Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Computer Science

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Database Solutions to Sports Applications

A Comparison and Performance Test of Graph Databases and Relational Databases

Master's thesis in Master of Informatics
Supervisor: Svein Erik Bratsberg
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Summary

The amount of data generated today is enormous. It is estimated that we generate 2,5 billion gigabytes of data every day. As a result of this, new trends in data analysis have emerged along with new methods and technologies within data storage, processing, management, search and visualization. Sports is a field that is known to use data analysis in order to improve athletes' performance and to analyze competitors. In addition, bookmakers rely heavily on data analysis to predict results and provide betting odds.

In this thesis, we developed an application that analyzes sports data provided by an external API. The data retrieved from the API is stored in two different databases, a graph database and a relational database. The application is then used to determine which database technology performs best for the given use case of analyzing sports data. For the graph database we used Neo4j and for the relational database we used MySQL by Oracle.

Our results suggest that relational databases perform better for small datasets, but as soon as the number of records surpasses a certain size, graph databases perform better. For our experiments, that size was approximately 1670 records. That size will differ depending upon the exact structure of the dataset, but our conclusion is that for larger datasets, there will be a performance advantage in storing the data in a graph database rather than in a relational database for our kind of data analysis.

Sammendrag

Hver eneste dag genereres det enorme mengder data. Det estimeres at vi genererer 2.5 milliarder gigabyte med data hver eneste dag. Det har resultert i at en ny trend har utviklet seg, en trend som har brakt med seg nye metoder og teknologier innen lagring, prosessering, søk og visualisering av data. Idrett er et felt som har tatt i bruk mange av disse metodene og teknologiene. I dag brukes de blant annet til å forbedre en idrettsutøvers ytelse og til å analysere motstandere. En annen bransje som også har tatt i bruk disse metodene er pengespillbransjen. De bruker datanalyse til å forutse resultater og produsere odds til idrettsarrangement.

I denne avhandlingen utvikler vi en applikasjon som analyserer sportsdata levert av et eksternt API. Dataen hentes fra API-et og lagres i to forskjellige databaser, en grafdatabase og en relasjonsdatabase. Applikasjonen benyttes så til å undersøke hvilken database som egner seg best til analyse av denne type data. Vi benyttet oss av grafdatabasen til Neo4j og Oracle sin relasjonsdatabase MySQL.

Resultatene våre indikerer at relasjonsdatabaser yter bedre for små datamengder, men ettersom antall poster passerer en viss størrelse, vil en grafdatabase yte bedre. Under våre forsøk gikk den grensen ved cirka 1670 poster. Denne grensen vil endre seg avhengig av datasettet sin struktur, men vår konklusjon er at det vil være en ytelsesmessing fordel å lagre dataen i en grafdatabase, i stedet for en relasjonsdatabase for vår type datanalyse.

Preface

This thesis was written at the Department of Computer and Information Science (IDI) at the Norwegian University of Science and Technology (NTNU) in Trondheim, in collaboration with the technology firm Sportradar AG. The research was conducted by Oscar Thån Conrad, under the supervision of Professor Svein Erik Bratsberg. It is assumed that the reader has a basic knowledge of database systems, algorithms, and data structures when reading this thesis.

The project was designed as a performance and usability test of two database management systems, Neo4j's graph database and Oracle's relational database MySQL. Both databases were populated with sports data from the English top division in soccer, the Premier League. Sportradar AG provided us with all the data through their developer APIs.

I would like to thank Svein Erik for his guidance and valuable feedback throughout the year. In addition, I would like to thank my father Mark Allan Conrad for being a valuable discussion partner and for helping me improve my work by proofreading and solving linguistic challenges. Lastly, I would like to thank Sportradar for providing me with data, by giving me access to their developer API.

Table of Contents

List of Tables

List of Figures

Listings

Abbreviations

ACID	=	Atomicity, Consistency, Isolation, Durability
API	=	Application Programming Interface
APOC	=	Awesome Procedures on Cypher
CAP	=	Consistency, Availability, Partition, Tolerance
CRUD	=	Create, Read, Update, Delete
DB	=	Database
DBTG	=	Data Base Task Group
GDB	=	Graph Database
GDBMS	=	Graph database management system
HTTP	=	Hypertext Transfer Protocol
I/O	=	Input/Output
JSON	=	JavaScript Object Notation
NoSQL	=	Not Only Structured Query Language
NFL	=	National Football League
NHL	=	National Hockey League
RDBMS	=	Relational database management system
REST	=	REpresentational State Transfer
RQ	=	Research Question
SQL	=	Structured Query Language
XML	=	Extensible Markup Language

Chapter 1

Introduction

This chapter introduces the project for this thesis. In addition, this chapter will present its relevance and context to the research community. Research goals, research questions are also presented in this chapter, together with a short description of the chosen research strategy.

1.1 Project Description

This project is a result of a Master's thesis in Informatics written at the Norwegian University of Science and Technology in the city of Trondheim. The research was conducted in cooperation with the technology firm Sportradar AG. The starting point for the project was the following description drafted by Sportradar AG:

> *Currently, we host all our sports and betting data in various relational databases. Google and Facebook have successfully structured a lot of their data as graphs, and we have seen several other interesting use cases for graph databases. Graph databases provide a different way of structuring our data that allows for different kinds of data queries. We would be interested in researching strategies for structuring sports data as graphs, and if this will allow us to search and aggregate our sports data.*

1.2 Background

A database management system is a system where users can organize, store, and retrieve data through a computer, and is a way of communicating with a computer's internal storage. In the 1950s, the early days of computers, computers were essentially huge

calculators, and punch cards were used to store data. Computers were quickly adopted by people and became available for commercial use. People adapted them to solve real-world problems, which made the demands regarding data processing and storage to skyrocket. In 1960 the American computer scientist Charles Bachman designed what is known as "The Integrated Data Store" (IDS), on behalf of General Electric. IDS is considered the world's first database management system [16].

By the middle of the 1960s, the development of computers was booming, and many kinds of databases became available for consumers. Resulting in a wide range of systems and standards. At the same time, Bachman formed the Database Task Group (DBTG), which took responsibility for creating a common standard for databases. In 1971 DTBG presented their new standard called Common Business Oriented Language (COBOL) [16].

COBOL was based on a model known as the network model, which represented data as different kinds of objects with relations between them. The Network Model was conceived as a graph and known for being schemaless. Many databases were built on this concept, and the COBOL standard came to be known as the CODASYL-approach [16].

There is, in many ways, a direct resemblance between the network model and graph databases as we know them today. However, there is one crucial element that separates the two. The CODASYL approach is a complex system, which makes it very hard to search and query data. Graph databases usually have their own query language which makes these kinds of operations much easier [8].

Due to the CODASYL approach's failing abilities to search for records, it eventually lost its popularity. A developer from IBM was not satisfied with the search engine in the CODASYL approach. Therefore he started to look at alternative ways to manage data. So in 1970, he published a series of papers describing a different way of constructing a database and storing data as rows in tables. This evolved into the relational database model as we know it today [16].

1.3 Motivation

Today, enormous amounts of data are collected. According to Forbes, we produce 2.5 quintillion bytes of data every year. During the last two years, 90% of all measured data in the world was generated [25]. According to a publication from the advisory firm EY [15], we will by 2020, generate about 1.7 megabytes of new information every second for every human being on the planet. Buzz words like "Big data" are often in found tech-blogs and other publications, which points to a trend, where enormous amounts of data go through comprehensive analytic processes.

The relational database model has been around since the 1970s. Relational database technology has been the choice for most traditional applications that require both data storage and retrieval. A relational database consists of tables with rows and columns. These tables can have thousands or even millions of rows, known as records.

With these vast amounts of data, both practical and ethical questions arise on how can we process and take advantage of this? What kind of data management systems can we utilize in order to process this data, and meet the new demands of analyzing data.

For decades traditional relational database management systems have been used in order to store and manage data. For a very long time they have worked well, and they have been rather easy to use and implement. With the massive data we produce today, we expect more from the data, and we are continually looking for new ways to apply all this data, in order to find new trends and patterns. For this kind of data processing, traditional RDBMS may come to short. Processing queries that output the kind of data that we often wish for today is usually very costly and may require many join operations. Besides, the queries can be complicated to write and may not very intuitive for people to interpret.

Meanwhile, many other database models and providers have come to the surface. Today, document, key-value and graph model databases have challenged the traditional relational database with different properties. A popular database that has emerged is the graph database Neo4j. Neo4j has grown quickly, and many big corporations have implemented their database.

1.3.1 Extended Friends Experiment

Partner and Vukotic present a very interesting experiment in their book [63]. The experiment is known as the extended friends experiment and is widely used to demonstrate the power of a graph database. The experiment seeks to find friends of friends in a social network, consisting of 1.000.000 people, where each person has 50 friends. The experiment is done in four iterations, seeking to find friends of friends in depth one to four. The social network is modeled as a graph in Neo4j and a relational database in MySQL. The results can be seen in Table 1.1 and it clearly shows how Neo4j outperforms MySQL for this kind of query.

Depth	MySQL Execution Time	Neo4j Execution Time	Records returned
2	0,016	0,01	∼2500
3	20,267	0,168	∼110.000
4	1543.305	1,359	∼600.000
5	Unfinished	2,132	∼800.000

Table 1.1: Results in seconds from extended friends experiment

1.4 Personal Motivation

The authors of this thesis have a great interest in both analyzation and management of data. The interest increased while completing a bachelor's degree in informatics prior to this thesis, which included several subjects within data management and information

retrieval. Discovering the extended friends experiment, revealing how powerful a graph database can be, supplemented to that curiosity. Also, the idea of working together with a firm, which is world-leading in its area and founded by two earlier computer science students from NTNU was highly motivating.

The background study, presented in Chapter 2, revealed that the research regarding the use of graph databases to manage sports data was somewhat limited. Therefore this thesis will also contribute to the research community within data management, processing and analyzation.

1.5 Sportradar AG

Sportradar AG hereafter, referred to as Sportradar, is a company founded in Trondheim in the year of 2000. It all started with two computer science students' master's thesis here at NTNU. Together they designed a high accuracy wrapper that could crawl the web, and gather betting odds and information from 25 different sports across 300 different online bookmaking platforms [5].

One of the co-founders of the company had been following different bookmakers' online betting platforms. He discovered the fact that the odds to a given sporting event tended to differ between different betting platforms depending on in which country the odds were determined. Knowing this, he could predict score results better than most other bookmakers. Further, he discovered that the different bookmakers tended to provide better odds for teams that represented their interests. For example, a Spanish bookmaker would give better odds to Spain's national soccer team for a given soccer match, than what an American bookmaker would do. Knowing all this and subsequently making more money on betting, than what he considered normal. The idea of developing an application that the rest of the world's bookmakers could have enormous use of emerged [52].

Today, Sportradar is a leading company providing live sports results, sports statistics, odds, and sports integrity services. They cover the entire value chain of collecting, processing, marketing and monitoring of sports-related live data as well as sports-related services. They consist of about 1700 employees and serve customers in approximately 100 countries [14].

Sportradar is in partnership with many international sporting federations, for example, the NHL, NFL and NASCAR and German Bundesliga where they are the leading provider of sporting statistics. Furthermore, they provide several bookmakers like Bet365, Ladbrokes, Svenska Spel and Norsk Tipping with betting services [55] [59].

1.6 Scope

Based on the description above, the goal of this research was to investigate how sports data from Sportradar performed when structured in a graph database. Since this was a

comprehensive problem, we had to narrow down our scope, in order to make the research feasible. One of the sports that Sportradar had excellent data coverage for was soccer, and especially the English Premier League. In combination with good data coverage and the fact that many people have a relationship with soccer, we chose to use that as our domain for our research. Therefore we developed out a pair of research questions with the purpose of supporting the overall goal. The research questions were as follows:

- **RQ1:** Identify a use case which is representative for the data and applications of Sportradar.
- **RQ2:** How does the Neo4j graph database management system compare against Oracle's MySQL relational database management system, in regard to target the problem?

1.7 Research Strategy

The findings we present in this thesis was a result of planning, implementing and conducting a research strategy. B. J. Oates [39] presents a model in his book, Figure 1.1 which highlights important elements of research.

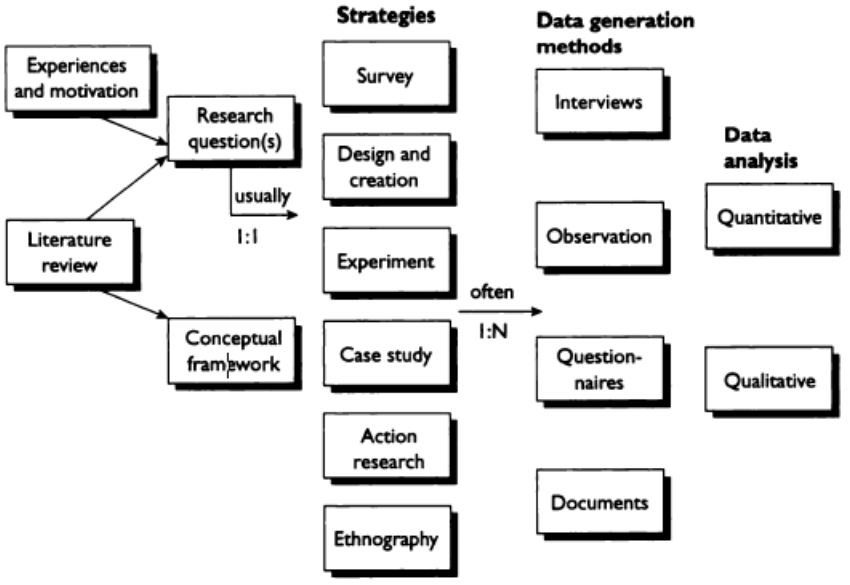


Figure 1.1: Model of research process [39]

Our Research strategy was rooted in this model. We developed our research questions based on experiences, motivation and previous work. We mainly used quantitative research

methods through experiments to generate data for our analysis. However, qualitative methods were also used in order to assess aspects of a DBMS that are not measurable by numbers. Babbie, Earl R [3] defines both quantitative and qualitative research methods as follows:

- *Quantitative methods emphasize objective measurements and the statistical, mathematical, or numerical analysis of data collected through polls, questionnaires, and surveys, or by manipulating pre-existing statistical data using computational techniques. Quantitative research focuses on gathering numerical data and generalizing it across groups of people or to explain a particular phenomenon*
- *Qualitative research is a scientific method of observation to gather non-numerical data. This type of research "refers to the meanings, concepts definitions, characteristics, metaphors, symbols, and description of things" and not to their "counts or measures.*

In our research, we designed two different databases, based on two different technologies, Neo4j and MySQL. Both databases were populated with identical data, provided by Sportradar. We collected numerical data by having the databases execute three different test cases each. Then we analyzed the databases' performance by comparing and analyzing the execution times for each of the test cases. The test cases were the same for both databases and consisted of different kinds of queries. However, they differed in the way that they were written and customized in order to meet the requirements of both database technologies. After obtaining results from our database performance testing, they were discussed with regards to previous related work, presented in Chapter 2. In the discussion, aspects such as documentation, durability and usability were enlightened.

1.8 Structure

This section presents a list, which in short, describes each chapter and its content.

- **Chapter 1 - Introduction** introduces the thesis as a whole and presents how this project came to life. Furthermore, it introduces Sportradar and gives a brief introduction to the history of databases.
- **Chapter 2 - Related Work** presents related work and studies which have played an important role in this research.
- **Chapter 3 - Background** introduces central concepts within graph databases and relational databases. The database management systems Neo4j and MySQL are presented, along with other related tools and technologies.
- **Chapter 4 - Design & Implementation** delves into how our solution was implemented step by step. By explaining how the databases import data from Sportradar's API, and how our Python scripts and queries interact with the databases.

- **Chapter 5 - Results & Discussion** presents all results and findings achieved through carrying out our different experiments. In addition, results are discussed in light of previous related work.
- **Chapter 6 - Conclusion & Future Work** summarizes the thesis, and evaluates how the project can be improved. Also, it presents advantages and disadvantages with both MySQL and Neo4j. Lastly, it discusses future work that may verify or discredit the results achieved through this project.

Chapter 2

Related Work

Graph database theory has been around for a pretty long time, compared to other computer science concepts. However, they have only been practiced to a small degree, until recently. Therefore the amount of relevant research and work within this topic is limited. Nevertheless, there has been significant research on graph database usage in other domains. Some of it is relevant to our research and can be adapted for our domain. This chapter will summarize that literature.

2.1 World Cup As a Graph

During the FIFA Soccer World Cup In 2014, the team behind Neo4j built two different graph data sets. One based on historic World Cup data, and the other on data from the 2014 World Cup in Brazil. With both databases, they were able to explore the World Cup data in new and different ways [29].

When graphing the historical data, and later querying the database, the developer team discovered many interesting findings. Some examples are as following:

- After losing to France, it took Mexico 82 years to get their revenge. Mexico lost in 1930 and did not beat France until 2012.
- During the tournament in 1954 Hungary met West Germany in the initial round, but then lost to them in the final.
- The following five players were all drafted to play in the World Cup three times, but were kept as substitutes and never brought on the field.
  - Anthony Seric (Croatia)
  - Antonio Juliano (Italy)

- Marek Kusto (Poland)
- Borislav Mikhailov (Bulgaria)
- Francisco Urruticoechea (Spain)

This list is an example of things that one can do with graph databases.

