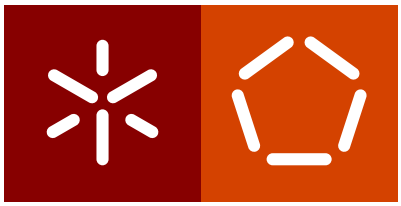

Universidade do Minho
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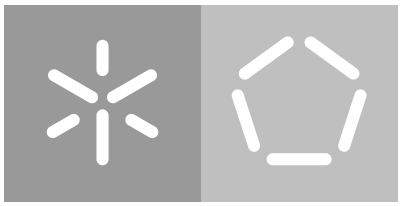
Daniel Araújo

Real-Time Intelligence

June 2016



Universidade do Minho
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Daniel Araújo

Real-Time Intelligence

Master dissertation
Master Degree in Computer Science

Dissertation supervised by
Paulo Novais - Universidade do Minho
André Ribeiro - Performetric

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ABSTRACT

Over the past 20 years, data has increased in a large scale in various fields. This explosive increase of global data led to the coin of the term Big Data. Big data is mainly used to describe enormous datasets that typically includes masses of unstructured data that may need real-time analysis. This paradigm brings important challenges on tasks like data acquisition, storage and analysis. The ability to perform these tasks efficiently got the attention of researchers as it brings a lot of oportunities for creating new value. Another topic with growing importance is the usage of biometrics, that have been used in a wide set of application areas as, for example, healthcare and security. In this work it is intended to handle the data pipeline of data generated by a large scale biometrics application providing basis for real-time analytics and behavioural classification. The challenges regarding analytical queries (with real-time requirements, due to the need of monitoring the metrics/behavior) and classifiers' training are particularly addressed.

Key Words: Real-Time Analytics, Big Data, NoSQL Databases, Machine Learning, Biometrics, Mouse Dynamics

RESUMO

Nos os últimos 20 anos, a quantidade de dados armazenados e passíveis de serem processados, tem vindo a aumentar em áreas bastante diversas. Este aumento explosivo, aliado às potencialidades que surgem como consequência do mesmo, levou ao aparecimento do termo *Big Data*. *Big Data* abrange essencialmente grandes volumes de dados, possivelmente com pouca estrutura e com necessidade de processamento em tempo real. As especificidades apresentadas levaram ao apareciemento de desafios nas diversas tarefas do *pipeline* típico de processamento de dados como, por exemplo, a aquisição, armazenamento e a análise. A capacidade de realizar estas tarefas de uma forma eficiente tem sido alvo de estudo tanto pela indústria como pela comunidade académica, abrindo portas para a criação de valor. Uma outra área onde a evolução tem sido notória é a utilização de biométicas comportamentais que tem vindo a ser cada vez mais acentuada em diferentes cenários como, por exemplo, na área dos cuidados de saúde ou na segurança. Neste trabalho um dos objetivos passa pela gestão do *pipeline* de processamento de dados de uma aplicação de larga escala, na área das biométricas comportamentais, de forma a possibilitar a obtenção de métricas em tempo real sobre os dados (viabilizando a sua monitorização) e a classificação automática de registos sobre fadiga na interação homem-máquina (em larga escala).

Palavras-chave: Indicadores em tempo real, *Big Data*, Bases de dados *NoSQL*, *Machine Learning*, Biométricas Comportamentais

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LIST OF ABBREVIATIONS

ACID Atomicity, Consistency, Isolation, Durability

ANN Artificial Neural Network

API Application Programming Interface

BASE Basically available, Soft state, Eventual consistency

BSON Binary JSON

CAP Consistency, Availability, Partition tolerance

CRUD Create, Read, Update, Delete

DBMS Data Base Management System

DFS Distributed File System

ETA Estimated Time of Arrival

ETL Extract, Transform, Load

GLM Generalized Linear Mode

GPS Global Positioning System

HTTP Hypertext Transfer Protocol

IaaS Infrastructure as a Service

JDK Java SE Development Kit

JMH Java Microbenchmark Harness

JSON JavaScript Object Notation

JVM Java Virtual Machine

KNN K-Nearest Neighbors

MSE Mean Squared Error

NoSQL Not Only SQL

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PaaS Platform As A Service

PBIAS Percent Bias

RDBMS Relational Database Management System

RMSE Root-Mean-Square Error

SaaS Software As A Service

SQL Structured Query Language

VAR Variance

WSN Wireless Sensor Network

1

INTRODUCTION

1.1 MOTIVATION

In recent years, data has increased in a large scale in various fields leading to the coin of the term Big Data, this term has been mainly used to describe enormous datasets that typically includes masses of unstructured data that may need real-time analysis. As human behaviour and personality can be captured through human-computer interaction a massive opportunity opens for providing wellness services (Carneiro et al. (2008); Pimenta et al. (2014)). Through the use of interaction data, behavioral biometrics (presented, for exemple, in Pimenta et al. (2015)) can be obtained. The usage of biometrics has increased due to several factors such as the rise of power and availability of computational power. One of the challenges in this kind of approaches has to do with handling the acquired data. The growing volumes, variety and velocity brings challenges in the tasks of pre-processing, storage and providing real-time analytics. In this remaining of this section the concepts that were introduced due the mentioned needs are introduced.

1.1.1 *Big Data*

A large amount of data is created every day by the interactions of billions of people with computers, wearable devices, GPS devices, smart phones, and medical devices. In a broad range of application areas, data is being collected at unprecedented scale Bertino et al. (2011). Not only the volume of data is growing, but also the variety (range of data types and sources) and velocity (speed of data in and out) of data being collected and stored. These are known as the 3V's of Big data, enumerated in a research report published by Gartner: "Big data is high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization" Gartner. In addition to those dimensions, the handling of data veracity (the biases, noise and abnormalities in data) constitutes the IBM's 4V's of Big Data, that give us a good intuition about the term IBM.

