hard to choose a representative spanning tree. Arbitrary spanning trees can also possibly deliver misleading information.

  – Spring Layout. This layout, also known as *Force-Directed* layout, is another popular strategy for general graph layouts. In spring layout, graphs are modeled as physical systems of rings or springs. The attractive idea about spring layout is that the physical analogy can be very naturally extended to include additional aesthetic information by adjusting the forces between nodes. As one of the first few practical algorithms for drawing general graphs, spring layout is proposed by Eades in 1984 (Eades, 1984). Since then, his method is revisited and improved in different ways (Fruchterman and Reingold, 1991; Gansner and North, 1998). Mathematically, Spring layout is based on a cost (energy) function, which maps different layouts of the same graph to different non-negative numbers. Through approaching the minimum energy, the layout results reaches better and better aesthetically pleasing results. The main differences between different spring approaches are in the choice of energy functions and the methods for their minimization.

- Space Division Layout. In this case, the parent-child relationship is indicated by attaching child node(s) to the parent node. Since the parent-child and sibling relationships are both expressed by adjacency, The layout should have a clear orientation cue to differentiate these two relationships
- Space Nested Layout. Nested layouts, such as Treemaps (Johnson and Shneiderman, 1991), draw the hierarchical structure in the nested way. They place child nodes within their parent node
- 3D Layout. In this case, the extra dimension can give more space and it would be easier to display large structures. Moreover, Due to the general human familiarity with 3D in the real world, there are some attempts to map hierarchical data to 3D objects we are familiar with
- Matrix Layout. Graphs can be presented by their connectivity matrixes. Each row and each column corresponds to a node. The glyph at the interaction of (i, j) encodes the edge from node i to node j. Edge attributes are encoded as visual characteristics of the glyphs. such as color, shape, and size. The major benefit of adjacency matrices is the scalability

Specifically regarding the visualization of WordNet, there are not many works in the literature. In (Kamps and Marx, 2002), the authors makes an attempt to visualize the WordNet structure from the vantage point of a particular word in the database, this in order to overcome the down-side of the large coverage of WordNet, i.e., the difficulty to get a good overview of particular parts of the lexical database. An attempt to apply design paradigms to generate visualizations which maximize the usability and utility of WordNet is made in (Collins, 2006), whereas, in (Collins, 2007) a radial, space-filling layout of hyponymy (IS-A relation) is presented with interactive techniques of zoom, filter, and details-on-demand for the task of document visualization, exploiting the WordNet lexical database. Finally, regarding the comparison between Neo4J Cypher language performances against the traditional SQL-based technologies, an interesting experience has been described in (Holzschuher and Peinl, 2013) where the authors compare Neo4j back-end different alternatives to each other and to the JPA-based sample back-end running on MySQL.

3 WordNet CASE STUDY

The case study presented in this paper consists in the *reification* of the WordNet database inside the Neo4J GraphDB (Webber, 2012; Robinson et al., 2013). WordNet (Fellbaum, 1998; Miller, 1995) is a large lexical database of English. Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of conceptual-semantic and lexical relations.

In this context we have defined and implemented a meta-model for the WordNet reification using a conceptualization as much as possible close to the way in which the concepts are organized and expressed in human language (Rinaldi, 2008; Rinaldi, 2014). We consider concepts and words as nodes in Neo4J, whereas semantic, linguistic and semantic-linguistic relations become Noeo4J links between nodes. For example, the hyponymy property can relate two concept nodes (nouns to nouns or verbs to verbs); on the other hand a semantic property links concept nodes to concepts and a syntactic one relates word nodes to word nodes. Concept and word nodes are considered with *DatatypeProperties*, which relate individuals with a predefined data type. Each word is related to the represented concept by the ObjectProperty *hasConcept* while a concept is related to words that represent it using the ObjectProperty *hasWord*. These are the only properties able to relate words with concepts and vice versa; all the other properties relate words to words and concepts to concepts. Concepts, words and properties are arranged in a class hierarchy, resulting from the syntactic category for concepts and words and from the semantic or lexical type for the properties.

Figures 1(a) and 1(b) show that the two main classes are: Concept, in which all the objects have defined as individuals and Word which represents all the terms in the ontology.

The subclasses have been derived from the related categories. There are some union classes useful to define properties domain and codomain. We define some attributes for Concept and Word respectively: Concept *hasName* that represents the concept name; *Description* that gives a short description of concept. On the other hand Word has Name as attribute that is the word name. All elements have an ID within the WordNet offset number or a user defined ID. The semantic and lexical properties are arranged in a hierarchy (see figure 2(a) and 2(b)). In table 1 some of the considered properties and their domain and range of definition are shown.