2.1.1 The World Cup Graph Domain Model

The Neo4j Team presented a model, Figure 2.1, that shows a subgraph of how they chose to model one match in the World Cup. With this starting point, the creators had many possibilities to expand the graph. It may look like as if the green node "Home vs. Away" is the center of the graph, but actually, it is the beige "World Cup" node that is the center-node in this example. The creators could have added more "World Cup" nodes, in order to represent additional World Cups in the graph. By adding the yellow "Round" node, one can by querying the complete graph, see how countries perform across different world cups. The orange "Time" node is there in order to discover happenings related to when teams play their matches [30].

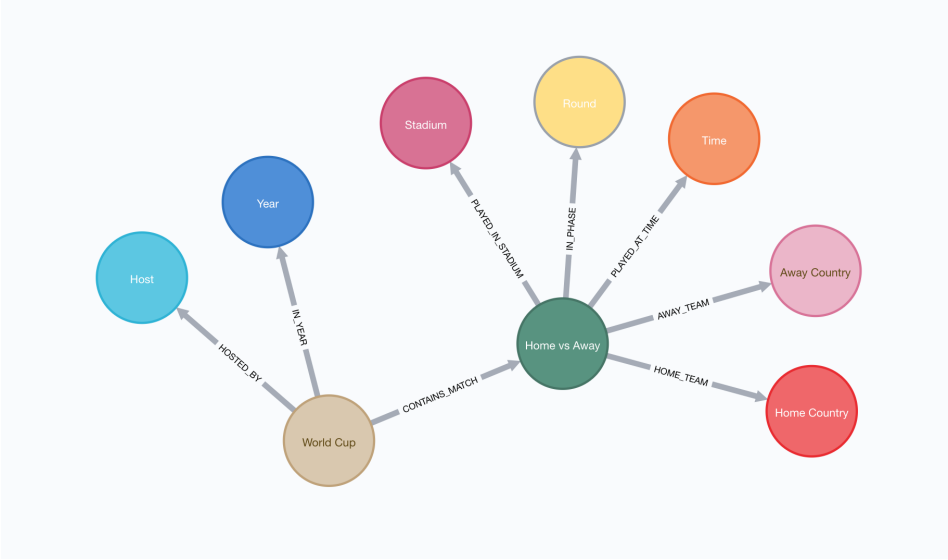


Figure 2.1: Remake of the World Cup graph model by Neo4j [30]

2.2 Medhi's Study

An Indian study conducted by Medhi at Gauhati University [26] did a comparative analysis on relational databases and graph databases. The study was rather simple. However, the

results were conclusive. Medhi used a dataset based on three different cricket tournaments, the Test Cricket Tournament, One Day International Tournament (ODI) and the Twenty-Twenty Tournament (T20). The dataset consisted of all the cricket players' information, team and which player had played which matches.

This dataset was modeled in both a relational database and a graph database. For the relational database MySQL version 5.1.0 was used, and for the graph database Neo4j version 2.0.3 was used. PHP and Cypher were respectively used as languages to query the database. A relational database consisting of three tables were then created, based on data from the dataset. Furthermore, a graph based on the same data was modeled. With the two different databases containing the exact same data. They executed the three following queries:

- Find the names of the teams.
- Find the names of the cricketers who have played in both the One Day International Tournament and the Test Tournament.
- Find the Cricket players who belong to team India.

These the queries were executed three times each. During each iteration the databases were modified to respectively contain 100, 300 and 400 objects. The results of these queries can be seen in Table 2.1:

No. of objects	**Query 1 MySQL**	**Query 1 Neo4j**	**Query 2 MySQL**	**Query 2 Neo4j**	**Query 3 MySQL**	**Query 3 Neo4j**
100	12.56ms	5ms	18.52ms	7.32ms	15.75ms	6ms
300	153ms	7ms	212.53ms	13ms	180.24ms	9.32ms
400	164.43ms	8.32ms	387.34ms	15.67ms	302.44ms	13.32ms

Table 2.1: Execution time for different queries based on database and size of database

As Table 2.1 shows, there were significant differences in the time it took to execute the above queries. As the size of the dataset increased, the execution time increased at a much faster rate with the MySQL database than with the Neo4j database. The study concluded that the graph database performed much better than the relational database concerning time. Also, it added that it was easier to model, maintain and expand the graph database due to the high connectivity of the data.

2.3 Import Time

Many studies have been conducted that assess the pros and cons of both graph databases and relational databases. A study [45] published in August 2018 compares the architectural structure between Neo4j, MySQL and the NoSQL database MongoDB. In this study, they focus on how the different databases perform while importing data. They performed an experiment using a dataset containing details on vehicle transactions between a car

dealership and their customers, consisting of about 100.000 records. The dataset had the following structure:

- transaction_id
- counter_id
- branch_id
- date_of_transaction
- hour
- high_level_territory
- staff_id
- product_id
- payment_amount
- bea_admin
- cust_id
- name

Before the dataset was imported, it was restructured into the respective schemas according to the database's requirements. For the relational database, the dataset was modeled into seven tables, containing six foreign-key relationships between them. Six tables contained actual data, while the last table only contained links between the different entities in the model, as shown in Figure 2.3.

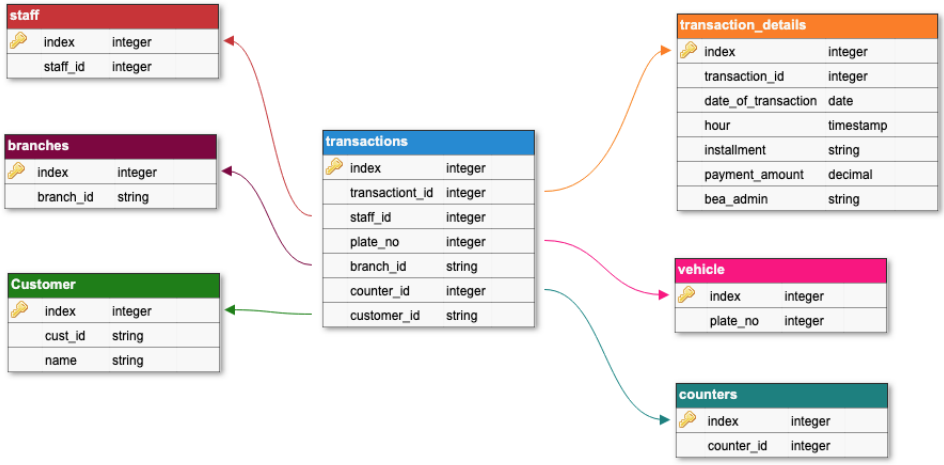


Figure 2.2: Relational model of dataset

Figure 2.3 shows how the graph database was modeled. By using six different nodes that represented the data, and seven different connections, that represented the relationships between the nodes.

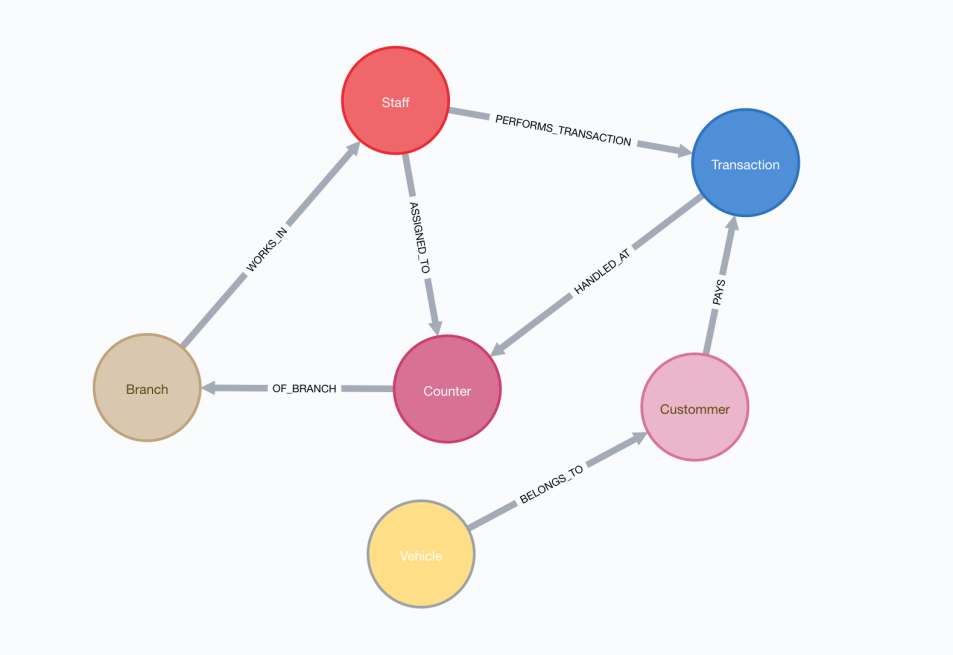


Figure 2.3: Graph model of dataset

During this experiment, they imported parts of the dataset at the time. They tested the different databases' abilities to import datasets containing 10.000, 30.000, 60.000, and 100.000 records. Figure 2.4 shows how the databases performed concerning time.

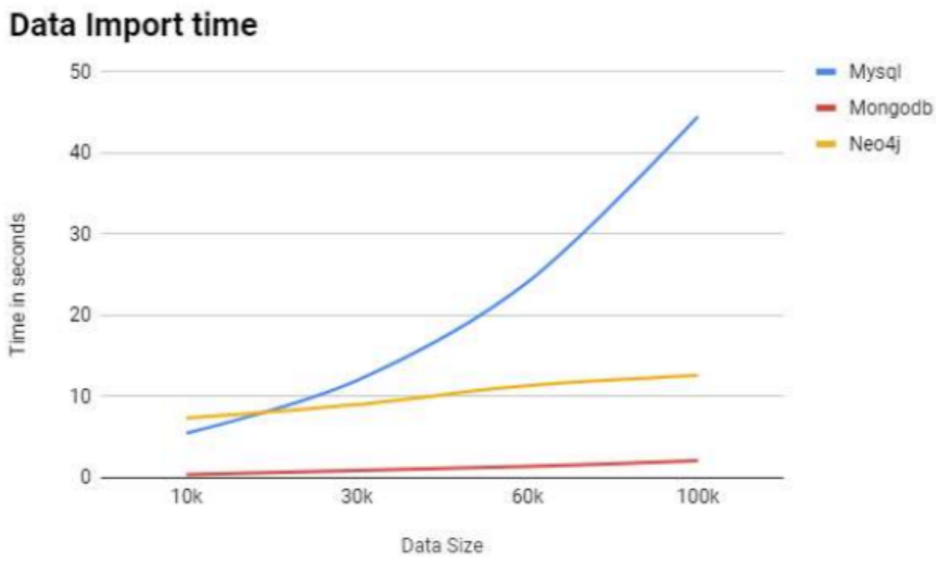


Figure 2.4: Data import time results adopted from [45]

From Pandey's study [45] we saw that the size of the dataset that was imported, affected how the different databases performed. We also noticed that MongoDB and Neo4j performed almost constant, only decreasing in performance with a few milliseconds as the dataset grew. On the other side, we found MySQL, when the dataset was smaller than 20.000 records, MySQL performed better than Neo4j, with regard to import time. Lastly, we observed that data import time grew close to exponentially as the dataset increased in size.

Chapter 3

Background

This chapter introduces central concepts related to graphs, graph theory and graph databases. In addition, other graph database management systems will be introduced to better evaluate and compare Neo4j against other providers of graph databases. Furthermore, this chapter will present one of Neo4j's biggest competitors, Oracle with its database management system MySQL, and relevant theory behind it. As graph database theory is a newer and less known concept than relational database theory, the focus in this chapter will mainly be on graph database theory.

3.1 Application Programming Interface

An Application Programming Interface (API) allows software applications to communicate with one another. It is a well defined set of functions and procedures that allow one application to interface with another [54]. Commonly used is the Web-API that uses RESTful methods, meaning that it uses HTTP requests to GET, PUT, POST and DELETE data. Communication is done via a defined request–response message system, that can be publicly available or restricted to certain users. The response from the endpoints is usually expressed in either JSON or XML. Developers typically build applications based on the data returned by calling the different endpoints [6].

3.1.1 Sportradar Developer API

The API developed by Sportradar delivers enormous amounts of data in both JSON format and XML format. It is Sportradar's main product, and their customers have to purchase a subscription in order to use the API. With the API, users can access sports statistics feeds, which contain vast amounts of data for different leagues, conferences, teams, games,

and players in their database. The API uses RESTful methods, making it possible for developers to integrate Sportradar's services directly into their application.

With regard to soccer, Sportradar covers almost all leagues and tournaments. Big leagues such as the Premier League is broader covered than less popular leagues such as the highest Norwegian league Eliteserien. Figure 3.1 is a mapping of the Soccer API that shows how all the different soccer APIs are connected and what kind of data they return.

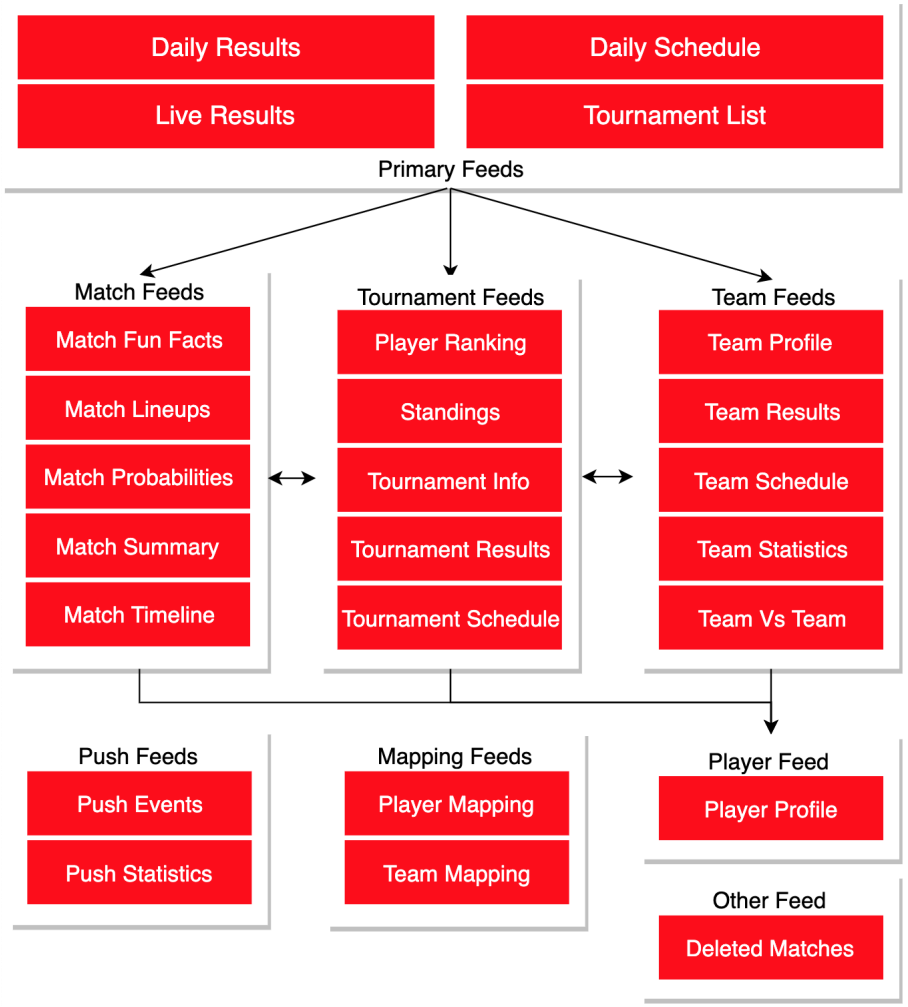
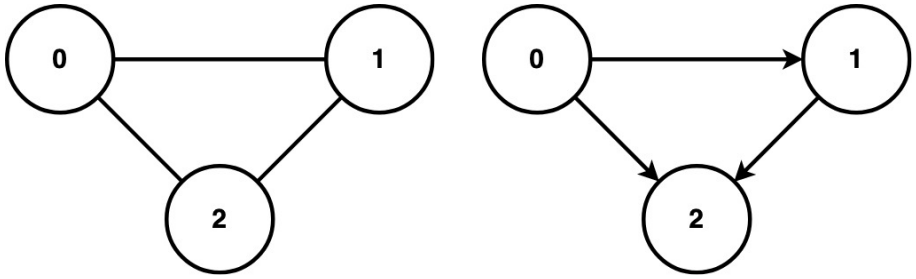


Figure 3.1: API map from Sportradar [56]

3.2 Graph

A graph is a way of representing a collection of vertices and edges and how they are connected to each other. Graph theory is the study of mathematical objects known as graphs, which consist of vertices (or nodes) connected by edges [10]. Figure 3.2a shows a simple graph where the vertices are the numbered circles, and the edges join the vertices.