Despite of its popularity Big Data remains somehow ill-defined, in order to give a better sense about the term here are two aditional relevant definitions by two of the industry leaders:

MICROSOFT "Big data is the term increasingly used to describe the process of applying serious computing power - the latest in machine learning and artificial intelligence - to seriously massive and often highly complex sets of information." Aggarwal (2015)

ORACLE "Big data is the derivation of value from traditional relational database-driven business decision making, augmented with new sources of unstructured data." Aggarwal (2015)

By analysing these large volumes of data, progress can be made. Advances in many scientific disciplines and enterprise profitability are among the potential beneficial consequences of right data usage, and areas like financial services (e.g. algorithmic trading), security (e.g. cybersecurity and fraud detection), healthcare and education are among the top beneficiaries. In order to do so, challanges related to the 4V's and also error-handling, privacy issues, and data visualization must be addressed. The data pipeline stages (from data acquisition to result interpretation) must be adapted to this new paradigm.

1.1.2 *Real-Time Analytics*

There is an undergoing transition in the Big Data analytics from being mostly offline (or batch) to primarily online (real-time) Kejariwal et al. (2015). This trend can be related to the Velocity dimension of the 4 V's of Big Data: "The high velocity, white-water flow of data from innumerable real-time data sources such as market data, Internet of Things, mobile, sensors, clickstream, and even transactions remain largely unnavigated by most firms. The opportunity to leverage streaming analytics has never been greater." Gualtieri and Curran (2014).

The term of real-time analytics can have two meanings considering the prespective of either the data arriving or the point of view of the end-user. The earlier translates into the ability of processing data as it arrives, making it possible to aggregate data and extract trends about the actual situation of the system (streaming analytics). The former refers to the ability to process data with low latency (processing huge amount of data with the results being available for the end user almost in real-time) making it possible, for example, to to provide recommendations for an user on a website based on its history or to do unpredictable, ad hoc queries against large data sets (online analytics).

Regarding this trend, examples of use cases are mainly related to: visualization of business metrics in real time, providing highly personalized experiences and acting during emergencies. These use cases are part of the emerging data-driven society and are used in

various domains such as: social media, health care, internet of things, e-commerce, financial services, connected vehicles and machine data Pentland (2013); Kejariwal et al. (2015).

1.2 CONTEXT

This project will be developed in cooperation and under the requirements of Performetric[1]. Performetric is a company that focuses its activity around the detection of mental fatigue. In order to do so, the developed software uses a set of computer peripherals as sensors. The main goal of the system is to provide a real time analytics platform. The problem that Performetric faces relates to the volume, heterogeneity and speed-of-arrival of the data it has to store and process. Data is generated every 5 minutes for every user, and the number of users is growing everyday (data volume grows as well). The basic need is the ability to store and to do data aggregations (in order to calculate the desired metrics) with great performance. Another issue that must be tackled is the performance on the training of the classifier (based on neural networks), since as the data volumes grow bigger and bigger it can become a bottleneck on the system.

1.3 OBJECTIVES

The main objective of this project is the development of techniques that enable Performetric system the handling of the growing volumes and velocity the generated data. The focus is on problem detection and the experiment and implementation of possible solutions for the gathered contextual needs.

1. To carry an in-depth study on Big Data, in the form a state-of-the-art document.
2. Problem analysis and gathering of the contextual needs, namely the implications of the usage of MongoDB as operational data store (and as basis for analytical needs) and the usage of neural networks as classifiers.
3. Design the architecture for a real-time analytics and learning system.
4. Developement of a analytical system that makes it possible to gather indicators in real-time, by aggregation and learning on large data volumes.
5. Performance tests and result analysis.

1 https://performetric.net

1.4 METHODOLOGY

This dissertation will be developed under an research-action methodology. According to this methodology, the first step when facing a challenge is to establish a solution hypothesis. Then, takes place the gathering and organization of the relevant pieces of information for the problem. After that, a proposal of solution will be implemented. The last step consists in the formulation of the conclusions regarding the obtained results.

Therefore, the project will be developed in the following steps:

- Bibliographic investigation while analysing existing solutions.
- Problem analysis and gathering of organizational context needs.
- Writing the State of the Art document.
- Development of a set of solutions that make it possible to obtain indicators based on existing data (in real-time).
- Development of a solution that makes it possible to improve the classifer based on existing data.
- Evaluation of the obtained results.
- Writing the Master's dissertation.

1.5 WORK PLAN

The development of this dissertation evolved through a set of well-defined stages that are shown if the figure 1. It is important to note that there is a constant awareness about the iterative nature of this process that may result in changes of the duration in each stage. At this moment, the literature review is complete and the architecture of the system is being defined. The work is being performed according to the plan (the kickoff of the project was at the beginning of October 2015).

1.6 DOCUMENT STRUCTURE

This document will be divided into 6 chapters where the first chapter, the current one, describes all the motivations for the development of the project and what this project proposes to offer at its final stage, as well as, the steps outlined for this process and the type of research that was used as a guideline.