Table 1: Properties.

Property	Domain	Range
hasWord	Concept	Word
hasConcept	Word	Concept
hypernym	NounsAnd VerbsConcept	NounsAnd VerbsConcept
holonym	NounConcept	NounConcept
entailment	VerbWord	VerbWord
similar	AdjectiveConcept	AdjectiveConcept

The use of domain and codomain reduces the property range application. For example, the hyponymy property is defined on the sets of nouns and verbs; if it is applied on the set of nouns, it has the set of nouns as range, otherwise, if it is applied to the set of verbs, it has the set of verbs as range. In table 2 there are some of defined constraints and we specify on which classes they have been applied w.r.t. the considered properties; the table shows the matching range too.

Table 2: Model constraints.

Costraint	Class	Property	Constraint range
AllValuesFrom	NounConcept	hyponym	NounConcept
AllValuesFrom	AdjectiveConcept	attribute	NounConcept
AllValuesFrom	NounWord	synonym	NounWord
AllValuesFrom	AdverbWord	synonym	AdverbWord
AllValuesFrom	VerbWord	also_see	VerbWord

Sometimes the existence of a property between two or more individuals entails the existence of other properties. For example, being the concept dog a hyponym of animal, we can assert that animal is a hypernymy of dog. We represent this characteristics in OWL, by means of property features shown in table 3.

Table 3: Property features.

Property	Features
hasWord	*inverse* of hasConcept
hasConcept	*inverse* of hasWord
hyponym	*inverse* of hypernym; *transitivity*
hypernym	*inverse* of hyponym; *transitivity*
cause	*transitivity*
verbGroup	*symmetry* and *transitivity*

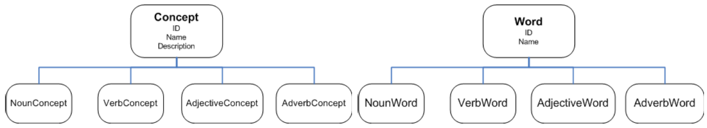
4 IMPORTING WordNet INTO Neo4J

The importing process of WordNet database within Neo4J graphDB (Webber, 2012) has been implemented according to the scheme shown in figure 3. The process involves three phases and three components: the *importing from WordNet* module, the *serializer* module and the *importing within Neo4J* module. The first phase has been implemented using a Java-based script that access the WordNet database through JWI (MIT Java Wordnet Interface) API (Finlayson, 2013; Finlayson, 2014) and passes all the information related to synsets, words, semantic relations and lexical relations to the serializer module, producing appropriate serialized data, following a proper schema that will be described in the following.

The last component, which is related to the third phase of the process, is responsible for importing the previously serialized information into Neo4J database. The importing from WordNet takes place via five different sub-operations which respectively retrieve: the information related to synsets, the semantic relations among synsets, the words, the lexical relations among words and finally the links between the semantic and the lexical world, i.e., how a word is related to its concepts (or its meaning) and *viceversa*.

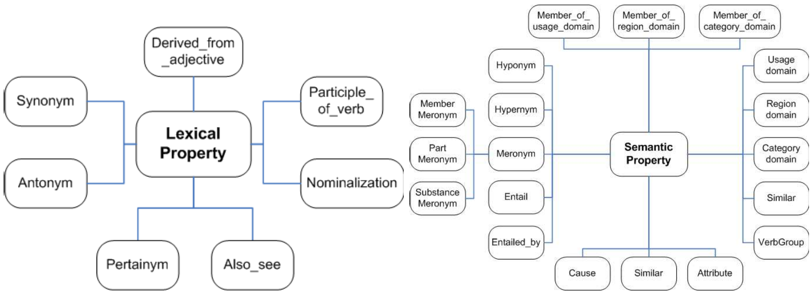
The intentional schema of each serialized data is shown as follow:

1. The synset file contains the following fields:
   (a) *Id*: the univoque indentifier for the synset;
   (b) *SID*: the Synset ID as reported in the WordNet database;
   (c) *POS*: the synset's part of speech;
   (d) *Gloss*: the synset's gloss which express its meaning.
2. The semantic relations file contains the following fields:
   (a) *Prop*: the semantic relation linking the source and the destination synsets;



(a) Concept (b) Word

Figure 1: Concept and Word.



(a) Lexical Properties (b) Semantic Properties

Figure 2: Linguistic properties.