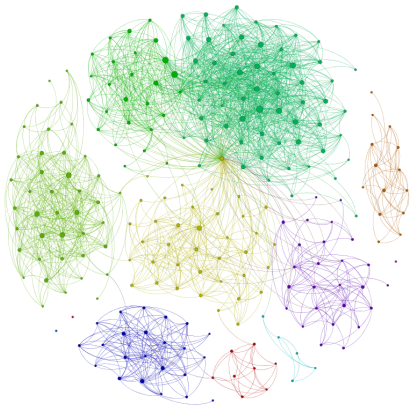
(a) Undirected graph **(b)** Directed graph

Figure 3.2: Graph examples

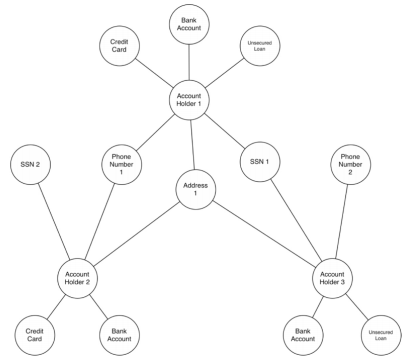
Edges in a graph are either directed as the edges are in Figure 3.2b or undirected as the edges are in Figure 3.2a. An edge (u, v) is directed from u to v if the pair (u, v) is ordered, with u preceding v. If all the edges in a graph are undirected, then the graph is undirected, and directed if all the edges are directed. Both graphs can also be weighted, which means that edges can be assigned either with a positive or negative value. Graphs are typically visualized by drawing the vertices as ovals or rectangles and the edges as segments or curves connecting pairs of ovals and rectangles. An undirected graph can be converted into a directed graph by replacing every undirected edge with a directed edge. It is often useful to keep undirected and mixed graphs represented as they are, for such graphs have several properties that can have different areas of use [20].

3.2.1 Use Cases

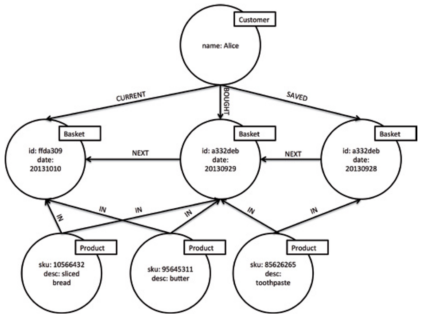
There is a wide range of real-world scenarios that can be modeled using graphs. Graph theory is used to model problems such as government administration, different fields within science, business strategies and social networks [50]. Figure 3.3 illustrates four different use cases, where graphs are used to model real-world scenarios.



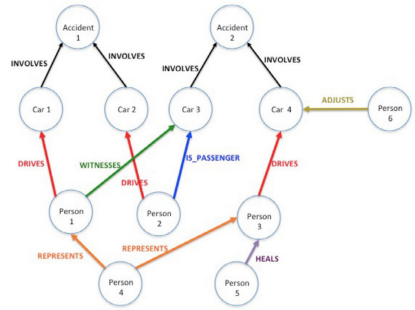
(a) Social network graph derived from [23]



(b) Fraud detection graph derived from [49]



(c) Recommendation System graph derived from [64]



(d) Insurance Fraud graph derived from [49]

Figure 3.3: Graph use cases

There is a wide range of well-developed graph algorithms that perform many kinds of graph operations such as clustering, pattern matching, shortest path calculations, depth search and other graphing functions. Some well-known examples are the following:

- **Depth & Breadth First Search:** A simple search algorithm used to find the shortest path from one node to another. Depth first search begins by inspecting the deepest nodes first. Breadth first search begins with inspecting the closest node first [7].
- **Belleman-Ford:** An algorithm used to find the shortest path to all other nodes from a given starting point. Used in graphs that have negatively weighted edges [17].
- **Dijkstra:** Algorithm used to find the shortest path between two nodes in a network with weighted edges [24].
- **K-means:** A clustering algorithm used to discover underlying patterns by grouping similar data points together [19].

3.3 Graph Storage

The term "Graph Storage" refers to the internal graph database structure, and how the data storage is actually implemented. Different systems use different ways of storing graphs. However, systems built specifically for storing graph data are called native graph storage. Native graph storage means that the system is optimized for graphs in every aspect, and considerations for other aspects may be down-prioritized [9]. A native graph storage enables traversal of connected nodes in constant time. It makes it possible to traverse, for example, a dataset consisting of one billion nodes, just as fast as a one million node dataset.

In order to achieve native storage, graph databases utilize an architecture known as "index-free adjacency", which is designed explicitly for graph databases. "Index-free adjacency" means that a data element is directly connected and points to another data element or relationship. This makes lookups extremely fast because there is no need to look up and follow index pointers [21].

The term non-native storage is used for systems where other sources handle how the graph is stored. If a relational or a different kind of NoSQL database has to store a graph, nodes and relationships may end up being placed far from each other, and performance will be drastically affected [9].

3.4 Neo4j

Neo4j is a native graph database management system written in Java and Scala, developed by Neo4j. Inc. The development of the system began in 2003 and was released for commercial use in 2007. Neo4j is an open-source, NoSQL, native graph database. The source code can be found on GitHub[1], and the service can also be used through a user-friendly desktop application. Neo4j is available in two different versions, a community edition and an enterprise edition. The enterprise edition includes all the same features as the community edition, but it also includes services to back up data and features clustering and failover abilities. Today, Neo4j is used by many big corporations, for example, Telenor, Nettbus(Vy), Volvo, Walmart, eBay, IBM and Microsoft [33].

3.4.1 Choosing Neo4j

The rationale behind choosing Neo4j as service for this project was mostly because Sportradar already used Neo4j for parts of their data. Furthermore, Neo4j is one of the most used graph database management systems. Naturally, there exists more documentation for Neo4j compared to other graph databases. The research and use of graph databases are quite limited; therefore choosing a well-known provider was important.

[1] `https://github.com/neo4j/neo4j`

Community

Neo4j has a large online community with more than one thousand users. The community consists of a global forum for online discussion on how graphs work. Furthermore, Neo4j has its own workspace on Slack[2]; "neo4j-users.slack.com" where users can register. Today there are 10.000 active users on Neo4j's Slack. Both the forum and the workspace on Slack are two reliable sources to explore when looking for documentation and answers regarding Neo4j.

3.4.2 The Property Graph Model

Neo4j has its own unique object model, called The Property Graph Model, which describes how its system works in terms of objects, classes and the relationships between them. It is shown in Figure 3.4. The Property Graph Model organizes data as nodes, relationships and properties. Nodes and relationships are the graph's vertices and edges. Properties are various kinds of information that are stored on both the nodes and the relationships [36].

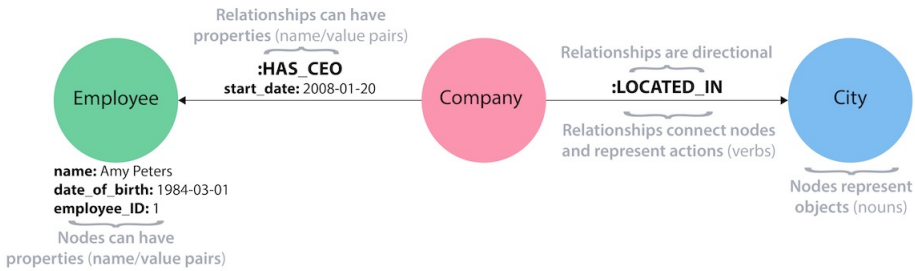


Figure 3.4: Property Graph Model by Neo4j [36]

3.4.3 Neo4j Browser

The Neo4j Browser is Neo4j's graphical user interface. The browser is easy to use and can be run through the web browser. With the Neo4j Browser, users can query, visualize, administer and monitor a graph database.

[2] `https://slack.com`

3.4.4 Cypher

Cypher is Neo4j's own query language created for describing visual patterns in graphs. It is a declarative language and is highly inspired by SQL. Cypher supports the use of all CRUD-operations on a graph without having to explicitly describe how to do it. CRUD stands for create, read, update and delete, and together they make up the basic operations of a database. As mentioned earlier in this chapter, a graph consists of nodes and relationships. Both nodes and relationships can have additional info known as labels. Figure 3.5 shows a simple graph containing two nodes and one relationship. Cypher makes it possible to ask and answer complex questions on datasets by lay or application users and not just developers [31].

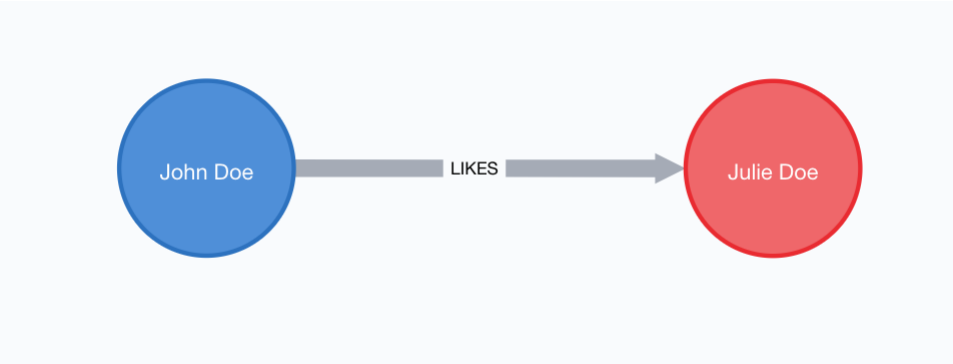


Figure 3.5: Relationship between two nodes

Cypher's syntax is quite simple. Nodes are enclosed by parentheses, "*(node)*", relationships by straight brackets, "*[relationship]*" and properties by curly brackets, "{*property*}". The relationships must be directed, meaning they have to point from one node to another. Arrows such as "`->`" and "`<-`" are used to indicate the direction of the relationship. Listing 3.1 shows how the graph in Figure 3.5 can be created.

```
1 CREATE(:John{name:"John Doe"})
2 -[:LIKES]->(:Julie{name:"Julie Doe"})
```

Listing 3.1: Cypher query used to create graph from Figure 3.5

The `CREATE` statement above displays a query that can be used to create the graph shown in Figure 3.5. The graph contains two kinds of nodes `(:John)` and `(:Julie)`. Each node has been given the property `name` which is respectively set to "John Doe" and "Julie Doe". The node types are used for accessing and referencing the nodes. For example, we can use `MATCH(person:John)`, which gives all nodes of type `(:John)` the label `person`. Then we can use `RETURN person.name` to access John Doe's full name. If the graph contained other nodes of the type `(:John)` representing different Johns, it would also return their full names.

3.4.5 APOC

APOC stands for Awesome Procedures on Cypher and is a utility library for Neo4j based on Cypher. It contains more than 450 different functions and procedures for different kinds of tasks including:

- Graph algorithms
- Metadata
- Manual indexes and relationship indexes
- Full-text search
- Integration with other databases like MongoDB, ElasticSearch, Cassandra and relational databases
- Loading of XML and JSON from APIs and files
- Collection and map utilities
- Date and time functions
- String and text functions
- Import and export
- Concurrent and batched Cypher execution
- Spatial functions
- Path expansion

Today, APOC is the largest literary developed for Neo4j. Before APOC was implemented, developers had to write their own methods for all the functions and procedures mentioned above, and the result was a lot of duplicated and poor quality code [22]. APOC made it possible for developers to only focus on writing business-logic and use-case specific code without having to deal with platform limitations. All functions and procedures are well-supported and easy to use by themselves, or in combination with other methods [37].

3.5 Alternative Graph Database Management Systems

There are many providers of graph database management systems out on the market. Some are open source, and public licensed and others are commercially licensed. The next following sections will present a few other alternatives to Neo4j.

3.5.1 Amazon Neptune

Amazon Neptune[3] is a commercially licensed cloud-based GDBMS, and it is one of the biggest providers of graph databases on the commercial market. Amazon released it 2017 so that users could create sophisticated, interactive graph applications that could query billions of relationships with minimum latency. Amazon Neptune supports a variety of the most popular graph models and their query languages. Along with complete ACID compliance, Amazon Neptune is fully managed, which means that users do not have to worry about database management tasks such as hardware provisioning, software patching, setup, configuration or backups. All of these tasks are completed automatically [53][61].

Amazon created the database with a high focus on availability, recoverability and durability. Amazon Neptune supports point-in-time recovery, which means an administrator can roll back the database to any given timestamp. Continuous backups are made automatically and stored using Amazon's S3 cloud storage services. Highly secure and encrypted storage is also offered using Amazon's own encryption algorithms [53].

3.5.2 OrientDB

OrientDB is an open source NoSQL database management system, developed by OrientDB Ltd and released in 2010. The database is a "multi-model" database, which means it supports various models such as key/value, document, object and graph model. In OrientDB, all connections between records are managed as relationships as in a graph database. Orient is written in Java and is designed to perform very fast. With the ability to store and process 220.000 records per second, it is according to their own website[4], the graph database with the highest performance available [44].

OrientDB comes in two different versions, a free community edition and an enterprise edition with professional support service. Furthermore, OrientDB has an enormous capacity. It can store up to 302,231,454,903,657 billion (2^{78}) records with the maximum capacity of 19.807.040.628.566.084 Terabytes of data on a single server or multiple nodes [44].

3.5.3 ArangoDB

ArangoDB is also a native multi-model database developed by ArangoDB Inc. The database was released in 2011 under the name AvocadoDB, but one year later in, 2012, it was changed to ArangoDB. On their website[5], they market themselves as a GDBMS with a high focus on search and index algorithms. Natively integrated into ArangoDB, is a C++ based full-text search engine, with included similarity ranking capabilities. This search engine utilizes two kinds of information retrieval techniques: boolean and generalized ranking retrieval. It enables ArangoDB to perform complex federated searches over a whole complex graph [1].

[3] `https://aws.amazon.com/neptune/`
[4] `https://orientdb.com`
[5] `https://www.arangodb.com`

The developers behind ArangoDB have also created a query language, ArangoDB Query Language (AQL), which is similar to SQL. AQL supports CRUD, aggregations, complex filter conditions, secondary indexes and real JOIN operations, which makes it possible for the users to alter their data access strategy just by changing a query [2].

3.6 Oracle

Oracle is a world-leading software company. According to an analysis [47], by the advisory firm PwC, Oracle was the second-largest software company by revenue in 2014 and is a global corporation that develops software and applications used for business. The company is best known for its relational database software. Oracle was founded in 1977 in the United States in Santa Clara, California. Today, Oracle has its headquarters in Redwood Shores, California [60]. They have about half a million customers in 173 different countries and 25.000 partners [40].

3.6.1 MySQL

MySQL is the world's most popular open source RDBMS [43]. It is based on SQL and can run on many different platforms including Linux, UNIX and Windows. MySQL is used in a wide range of applications, both small and large applications, but it is commonly found in web applications. Originally MySQL was a Swedish product, but was acquired by Sun Microsystems in 2008, and later taken over by Oracle in 2010. Today, MySQL is used in many top large scale websites such as Facebook, Google, Twitter and YouTube [51].

MySQL is based on a client-server model. The core of MySQL is a server, which handles all commands to the database. In order to communicate with the server, one typically uses a MySQL client to send commands. The client can be downloaded and installed on most computers today. Originally MySQL was designed to handle large databases quickly. However, most users only install MySQL on one machine, but the client can be installed on several machines and the database can be accessed through a broad range of client interfaces. Through the client, users can send SQL statements to the server and have it return the results.

3.6.2 Structured Query Language

SQL stands for Structured Query Language, which is the standard programming language for relational data manipulation and data management. The language was developed in the early 1970s at IBM by Raymond Boyce and Donald Chamberlin. Today, most RDBMS support SQL, including MySQL, and it is used to query, insert, update and modify data in relational databases. In 1979 Oracle adapted SQL and released its own modified version. Since then, SQL has played an important role in modern database development [38].

3.6.3 Support

An important aspect of MySQL is the fact that MySQL can store data across many different storage engines. Furthermore, MySQL has algorithms for replicating data and partitioning tables in order to increase performance and durability. Not only is MySQL free to download and use, but equally important is the fact that Oracle has a large technical support team focused just on MySQL. Oracle offers direct access to expert MySQL Support engineers who are capable of helping with development, deployment, and management of MySQL applications. Support is available 24 hours a day and 365 days a year [28]. Since MySQL has been around for a decade, a large community around it has emerged. On Stack Overflow[6], one can find over half a million posts that are tagged with MySQL [12].

Through their website[7], MySQL provides a broad array of different support and educational services. Users of MySQL can sign up for comprehensive MySQL training courses, which educate developers on how to build efficient database solutions. Followed by a certification program that developers can take in order to prove their knowledge within MySQL.

On the support side, MySQL offers a consulting service, which can assist developers to optimize or scale an existing solution, or it can be used to get help with setting up a new project. Lastly, the MySQL technical support team aid developers with their specific needs, helping them achieve higher levels of performance, reliability, and uptime.

3.6.4 Choosing MySQL

MySQL is the world's most used database [4]. It is Neo4j biggest competitor, and it is also the database that Sportradar primarily uses. Thus it was natural to select it as the relational database to use for this project.

3.6.5 InnoDB

MySQL 8.0 is powered by InnoDB, a general purpose storage-engine created by Oracle. Today, InnoDB is the storage-engine used by default in MySQL, unless other configurations are made. Until December 2010, MySQL was powered by an engine called MyISAM, but was replaced by InnoDB. InnoDB serves the purpose of balancing high reliability with high performance within MySQL. In addition, InnoDB follows the standard ACID model, which features transactions with commit, rollback, and crash-recovery capability in order to protect user data. Based on primary keys, InnoDB arranges data on disk in order to optimize queries. This means that each table has a primary key index that is used to organize data so that the amount I/O lookups for primary keys are reduced [41].

