Analysis of a NoSQL Graph DBMS for a Hospital Social Network

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***Abstract*—Nowadays, the possibility of using social media in the healthcare domain is attracting the attention of many clinical professionals all around the world. In this panorama, many Healthcare Social Network (HSN) platforms are emerging with the purpose to enhance patient care and education. However, many clinical operators are reluctant to use them because they do not fulfil their requirements and are looking at the possibility to develop their own HSN platforms in order to perform social science studies. In this context, one of the major issue is the management of generated big data presenting a huge amount of relations and for this reason, traditional Relational Database management Systems (RDBMSs) are not adequate. The objective of this preliminary scientific work is to prove that a NoSQL graph DBMS can address such an issue, paving the way toward future social science studies. Experiments results show that Neo4j, i.e., one of the major NoSQL graph DBMS, simplifies the management of HSN data also guaranteeing acceptable performances in the perspective of future social science studies.**

***Index Terms*—Healthcare, social network, Cloud computing, NoSQL, graph database.**

I. Introduction

Nowadays, there is an increasing interest of clinical operators in social media, big data analytics and Cloud computing. All over the world, the number of investments in Information and Communication Technology (ICT) for health and well-being (eHealth) is rapidly increasing specifically looking at Cloud computing [1] and other emerging technologies. Global eHealth market is expected to reach USD 308.0 billions by 2022, according to a new report by Grand View Research Inc. In particular, the transition of the healthcare industry into digital healthcare system for management and analysis of patients' health is expected to be the most vital driver of the market [2]. The European Commission's eHealth Action Plan 2012-2020 has already provided a roadmap to empower patients and healthcare workers, to link up devices and technologies, and to invest in research towards the personalised medicine of the future [3]. In 2015, the European initiative called FICHE had the purpose to accelerate small medium enterprises for the development of new cutting-edge eHealth applications by means of the FIWARE technology [4]. In February 2017, the European Commission set up an internal task force bringing together technology and health policy makers to examine EU policy actions to ensure the transformation of health care into a Digital Single Market (DSM) bringing benefits for people, health care systems and the economy [5]. Guaranteeing access to high-quality health care is a key objective of social protection systems in European countries and it represents the second largest social expenditure item after pensions.

In this panorama, social media represent a tempting opportunity for healthcare operators for improving the patients' well-being. Many social media tools are available over the Internet such as social networking, professional networking, media sharing, content production including blogs (e.g., Tumblr) and microblogs (e.g., Twitter), knowledge/information aggregation (e.g., wikipedia), virtual reality and gaming environments (e.g., Second Life). In particular, many Healthcare Social Network (HSN) platforms have emerged with the purpose to enhance patient care and education. Popular HSB platforms include Sermo, Doximity, Orthomind, QuantiaMD, WeMedUp, Digital Healthcare and so on. However, these social networks require the massive action of medical professionals acting as moderators. In fact, healthcare social networks present potential risks for patients due to the possible distribution of poor-quality or wrong information. On one hand clinical operators want to promote the exchange of information among patients about a specific disease, but on the other hand they do not have the time to read patients' posts and moderate them when required.

However, Clinical operators are reluctant to use public HSNs because i) they do not have the full control on them; ii) they are often specialized on particular healthcare aspects; iii) their internal data model is hidden; iv) they do not provide APIs allowing an in depth big data analytics supporting social science studies. Therefore, clinical operators are looking at customized HSNs solutions. In this context, a RDBMS presents two main issues: i) it does not scale up very well when the size of the dataset increases and ii) it is not adequate for big data analytics. The objective of this preliminary scientific work is to prove the suitability of a NoSQL graph DBMS for the management of the Big Data coming from an HSN in order to pave the way toward future social science studies.

The rest of the paper is organized as follows. Related works are summarized in Section II. In Section III, we discuss the benefits of HSN. In Section IV we discuss an example of HSN data model. Data scalability tests carried out on one of the

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major NoSQL graph database managemement systems, that is Neo4j, are discussed in Section V. Conclusion and future challenges are provided in Section VI.