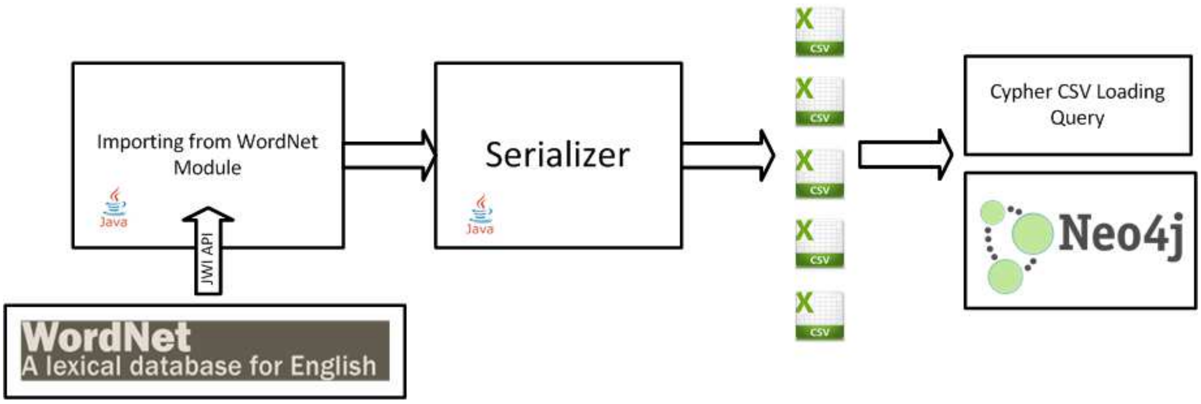


Figure 3: High-level view of the WordNet importing architecture.

   (b) *Src*: the source synset;
   (c) *Dest*: the destination synset;
3. The words file contains the following fields:
   (a) *Id*: the univoque indentifier for the word;
   (b) *WID*: the Word ID as reported in the WordNet database;
   (c) *POS*: the word's part of speech;
   (d) *Lemma*: lexical representation of the word;
   (e) *SID*: the synset Id whose the word is related.
4. The lexical relations file contains the following fields:
   (a) *Prop*: the lexical relation linking the source and the destination words;
   (b) *Src*: the source word;
   (c) *Dest*: the destination word;
5. The lexical-semantic relations file contains the following fields:
   (a) *Word Id*: the word id of the word that is linked to the synset on the right via the *hasConcept* relation;
   (b) *Synset Id*: the synset id of the synset that is linked to the word on the left via the *hasWord* relation;;

In order to import all the information contained in the serialized data and translate them into a graph data structure, the meta-model described in the previous section has been used: each synset and word has been converted into a node of the graph with label respectively: *Concept* and *Word*. Each semantic relation has become an edge between two concept nodes with the *type* property expressing the specific semantic relation holding between the concepts. Each lexical relation has been converted into an edge between two word nodes with a type property expressing the specific lexical relation between the word nodes. Finally, the word nodes have been connected to their related concept nodes through the *hasConcept* relation.

The Cypher query code used to import all the serialized information stored into csv lines is shown as follows:

```
USING PERIODIC COMMIT 1000
LOAD CSV WITH HEADERS FROM
        "PATH_TO_THE_FIRST_FILE" AS csvLine

CREATE (c: Concept {
        id: toInt(csvLine.id),
        sid: csvLine.SID, POS:
        csvLine.POS,
        gloss: csvLine.gloss })

CREATE CONSTRAINT ON (c: Concept)
        ASSERT c.id IS UNIQUE

USING PERIODIC COMMIT 1000
LOAD CSV WITH HEADERS FROM
        "PATH_TO_THE_SECOND_FILE" AS csvLine
MATCH (src:Concept { id: toInt(csvLine.Src)}),
(dest:Concept { id: toInt(csvLine.Dest)})

CREATE (src)-[:semantic_property
        { type: csvLine.Prop }]->(dest)

USING PERIODIC COMMIT 1000
LOAD CSV WITH HEADERS FROM
        "PATH_TO_THE_THIRD_FILE" AS csvLine

CREATE (w: Word {
        id: toInt(csvLine.id),
        wid: csvLine.WID,
        POS: csvLine.POS,
        lemma: csvLine.lemma,
        sid: toInt(csvLine.SID) })

CREATE CONSTRAINT ON (w: Word)
        ASSERT w.id IS UNIQUE

USING PERIODIC COMMIT 1000
LOAD CSV WITH HEADERS FROM
        "PATH_TO_THE_FOURTH_FILE" AS csvLine

MATCH (src:Word { id: toInt(csvLine.Src)}),
        (dest:Word { id: toInt(csvLine.Dest)})

CREATE (src)-[:lexical_property
        { type: csvLine.Prop }]->(dest)

USING PERIODIC COMMIT 1000
LOAD CSV WITH HEADERS FROM
        "PATH_TO_THE_FIFTH_FILE" AS csvLine

MATCH (src:Word { id: toInt(csvLine.Word)}),
(dest:Concept { id: toInt(csvLine.SID)})
        CREATE (src)-[:hasConcept]->(dest)
```