The second chapter describes the analysis made to the state of the art, in which are included an overview over the Big Data scene and the current challenges. In each section,

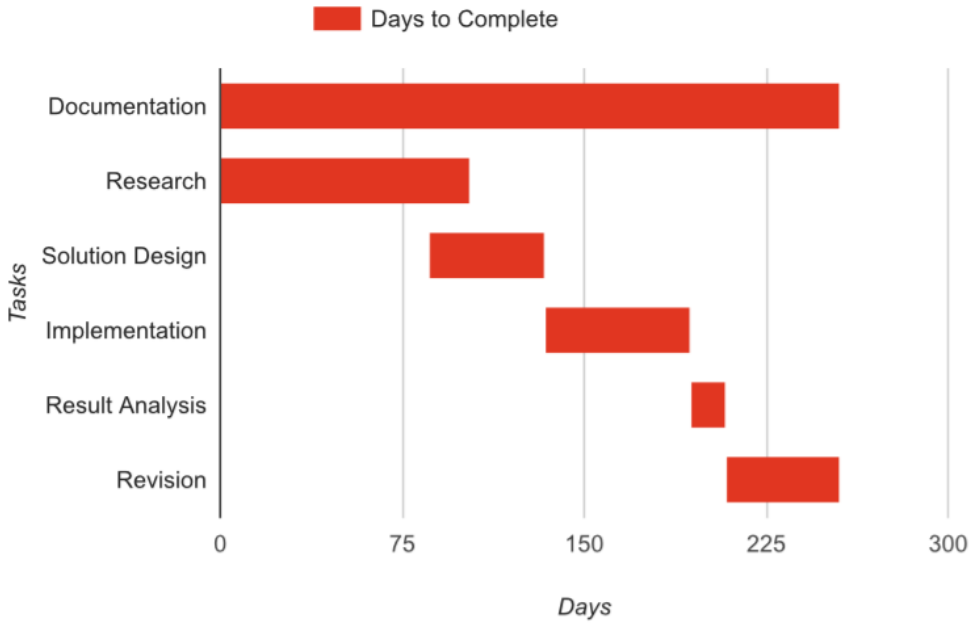

Figure 1.: Work plan showing the timeline of the set of tasks in this dissertation.

there will be an description of the steps of the data pipeline, and relevant findings on each topic. The most used tools will be introduced and a comparative analysis will be made, as it will serve as a basis for the following steps of this work. An introduction to the tool MongoDB aswell as a critical analysis is also part of this chapter. The last section provides an overview of Big Data projects on a wide set of areas.

The third chapter introduces the problem. By describing the architecture of the system through adequated documentation the reasinong about the contextual needs becomes simpler. The gathered needs are then discussed and quantified, the requirements are established.

In the fourth chapter the improvemetns to the system are discussed and introduced to the reader. The important and unique aspects of the setup are described. Additionally, the testing methodology is presented along with the obtained results. Some additional details are included in order to give helpful hints to those who work with this or similar systems in the future.

A careful analysis on the data collected and the results accomplished is made on the fifth chapter. The results are evaluated and compared. The discussion is made around possible explanations for the observed results and possible improvements on the testing setup. In this chapter valuable conclusions are infered that enable the orientation of data decisions on Performetric.

In the last chapter, it is put together a review of all the work developed and the results obtained. Furthermore, the future work that can be done to improve this platform and to better validate the results is indicated.

2

STATE OF THE ART

Big Data refers to things one can do at a large scale that cannot be done at a a smaller one: to extract new insights or create new forms of value, in ways that change markets, organizations, the relationship between citizens and governments, and more Mayer-Schönberger and Cukier (2013). Despite still being somewhat an abstract concept it can be clearly said that Big Data encomprises the a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling the high-velocity capture, discovery and analysis Gantz and Reinsel (2011).

The continuous evolution of Big Data applications has brought advances in architectures used in the data centers. Sometimes these architectures are unique and have specific solutions for storage, networking and computing solutions regarding the particular contextual needs of the underlying organization. Therefore, when analysing Big Data we should follow a top down approach avoiding the risk of losing focus on the initial topic. Hence, this revision of the state of the art will be structured acording to the value chain of big data Chen et al. (2014) and its contents will be conditioned by the contextual needs evidenced by Performetric's system. The value chain of big data can be generally divided into four phases: data generation, data acquisition, data storage, and data analytics. This approach is similar to the one that is shown it the figure 2 Bertino et al. (2011). Each of the first four phases of the presented pipeline can be matched with one of the phases of the Big Data value chain. For each phase the main concepts, techniques, tools and current challenges will be introduced and discussed. As it is expressed in the figure 2, there are needs that are common to all phases these include, but are not limited to: data representation, data compression (redudancy reduction), data confidentiality and energy management Bertino et al. (2011); Chen et al. (2014).

2.1 DATA GENERATION AND DATA ACQUISITION

Data is being generated in a wide set of fields. The main sources are enterprise operational and trading data, sensor data (Internet of Things), human-computer interaction data and data generated from scientific research.