[6] `https://stackoverflow.com/`
[7] `https://www.mysql.com/services/`

3.6.6 B$^+$-Tree

InnoDB uses the B$^+$-tree data structure to index data in a MySQL database. A B$^+$-tree is a self-balancing tree structure that stores records in a sorted manner. The tree consists of pages located on different levels with links between them. At the top, the root page is located and at the bottom, the leaf page is located. Pages located between the root level and the leaf level are referred to as internal pages. The leaf pages are where data is actually stored. Pages located at the leaf level of the tree may hold complete records in a table, or they may hold an indexed key pointing to a record located in a different file or tree. Figure 3.6 shows a B$^+$-tree of three levels [11].

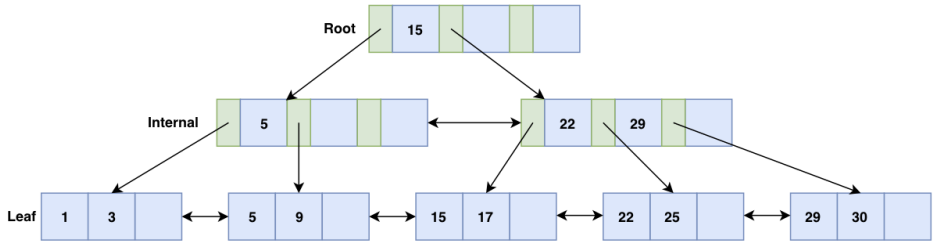


Figure 3.6: B$^+$-tree of three levels

A B$^+$-tree is a self-balancing tree, meaning that all branches always have the same depth. This makes B$^+$-trees particularly efficient for lookups because the depth of the tree limits the number of reads required to access data. A lookup is done by traversing the tree from the root level down to the leaf level. At the leaf level, a binary search is used to find the desired record. For range scans, the same procedure applies, followed by a sideways traversal of the linked leaf pages [11].

Insertions are handled similarly as lookups. First, a search for the leaf page which should contain the new key is performed. If the page has room for another key, the key is inserted. If the page is full before insertion, a page split operation is performed. A page split is an operation that splits a page into two, making room for additional records [46].

3.6.7 MySQL Workbench

MySQL Workbench is a visual database management tool developed by the MySQL team. The tool is used by developers, administrators and architects when working with a SQL database. MySQL Workbench provides data modeling, SQL development, and comprehensive administration tools for server configuration, user administration, backup, and much more [42].

3.7 Python

Python is a high-level programming language. It is an interpreted language which means that its code is executed directly without the need of a compiler to first translate or compile the program into machine language instructions. Python was released in 1990 and has been continuously updated and improved ever since. The language is easy to learn and has many areas of use. Most programming paradigms such as object-oriented, functional and procedural programming are well supported [48].

3.8 Premier League

The Premier League is the top level of English soccer. The league was founded in 1992 after numerous conflicts and discussions between soccer authorities, players, television broadcasters and the previous top-level league management [62]. This season, the 2018/2019 season, is the 27th season of the Premier League. Today the league consists of 20 competing teams, and is the most followed sports league in the world. The League is broadcasted in 212 territories and to 643 million homes which potentially can reach 4.7 billion people. A season starts in August and lasts until May. In the course of that time period, 387 soccer matches are played [13]. According to BBC [57] the television rights for a three year period 2016-2019 are worth £5.14bn.

Chapter 4

Design & Implementation

This chapter will describe how we designed and implemented our solution in order to address the proposed research questions from Chapter 1, which were the following:

- **RQ1:** Identify a use case which is representative for the data and applications of Sportradar.
- **RQ2:** How does the Neo4j graph database management system compare against Oracle's MySQL relational database management system, in regard to target the problem?

4.1 Approach

We chose the problem of analyzing the performance of a home team in a soccer match with respect to the number of match events that the home team produced and the score of the match, by using Sportradar's Premier League soccer data. To do this, we identified the following soccer events that are relevant to a team's performance:

- corner kick
- free kick
- goal kick
- injury
- injury return
- offside
- penalty awarded

- penalty missed
- red card
- score change
- shot off target
- shot on target
- shot saved
- throw in
- yellow card
- yellow red card

For each event type, we calculated the number of events created per minute for each of the three possible states a soccer match can be in with respect to home team score:

- Score is tied
- Home team is winning
- Home team is losing

In order to performance test Neo4j and MySQL, we developed two databases, one graph database and one relational database. Both databases contained the exact same data, but structured differently. With all this information, we developed an application that retrieved event information from a database, and analyzed it according to our preferences. We defined three test cases, described below, in order to compare performance between the graph and the relational database. The application was by turn connected to each of the databases, and for each database, each test case was executed 25 times.

- **Single Match** - Select a random soccer match and calculate events produced per minute by the home team based on score.
- **Team Season** - Calculate events produced per minute based on the score for all soccer matches played on home ground during the season for a specific team.
- **Complete Season** - Calculate events produced per minute based on the score for the home team for all matches that have been played during the season.

Figure 4.1 shows a complete overview of the system design. The remainder of this chapter will describe what the different elements in the figure are, and how they work together.

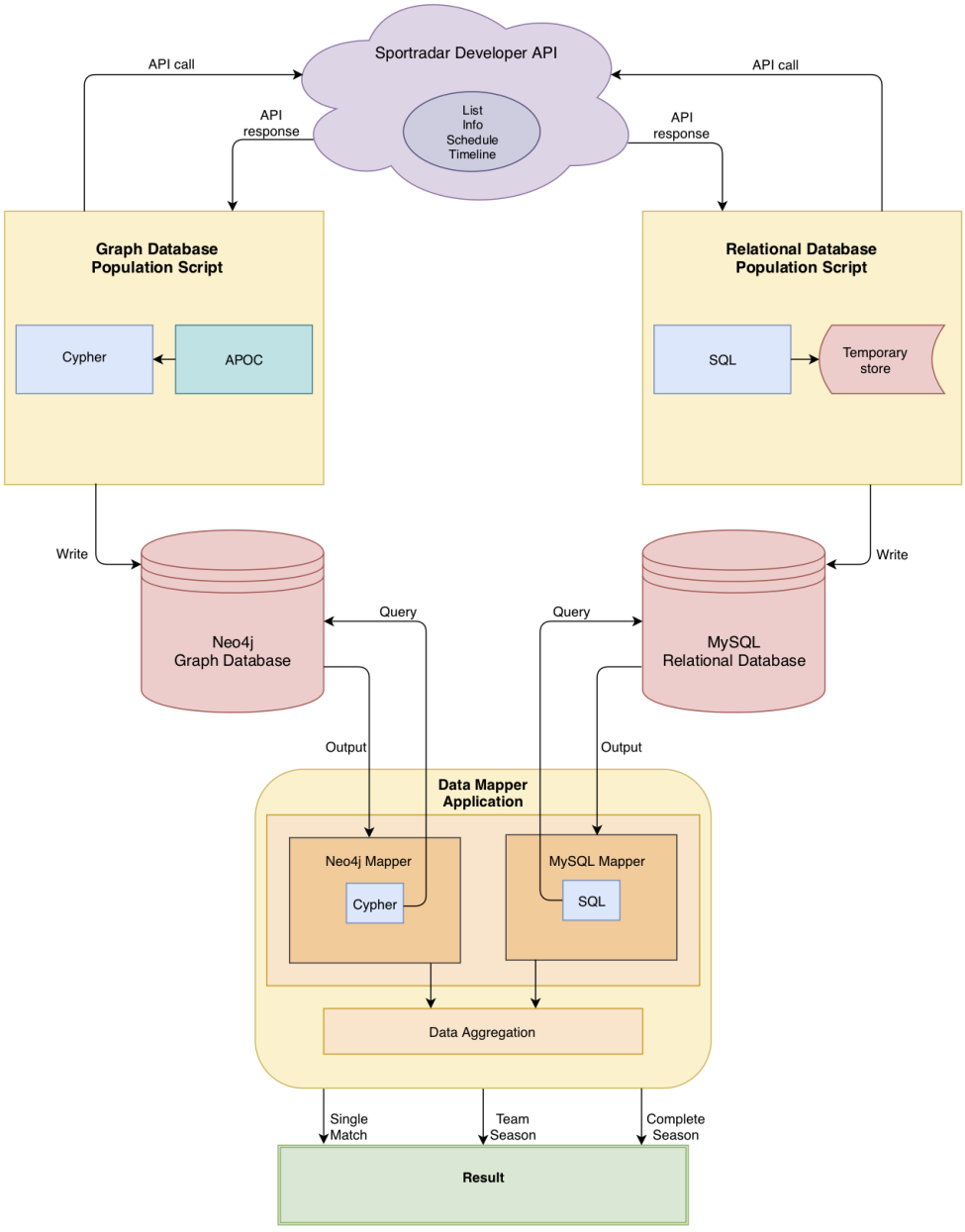


Figure 4.1: System design

4.2 Database Design

As previously mentioned, we created two databases for this project. To retrieve the necessary data to populate our databases, we used four specific Sportradar API calls:

- Tournament List API
- Tournament Info API
- Tournament Schedule API
- Match Timeline API

These API calls are represented in Figure 4.1 as the purple cloud on top named “Sportradar Developer API”.

The Tournament List API returns a list of all major soccer tournaments in Europe. We called that first to retrieve the necessary information regarding the Premier League, here identified by the “tournament id” field, shown in Listing 4.1, which is a fragment of the results we received when we called the Tournament List API.

```
{
"id": "sr:tournament:17",
"name": "Premier League",
"sport": {
    "id": "sr:sport:1",
    "name": "Soccer"
},
"category": {
    "id": "sr:category:1",
    "name": "England",
    "country_code": "ENG"
},
"current_season": {
    "id": "sr:season:54571",
    "name": "Premier League 18/19",
    "start_date": "2018-08-10",
    "end_date": "2019-05-13",
    "year": "18/19"
}
```

Listing 4.1: Result from calling the Tournament List API

The Tournament Info API returns a complete overview of all teams that participate in a specific tournament, along with information about the tournament such as season, name and start and end date. Listing 4.2 shows a selection of the result from calling the Tournament Info API using the “tournament id” received from the Tournament List API.

```
{
"season": {
    "id": "sr:season:54571",
    "name": "Premier League 18/19",
    "start_date": "2018-08-10",
    "end_date": "2019-05-13",
    "year": "18/19",
    "tournament_id": "sr:tournament:17"
},
"groups": [
    {
        "teams": [
            {
                "id": "sr:competitor:35",
                "name": "Manchester United",
                "country": "England",
                "country_code": "ENG",
                "abbreviation": "MUN"
            },
            {
                "id": "sr:competitor:37",
                "name": "West Ham United",
                "country": "England",
                "country_code": "ENG",
                "abbreviation": "WHU"
            },
            {
                "id": "sr:competitor:48",
                "name": "Everton FC",
                "country": "England",
                "country_code": "ENG",
                "abbreviation": "EVE"
            }
        ]
    }
}
```


Listing 4.2: Result from calling the Tournament Info API

The Tournament Schedule API returns date and time information for specific matches. We iterated over the results of the Tournament Info API to create representations of the teams in our databases, nodes for the graph database and rows for the relational database, and then imported all matches played in the season using the Tournament Schedule API. Listing 4.3 displays the result from calling the Tournament Info API.

```
1
2    {
3    "sport_evnts": {
4        "id": "sr:match:14735957",
5        "scheduled": "2018-08-10T19:00:00+00:00",
6        "tournament": {
7            "id": "sr:tournament:17"
8        }
9            "competitors": [
10           {
11               "id": "sr:competitor:35",
12               "name": "Manchester United",
13               "country": "England",
14               "country_code": "ENG",
15               "abbreviation": "MUN",
16               "qualifier": "home"
17           },
18           {
19               "id": "sr:competitor:31",
20               "name": "Leicester City",
21               "country": "England",
22               "country_code": "ENG",
23               "abbreviation": "LEI",
24               "qualifier": "away"
25           }
26       ]
27   }
```

Listing 4.3: Result from calling the Tournament Schedule API

The Match Timeline API returns information regarding each soccer event for a given match or game: event type, clock time, period and team type (home or visiting). Listing 4.3 above displays the results for a single soccer match. We received the results for 387 matches, and each one resulted in a new match node or row in our databases. For each match, we called the Match Timeline API in order to collect all its game events, and each individual event resulted in a new node or row in our databases. Listing 4.4 shows parts of a timeline from calling the Match Timeline API.

```
{
"sport_event": {
    "id": "sr:match:14735957"
},
"competitors": [
    {
        "id": "sr:competitor:35",
        "name": "Manchester United"
    },
    {
        "id": "sr:competitor:31",
        "name": "Leicester City"
    }
],
"timeline": [
    {
        "id": 447784954,
        "type": "match_started",
        "time": "2018-08-10T19:00:10+00:00"
    },
    {
        "id": 447785488,
        "type": "penalty_awarded",
        "match_clock": "1:27",
        "team": "home",
        "period": 1
    },
    {
        "id": 447785902,
        "type": "score_change",
        "match_clock": "2:28",
        "team": "home",
        "period": 1
    },
    {
        "id": 447786246,
        "type": "throw_in",
        "match_clock": "3:16",
        "team": "home",
        "period": 1
    }
]
}
```

Listing 4.4: Result from calling the Match Timeline API

With the information from Listing 4.3, we iterated through each event in the timeline, for every match played in the season, and created rows and nodes for each game event. We then combined all the information we had retrieved from calling the four different APIs, which resulted in databases containing information regarding all teams and matches played in the Premier League season 18/19. The two squared yellow boxes in Figure 4.1 represents this process.

4.3 Neo4j Graph Database

Figure 4.2 is a visualization of the graph database we created to hold the soccer data. Each red node represents a team playing in the Premier League during the 2018/2019 season. The red nodes are connected to many blue nodes that represent individual soccer matches. Each blue node connects to exactly two red nodes, connecting teams with the matches they have played. Each blue node is connected to many pink nodes where each one represents an event that occurred during the soccer match. Figure 4.2 displays a small subset of the database. It displays 2.000 nodes, whereas the actual database contains over 40.000 nodes.

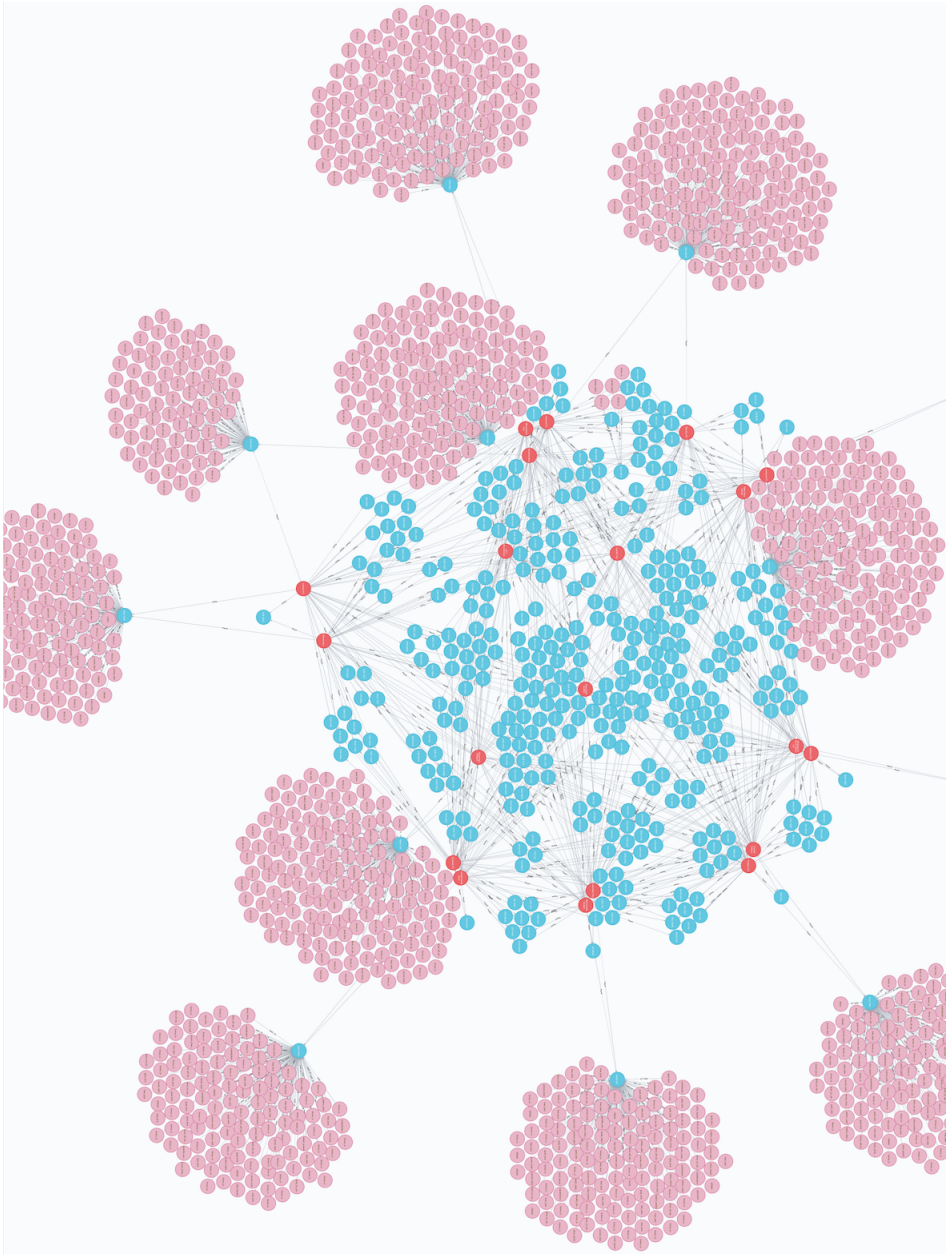


Figure 4.2: Visualized subset of the graph database

When creating our database, we started with importing all the data that we needed. In order to import data from the APIs, we had to use the APOC plugin, described in Section 3.4.5. APOC contained a function that let us directly import JSON formatted data into

our graph database. This process was wrapped inside a script which is represented by the yellow box called “Graph Database Population Scrip” in Figure 4.1.

```
1
2  :param tournament_info:"https://api.sportradar.us
3  /soccer-t3/eu/en/tournaments/sr:tournament:17/info.json?
4  api_key={your_api_key}"
5
6  CALL apoc.load.json(tournament_info,'.groups')
7  YIELD value unwind value.teams as t
8  CREATE (team:Team)
9  SET team.name = t.name, team.id = t.id, team.abbreviation
10       = t.abbreviation
```

Listing 4.5: Query for importing all teams to the graph database

Listing 4.5 shows how we used APOC in a Cypher query to populate the database with all the teams. First, we declared the parameter `tournament_info` and assigned it to the API call, which returned information regarding all soccer teams competing in the Premier League. Then we called APOC’s load procedure and passed in our newly created `tournament_info` parameter together with a parameter called `.groups`. We included the `.groups` parameter because we were only interested in the contents of the `groups` property shown on line 10 in Listing 4.2. Next, we used the `YIELD` keyword, which enabled us to create new internal variables for fields that were within the `groups` property. By using the `unwind` clause, we reduced the newly created variables into a list consisting of team-objects. Finally, we used the `CREATE` statement together with the `SET` statement to create “(team:Team)”-nodes containing information for each team.