Having identified each synset and word with a unique and sequential integer, it has been possible for Neo4J to efficiently create nodes and arcs from csv lines. Furthermore, since the csv file contains a significant number of rows (approaching hundreds of thousands) USING PERIODIC COMMIT can be used to instruct Neo4j to perform a commit after a number of rows. This reduces the memory overhead of the transaction state. Table 4 shows the time performance in importing all the csv file on a laptop computer with an Intel Core i7-4800MQ processor at 2.70 GHz (64-bit) and 8 GB RAM:

Table 4: Neo4J query execution times for each importing query.

Query no.	[ms]
Q1	13015
Q2	23779
Q3	25787
Q4	17358
Q5	36907

5 QUERYING THE WordNet GRAPH

The first attempt to visualize the graph-based version of the WordNet database within Neo4j has been carried out using the Neo4j built-in web visualizer. Although it is a power and flexible tool allowing the user to easily customize the view according to her preferences, it suffers a lot when the number of elements to be visualized approaches few hundreds. Figure 4 shows the first result obtained with a simple customization involving the usage of two different colors for the two type of nodes, namely, the green for the *Word* node and the blue for the *Concept* (or *Synset*) node. Semantic relations have been represented with an edge thicker than the one used for the lexical relations or for the *hasConcept* relations.

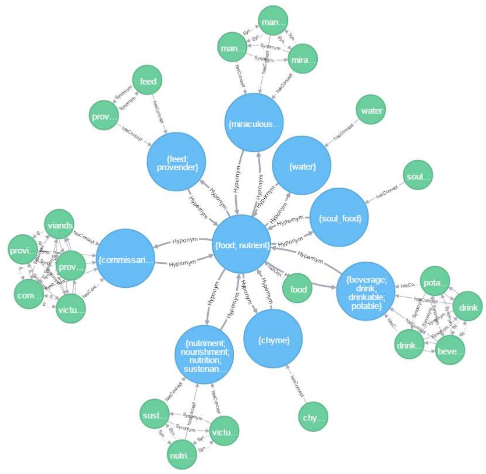


Figure 4: First view of Neo4j WordNet graph excerpt.

Table 5: Cypher and SQL-based query version.

Cypher Version and SQL Version

```
MATCH (w_src: Word {lemma: 'politics'})-[r: hasConcept]->(c: Concept) -[*..N]->(d: Concept)<-[s: hasConcept]-(w_dst: Word
      ) return w_src, c, d, w_dst

SELECT Word.lemma AS src_lemma, Word.hasConcept AS src_concept, SemanticRelation.type AS Property_1, SemanticRelation.
      dst AS Intermediate_Concept1, ..., SemanticRelation.type AS Property_N, SemanticRelation.dst AS
      Intermediate_ConceptN, Word.lemma AS dst_lemma
FROM Word JOIN Concept ON Word.conceptID = Concept.SID JOIN SemanticRelation ON SemanticRelation.src = Concept.SID JOIN
      SemanticRelation ON SemanticRelation.dst = SemanticRelation.src ... JOIN SemanticRelation ON SemanticRelation.dst
      = SemanticRelation.src
WHERE word.wid = (SELECT Word.wid FROM Word WHERE Word.lemma = "politics")
```

```
MATCH (n:Concept {words: '{politics}'})-[r: semantic_property*..N {type: 'Hyponym'}]-(m: Concept) RETURN COUNT(r)

SELECT SemanticRelation.src AS Source, COUNT(*)
FROM SemanticRelation Relation_1 JOIN SemanticRelation Relation_2 ON Relation_1.dst = Relation_2.src .... JOIN
      SemanticRelation Relation_N
        ON Relation_N-1.dst = Relation_N.src
WHERE Source.words = 'politics' AND Relation_1.type = 'Hyponym' ... AND Relation_N.type = 'Hyponym'
```

```
MATCH (w:Word { lemma:"food" }),(v:Word { lemma:"lunch" }),
   p = shortestPath((w)-[*]-(v))
RETURN p

(No equivalent)
```

Each Concept node is labeled with the lexical chain of the synonyms related to such concept. A set edges ends to the synset node and comes from all the words belonging to the synset. These ones also are connected one with each other through the synonymy lexical relation. The concept nodes, in blue, are mainly connected through the *hypernym-hyponym* semantic relations. The greatest value of importing WordNet database into a Neo4j graph, it is not related to the graph visualization capabilities of the web visualizer, but, mainly, to the power of the *Cypher* query language, a declarative graph query language that allows for expressive and efficient querying and updating of the graph store. Since very complicated database queries can easily be expressed through Cypher, this allows the user to focus on the data model domain instead of getting lost in database access. Most of the keywords like WHERE and ORDER BY are inspired by SQL, while pattern matching borrows expression approaches from SPARQL (Van Bruggen, 2014).