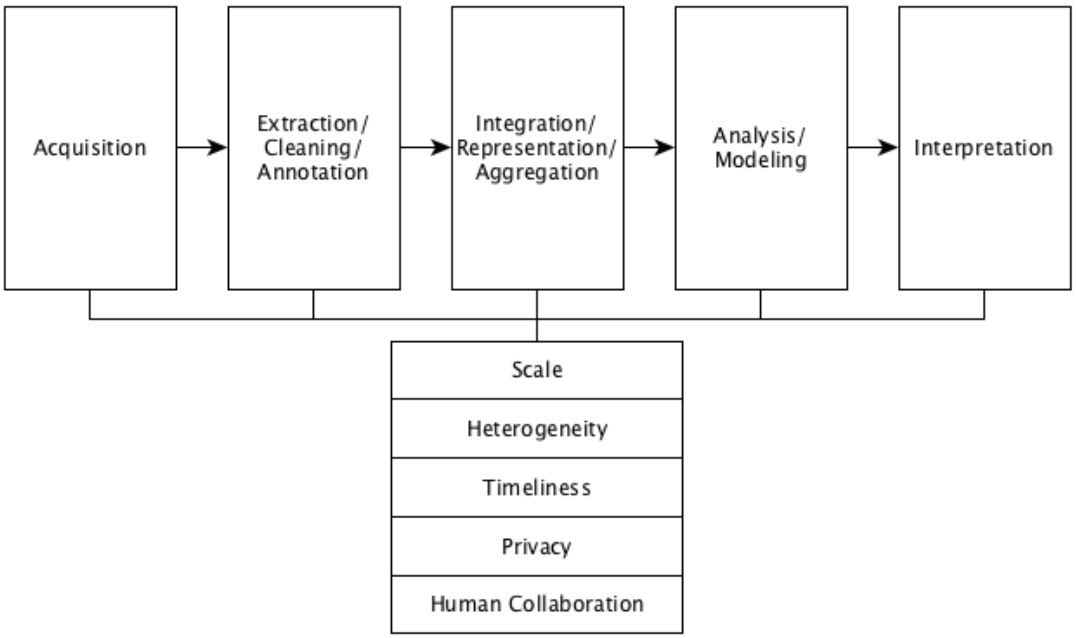

Figure 2.: The Big Data analysis Pipeline according to Bertino et al. (2011).

Enterprise data is mainly data stored in traditional RDBMSs and it is related to production, inventory, sales, and financial departments and, in addition to this, there is online trading data. It is estimated that the business data volume of all companies in the world may double around every year (1.2 years according to Manyika et al. (2011)). The datasets that are a product of scientific applications are also part of the Big Data. Research in areas like bio-medical applications, computational biology, high-energy physics (for example the Large Hadron Collider) and behavior analysis (such as in Kandias et al. (2013)) generates data at an unprecedented rate.

Sensor applications, commonly known as part of the Internet of things is also a big source of data that needs to be processed. Sensors and tiny devices (actuators) embedded in physical objects—from roadways to pacemakers—are linked through wired and wireless networks, often using the same Internet Protocol (IP) that connects the Internet Chui et al. (2010). Typically, this kind of data may contain redudancy (for example data streams) and has strong time and space correlation (every data acquisition device are placed at a specific geographic location and every piece of data has time stamp). The domains of application are as diverse as industry Da Xu et al. (2014), agriculture Ruiz-Garcia et al. (2009), traffic Gentili and Mirchandani (2012) and medical care Dishongh et al. (2014).

Two important challenges rise regarding data generation, particularly regarding the volume of and the heterogeneity. The first challange is about dealing with the fact that a significant amount of data is not relevant due to redudancy, and thus having the possibility

of being filtered and compressed by orders of magnitude. Defining the filters and being able to do so online (in order to reduce data sizes from data streams) are the main questions regarding this challenge. The second challenge is to automate the generation of right metadata in order to describe what data is recorded and how it is recorded and measured as the value of data explodes when it can be linked with other data Bertino et al. (2011).

2.1.1 *Data Collection*

According to the International Data Corporation (IDC) the collected data can be organized in three types:

STRUCTURED DATA This type describes data which is grouped into a relational scheme (e.g., rows and columns within a standard database).

SEMI-STRUCTURED DATA : This is a form of structured data that does not conform to an explicit and fixed schema. The data is inherently self-describing and contains tags or other markers to enforce hierarchies of records and fields within the data. Examples include weblogs and social media feeds Buneman (1997).

UNSTRUCTURED DATA This type of data consists of formats which cannot easily be indexed into relational tables for analysis or querying. Examples include images, audio and video files.

As it was previously introduced, data can be acquired in a wide set of domains and through different techniques. Record files automatically generated by the system or log files are used in nearly all digital devices. Web servers, for example, record navigation data such as number of clicks, click rates, number of visits, number of unique visitors, visit durations and other properties of web users Wahab et al. (2008). The following are examples of log storage formats: NCSA, W3C Extended (used by Microsoft IIS 4.0 and 5.0), WebSphere Application Server Logs, FTP Logs.[1]

Another category of collected data is sensor data. Sensors are common in daily life to measure physical quantities and transform physical quantities into readable digital signals for subsequent processing (and storage). In recent years wireless sensor networks (WSN) emerged as a data sensing architechture. In a WSN, each sensor node is powered by a battery and uses wireless communications. The sensor node is usually small in size and can be easily attached to any location without causing major disturbances on the surrounding environment. Examples are across wildlife habitat monitoring, environmental research, volcano monitoring, water monitoring, civil engineering and wildland fire forecast/detection Wang and Liu (2011).

1 http://publib.boulder.ibm.com/tividd/td/ITWSA/ITWSA_info45/en_US/HTML/guide/c-logs.html

Methods for acquiring network data such as web crawlers (program used by search engines for downloading and storing web pages) are also widely used for data collection. Specialized network monitoring software like Wireshark [2] and SmartSniff [3] are also used in this context.

2.1.2 *Data Pre-processing*

In order to improve the data analysis process, a set of techniques should be used. These are part of the data pre-processing stage and have the objective of dealing with noise in data, redudancy and consistency issues (i.e. data quality). Data integration is a mature research field in the database research community. Data warehousing processes, namely ETL (Extract, Transform and Load) are the most used for data integration. Extraction is the process of collecting data (selection and analysis of sources). Transformation is the definition of a series of data flows that transform and integrate the extracted data into the desired formats. Loading means importing the data resulting from the previous operation into the target storage infrastructure. In order to deal with inacurate and incomplete data, data cleaning procedures may take place. Generally these are associated with the following complementary procedures: defining and determining error types, searching and identifying errors, correcting errors, documenting error examples and error types, and modifying data acquisition procedures to reduce future errors Maletic and Marcus (2000). Classic data quality problems mainly come from software defects or system misconfiguration. Data redundancy means an increment of unnecessary data transmission resulting in waste of storage space and possibly leads to data inconsistency. Techniques like redundancy detection, data filtering, and data compression can be used in order to deal with data redudancy, however its usage should be carefully weighted as it requires extra processing power.