In order to populate the database with nodes representing soccer matches and in-game events, we set the Tournament Schedule API and the Match Timeline API as parameters, and executed very similar procedures as the one explained above with the new parameters.

The final part of populating the database was to create relationships between the nodes. After all the nodes where created, we made sure that they had a unique identification and that they had an identifier that pointed to either their parent or child node. Team nodes contained the team’s name, abbreviation and an identification number. The Match nodes were given an identifier that consisted of the playing team’s abbreviations. For example, the match between Newcastle and Chelsea FC was identified with “NEW-CHE”, where the team listed first was also the home team. Listing 4.6 and Listing 4.7 shows how the Cypher statements connected teams to matches and matches to events.

```
1  MATCH (t:Team), (s:SportEvent) WHERE t.name = s.homeTeam
2  CREATE (t)-[played:PLAYED]->(s)
```

Listing 4.6: Cypher statement for connecting home teams with matches

```
1 MATCH (se:SportEvent),(ge:GameEvent) WHERE se.sportEventId
2  = ge.sportEventId CREATE (ge)-[part_of:PART_OF]->(se)
```

Listing 4.7: Cypher statement for connecting a match with its corresponding events

4.3.1 Neo4j Driver

There are many ways to interact with a Neo4j database and many different drivers to choose from. For this research, we chose Neo4j's official driver, as this was the one recommended when working with Python as a programming language, according to the community on Neo4j's own Slack workspace. The driver is built on the "Bolt-protocol", which is a binary protocol used for communication between client applications and database servers [34]. The driver provided us with a connection setup, which we needed to use when connecting to the database. Additionally, the driver gave us access to functions that we used to read and write to the database.

4.3.2 Neo4j Configuration

The graph database solution was created by using version 3.5.3 of Neo4j, together with version 3.5.0.2 of the APOC plugin. Not all versions of Neo4j and APOC are compatible with each other, so it is important to be sure that the correct versions are being used. For visualization and administration of the graph database, we used version 1.1.13 of Neo4j's desktop application.

4.4 MySQL Relational Database

To better evaluate our graph database results, we created a relational MySQL database for comparison, and populated with the same data from the same Sportradar APIs.

4.4.1 Design

The MySQL database was designed similarly to the Neo4j database. The schema consisted of three tables shown in figure 4.3. The "Team" table contained a row for each team that played in Premier League 18/19. The "SportEvent" table contained a row for all soccer matches that had been played during the season. The "GameEvent" table contained a row for each event that took place in a match.

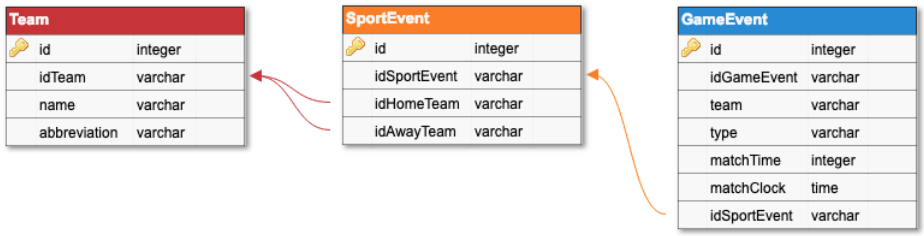


Figure 4.3: Relational database design

To populate the different tables we wrote scripts in Python. They imported data from the APIs, retrieved relevant information and applied string operations to clean the data. Lastly, the scripts wrote the data into the correct tables. In order to write data to the database, we created an SQL statement similar to the Cypher statement from Listing 4.5. Populating the Team table in MySQL was, however, a more complex process. Instead of writing to the database directly from the Tournament Info API, we had to store all data temporarily. This was done in our Python scripts. To import the teams we defined the function `getTeamInformation(jsonObject)` seen in Listing 4.8. Receiving the results from the Tournament Info API (Listing 4.2) as input, the function temporarily stored each team's details in different lists.

```
tempTeamId = []
tempTeamName = []
tempTeamAbbreviation = []
def getTeamInformation(jsonObject):
  groups = jsonObject["groups"]
  for group in groups:
      teams = (group["teams"])
      for team in teams:
          tempTeam.append(team["id"])
          tempTeamName.append(team["name"])
          tempTeamAbbreviation.append(team["abbreviation"])
```

Listing 4.8: Python function that temporary stores team attributes

Upon completion of `getTeamInformation(jsonObject)`, we were able to populate the Team table using the function `updateTeamTable(db)` shown in Listing 4.9. It iteratively wrote the contents of each temporary attribute list to the table. The variable `sqlString`, was the actual SQL statement that was processed by the database.

```
def populateTeamTable(db):
  cursor = db.cursor()
  for x in range(0, len(teamId)):
      idTeam = tempTeamId[x]
      name = tempTeamName[x]
      abbreviation = tempTeamAbbreviation[x]
      sqlString = "INSERT INTO Team VALUES
      (" + "'" + str(idTeam) + "'" + ", " + '"' +
      str(name) + '"' + ", " + '"' +
      str(abbreviation) + '"' + ")"
      cursor.execute(sqlString)
  print("Team table updated")
```

Listing 4.9: Python function that writes each team with attributes to database

This procedure was repeated in a similar way for writing soccer matches and in-game events to the database. The table population is indicated by the yellow box named "Relational Database Population Script" in Figure 4.1.

4.4.2 MySQL Server

We used MySQL version 8.0.15 for the database. The database was hosted on localhost. Having the database hosted locally made it simple to handle, and we were not dependent on third-party vendors, which gave us complete control over the database.

4.4.3 MySQL Workbench

When creating the database, we used Oracle's MySQL Workbench version 8.0.15. MySQL Workbench provided us with a graphical user interface for our relational database. This was a useful tool for testing and debugging the database. Also, MySQL Workbench was used to define the schema for the relational database.

4.5 Data Mapper Application

A mapper is a layer that moves or separates data between an object and a database [18]. In this case, we needed an application that could calculate the score and number of events occurring in each match, based on data returned from querying the databases. We wrote our mapping application in Python. The application consisted of two parts; the first part separately performed the mapping for databases and the second part aggregated the mapping results. This part is illustrated in Figure 4.1 as the yellow box with rounded edges.

4.5.1 Neo4j Data Mapper

To get the game events for a given soccer match (SportEvent), we used each match's own unique match identification "matchId". Each event (GameEvent) that took place in a soccer match was a single node. All GameEvents were connected to a SportEvent with the relation [PART_OF]. With this structure, we used the "matchId" for the match we wanted, and got the corresponding node which represented that match. Furthermore, we followed the [PART_OF] relation and retrieved all events that took place in that given match. Listing 4.10 shows what the query looked like.

```
1 MATCH (ge:GameEvent)-[PART_OF]->(se:SportEvent)
2 WHERE se.sportEventId = "matchId"
3 RETURN ge.team, ge.type, ge.matchTime, ge.matchClock,
4        ge.gameEventId
```

Listing 4.10: Cypher query that returns relevant information for a given matchId

Different teams played each soccer match, and the node that represented a soccer match (SportEvent) held the name of both the home and the visiting team. The query in Listing 4.11 was used to retrieve the name of the teams that played each other for a given "matchId".

```
1 MATCH (se:SportEvent) WHERE se.sportEventId = "matchId"
2 RETURN se.homeTeam, se.awayTeam, se.sportEventId"
```

Listing 4.11: Cypher query that returns name for home and away team for a given matchId

4.5.2 MySQL Data Mapper

The MySQL data mapper functioned similarly as the Neo4j data mapper. They both queried their respective databases to retrieve the same information. Naturally, the query language was different. For the MySQL mapper, all soccer matches stored in the "SportEvent"-table were identified with the same "matchId" as in the graph database. Events that occurred in soccer matches were stored in the table called "GameEvent". Each record in the "GameEvent"-table used "matchId" as foreign key, and pointed to the "SportEvent"-table, which held all the soccer matches. This way we could query the "GameEvent"-table for a given "matchId" and return the properties we wanted for an in-game event. Listing 4.12 shows the query we used for this operation.

```
1 SELECT team, type, matchTime, matchClock
2 FROM GameEvent
3 WHERE idSportEvent = "matchId"
```

Listing 4.12: SQL query that returns relevant information for a given matchId

The query in Listing 4.13 served the same purpose as the query in Listing 4.11, retrieving the names of the competing teams. However, this operation was performed in two rounds. First retrieving the name of the home team, then the name of the visiting team.

```
1 SELECT name
2 FROM Team INNER JOIN SportEvent
3 ON Team.idTeam = SportEvent.idHomeTeam
4 WHERE SportEvent.idSportEvent = "matchId"
```

Listing 4.13: SQL query used to retrieve name of home team

4.5.3 Data Aggregation

The second part of the data mapping phase was the actual aggregation of the data that was returned after querying both databases. A Python script also handled this part. For each match, the script iterated through all the belonging game events, and kept track of them. While keeping track of the score during the game, the script counted all game events that occurred. This way, the script could keep track of how many game events that occurred while the score was in favor of the home team, the visiting team or if the score was tied. In addition to counting events, the script also kept track of time. With all this information, we could easily find out how many events such as goals scored, free kicks, offsides or shots on target a team produced based on the current score. This created a result that could be used to analyze trends in soccer matches based on how a team's performance. This script did not access the databases directly, so it had no influence on their performances. It was used to aggregate their results, and was used in all three test cases, "Single Match", "Team Season" and "Complete Season". The output with results in seconds for each case are shown in respectively Figure 4.4, Figure 4.4b and Figure 4.4c.

```
Cardiff City - Wolverhampton Wanderers
Total eventes in match: 155
Final score: 2 - 1
Time spent losing match: 0
Time spent winning match: 13
Time during match where score is tie: 77
Events while losing: 0
Events while winning: 126
Events while tie: 29
Team was never loosing the game
During this game the home team created: 9.69 events per minute while winning the game
During this game the home team created: 0.38 events per minute while the score was tied
############################################################
Runtime for Neo4j graph database: 0.10975408554077148
```

(a) Results of data aggregation for a single match (Cardiff City - Wolverhampton Wanderers)

```
Total scored goals : 46
Total goals let in : 10
Total time losing in mintutes: 28
Total time winning in mintutes: 857
Total time where score is tied: 555
Total events while losing: 39
Total events while winning: 1091
Total events while score is tie: 759
During this season the home team created: 1.39 events per minute while loosing the game
During this season the home team created: 1.27 events per minute while winning the game
During this season the home team created: 1.37 events per minute while the score was tied
Runtime for MySQL databse: 0.4917018413543701
```

(b) Results of data aggregation for all of Liverpool's home matches

```
Total scored goals : 511
Total goals let in : 397
Total time losing in mintutes: 6926
Total time winning in mintutes: 8970
Total time where score is tied: 13354
Total events while losing: 10063
Total events while winning: 12666
Total events while score is tie: 17889
During this season the home team created: 1.45 events per minute while loosing the game
During this season the home team created: 1.41 events per minute while winning the game
During this season the home team created: 1.34 events per minute while the score was tied
Runtime for MySQL databse: 10.6839280128479
```

(c) Results of data aggregation of all home matches played so far at the time in the Premier League season 18/19

Figure 4.4: Output from executing each of the test cases

4.6 Hardware

All development and test case execution were conducted on a single computer, a MacBook Pro Early 2013, running macOS Mojave Version 10.14.4 with these components:

- Processor: 2.6 Ghz Intel Core i5 (2 cores)
- Memory: 8 GB 1600 MHz DDR3
- Storage: Apple SSD 256 GB
- Graphics: Intel HD Graphics 4000 1536 MB

Chapter 5

Results & Discussion

Our research project consisted of three different test cases. The test cases were each performed on a graph database and a relational database. This chapter will first present the results of our research. It will then analyze and discuss them in light of previous work and our own expectations.

5.1 Expectations

Based on the project description from Sportradar, we had high expectations for Neo4j. In addition, most of the related work we studied indicated that Neo4j would outperform MySQL for most of our test cases. The index-free adjacency property was also a factor that contributed to raising the expectations of Neo4j. We therefore assumed that our graph database would tackle the three test cases without any problems. Based on the long lifetime of MySQL and its widespread use, we assumed that MySQL also would perform well all over.

5.2 Results

We produced the results in this project by measuring the time it took to complete each of the three test cases for each of the two databases. To ensure accurate and unbiased timing results, the test cases were executed one at a time on the same computer, described in Section 4.6, with only the most minimal services running. The database servers were also both hosted locally so that there would not be bias from network irregularities.

The processing time was different for every individual execution. Therefore all experiments were performed 25 times for each test case in order to give representative results, and

further reduce the possibilities that other run time factors could distort the overall trends.

5.2.1 Execution Time Neo4j

Table 5.1 shows all the results for the three test cases executed on the Neo4j graph database. From the table, we see that Neo4j performed quite stable for all 25 iterations for all the cases, except for the very first iteration.

No. of Iteration	Single Match	Team Season	Complete Season
1	0,5711	1,2080	15,6887
2	0,1633	0,4387	6,0042
3	0,1339	0,5542	6,1819
4	0,1365	0,4257	5,8944
5	0,1318	0,4396	6,4219
6	0,1146	0,4179	6,6423
7	0,1254	0,4422	5,6963
8	0,1632	0,3821	5,4230
9	0,1410	0,3395	5,3633
10	0,1134	0,2941	5,2624
11	0,1030	0,3111	5,2404
12	0,0945	0,3285	5,3711
13	0,1103	0,3162	5,3995
14	0,1103	0,3381	5,5641
15	0,0950	0,3846	6,4124
16	0,0641	0,2869	4,4618
17	0,1028	0,3040	5,2319
18	0,0960	0,3398	5,1829
19	0,1129	0,2998	5,2770
20	0,1063	0,3946	5,2770
21	0,1107	0,3459	5,5037
22	0,1094	0,2911	5,0510
23	0,0840	0,2940	4,5883
24	0,0843	0,3323	4,5249
25	0,1198	0,2912	4,4731

Table 5.1: Execution times for Neo4j database in seconds

In Table 5.2 we have collected the most interesting findings from Table 5.1. We see that maximum values are all from the same first outlier row in Table 5.1. The minimum values in Table 5.2 does not correspond to any specific row on Table 5.1. The average processing time for each query is also presented in Table 5.2, as well as the median average processing time.

	Single Match	Team Season	Complete Season
Maximum	0,5711	1,2080	15,6887
Minimum	0,0641	0,2869	4,4618
Average	0,1319	0,3920	5,8455
Median	0,1107	0,3395	5,3711

Table 5.2: Neo4j test case results in seconds

5.2.2 Execution Time MySQL

Table 5.2 contains the results of the experiments done with the relational database. In this table, we see that MySQL also performs very stable, and that there are no big spikes in any of the test cases results.

No. of Iteration	Single Match	Team Season	Complete Season
1	0,0775	0,5514	11,1797
2	0,0345	0,5455	11,8369
3	0,0349	0,5823	12,0251
4	0,0346	0,5457	11,9445
5	0,0366	0,5455	11,5366
6	0,0360	0,5407	11,0441
7	0,0378	0,5355	11,5504
8	0,0342	0,5516	11,9572
9	0,0349	0,5447	12,1375
10	0,0381	0,5742	11,7290
11	0,0382	0,5533	11,1312
12	0,0374	0,6088	11,9183
13	0,0365	0,5601	11,8979
14	0,0342	0,5524	10,9915
15	0,0340	0,5485	11,1725
16	0,0334	0,5463	11,8509
17	0,0365	0,5378	11,7444
18	0,0343	0,5352	11,8615
19	0,0342	0,5509	11,1268
20	0,0343	0,5301	12,1206
21	0,0347	0,5404	11,8579
22	0,0357	0,5382	11,5187
23	0,0374	0,5467	11,8180
24	0,0349	0,5285	11,7048
25	0,0331	0,6135	11,2135

Table 5.3: Execution times for MySQL database in seconds

Table 5.4 sums up the most interesting findings from Table 5.3, presenting the fastest and slowest processing time for each test case. In addition, the table presents the regular average and median average for processing time.