In the attempt to extract some useful information from the WordNet implementation in Neo4j, we have run few queries and have compared them to an equivalent version expressed in SQL languages. Table 5 reports a comparison of the Cypher-based and SQL-based version of each query. It is not a quantitative comparison but just a qualitative one that clearly shows how complex (or in in some circumstances impossible at all) is to translate a query from the graph query language into the relational-based SQL language.

The objective of the first query is to get all concept nodes between the source and the target synset, where the source concept is fixed and has a lemma equal to *politics*, whereas the target node can be any node of the network. The only constraint is that between the first and the last synset there may be *N* (depth level) relations (*semantic relations* in this case) and *N-1* intermediate nodes. The Neo4j web-based tool provides two ways of visualizing results: the table-based and the graph-based. By analysing the query structure in the two columns, it appears quite clear that a graph-based query language is most suitable in order to select sub-graphs, as in this case. In fact, it comes very natural to select a bunch of nodes and relations just by using patterns and pattern-matching, expressed in an intuitive and iconic syntax, to describe the shape of the data you are looking for (Holzschuher and Peinl, 2013). On the contrary, the SQL-based version requires more and more intricate combination of JOIN clauses to link synsets from the SemanticRelation and Concept tables. Each JOIN clause involves a cartesian product between the SemanticRelation table, which contains 283.836 rows, and itself with an order that increases with the degree of separation between the source and the target node (N). The second query in table, uses the COUNT aggregation function both in the Cypher and SQL-based version. It gets the number of the *Hyponym* relations holding between the *politics* source concept and any other concept that is at most N hops from the source. According to (Mathur and Dalal, 2015), aggregation operators make worse the performances of the SQL-based query especially when N increases (N<6) with respect to the equivalent queries in Cypher. Also in this case, the SQL-based query require N JOIN clauses which corresponds to an equal number of cartesian products. Finally, the last query gets the shortest path between the *food* and *lunch* concepts. While the Cypher language offers utility functions like *shortestPath()* or *AllShortestPath()* making very easy to respond to such queries, the SQL language do not has similar ready-to-use functions. Furthermore, a graph-based data structure allows users to use *Traversal API* to specify desired movements through a graph in a programmatic way.

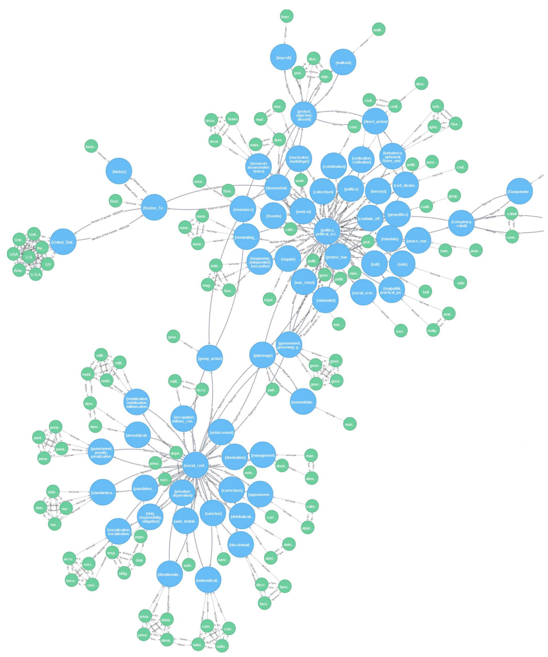


Figure 5: Second view of Neo4j WordNet graph excerpt.