2.2 DATA STORAGE

Big data brings more strict requirements on how data is stored and managed. This section will elaborate on the developments in different (technological) fields making big data data possible. Cloud computing, distributed file systems and NoSQL databases. A comparision based on quality attributes of the different NoSQL solutions is hereby presented.

2 https://www.wireshark.org
3 http://www.nirsoft.net/utils/smsniff.html

2.2.1 *Cloud Computing*

The rise of the cloud plays a significant role in big data analytics as it offers the demanded computing resources when needed. This translates to a pay for use stategy that enables the use of resources on a short-term bases (e.g. more resources on peak hours). Additionally there is no need for a upfront commitment about the allocated resources: users can start small but think big. Improved avalilability is another big advantage of cloud solutions. Clouds vary significantly in their specific technologies and implementation, but often provide infrastructure (IaaS), platform (PaaS), and software resources as services (SaaS) Assunção et al. (2015). Cloud solutions may be private, public or hybrid (additional resources from a public Cloud can be provided as needed to a private Cloud). A private Cloud is suitable for organizations that require data privacy and security. Typically are used by large organizations as it enables resource sharing across the different departments. Public clouds are deployed off-site over the Internet and available to the general public, offering high efficiency and shared resources with low cost. The analytics services and data management are handled by the provider and the quality of service (e.g. privacy, security, and availability) is specified in a contract. The most popular examples of IaaS are: Amazon EC2, Windows Azure, Rackspace, Google Compute Engine. Regarding PaaS, AWS Elastic Beanstalk, Windows Azure, Heroku, Force.com, Google App Engine, Apache Stratos, are among the most widely used.

2.2.2 *Distributed File Systems*

An important feature of public cloud servers and Big Data systems is its file system. The most popular example of a DFS is Google File System (GFS), which as the name sugests is a proprietary system, designed by Google. Its main design features are effeciency and reliable access to data and it is designed to run on large clusters of commodity servers Zhang et al. (2010). In GFS, files are divided into chunks of 64 megabytes, and are usually appended to or read and only extremely rarely overwritten or shrunk. Compared with traditional file systems, GFS design differences are on the fact that it is designed to deal with extremely high data throughputs, provide low latency and to survive to individual server failures. The Hadoop Distributed File Systems (HDFS)[4] is inspired by GFS. It is also designed to achieve reliability by replicating the data across multiple servers. Data nodes comunicate with each other to rebalance data distribution, to move copies around, and to keep the replication of data high.

HDFS has a master/slave architecture (see figure 3). An HDFS cluster consists of a single NameNode, a master server that manages the file system namespace and regulates access

4 https://hadoop.apache.org/docs/r1.2.1/hdfs_design.html

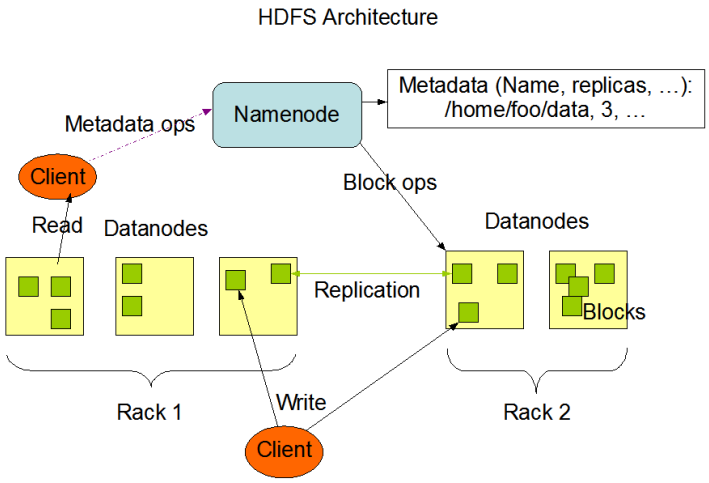

Figure 3.: HDFS Architecture from https://hadoop.apache.org/docs/r1.2.1/hdfs_design.html.

to files by clients. Additionaly, in the nodes of the cluster there are a number of DataNodes, usually one per node in the cluster. Data Nodes manage storage attached to the nodes that they run on. Internally, a file is split into one or more blocks and these blocks are stored in a set of DataNodes. The functions of the NameNode are to execute file system namespace operations like opening, closing, and renaming files and directories. The NameNode also determines the mapping of file ablocks to DataNodes. The DataNodes are responsible for serving read and write requests from the file system's clients. The DataNodes also perform block creation, deletion, and replication upon instruction from the NameNode. The NameNode is the broker and the repository for all HDFS metadata. The existence of a single NameNode in a cluster simplifies the architecture of the system. One benefit of this distributed design is that user data never flows through the NameNode, so there is not a single point of failure.

2.2.3 *CAP Theorem*

The CAP theorem states that no distributed computing system can fulfill all three of the following properties at the same time Gilbert and Lynch (2002):

CONSISTENCY means that each node always has the same view of the data.

AVAILABILITY every request received by a non-failing node in the system must result in a response.

PARTITION TOLERANCE the system continues to operate despite arbitrary message loss or failure of part of the system (the system works well across physical network partitions).

Since consistency, availability, and partition tolerance can not be achieved simultaneously, we can classify existing systems into: CA systems (by ignoring partition tolerance), a CP system (by ignoring availability), and an AP system (ignores consistency), selected according to different design goals.