II. Related Work

Social media and healthcare quality improvement is an emerging topic [6]. Recently many scientific works have been proposed facing different aspects of social media for healthcare purposes.

Regarding the social implication of such systems, the benefits, best practices, risks and ethical issues of applying social media to healthcare professionals are discussed in [7], [8] and [9]. Social media can be used to enhance professional networking and education, organizational promotion, patient care, patient education, and public health programs, but they can also present several potential risks for patients regarding the distribution of poor-quality information, damage to professional image, breaches of patient privacy, violation of personal-professional boundaries, and licensing or legal issues. However, social media are also changing the healthcare industry [10] and marketing [11]. Evolution of social media in scientific research in the domain of ICT and healthcare professionals in Saudi Arabia Universities are discussed in [12], whereas a similar study performed on young people in Russia is available in [13]. Studies on the effectiveness of social media data in healthcare communication involving both medical personnel and patients is proposed in [14], [15] and [16]. The role of social media in menopausal healthcare is discussed in [17]. There is also a strong correlation among online data coming from search engines and social media in the healthcare domain. In this regard, in [18] it is discussed an approach for collecting twitter data by exploring contextual information gleaned from Google search queries logs.

Due to the huge amount of information to be analysed and processed, many scientific works have faced the need of decisional support systems. In this regard, a recommendation approach helping social media users to identify topics of interests is discussed in [19]. An analogous approach [20] was also used for the assessment of user similarity in heterogeneous networks with the purpose to look for people that can give informational and emotional support in a more efficient way. Another user similarity study in healthcare social media using content similarity and structural similarity is presented in [21]. A study on healthcare social media aimed at undeserved communities based on a mobile decision support system (MDSS) providing information dissemination is discussed in [22]. The need for pervasive decision support systems in healthcare using intelligent robots in social media is discussed in [23]. In [24] authors presented an Artificial Intelligence (AI) approach that allows to automatically analyse the patients posts of a HSN platform and identify possible critical issues so as to enable doctors to intervene when required.

All aforementioned scientific works consider the benefits of using healthcare social media but, to the best of our knowledge, no scientific works that model data of an HSN by means of a NoSQL Graph database have been proposed so far. The works that will be described in the remainder of this Section represent an exception, even if none of them really uses a NoSQL Graph database. A graph database management system called GBase is presented in [25] and used in [26] to analyze a large enterprise multimedia social network. GBase is a graph database for Hadoop[1] framework, designed and implemented to store and manage large graphs.

Large graphs cannot usually be stored in the main memory or the disk of a single workstation. Storage must be distributed and algorithms need to be redesigned in order to exploit the parallel/distributed environments in which are deployed. In order to efficiently manage storage, the original adjacency matrix (which is usually employed to describe relations among the nodes of the graph) is block clustered (along the main diagonal). This allows a plain distribution among processing units without the necessity of cumbersome communications among units. Before the real storage on GBase takes place, the blocks are compressed, if necessary.

DEX [27] is another graph database management system. Due to the huge amount of information contained in a massive graph, the graph itself must be split into smaller structures thus resulting in a more efficient caching and less expensive memory use. The basic idea is that a node or an edge, called *oid*, is represented by a positive integer number. Bitmaps are then used to store relationships among these oids. These greatly reduce memory footprint and increase computation efficiency due to fast logical operations employment.

Finally, a graph database is simulated in [28]. An architectural design is first introduced aimed at storing and querying data extracted from general purpose social networks such as Facebook, LiveJournal and Twitter. The architecture is composed of three main sections: a crawler, which is in charge of extracting publicly available information, the repository and the analyzer. This is in charge of analyzing and finding the patterns in the data extracted from the repository. The graph structure is stored in two tables of a relational database, one containing the nodes (actually the users of the social networks) and the other containing the edges, namely followee/follower relationship existing among users.