6 LARGE-SCALE REPRESENTATION OF WordNet GRAPH

The proposed representation of WordNet, within Neo4j, approaches very closely the Big Data challenges. In particular, the volume dimension must be taken into consideration here: this version of the WordNet graph, in fact, includes near to 2 millions different relations linking more than 3 hundred thousand nodes with each other. With these big numbers, the manipulation, the querying and the visualization of the graph become quite challenging. Before describing the attempts made in this direction, it is important to note that the visualization of the entire structure of WordNet in terms of all synsets, words, semantic and lexical relations in a way that is elegant and human friendly at the same time, is a *chimera*, due to the performance issues of the visualization tools, in particular when sophisticated drawing algorithms are used, and to the strongly connected nature of information to be represented, which often results in a messy and dense structure of nodes and edges. Figure 6 shows a representation of near 15.000 nodes and 30.000 relations of WordNet using the *Cytoscape* v. 3 graph visualization tool (Mathur and Dalal, 2015). The image has been obtained by limiting to 30.000 relations a simple cypher query that gets some data from the Neo4j implementation of WordNet. The Neo4j running instance has been accessed via the cyNeo4j plugin, that converts the query results into Cytoscape table format. Afterward, starting from the query tables, a view has been created by defining a custom style and the default layout. This latter is the *Force-directed graph drawing algorithm* that draws graphs in an aesthetically pleasing way by positioning the nodes of a graph in two-dimensional or three-dimensional space, so that all the edges are of more or less equal length and there are as few crossing edges as possible (Kobourov, 2012). The resulting figure is more considerable for global analysis than for information that you can retrieve from it. Nevertheless, thanks to the force-directed algorithm, it is possible to observe agglomerates of nodes and edges which correspond to specific semantic categories. The figure also shows a zoomed area selection where it is possible to visualize and read the synset labels belonging to the selected *semantic zone*. Figure 6 shows only synsets and their semantic relations; an attempt to add also the lexical relations and the *Word* nodes results in an even more confused tangle of points and arcs. Thus, it is necessary to simplify the representation of the network by following some functional and esthetic criteria. In this regards, we have selected two simple criteria:

1. the efficiency of the visualization; i.e., avoid the information redundancy and the proliferation of useless signs and graphics as much as possible;
2. the effectiveness of the visualization; i.e., grant that the graphical representation of the network covers the whole informative content of the WordNet graph-based implementation.

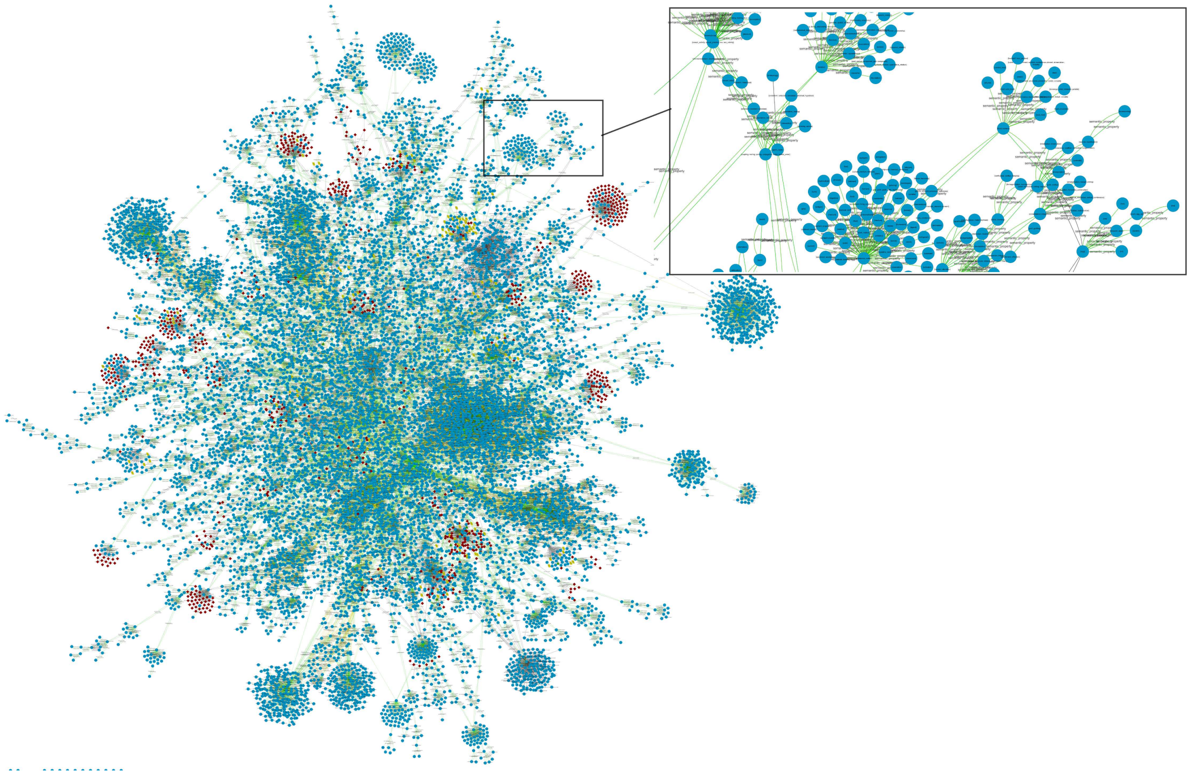


Figure 6: WordNet graph excerpt with 30000 edges and about 15000 nodes.