2.2.4 *NoSQL - Not only SQL*

The term NoSQL was introduced in 1998 by Carlo Strozzi to name his RDBMS, Strozzi NoSQL (a solution that did not expose a SQL interface - the standard for RDBMS), but it was not until the Big Data era that the term became a mainstram defintion in the database world. Convetional relational databases have proven to be highly efficient, reliable and consistent in terms of storing and processing structered data Khazaei et al. (2015). However, regarding the 3 V's of big data the relational model has serveral shortcomings. Companies like Amazon, Facebook and Google started to work on thein own data engines in order to deal with their Big Data pipeline, and this trend inspired other vendors and open source communities to do similarly for other use cases. As Sonebraker argues in Stonebraker (2010) the main reasons to adopt NoSQL databases are performance (the ability to manage distributed data) and flexibility (to deal with semi-structured or unstructured data that may arise on the web) issues.

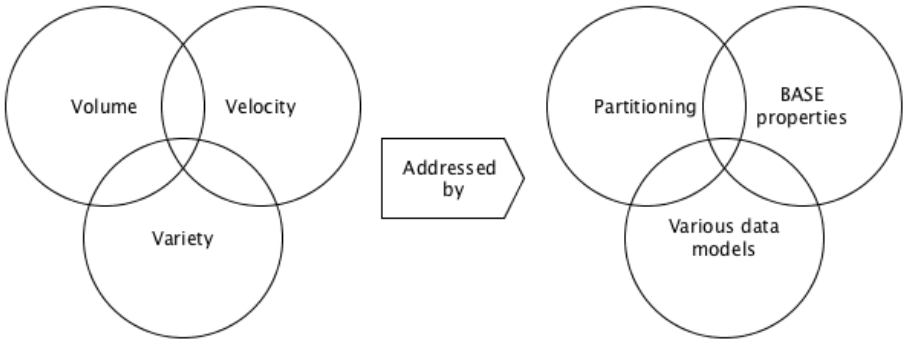

Figure 4.: Mapping between Big Data 3 V's and NoSQL System features.

In figure 4 we can see a mapping between Big Data characteristics (the 3V's) and NoSQL features that address them. NoSQL data stores can manage large volumes of data by enabling data partitioning across many storage nodes and virtual structures, overcoming traditional infrastructure constrains (and ensuring basic availability). By compromising on ACID (Atomicity, Consistency, Isolation, Durability ensured by RDBMS in database transactions) properties NoSQL opens the way for less blocking between user queries. The altenative is the BASE system Pritchett (2008) that translates to basic availabilty, soft state and eventual consistency. By being basically available the system is guaranteed to be mostly

available, in terms of the CAP theorem. Eventual consistency indicates that given that the system does not receive input during an interval of time, it will become consistent. The soft state propriety means that the system may change over time even without input. According to Cattell (2011), the key characterisitcs that generally are part of NoSQL systems are:

1. the ability to horizontally scale CRUD operations throughput over many servers,
2. the ability to replicate and to distribute (i.e.,partition or shard) data over many servers,
3. a simple call level interface or protocol (in contrast to a SQL binding),
4. a weaker concurrency model than the ACID transactions of most relational (SQL) database systems,
5. efficient use of distributed indexes and RAM for data storage, and
6. the ability to dynamically add new attributes to data records.

However, the systems differ in many points, as the funcionality ranges from a simple distributed hashing (as supported by memcached[5], an open source cache), to highly scalable partitioned tables (as supported by Google's BigTable Chang et al. (2008)). NoSQL data stores come in many flavors, namely data models, and that permits to accommodate the data variety that is present in real problems.

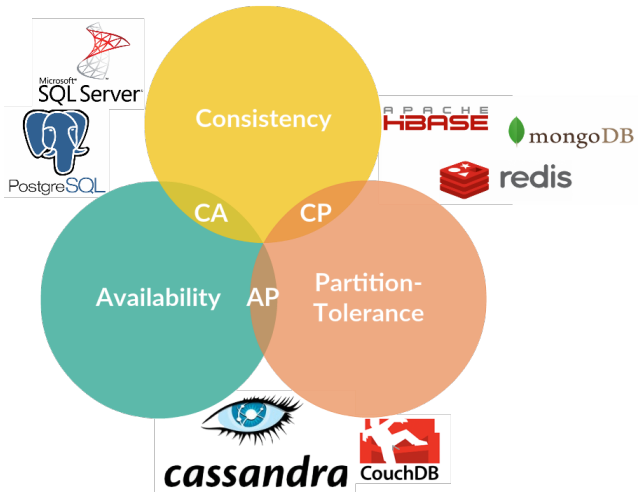

Figure 5.: Classification of popular DBMSs according to the CAP theorem.

As it shown in figure 5, regarding the CAP theory, NoSQL (and relational) can be divided in CP and AP (from the CAP theorem), with CA being the relational DBMSs. Examples

5 http://memcached.org

of CP systems (that compromise availability) are Apache HBase[6], MongoDB[7] and Redis[8]. On the other side, favouring availability and partition-tolerance over consistency (AP) there is Apache Cassandra[9], Apache CouchDB[10] and Riak[11]. Another criterion widely used to classify NoSQL databases is based on the supported data model. According to this, we can divide the systems in the following categories: Key-value stores, document stores, graph databases and wide column stores.

Key-value Stores

The simplest form of database management systems are these. A Key-value DBMS can only perform two operations: store pairs of keys and values, and retrieve the stored values given a key. These kind of systems are suitable for applications with simple data models that require a resource-efficient data store like, for example, embedded systems or applications that require a high performance in-process database.