	Single Match	Team Season	Complete Season
Maximum	0,0775	0,6135	12,1375
Minimum	0,0331	0,5285	10,9915
Average	0,0371	0,5523	11,6348
Median	0,0349	0,5463	11,7444

Table 5.4: MySQL test case results in seconds

5.3 Analysis

With the results presented in the previous section we have created three graphs, one for each test case. The graphs consist of two plots showing how the two databases compared with respect to each other. In this section, we will use the plots to analyze these results.

5.3.1 Single Match

The "Single Match" test case computed the number of events produced by the home team per minute based on the score of a single soccer match.

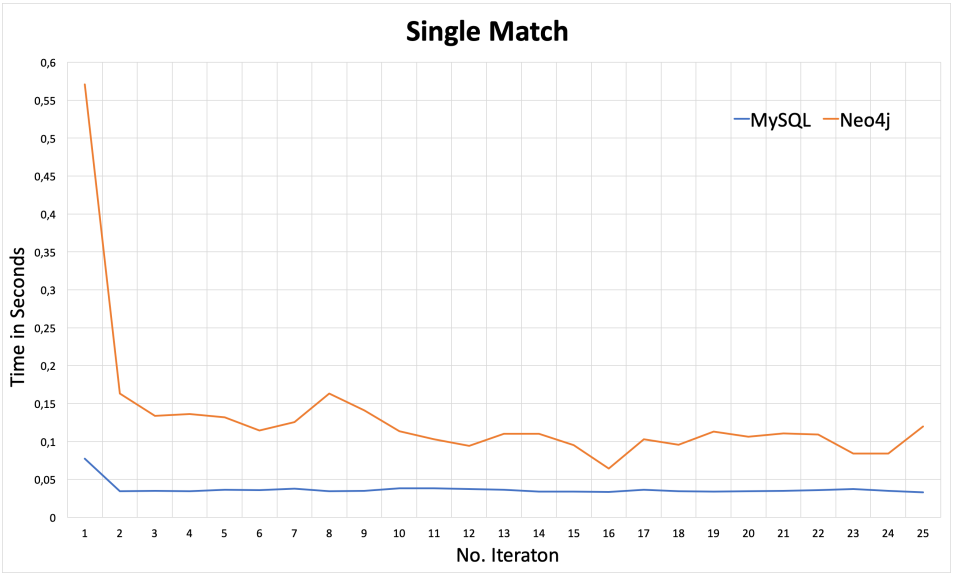


Figure 5.1: Graphed results of the first test case

Figure 5.1 is a performance graph of all 25 iterations for the “Single Match” test case, and shows how Neo4j and MySQL performed with respect to each other. From the graph, we see the same as Table 5.1 shows that the first iteration for Neo4j was much slower than the remaining 24 iterations. The Figure also shows that there was almost a 0.1 second time difference on average between querying the Neo4j database and the MySQL database, making MySQL perform more than 250% faster than Neo4j. Furthermore, we see a big difference in stability between the two databases. The blue line is much flatter than the orange, indicating that MySQL has a more predictable run time than Neo4j.

5.3.2 Team Season

The “Team Season” test case computed the total number of events per minute for a given single team playing on its home ground for a single season. Meaning we analyzed 19 soccer matches.

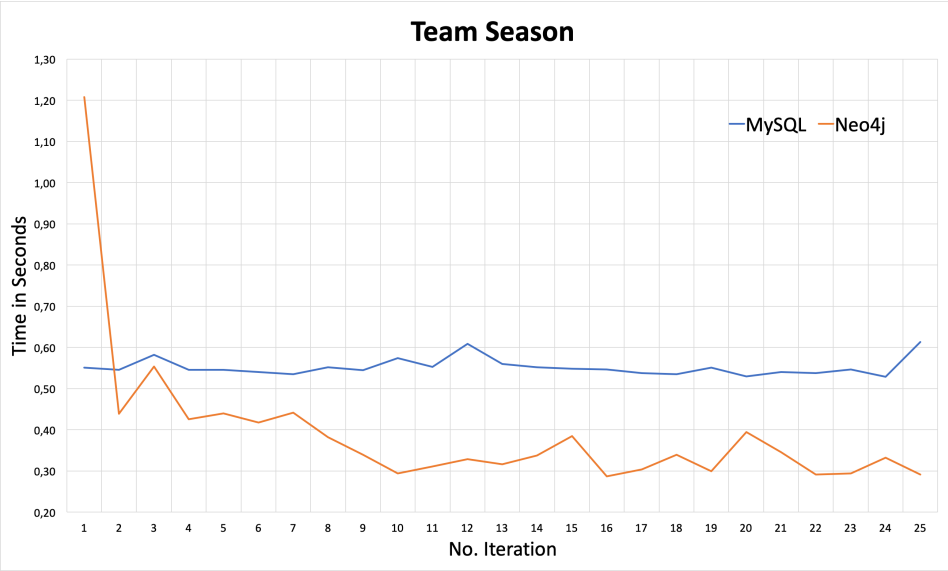


Figure 5.2: Graphed results of the second test case

Here we see that Neo4j performed better than MySQL for all iterations except the first which we noted as an outlier earlier. Neo4j performed, on average, 0,16 seconds faster than MySQL, but it is noteworthy that MySQL performance was more stable. As we can see, the blue line is much flatter than the orange line in Figure 5.2.

5.3.3 Complete Season

For the last and two experiments, we examined the performance based on the number of events per minute, for the home team of all matches that took place that season. That means our test case consisted of examining 387 soccer matches.

The "Complete Season" test case computed the number of events per minute, for the home team for all matches that took place in the season. In total, that was 387 soccer matches.

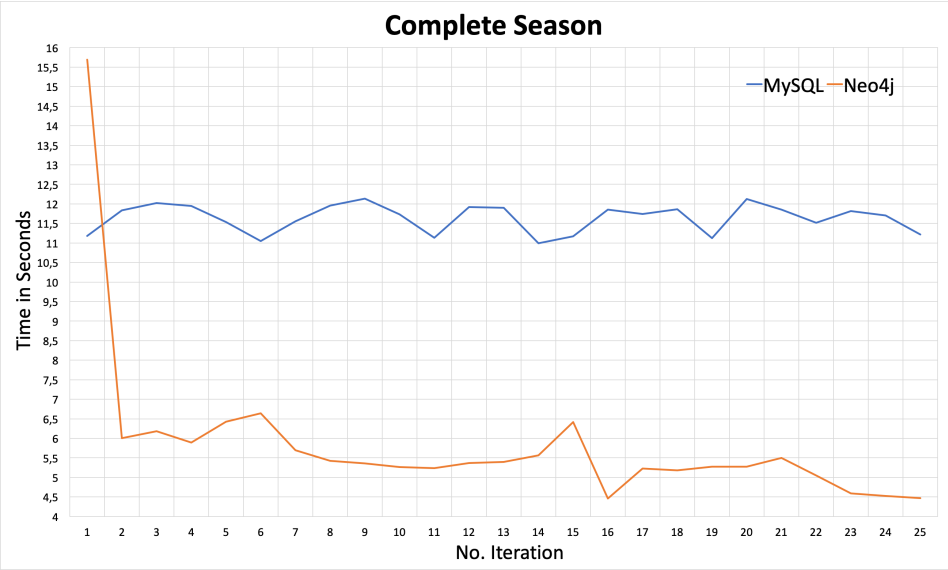


Figure 5.3: Graphed results of the third test case

Here again, in Figure 5.3 we see that Neo4j performed better than MySQL for all iterations except the first. Neo4j performed, on average, 10 seconds faster than MySQL. In this case, however, ignoring the first iteration, Neo4j was not less stable than MySQL.

5.4 Discussion

From the experiments we conducted, we discovered a few trends. The first trend we discovered was the fact that Neo4j performed very poorly on the first iteration for all three test cases. The processing time for the first iteration was, on average, 300% longer than the remaining 24 iterations. This was not very unexpected, because Neo4j is known to be affected by a cold start. Cold start is a reference from the automotive world. It refers to the challenges when starting the engine of a car that has not been driven for a very long time. This analogy is applied to databases that perform slowly when being accessed for the first time after being idle for a longer period.

An article written by the developers of Neo4j [35] revealed that cold start is a known challenge when utilizing graph databases in Neo4j. Cold start occurs when the database has just recently been booted up, and indexes have not yet been cached. When this is the case, the database needs to look up all records directly on the disk which is a costly operation. However, after the first disk lookup, all indices are cached, which makes upcoming queries much faster. Because cold start has become a common phenomenon, there now exists workarounds and patches that keep the database warm, reducing the impact of cold start.

Another interesting finding was the fact that MySQL performed better than Neo4j for the first test case, but not in the two other. By looking at this in the light of the study by Medhi presented in Chapter 2 this result was on one side unexpected. Medhi's study concluded that Neo4j perform better when querying densely connected sports related data. However, the difference in performance between the two databases increases as the dataset grows. The same trend we can see in our results, but the significant difference is the fact that MySQL performed best for the most uncomplicated query.

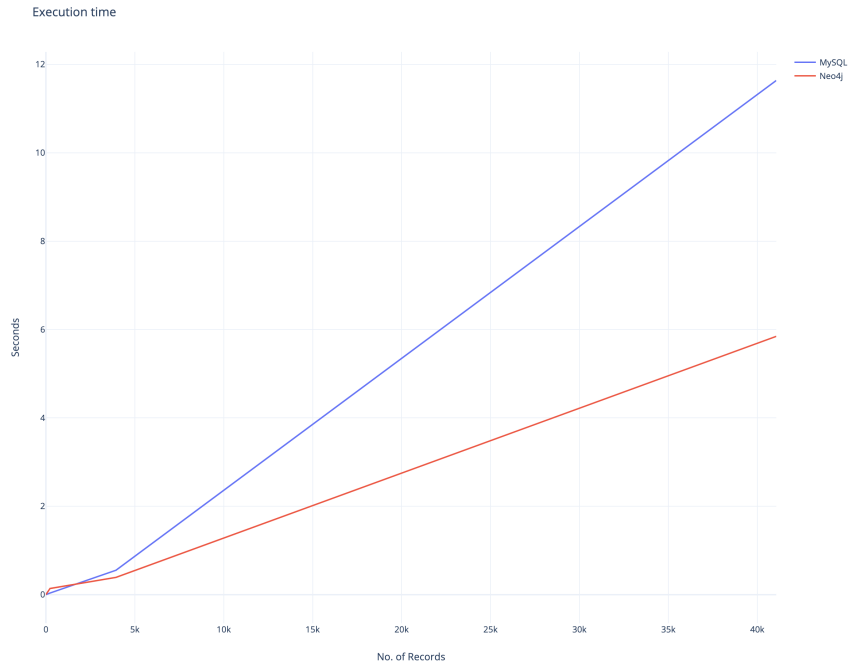
On the other side, it was not unexpected that MySQL performed better than Neo4j for the "Single Match" test case. MySQL utilizes B^+-trees in order to index its data. B^+-tree indexation facilitates for very fast read operations. For queries on small tables or queries that require most of the rows in a larger table, it is often faster to read sequentially through the table instead of working through an index. This can explain why MySQL performs better than Neo4j for the test case that required the lookup of the smallest amount of data. Neo4j utilizes index-free adjacency, which provides lightning-fast lookups. This means that only the index for the starting node of the query needs to be looked up. From there on, each node has a pointer pointing to its neighboring node, supporting a time complexity of O(n), where "n" equals the number of nodes in the graph. This lets Neo4j perform better for the last two test cases, which required the lookup of larger amounts of data.

5.4.1 Response time

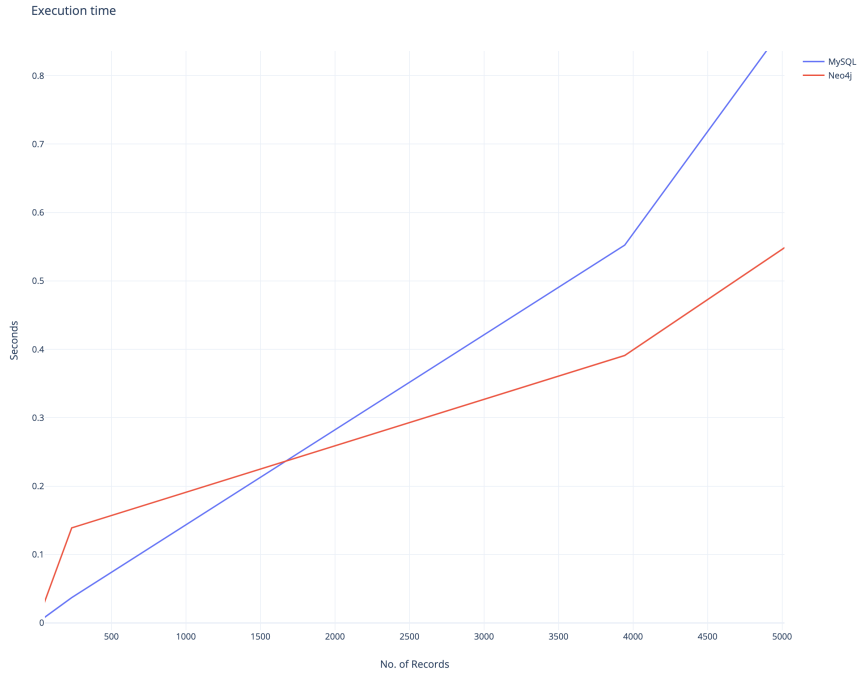
A trend that was harder to account for was the fact that MySQL's response time seemed to be much more stable than Neo4j's. Especially in Figure 5.1 and Figure 5.2, the blue lines are smoother than the orange ones. This could be explained by the fact that MySQL is more memory efficient than Neo4j because MySQL does not cache indices in the same way as Neo4j. Keeping all pointers in memory as Neo4j does, requires a lot of memory. A lack of memory will affect Neo4j's performance. On the other hand we noticed that MySQL performed very stable for the first test case, but as the the test cases became more challenging, the blue line became more and more rocky. For the "Complete Season" it is hard to tell which database performed the most stable by looking at the plots in Figure 5.3.

Because of the way we chose to model our databases, using three different tables for the relational database and using three different types of nodes. The number of records in the relational database equaled the number of nodes in the graph database. With this in mind, we discovered some interesting findings regarding the overall response time. We used the average processing time and the number of records accessed for each of the three test cases

to estimate the difference in performance between the two databases. Table 5.4a shows the estimation of how Neo4j and MySQL compare to each other with regard to execution time. We see that it corresponds with Table 5.2 and Table 5.4. Although the graphs only consisted of three points each, we can still see a clear difference in performance. From Table 5.4b, which is an enlarged selected area from Table 5.4a, we see that the blue and orange lines intersect after 0.236 seconds when the amount of records is about 1670. This means that Neo4j and MySQL performed equally well when the number of records that had to be processed approached 1670.



(a) Execution time



(b) Selected section of execution time

Figure 5.4: Complete overview of execution times

5.5 Database Querying

As expected, our results show that it took a longer time for both databases to process the "Complete Season" test case, than it took to process the "Single Match" test case. The execution of "Complete Season" requires much more data retrieval than "Single Match".

Another relevant observation concerns the difference in how the queries are expressed. As mentioned in Chapter 3, Neo4j and MySQL use two different query languages which have their own linguistic differences. In Chapter 4 there are many examples of Neo4j-specific queries and MySQL-specific queries that retrieve the same kind of data, but as we see, they are expressed quite differently.

Using the SQL language, it is easy to query a relational database, and it is excellent when used together with a database management tool such as MySQL Workbench. However, SQL struggles with performance when the data becomes too connected. That is the case in the Extended Friends Experiment from Section 1.3.1. Querying densely connected data using SQL requires the use of many JOIN operations, which are costly with regard to time and computational power. Also, the queries quickly become quite long, which increases the probability of human error. Listing 5.1 shows an SQL query that returns all offsides that Chelsea FC has created when playing on their home ground for the season. Although this kind of data is not very advanced, we still see that the query quickly becomes long and it contains many JOIN statements. Listing 5.2 is a graph query written in Cypher, which returns the same data as the query in Listing 5.1.

```
1  SELECT HomeTeam.name AS HomeTeam, AwayTeam.name AS
2  AwayTeam, SportEvent.idSportEvent, GameEvent.team,
3  GameEvent.type
4  FROM soccerDB.SportEvent  AS SportEvent
5  INNER JOIN soccerDB.Team AS HomeTeam ON
6  SportEvent.idHomeTeam = HomeTeam.idTeam
7  INNER JOIN soccerDB.Team AS AwayTeam ON
8  SportEvent.idAwayTeam = AwayTeam.idTeam
9  INNER JOIN soccerDB.GameEvent AS GameEvent ON
10 SportEvent.idSportEvent = GameEvent.idSportEvent
11 WHERE HomeTeam.name = "Chelsea FC" AND
12 GameEvent.team = "home" AND GameEvent.type = "offside"
```

Listing 5.1: SQL query that returns all offsides that Chelsea have produced on home ground

```
1 MATCH result = (t:Team)-[:PLAYED]->(se:SportEvent)
2 <-[:PART_OF]-(ge:GameEvent)
3 WHERE t.name = "Chelsea FC" <> ge.type = "offside" <>
4 se.homeTeam = t.name <> ge.team = "home"
5 RETURN result
```

Listing 5.2: Cypher query that returns all offsides that Chelsea have produced on home ground

From the listings above, it is quite clear that the Cypher query is simpler to read and write. The utilization of relationships inside the query makes it much easier to follow and understand precisely what the query does. This also reflects the fact that when the developers created Neo4j and Cypher, they focused on making it as understandable as possible, for both technical and non-technical users.