III. Why Healthcare Social Networks?

Social media applied in a healthcare context represent a tempting opportunity to improve the patients' well-being promoting care and education. A HSN presents several benefits including:

- promoting networking and information exchange enabling self-education among patients about particular diseases.
- sharing patients' experiences that can be helpful for other ones;
- supporting the treatment process;
- reducing the patient's stress when s/he is waiting for a diagnosis or when s/he discovers to be affected by a particular disease;

[1] http://www.hadoop.org

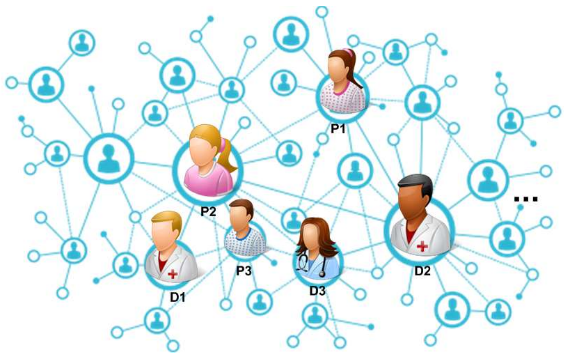

Fig. 1. Example of HSN scenario including doctors and patients.

- promoting information gathering and prevention campaign regarding specific diseases;
- optimizing the work of the clinical personnel who interact with patients skilled on their diseases;
- promoting knowledge management;
- promoting research and monitoring activities.

All the aforementioned benefits can potentially improve the whole world healthcare education system. On the other hand, HSNs present several disadvantages including:

- possible distribution of poor-quality or wrong information among patients;
- the need of qualified medical personnel promptly reading and replying patients' posts;
- often the medical personnel do not have the time to read patients' posts and to reply them;
- the medical personnel do not want the responsibility of the consequences on patients (worsening, risk of death or death) when they do not reply in tim;.
- possible legal issues for the medical personnel;
- risks for the reputation of the medical personnel.

From a technical point of view, one of the major issues that has to be overcome is the management of big data with a high number of relations among the involved entities. Such entities include, for example, patients, their families, clinical reports, doctors, nurses and any kind of clinical personnel in general. In Figure 1 is shown a general healthcare social network scenario including both clinical personnel and patients. For example, let us consider three patients, i.e., P1, P2, P3, and three doctors, i.e, D1, D2, D3. P1 shares the same disease of P2 and s/he is treated by D2. P1 and P2 share the same disease and they are treated by D1 and D2. P2 and P3 share the same disease and they are treated by D2. P1 and P2 share the same disease and they are treated by D1 and D3. D2 and D3 work in the same hospital cast.

In this context, an RDBMS presents two main issues: i) it does not scale up very well with the size of the dataset and ii) it is not adequate for social science study. In the reminder of this paper we focus on the first issue considering a NoSQL graph DBMS solution.

IV. Graph-Based Data Model Design

In this Section we describe the design of a NoSQL Graph DBMS data model suitable for an HSN scenario. The design and development of Graph NoSQL databases is mainly empirical. In particular, the absence or the unknown schema offers a certain flexibility, but it can induce some overhead and complexity, especially for complex queries. However, it is important to have some information about the structure of the datasets in order to facilitate their processing. A logical model, associated with a conceptual model, is relevant, even in the domain of Graph NoSQL databases. Specifically, we present an approach based on a model driven reverse engineering of NoSQL property graph databases. First of all, starting from the Entity-Relationship (ER) model of the RDBMS illustrated in Figure 2, we present the conversion procedure which translates the RDBMS ER model into a graph data model illustrated in Figure 3.

A graph database can be defined as a collection of vertices and edges. Vertices, also referred to as nodes or records in RDBMS analogy, contain one or more immutable properties which all together constitute an entity's identity. Edges express relationships among entities.

We first transform entities into nodes. This is accomplished by associating to each node its entity name and its identifier. Thus, analyzing the ER model, we identify the following six entities representing the main HSN actors: Doctors, Patients, Nurses, Medical Reports, Technicians, and Healthcare Workers. Each entity is characterized by means of two main properties ID and NAME.