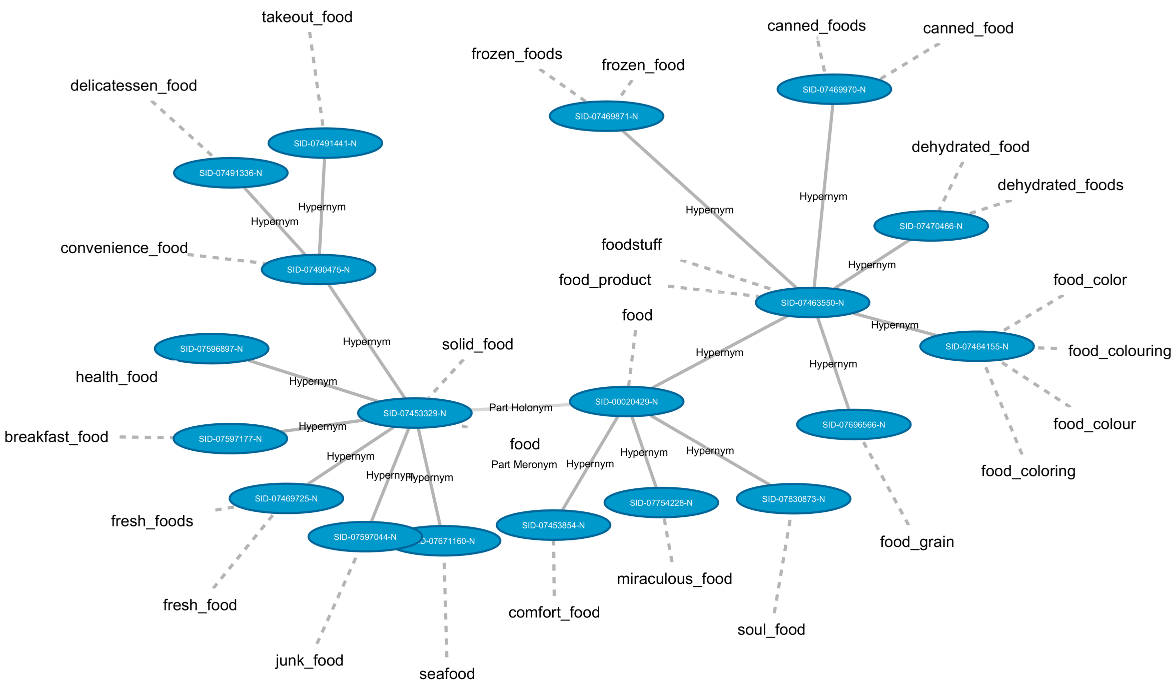


Figure 7: First layout of WordNet graph excerpt.

3. the clearness of visualization, i.e., use light colors, such as gray, light blue, dark green, etc. with a proper level of brightness and with an appreciable contrast.