As the developers behind the "World Cup As a Graph" project from Section 2.1 suggest, Neo4j is very useful when being used to analyze and explore sports data that is already modeled as a graph. The APOC library contains many well-documented graph procedures that can easily be utilized in order to examine a graph. Our query comparison of using Cypher and SQL to find offside events created by the home team for a gives soccer match (Listing 5.1 and Listing 5.2), shows how Neo4j has advantages when it comes to writing and processing certain kinds of specific data lookups.

Another difference between the two query language is how the return statements are expressed. A SQL query always begins with stating which fields or columns it is going to return, and does not end with a return statement. Cypher is the opposite. Cypher first declares which nodes and relationships it is going to use, then ends with specifying which fields or labels it will return. In other words, Cypher lets the user design custom and patterns and returns all nodes that match the specified pattern.

5.5.1 Query Performance

When we had almost finished with the development and were examining the first results, we saw that the graph database performed much worse than the relational database. This was unexpected so we decided to review how our queries were written. That is when we realized that our Cypher query was not utilizing the benefits of relations in a graph database. Listing 5.3 shows how the original query for returning all events that took place in a match looked like.

```
1 MATCH (ge:GameEvent) WHERE ge.sportEventId = "matchId"
2 RETURN ge.team, ge.type, ge.matchTime, ge.matchClock,
3 ge.gameEventId
```

Listing 5.3: Un-optimized cypher query not utilizing relationships

The query produced the results shown in Table 5.5. After updating to our final query (Listing 4.10), we achieved the much better results displayed earlier in Table 5.2.

	Single Match	Team Season	Complete Season
Maximum	0,1842	1,9833	38,7823
Minimum	0,0973	0,7915	15,1158
Average	0,1349	1,0626	21,0334
Median	0,1302	0,9065	16,8275

Table 5.5: Results for Neo4j un-optimized Neo4j queries in seconds

Table 5.5 shows the result of writing Cyber queries with an SQL mindset. The un-optimized query had to iterate through all the GameEvent-nodes in order to join them with a matchId. When the graph database consisted of 40.0000 GameEvent-nodes, the query was destined to take a long time with almost 400 soccer matches. However, our final query took advantage of the [PART_OF] relation between SportEvents and GameEvents. By that, it was utilizing the properties of index-free adjacency. This meant that when requesting the same data, the only thing that needed to be looked up was the SportEvent-node which contained the corresponding matchId. This was because all the GameEvents were connected to that SportEvent-node through the [PART_OF] relation. By making this change in the query, we were able to reduce the average execution time by 360%. Results for all 25 iterations of the three test-cases with the un-optimized query can be found in a table located in the appendix.

5.6 Visualization

When working with queries and databases, it is beneficial to see the data that one is working with. Also other people involved in the project, such as stakeholders, business owners and analysts, can benefit greatly from good data visualization. Then they can use the visualization to determine areas of interest or assess easily the current state and organization of the data [32]. Neo4j provides with its desktop application a browser that is excellent for data visualization along with query creation. MySQL Workbench provides many of the query creation tools, but the data visualization is limited to table format. Figure 5.5 illustrates how MySQL Workbench returns the Listing 5.1 query. Figure 5.6 shows the Neo4j browser results for the same query.

The graph visualization is simple and makes it intuitive for most people to understand what data is returned and how it is connected. The process of creating the graph, however, is very costly. Whenever the results are more than 100 nodes, for instance, our computer struggled to render the graph and it took a very long time. With more than 1000 nodes, there was no point of even trying to render the graph. That would not be a problem, however, with MySQL Workbench.

Note that Neo4j also provides the option to return data in table format as well as in XML or JSON.

HomeTeam	AwayTeam	team	type	matchTime
Chelsea FC	Arsenal FC	home	offside	8
Chelsea FC	Arsenal FC	home	offside	40
Chelsea FC	Arsenal FC	home	offside	63
Chelsea FC	AFC Bournemouth	home	offside	14
Chelsea FC	AFC Bournemouth	home	offside	75
Chelsea FC	Liverpool FC	home	offside	60
Chelsea FC	Liverpool FC	home	offside	90
Chelsea FC	Manchester United	home	offside	46
Chelsea FC	Manchester United	home	offside	50
Chelsea FC	Crystal Palace	home	offside	18
Chelsea FC	Crystal Palace	home	offside	28
Chelsea FC	Crystal Palace	home	offside	35
Chelsea FC	Crystal Palace	home	offside	45
Chelsea FC	Crystal Palace	home	offside	57
Chelsea FC	Crystal Palace	home	offside	84
Chelsea FC	Everton FC	home	offside	49
Chelsea FC	Everton FC	home	offside	72
Chelsea FC	Everton FC	home	offside	76
Chelsea FC	Everton FC	home	offside	90
Chelsea FC	Everton FC	home	offside	90
Chelsea FC	Manchester City	home	offside	49
Chelsea FC	Leicester City	home	offside	23
Chelsea FC	Leicester City	home	offside	28
Chelsea FC	Leicester City	home	offside	68
Chelsea FC	Southampton FC	home	offside	39
Chelsea FC	Southampton FC	home	offside	45
Chelsea FC	Southampton FC	home	offside	55
Chelsea FC	Southampton FC	home	offside	70
Chelsea FC	Southampton FC	home	offside	90
Chelsea FC	Newcastle United	home	offside	36
Chelsea FC	Newcastle United	home	offside	58
Chelsea FC	Newcastle United	home	offside	75
Chelsea FC	Newcastle United	home	offside	85
Chelsea FC	Newcastle United	home	offside	90
Chelsea FC	Huddersfield Town	home	offside	10
Chelsea FC	Huddersfield Town	home	offside	63
Chelsea FC	Tottenham Hotspur	home	offside	53
Chelsea FC	Wolverhampton W…	home	offside	31
Chelsea FC	West Ham United	home	offside	6
Chelsea FC	West Ham United	home	offside	62
Chelsea FC	West Ham United	home	offside	69

Figure 5.5: Returned results from SQL query

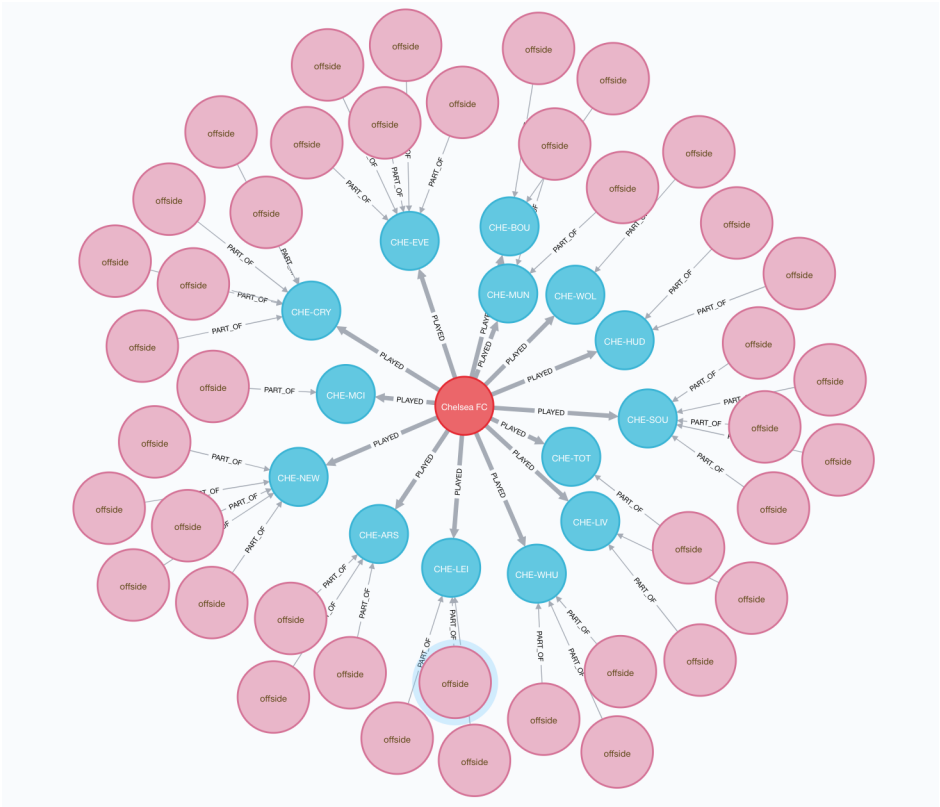


Figure 5.6: Returned results from Cypher query

5.7 Data Import

When evaluating different database technologies and database management systems, data import can be an important aspect. In the study by Pandey [45], presented in Chapter 2, we see that there are big differences in how MySQL and Neo4j perform with respect to data size and time. Neo4j clearly outperforms MySQL as the size of the dataset grows.

The time aspect of data import does not always have to play such an important role. It is very dependent on how the database is used and what it is being used for. If a company wanted to migrate their database from their existing solution to either MySQL or Neo4j, the time aspect of data import would probably not be a decisive factor. Because such a migration is usually a one-time thing and other factors would play a more important role. Nonetheless, if the database were to be used as explained in the World Cup Model from Chapter 2, import time can be an essential factor. With projects where the database is continuously being updated or expanded with new records, it is more important that the database can perform well while importing data. The same issue would be applicable

to our experiment as well, if we were to expand the scope of our project. It would be interesting to conduct the same experiments, as explained in Chapter 4, with significantly larger datasets. Then more would be required from the database technologies with regard to import time.

5.8 Data Model

With the property graph model that Neo4j provides, it is simple to alter the graph database's data model. Nodes, relationships and properties can continually be added without affecting the performance of the database. This makes Neo4j suitable for handling a database that may often change its data model. On the other hand, MySQL's data model is much stricter in order to guarantee ACID properties. This makes MySQL less flexible with regard to data model alterations.

For databases containing live updates, historical data and other sports related data, it may be hard to predict how the database should be modeled. The methods for generating such data are constantly changing, and the requirements from clients who are using the data are also changing. Thus it is hard to determine in advance how the data model should look like. This is an important aspect where Neo4j has a great advantage with its flexible model.

Chapter 6

Conclusion & Future Work

This chapter summarizes the thesis, and presents pros and cons with using Neo4j and MySQL for the application we developed. The goal of our research was to explore how graph databases can be used together with the Sportradar developer API, and to investigate potential advantages or disadvantages. In order to approach this problem we formulated the two following research questions:

- **RQ1:** Identify a use case which is representative for the data and applications of Sportradar.
- **RQ2:** How does the Neo4j graph database management system compare against Oracle's MySQL relational database management system, in regard to target the problem?

To answer RQ1, we created an application that calculated how the home team performed in a soccer match, from the English Premier League, based on the score. The application calculated performance based on how many events the home team produced. The following events were defined:

- corner kick
- free kick
- goal kick
- injury
- injury return
- offside
- penalty awarded
- penalty missed

- red card
- score change
- shot off target
- shot on target
- shot saved
- throw in
- yellow card
- yellow red card

For the application, we created two databases; a Neo4j graph database and a MySQL relational database. The databases varied in structure, but contained the exact same data. The application retrieved the event information from the databases. During runtime, the application kept track of occurred events based on score and time played. For each soccer match, the application returned the total number of events that the home team produced. In addition, the application calculated events produced per minute while the match was tied or if the home team was either winning or losing.

To address RQ2, we created three different test cases for our application, which we used to performance test our databases. First, we executed and timed each test case 25 times having the application connected to the graph database. Then we disconnected the graph database and connected the relational database, and executed all three test cases another 25 times. The test cases were defined as the following:

- **Single Match** - Select a random soccer match and calculate events produced per minute by the home team based on score.
- **Team Season** - Calculate events produced per minute based on the score for all soccer matches played on home ground during the season for a specific team.
- **Complete Season** - Calculate events produced per minute based on the score for the home team for all matches that have been played during the season.

6.1 Conclusion

We found that both Neo4j and MySQL were suitable for our application to measure soccer teams' performance with respect to match events. Both databases have their advantages and disadvantages, but for this project, none of them serious enough to play a major role. If the dataset was significantly larger, however, our research indicates that Neo4j would be a better choice of a database management system with regard to processing time.

Table 6.2 shows the average processing of out test cases, while Table 6.1 shows the median processing time. The median processing time is more interesting than the average processing time because it is not affected by cold start.

Test Case	Neo4j	MySQL
Single Match	0,1107	0,0349
Team Season	0,3395	0,5463
Complete Season	5,3711	11,7444

Table 6.1: The median processing time in seconds

Test Case	Neo4j	MySQL
Single Match	0,1319	0,0371
Team Season	0,3920	0,5523
Complete Season	5,8455	11,6348

Table 6.2: The average processing time in seconds

Our results indicate that MySQL performs better for queries that require the lookup of about 1670 or fewer records, in databases based on our design. When the amount of required records that need to be looked up exceeds 1670, Neo4j performs much better. This explains why MySQL performs better for the "Single Match" test case than Neo4j, but Neo4j outperforms MySQL for the other two test cases. Besides, previous work also suggests that the more connected the data is, the better a graph database performs compared to a relational database. This corresponds with our results indicating that the more advanced a query is, requiring the lookup of denser connected data, the better a graph database performs compared to a relational database.

When setting up and populating the databases with data from Sportradar's API, MySQL has a significant advantage because it is so widely used. MySQL is heavily documented and is a more stable database, whereas Neo4j has some issues with compatibility and integration with other frameworks and services.

Regarding query languages, both databases have strong and well-functioning query languages. SQL is a traditional, well-known land widely used language. Cypher is Neo4j specific and much less used, but is intuitive and easy to learn. Where SQL uses advanced JOIN statements, Cypher takes advantage of relationships instead, which are less complicated, easier to understand and require shorter queries, reducing the possibility of human error. It is important that Cypher statements are expressed in the correct way, in order to fully utilize the power of a graph database.

With regard to data administration and data visualization, both providers have powerful tools. The Neo4j Browser is an excellent tool for visualizing a graph database. However, it is highly demanding regarding hardware. MySQL Workbench is a useful tool when it comes to monitoring a database, and designing a data model. However, it does not visualize data as neat as the Neo4j Browser.

6.2 Future work

There are a lot of areas in this project that could benefit from further research. First of all, it would be interesting if more studies similar to this one were conducted to see if they identified the same or different trends than this project found. Using other studies as a form of verification, we could feel more confident about our results.

This project only compared performance between the two databases that we have created, based on data from Sportradar's API. The next step for Sportradar would be to conduct a similar study on Sportradar's internal data storage, where the API gets its data from. Our results give an indication of which prerequisites that are important in order for a database to function optimally. Such a study could also verify if our design and implementation are applicable to a real-world scenarios.

6.2.1 Hardware & Architecture

Since the design and experiments described Chapter 4 and Chapter 5 in this project, all have been completed on one single computer, it would be interesting to perform the same experiments on different hardware, both less and more powerful. This would generate results that are more representative.

A typical architecture for this kind application is the client-server architecture [58]. By hosting our database on one or more external servers instead of hosting it locally, we would achieve this architecture. The application and database would then run on different resources, which could impact the results of our experiments.

6.2.2 Memory Consumption

Graph databases are known to require a lot of memory to function optimally [27]. This research does not investigate how the use of memory affects the performance of Neo4j. Memory consumption is an essential factor when choosing database technology. Therefore, researching how the amount of available memory affects the performance of Neo4j and MySQL would be very helpful.

6.2.3 Import time

Limitations on how often we were allowed to call Sportradar's API per second, made it impossible for us to investigate how our two databases compared to each other regarding import time. Even though previous work indicates that there is a big difference between Neo4j and MySQL regarding import time [45], it would be useful to see if that applies to our databases as well when populated with sports data from Sportradar.

6.2.4 Different dataset

Another way to validate our results would be to perform similar experiments on a different, but similar dataset. For example, using data from the National Hockey League (NHL). The league is structured differently from the Premier League, consisting of a different match setup, more teams and more players. The difference between the sports is significant enough to create a completely different data model with regard to connections and relationships between the data. In addition, one could do even heavier performance testing by designing test cases that are more complex in terms of queries.

6.2.5 Mitigate Cold Start

Cold start is a well-known challenge with Neo4j, and there exist many ways to work around it. Modern implementations of Neo4j, depending on use, usually have implemented workarounds keeping the database warm. Implementing such a workaround could make the database perform different, thus affecting the results.

6.3 Threats to Validity & Limitations

Both databases have been modeled to the best of our abilities. We have followed the standards in the field of our research when modeling both the relational database and the graph database. As with most research, there exists a possibility for human error. There is always a chance that we have misinterpreted something when it comes to database design or query design, which may have affected our results.