As a first remark, we note that the central element of our ER model is represented by the Medical Report entity. Then, in order to produce the corresponding graph model, we create nodes labeled with the entity type name, and having as properties the identifiers of this entity type. These entities are represented by the corresponding nodes in the graph data model. In particular, we adopt the following convention for nodes colors: blue Medical Report, pink - Doctors, yellow Technicians, red Nurses, gray Healthcare Workers and salmon Patients.

Following the relational approach of the ER model, substantial complexity is introduced because of the occurrence of foreign keys. A key is defined for each entity or association class. A key is a minimal set of attributes that uniquely identifies an entity or association instance. Foreign key are constraints set up in order to facilitate one-to-many relationships. In fact, we notice that all the entities are connected to each other by means of a one-to-many relationship.

For example, the LIKE relationship indicates that a patient can evaluate each doctor by assigning to it one or more likes. Analogously, we notice that the realization of a patients medical report requires the involvement of one or more Doctors described by the CONTRIBUTED relationship, as well as the involvement of one of more Nurses CONTRIBUTEN, one or more Technicians CONTRIBUTET, and so on. In order to implement these relationships, represented by edges, in graph

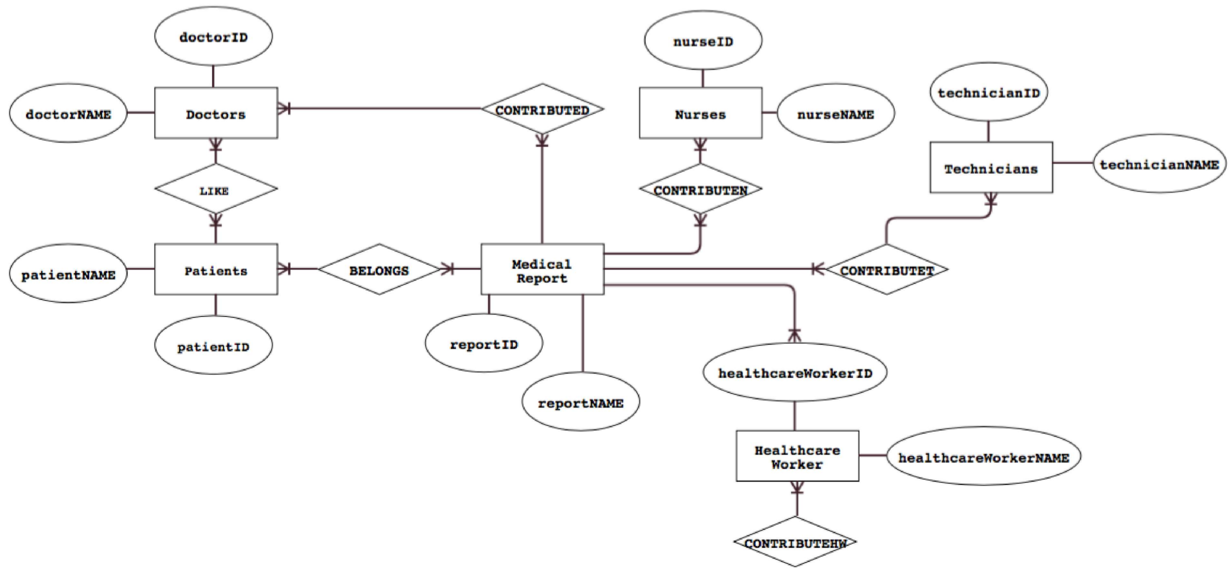

Fig. 2. Example of ER scheme.

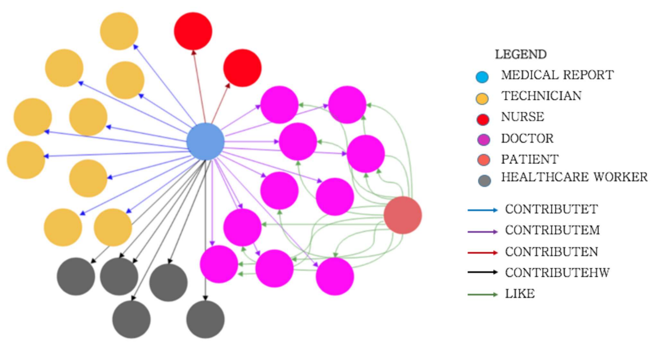

Fig. 3. Example of graph scheme.

databases, we only need to ensure that nodes are assigned appropriate labels and properties, as well as they are connected with appropriate relationships so that the implemented database complies with the corresponding domain.