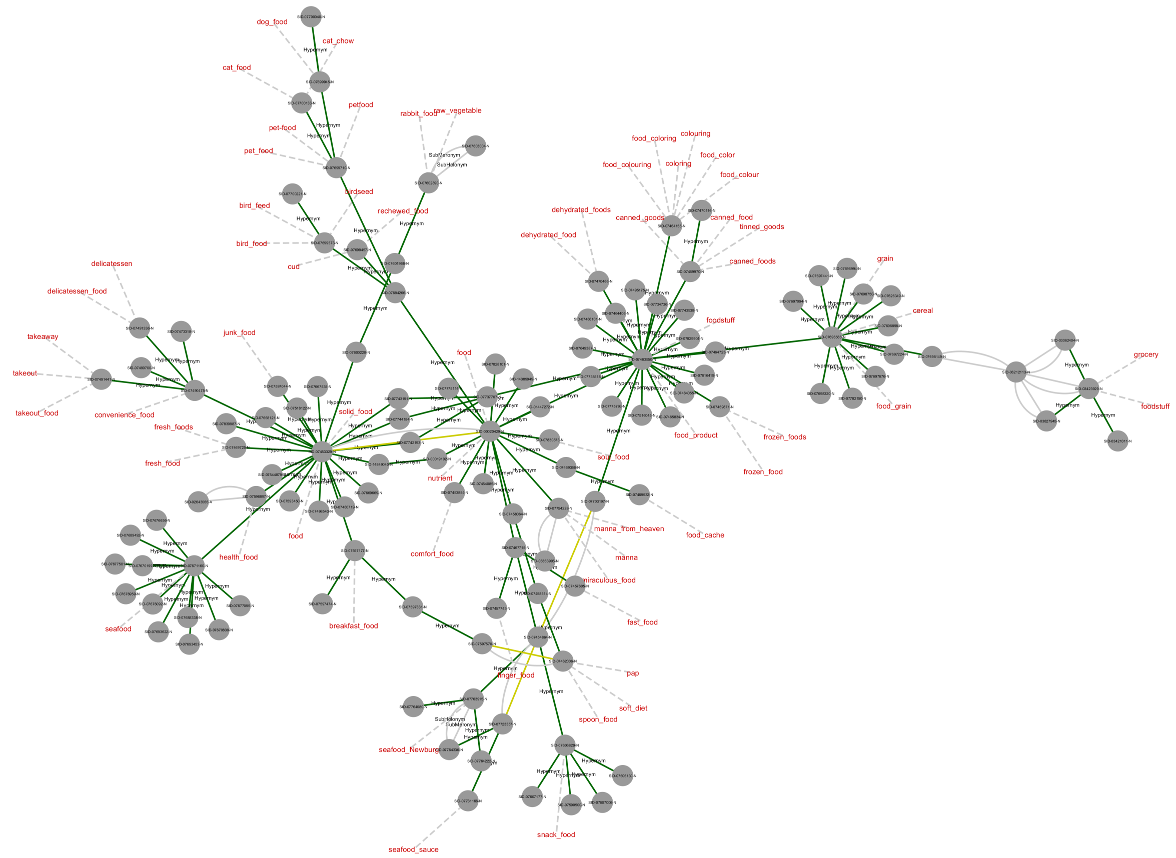


Figure 8: Second layout of WordNet graph excerpt.

Along the efficiency criteria, we decided to visualize only *Words* labels, avoiding to show again the lexical chain of words representing the corresponding concept into the synset nodes. These ones only show the synset ID as retrieved from the WordNet database inside the stretched blue oval. Furthermore, since for each *Hyponym* relation between synsets corresponds an *Hypernym* relation, we decided to show only one of the two, namely the *Hypernym*, in order to increase the clearness of the representation. The same approach has been adopted for the other pairs of antinomical relations like *Meronym-Holonym*. This approach also satisfies the effectiveness criteria, in fact, even if there is not an explicit representation of the *Hyponym* relations, these ones can be inferred from the corresponding *Hypernym* ones. Each synset is linked to the corresponding lemmas through the *hasConcept* relation which has been represented with a dashed line with a light gray color without an explicit label. This improves the efficiency of the visualization and the effectiveness, since no informative contents is sacrificed for clearness. Figure 7 shows an excerpt of the WordNet representation using the previously described style and layout. It appears evidently clearer than the representation in figure 4 (also with respect to the zoomed selected area), also adding the words nodes and the *hasConcept* relations. Figure 7 makes some changes compared to the figure 8, mainly regarding the shape of the synset and words nodes, its color and try to distinguish semantic relation by using different colors.

7 CONCLUSIONS

In this paper we have described an experience of importing, exploring and visualizing WordNet into a graphDB. To achieve this objective we have faced different issues involving Big Data challenges through all the phases of graph management. The import procedure has been accomplished using he Cypher import functions; queries running has also resulted quite simple by exploiting the potentiality of the Cypher language (such as, its iconicity, the pattern-matching mechanism and the built-in functions to traverse the graph), with respect to the equivalent queries in SQL language. Eventually, the visualization task has resulted more challenging, due to the intricate nature of the WodrNet graph and its "'Big"' dimensions in terms of nodes and edges, particularly, when it is requested a large-scale visualization. Thus, if we want to simplify the visualization of WordNet, a redefinition of the custom style and also the layout manager is needed. In this regard, we have introduced three criteria to simplify the view, with respect to efficiency, effectiveness and clearness and have adopted them in order to obtain two different representation of WordNet, which results more clear at first glance.

Starting from the consideration emerged in this work, at least two different directions could be taken for future investigations or researches. From the one hand, it worth to deepen the comparison between Cypher and SQL languages also through a performance analysis, in order to appreciate the efficiency of the language, in addition to the immediacy of the first language; on the other hand, an improved characterization of the criteria to simplify the view could be investigated, and validated by usability tests in which the user can express a consensus whether the representation is friendly or not, and the information inside WordNet is easily accessible or not. Finally, also the choice of the layout manager requires more attention: ranging from the simple grid layout to the elegant force-directed layout, it is important to understand what is the layout that best suits the nature of the data itself.

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