Since we only conducted experiments on three different test cases. It was hard to determine exact for how many records the two databases performed equally well. Therefore, the number 1670, which we presented earlier, must be considered as an estimate for when Neo4j and MySQL perform evenly.

6.4 Contribution

This thesis has identified a relevant field of use for Sportradar's Developer API, and developed an application for analysis of soccer matches. The application alternated between using a graph database and relational database as a means of data source. The application was used to do a performance test and a comparison of the two databases. Three test cases were developed for the application in order to measure the databases' performance. Other aspects such as maintainability, compatibility and query language were also taken into consideration.

We have presented a solution to how the two databases can be structured and organized to serve the purpose of the application. In addition, we have identified which circumstances

the different databases require in order to perform best, based on theory, previous work and our own results with regard to the target problem.

Bibliography

[1] ArangoDB, Unknown. Arangosearch: Full-text search engine including similarity ranking capabilities. Accessed May 6, 2019.
URL https://www.arangodb.com/why-arangodb/full-text-search-engine-arangosearch/

[2] ArangoDB, Unknown. Sql / aql - comparison. Accessed May 6, 2019.
URL https://www.arangodb.com/why-arangodb/sql-aql-comparison/

[3] Babbie, R., 2012. The Practice of Social Research. Cengage Learning, pp. 414–416.
URL https://books.google.no/books?id=k-aza3qSULoC

[4] Babeni, S., 2019. https://ormuco.com/blog/most-popular-databases. Accessed May 31, 2019.
URL https://ormuco.com/blog/most-popular-databases

[5] Bazilchuk, N., 2005. Student programming project becomes multi-million dollar company. Accessed September 19, 2018.
URL https://www.ercim.eu/publication/Ercim_News/enw61/bazilchuk.html

[6] Berlind, D., 2015. Why did they put the web in web apis? Accessed April 19, 2019.
URL https://www.programmableweb.com/news/why-did-they-put-web-web-apis/analysis/2015/12/03

[7] Bettilyon, E., 2019. Breadth first search and depth first search. Accessed May 14, 2019.
URL https://medium.com/tebs-lab/breadth-first-search-and-depth-first-search-4310f3bf8416

[8] bitn!ne, 2016. History of databases and graph database. Accessed 8 May, 2019.
URL https://bitnine.net/blog-graph-database/history-of-databases-and-graph-database/

[9] Chao, J., 2018. Graph databases for beginners: Native vs. non-native graph technology. Accessed March 11, 2019.
URL https://neo4j.com/blog/native-vs-non-native-graph-technology/?ref=blog

[10] Chiou, L., 2019. Graph theory. Accessed May 14, 2019.
URL https://brilliant.org/wiki/graph-theory/

[11] Cole, J., 2014. B+tree index structures in innodb. Accessed June 1, 2019.
URL https://blog.jcole.us/2013/01/10/btree-index-structures-in-innodb/

[12] Community, S. O., 2018. Questions tagged [mysql]. Accessed November 7, 2018.
URL https://stackoverflow.com/questions/tagged/mysql

[13] Ebner, S., 2013. History and time are key to power of football, says premier league chief. Accessed March 27, 2019.
URL https://www.thetimes.co.uk/article/history-and-time-are-key-to-power-of-football-says-premier-league-chief-3d3zf5kb35m

[14] EQT, 2018. Sportradar. Accessed September 19, 2018.
URL http://www.eqtpartners.com/Investments/Current-Portfolio/Sportradar/

[15] Ernst & Young, A., 2017. Big Data: Beyond the buzzword. Ernst & Young Australia, p. 3.

[16] Foote, K. D., 2017. A brief history of database management. Accessed May 8, 2019.
URL https://www.dataversity.net/brief-history-database-management/#

[17] for Geeks, G., 2018. Bellman–ford algorithm — dp-23. Accessed May 14, 2019.
URL https://www.geeksforgeeks.org/bellman-ford-algorithm-dp-23/

[18] Fowler, M., Rice, D., 2003. Patterns of Enterprise Application Architecture. A Martin Fowler signature book. Addison-Wesley, pp. 165–167.
URL https://books.google.no/books?id=FyWZt5DdvFkC

[19] Garbade, D. M. J., 2018. Understanding k-means clustering in machine learning. Accessed May 14, 2019.
URL https://towardsdatascience.com/understanding-k-means-clustering-in-machine-learning-6a6e67336aa1

[20] Goodrich, M. T., Tamassia, R., Goldwasser, M. H., 2004. Data structures and algorithms in Java Fourth Edition. John Wiley & Sons, p. 793.

[21] GraphGrid, 2016. Native graph databases versus non-native graph databases. Accessed March 28, 2019.

URL https://www.graphgrid.com/native-graph-databases-versus-non-native-graph-databases/

[22] Hunger, M., 2016. Apoc: An introduction to user-defined procedures and apoc. Accessed October 7, 2018.
URL https://neo4j.com/blog/intro-user-defined-procedures-apoc/

[23] Jones, C., 2014. How to visualize your facebook friend network. Accessed May 6, 2019.
URL http://allthingsgraphed.com/2014/08/28/facebook-friends-network/

[24] Joshi, V., 2017. Finding the shortest path, with a little help from dijkstra. Accessed May 14, 2019.
URL https://medium.com/basecs/finding-the-shortest-path-with-a-little-help-from-dijkstra-613149fbdc8e

[25] Marr, B., 2018. How much data do we create every day? the mind-blowing stats everyone should read. Accessed September 20, 2018.
URL https://www.forbes.com/sites/bernardmarr/2018/05/21/how-much-data-do-we-create-every-day-the-mind-blowing-stats-everyone-should-read/#7bbb1ccd60ba

[26] Medhi, S., Baruah, H. K., 2017. Relational database and graph database: A comparative analysis. Journal of Process Management. New Technologies 5 (2), 1–9.

[27] Mendel-Gleason, G., 2018. Databases of the future: How changes in hardware are driving a revolution. Accessed May 28, 2019.
URL https://www.datachemist.com/blog/databases-of-the-future-how-changes-in-hardware-are-driving-a-revolution

[28] MySQL, 2018. Mysql technical support. Accessed November 6, 2018.
URL https://www.mysql.com/support/

[29] Neo4j-Team, 2014. 5 things you didn't know about the world cup. Accessed March 8, 2019.
URL http://worldcup.neo4j.org/5-things-you-didnt-know-about-the-world-cup/

[30] Neo4j-Team, 2014. The world cup graph domain model. Accessed March 9, 2019.
URL http://worldcup.neo4j.org/the-world-cup-graph-domain-model/

[31] Neo4j-Team, 2019. Cypher basics i. Accessed May 28, 2019.
URL https://neo4j.com/developer/cypher-query-language/

[32] Neo4j-Team, 2019. Graph visualization. Accessed April 28, 2019.
URL https://neo4j.com/developer/graph-visualization/

[33] Neo4j-Team, 2019. Neo4j customers. Accessed April 28, 2019.
URL https://neo4j.com/customers/

[34] Neo4j-Team, 2019. The neo4j drivers manual v1.7 for python. Accessed April 19, 2019.
URL https://neo4j.com/docs/pdf/neo4j-driver-manual-1.7-python.pdf

[35] Neo4j-Team, 2019. Warm the cache to improve performance from cold start. Accessed May 26, 2019.
URL https://neo4j.com/developer/kb/warm-the-cache-to-improve-performance-from-cold-start/

[36] Neo4j-Team, 2019. What is a graph database? Accessed May 6, 2019.
URL https://neo4j.com/developer/graph-database/

[37] Neo4j-Team, Unknown. Neo4j apoc library. Accessed October 7, 2018.
URL https://neo4j.com/developer/apoc/

[38] {ntc}, 2019. Sql (structured query language). Accessed May 9, 2019.
URL https://www.ntchosting.com/encyclopedia/databases/structured-query-language/

[39] Oates, B. J., 2005. Researching information systems and computing. Sage, pp. 32–33.
URL https://books.google.no/books?id=ztrj8aph-4sC

[40] Oracle, 2018. Create tomorrow, today. Accessed November 5, 2018.
URL http://www.oracle.com/us/corporate/oracle-fact-sheet-079219.pdf

[41] Oracle, 2019. Introduction to innodb. Accessed April 26, 2019.
URL https://dev.mysql.com/doc/refman/8.0/en/innodb-introduction.html

[42] Oracle, 2019. Mysql workbench. Accessed March 28, 2019.
URL https://www.mysql.com/products/workbench/

[43] Oralce, 2019. Top 10 reasons to choose mysql for next generation web applications. Accessed May 7, 2019.
URL https://www.mysql.com/why-mysql/white-papers/top-10-reasons-to-choose-mysql-for-next-generation-web-applications/

[44] Orientechnologies, 2016. Orientdb. Accessed November 13, 2018.
URL https://github.com/orientechnologies/orientdb

[45] Pandey, S., Joshi, E., Maharjan, M., Karki, N., 08 2018. A research on architectural and performance comparison of relational database, nosql and graph database (neo4j).

[46] Pollari-Malmi, K., 2010. B^+-trees. Accessed June 1, 2019.
URL https://www.cs.helsinki.fi/u/mluukkai/tirak2010/B-tree.pdf

[47] Pwc, 2014. Global 100 software leaders by revenue. Accessed May 31, 2019.
URL https://www.pwc.com/gx/en/industries/technology/publications/global-100-software-leaders/explore-the-data.html

[48] Python-Software-Foundation, 2019. What is python? executive summary. Accessed March 28, 2019.
URL https://www.python.org/doc/essays/blurb/

[49] Rathle, G. S. . P., 2017. Fraud detection: Discovering connections with graph databases. Accessed May 6, 2019.

[50] Robinson, I., Webber, J., Eifrem, E., 2015. Graph databases: new opportunities for connected data. " O'Reilly Media, Inc.", pp. 105–109.
URL https://books.google.no/books?id=RTvcCQAAQBAJ&printsec=frontcover&redir_esc=y#v=onepage&q&f=false

[51] Rouse, M., 2081. Mysql. Accessed November 5, 2018.
URL https://searchoracle.techtarget.com/definition/MySQL

[52] Sellæg, A., 2011. Perleporten åpen for petter smart. Accessed September 19, 2018.
URL https://www.ntnu.no/documents/304978/0/IG+i+Ukeadressa+08+10+11+(3).pdf/b7900abd-c0d5-4e62-bfee-e17b32b1c6e7

[53] Services, A. W., 2018. Amazon neptune. Accessed November 12, 2018.
URL https://aws.amazon.com/neptune/

[54] Soft, M., 2019. What is an api? (application programming interface). Accessed April 19, 2019.
URL https://www.mulesoft.com/resources/api/what-is-an-api

[55] Soshnick, S., 2015. Jordan, cuban, leonsis put millions on sports betting's future. Accessed September 19, 2018.
URL https://www.bloomberg.com/news/articles/2015-10-27/jordan-cuban-leonsis-put-millions-on-sports-betting-s-future

[56] Sportradar, 2019. Soccer extended v3. Accessed May 15, 2019.
URL https://developer.sportradar.com/docs/read/football_soccer/Soccer_Extended_v3#soccer-extended-v3-api-map

[57] Sports, B., 2018. Premier league tv rights: Five of seven live packages sold for £4.464bn. Accessed March 27, 2019.
URL https://www.bbc.com/sport/football/43002985

[58] Techopedia, 2019. Client/server architecture. Accessed May 12, 2019.
URL https://www.techopedia.com/definition/438/clientserver-architecture

[59] Trondheimsregionen, N., 2017. Sportradar ble Årets bedrift! Accessed September 19, 2018.
URL https://www.nitr.no/no/aktuelt/sportradar+ble+arets+bedrift+2017.html

[60] Unknon, 2017. Oracle corporation. Accessed November 5, 2018.
URL http://www.orafaq.com/wiki/Oracle_Corporation#WHO

[61] Unknown, 2018. System properties comparison amazon neptune vs. neo4j. Accessed November 12, 2018.
URL https://db-engines.com/en/system/Amazon+Neptune%3BNeo4j

[62] Unknown, 2019. Discover the origins and history of the top tier of english football. Accessed March 27, 2019.
URL https://www.premierleague.com/history

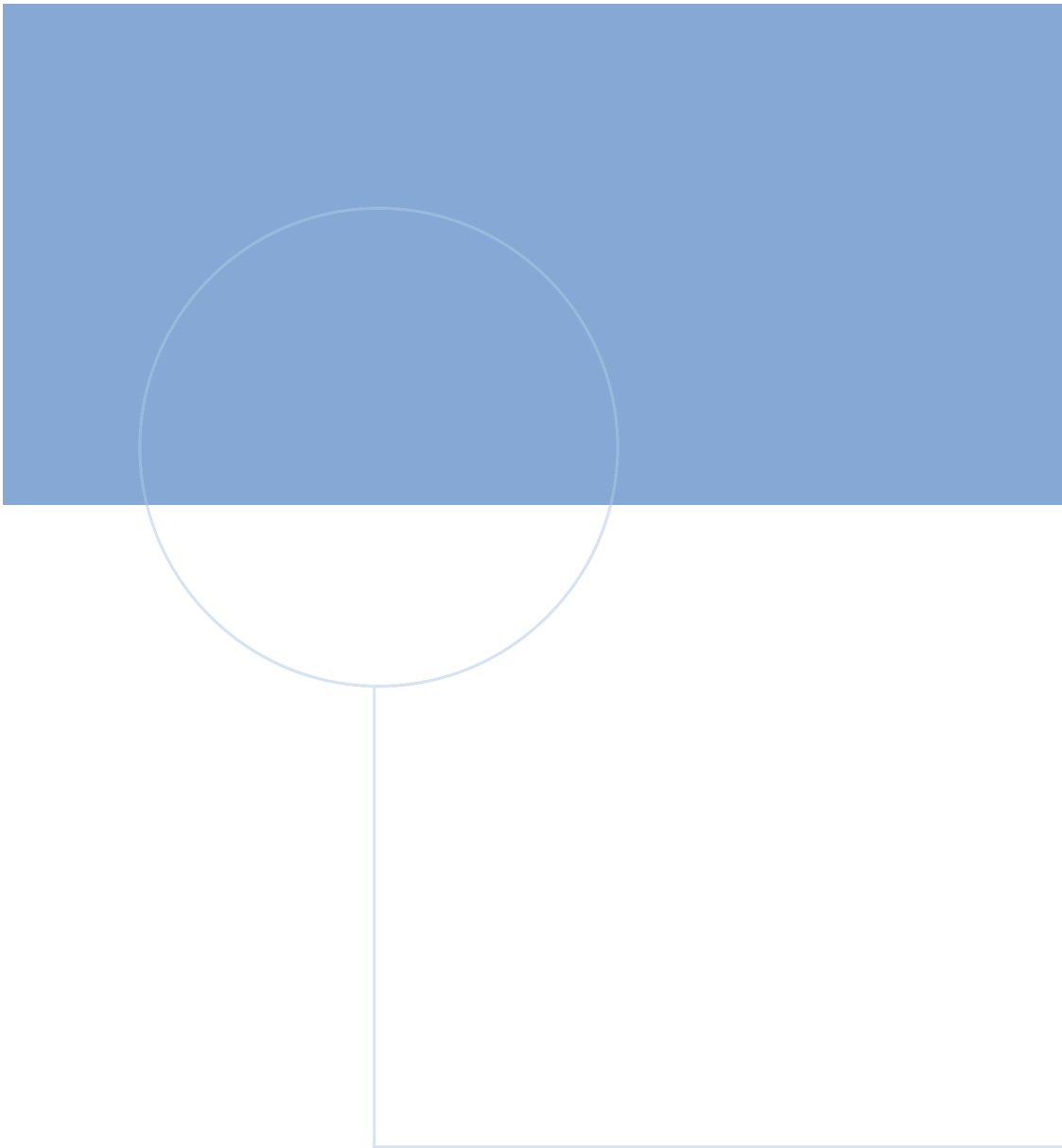
[63] Vukotic, A., Watt, N., Abedrabbo, T., Fox, D., Partner, J., 2014. Neo4j in action. Manning Publications Co., pp. 12–13.
URL https://books.google.no/books?id=61GdmgEACAAJ

[64] Webber, J., 2018. Powering real-time recommendations with graph database technology. Accessed May 6, 2019.

Appendix

Below is a table containing execution times in seconds from querying the graph database using un-optimized queries.

No. of Iteration	Single match	Team Season	Complete Season
1	0,1386	1,9833	38,7823
2	0,1392	1,5113	31,0692
3	0,1302	1,4360	30,7304
4	0,1541	1,2986	29,8388
5	0,1334	1,3195	28,6499
6	0,1317	1,3570	25,5633
7	0,1277	1,2485	25,6966
8	0,1373	1,1795	24,4926
9	0,1439	1,4090	24,2195
10	0,1287	0,9569	22,5575
11	0,1299	0,8489	20,3340
12	0,1359	0,8491	16,7012
13	0,1280	0,8377	16,8002
14	0,1278	0,8545	16,8275
15	0,1034	0,8262	15,5818
16	0,1842	0,8711	16,3460
17	0,1671	0,9101	15,1158
18	0,1488	0,8292	15,5701
19	0,1297	0,8587	15,2688
20	0,1286	0,8529	15,4075
21	0,1247	0,8249	16,2094
22	0,1216	0,7915	17,0890
23	0,0973	0,9065	16,2204
24	0,1565	0,9317	15,1809
25	0,1243	0,8721	15,5813



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