Memcached[12] Fitzpatrick (2004) is a high-performance, distributed, memory object caching system, originally designed to speed up web applications by reducing database load. Memcached has features similar to other key-value stores: persistence, replication, high availability, dynamic growth, backups and so on. In Memcached the identification of the destination server is done at the client side using a hash function on the key. Therefore, the architecture is inherently scalable as there is no central server to consult while trying to locate values from keys Jose et al. (2011). Basically, Memcached consists of a client software, which is given a list of available memcached servers and a client-based hashing algorithm, which chooses a server based on the "key" input. On the server side, there is an internal hash table that stores the values with their keys and an a set of algorithms that determine when to throw out old data or reuse memory.

Another example of a key-value store is Redis (REmote DIctionary Server). Redis is an in-memory database where complex objects such as lists and sets can be associated with a key. In Redis, data may have customizable time-to-live (TTL) values, after which keys are removed from memory. Redis uses locking for atomic updates and performs asynchronous replications Khazaei et al. (2015). Redis performs very well compared to writing the data into the disk for any changes in the data, in applications that do not need durability of data. As it is in-memory database, Redis might not be the right option for data-intensive

6 https://hbase.apache.org
7 https://www.mongodb.com
8 http://redis.io
9 http://cassandra.apache.org
10 http://couchdb.apache.org
11 http://docs.basho.com/riak/latest/
12 http://memcached.org

applications with dominant read operations, because the maximum Redis data set cant be bigger than memory [13].

Document-oriented Databases

Document-oriented databases are, as the name implies, data stores designed to store and manage documents. Typically, these documents are encoded in standard data exchange formats such as XML, JSON (Java Script Option Notation), YAML (YAML Ain't Markup Language), or BSON (Binary JSON). These kind of stores allow nested documents or lists as values as well as scalar values, and the attribute names are dynamically defined for each document at runtime. When comparing to the relational model, we can say that a single column can hold hundreds of attributes, and the number and type of attributes recorded can vary from row to row, since its schema free. Unlike key-value stores, these kind of stores allows to search on both keys and values, and support complex keys and secondary indexes.

Apache CouchDB[14] is a flexible, fault-tolerant database that stores collections, forming a richer data model compared to similar solutions. This solution supports as data formats JSON and AtomPub[15]. Queries are done with what CouchDB calls "views", which are the primary tool used for querying and reporting, defined with Javascript to specify field constraints. Views are built on-demand to aggregate, join and report on database documents. The indexes are B-trees, so the results of queries can be ordered or value ranges. Queries can be distributed in parallel over multiple nodes using a map-reduce mechanism. However, CouchDBs view mechanism puts more burden on programmers than a declarative query language Foundation (2014).

MongoDB[16] is a database that is half way between relational and non-relational systems. Like CouchDB, it provides indexes on collections, it is lockless and it provides a query mechanism. However, there are some differences: CouchDB provides multiversion concurrency control while MongoDB provides atomic operations on fields; l MongoDB supports automatic sharding by distributing the load across many nodes with automatic failover and load balancing, on the other hand CouchDB achieves scalability through asynchronous replication Khazaei et al. (2015). MongoDB supports master-slave replication with automatic failover and recovery. The data is stored in a binary JSON-like format called BSON that supports boolean, integer, float, date, string and binary types. The communication is made over a socket connection (in CouchDB it is made over an HTTP REST interface).

13 http://redis.io/documentation
14 http://couchdb.apache.org
15 http://bitworking.org/projects/atom/rfc5023.html
16 https://www.mongodb.com

Graph-oriented Databases

Graph databases are data stores that employ graph theory concepts. In this model, nodes are entities in the data domain and edges are the relationship between two entities. Nodes can have properties or attributes to describe them. These kind of systems are used for implementing graph data modeling requirements without the extra layer of abstraction for graph nodes and edges. This means less overhead for graph-related processing and more flexibility and performance.

Neo4j[17] is the most known and used graph storage project. It has various native APIs in most of programming languages such as Java, Go, PHP, and others. Neo4j is fully ACID compatible and schema-free. Additionally, it uses its own query language called Cypher that is inspired by SQL, and supports syntax related to graph nodes and edges. Neo4j does not allow data partiitioning, and this means that data size should be less than the capacity of the server. However, it supports data replication in a master-slave fashion which ensures fault tolerance against server failures.

Column-oriented Databases

Column-oriented databases are the kind of data store that most resembles the relational model on a conceptual level. They retain notions of tables, rows and columns, creating the notion of a schema, explicit from the client's perspective. However, the design principles, architecture and implementation are quite different from traditional RDBMS. While the notion of tables' main function is to interact with clients, the storage, indexing and distribution of data is taken care by a file and a management system. In this approach, rows are split across nodes through sharding on the primary key. They typically split by range rather than a hash function. This means that queries on ranges of values do not have to go to every node. Columns of a table are distributed over multiple nodes by using "column groups". These may seem like a new complexity, but column groups are simply a way for the customer to indicate which columns are best stored together Cattell (2011). Rows are analogous to documents: they can have a variable number of attributes (fields), the attribute names must be unique, rows are grouped into collections (tables), and an individual row's attributes can be of any type. For applications that scan a few columns of many rows, they are more efficient, because this kind of operations lead to less loaded data than reading the whole row. Most wide-column data store systems are based on a distributed file system. Google BigTable, the precursor of the popular data store systems of this kind, is built on top of GFS (Google File System).

Apache HBase is the NoSQL wide-column store for Hadoop, the open-source implementation of MapReduce for Big Data analytics. The purpose of HBase is to support random,

17 http://neo4j.com

real-time read and write access to very large tables with billions of rows and millions of columns. HBase uses the Hadoop distributed file system in place of the Google file system. It puts updates into memory and periodically writes them out to files on the disk. Row operations are atomic, with row-level locking and transactions. Partitioning and distribution are transparent; there is no client-side hashing or fixed keyspace as in some NoSQL systems. There is multiple master support, to avoid a single point of failure. MapReduce support allows operations to be distributed efficiently.