V. Performance Analysis

In this Section, considering the HSN data model presented previously, we discuss data scalability tests considering one of the major NoSQL graph DBMS, that is Neo4j. In particular, we insist that the goal of our experiments is to prove that Neo4j can be used to manage the big data of an HSN in order to pave the way toward future social science studies.

A. Neo4j Overview

To follow the today's business and user requirements demanding to store more and more data, we need to use different storage technologies. RDBMS is a mature well grounded technology in use across many industries for over 40 years, but some items may arise which eventually cause their fall down. The rapid growth of social networks, the increase of relations among data items and patterns of relationships or interactions are among the most important features that may compel data scientists to adopt new database management systems.

Moreover, since the advent of ACID[2] graph databases in the 2000s, their adoption has registered a rapid growth. In recent years many high-performance graph database management systems have been proposed, such as Neo4j, Infinite, DEX, InfoGrid, HyperGraphDB. Among them, Neo4j appears to be the most outstanding. It is a graph database management system developed by Neo4j Inc. and implemented in Java. It is accessible from software written in other languages by means of the Cypher Query Language through a transactional HTTP endpoint, or through the binary "bolt" protocol. What makes Neo4j interesting is the use of the so called "network oriented database", that stores data structured in networks rather than in tables.

The Neo4j model provides a convenient way to visualize data with its inherent graph structure, where data is expressed in a "node space" - a network of nodes, relationships and properties (key value pairs) in analogy to the tables, rows and columns of the relational model. The network model is well suited to problem domains that are organized in a naturally hierarchical way.

B. Testbed Setup

In order to deploy our prototype we used two different machines: a blade server that runs a Neo4j instance and a workstation that runs the software application.

[2](Atomicity, Consistency, Isolation, and Durability, the four requirements of a robust database)

Neo4j server was equipped with: CPU Intel(R) Core(TM) Xeon E7-8860V3 CPU @ 3.20GHz, RAM 32GB, OS: Ubuntu server 16.04 LTS 64 BIT. The hardware configuration of the workstation that runs the software application is: CPU Intel(R) Core(TM) i7-6700 CPU @ 3.40GHz, RAM 16GB, OS: Ubuntu server 16.04 LTS 64 BIT. Each experiment has been repeated 30 times considering increasing datasets. In particular we considered 5 different datasets composed respectively of: 100, 1000, 10000, 100000 and 1000000 nodes.

C. Performance Analysis

In order to carry out experimental tests we considered 4 different queries:

- **A**: returns all medical records. In order to accomplish this task we performed a “MATCH” on Neo4j nodes:

```
MATCH (r:Records)
RETURN r.RecordsName
```

  Execution times vs dataset size are shown in Figure 4. They increase as the dataset size increases, but the overall performances are somewhat acceptable for every size.
- **B**: returns all medical records of a specific patient. In order to accomplish this task we performed a “MATCH” on the edge ”BELONGS” that connects medical reports and patients nodes:

```
MATCH (p:patient)-[:belongs]-
(r:records)
WHERE p.patientName = 'Patient1'
RETURN r.medicalRecordName
```

  Execution times vs dataset size are shown in Figure 5. Also in this case time the execution time grows up as the dataset size increases;
- **C**: retrieves the name of doctors who treated patients. In order to accomplish this task we performed two different “MATCH” operations, one on the edge ”BELONGS” that connects medical reports and patients nodes, another one on the edge ”TREAT” that connects doctors and medical reports. Furthermore in order to avoid any duplication we used the ”DISTINCT” clause:

```
MATCH (p:patients)-[:belongs]-
(r:records)-[:treat]-
(d:doctors)
WHERE p.patientName = 'Patient1'
RETURN DISTINCT d.doctorName
```

  Execution times vs dataset size, shown in Figure 6, exhibit a behavior similar to query B;
- **D**: amount of likes attributed to a specific doctor. In order to accomplish this task we performed a “MATCH” on the edge ”LIKE” that connects doctors and patients nodes:

```
MATCH (:patients)-[:like]-
(d:doctors)
WHERE d.doctorName = 'Doctor1'
RETURN count(d.doctorName)
```

  As observed for queries B and C, execution times vs dataset size (shown in Figure 7), are approximately the same.

Times needed to execute simple queries such as those presented in this Section are quite acceptable. They scale in a very promising way up to 1 million elements large datasets, which suggests the possibility of using a graph database management system even for Big Data.

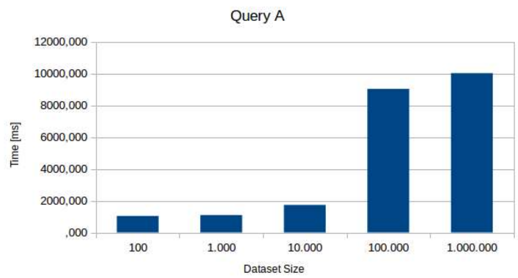

Fig. 4. Time performance for retrieve all medical records.

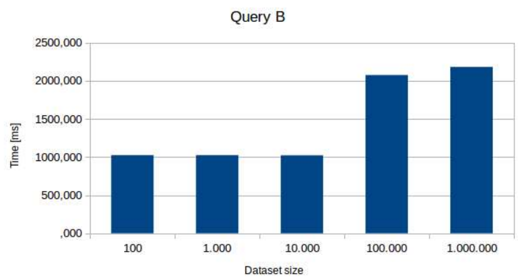

Fig. 5. Time performance for retrieve all medical records of a specific patient.

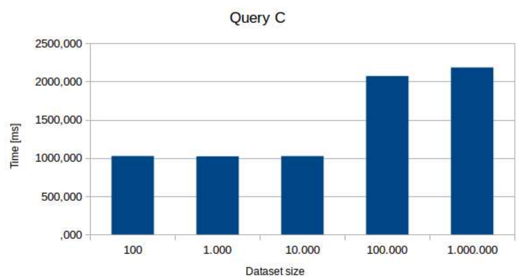

Fig. 6. Time performance for retrieve the name of doctors who treated patients.

VI. Conclusion

Recently, many HSN platforms are emerging aiming at enhancing patient care and information. However, many clinical operators are reluctant to use them because they do not fulfil their requirements and are looking at the possibility to develop their own HSN platforms in order to perform social science studies involving innovative techniques such as deep artificial neural networks [29] in order to understand hidden relations [30].

In this context, NoSQL graph DBMS can overcome the limits of RDBMS. The objective of this preliminary scientific

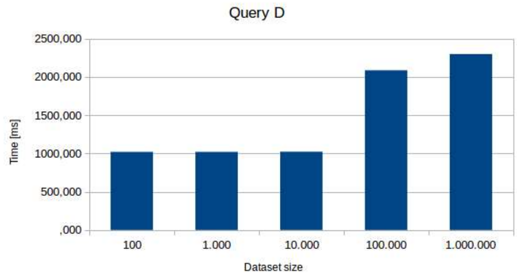

Fig. 7. Time performance for retrieve amount of like of a specific doctor.

work is to prove that a NoSQL graph DBMS can address such limits, paving the way toward future social science studies.

Experimental results showed that Neo4j, one of the major NoSQL graph DBMS, simplifies the management of HSN data also guaranteeing acceptable performances in the perspective of future social science studies.

This positive preliminary results are a good starting point. In future works, we plan to exploit the potentialities of the graph data model specifically focusing on social science studies. Among other possible developments, we plan to analyse the social implications deriving from the healthcare workflow from the point of view of patients, clinicians and healthcare operators at large.

Acknowledgements

This work was partially supported by the FP7 Project frontierCities under grant agreement no. 632853.

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