Apache Cassandra is designed under the premise that failures may happen both in software and hardware, being practically inevitable. It has column groups, updates are cached in memory and then flushed to disk, and the disk representation is periodically compacted. It does partitioning and replication. Failure detection and recovery are fully automatic. However, Cassandra has a weaker concurrency model than some other systems: there is no locking mechanism, and replicas are updated asynchronously.

Comparative Evaluation of NoSQL Databases

As it was presented, there are several options when it comes the time to choose a NoSQL database, and the different categories and architectures serve different purposes. Although four categories were presented, only two of them are adequate for the purposes of this work. Regarding support for complex queries column-oriented and document-oriented data store systems are more adequate than key-value stores (e.g. simple hash tables) and graph databases (which are ideal for situations that are modeled as graph problems). Considering the last presented fact, we selected Apache Cassandra, CouchDB, Apache HBase and MongoDB as the object of this evaluation. The following table is based in the work presented in Lourenço et al. (2015), where several DBMS are classified in a 5-point scale (Great, good, average, mediocre and bad) regarding a set of quality atributes.

DBMS	Cassandra	CouchDB	HBase	MongoDB
Availability	Great	Great	Mediocre	Mediocre
Consistency	Great	Good	Average	Great
Durability	Mediocre	Mediocre	Good	Good
Maintainability	Good	Good	Mediocre	Average
Read-Performance	Good	Average	Mediocre	Great
Recovery Time	Great	Unknown	Unknown	Great
Reliability	Mediocre	Good	Good	Great
Robustness	Good	Average	Bad	Average
Scalability	Great	Mediocre	Great	Mediocre
Stabilization Time	Bad	Unknown	Unknown	Bad
Write-Performance	Good	Mediocre	Good	Mediocre

Table 1.: NoSQL DBMS comparison.

As it is mentioned in Lourenço et al. (2015), the follwing criteria were used:

AVAILABILITY the downtime was used as a primary measure, together with relevant studies such as Nelubin and Engber (2013).

CONSISTENCY was graded according to how much the database can provide ACID-semantics and how much can consistency be fine-tuned.

DURABILITY was measured according to the use of single or multi version concurrency control schemes, the way that data are persisted to disk (e.g. if data is always asynchronously persisted, this hinders durability), and studies that specifically targeted durability.

MAINTAINABILITY the currently available literature studies of real world experiments, the ease of setup and use, as well as the accessibility of tools to interact with the database.

READ AND WRITE PERFORMANCE the grading of this point was done by considering recent studies (Nelubin and Engber (2013)) and the fine-tuning of each database.

RELIABILITY is graded by looking at synchronous propagation modes.

ROBUSTNESS was assessed with the real world experiments carried by researchers, as well as the available documentation on possible tendency of databases to have problems dealing with crashes or attacks.

SCALABILITY was assessed by looking at each database's elasticity, its increase in performance due to horizontal scaling, and the ease of live addition of nodes.

STABILIZATION AND RECOVERY TIME this measure is highly related to availability and is based our classification on the results shown in Nelubin and Engber (2013).

Although there have been a variety of studies and evaluations of NoSQL technology, there is still not enough information to verify how suited each non-relational database is in a specific scenario or system. Moreover, each working system differs from another and all the necessary functionality and mechanisms highly affect the database choice. Sometimes there is no possibility of clearly stating the best database solution Lourenço et al. (2015).

2.3 DATA ANALYTICS

Data analytics encomprises the set of complex procedures running over large-scale, data repositories (like big data repositories) whose main goal is that of extracting useful knowledge kept in such repositories Cuzzocrea et al. (2011). Along with the storage problem (conveying big data stored in heterogeneous and different-in-nature data sources into a

structured format), the issue of processing and transforming the extracted structured data repositories in order to derive Business Intelligence (BI) components like diagrams, plots, dashboards, and so forth, for decision making purposes, is the most addressed aspect by organizations.

In this section, one of the most widely used tool for data aggregation, Hadoop MapReduce Framework[18] (and its programming modet that enables parallel and distributed data processing) is introduced, alongside with its architecture. MongoDB Aggregation Framework is also introduced as it provides a recent and different approach by providing a tool for data aggregation contained in the database environment. Additionally, the concept of Real-time analytics is explored and examples of supporting tools are provided.

2.3.1 *MapReduce*

MapReduce is a scalable and fault-tolerant data processing tool that enable the processing of massive volumes of data in parallel with many low-end computing nodes Lee et al. (2012). In the context of Big Data analytics, MapReduce presents an interesting model where data locality is explored to improve the performance of applications. The main idea of the MapReduce model is to hide details of parallel execution, allowing the users to focus on data processing strategies. MapReduce utilizes the GFS while Hadoop MapReduce, the popular open source alternative, runs above the HDFS.

The computation takes a set of input key/value pairs, and produces a set of output key/value pairs. The MapReduce model consists of two primitive functions: *Map* and *Reduce*. *Map*, written by the user, takes an input pair and produces a set of intermediate key/value pairs. The MapReduce library groups together all intermediate values associated with the same intermediate key and passes them to the *Reduce* function. The *Reduce* function accepts an intermediate key and a set of values for that key. It merges together these values to form a possibly smaller set of values. Typically just zero or one output value is produced per *Reduce* invocation. The intermediate values are supplied to the user's reduce function via an iterator. This allows the handling of lists of values that are too large to fit in memory Dean and Ghemawat (2008). The following example (see figure 7) is about the problem of counting the number of occurrences of each word in a large collection of documents.

18 https://hadoop.apache.org/docs/current/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial.html

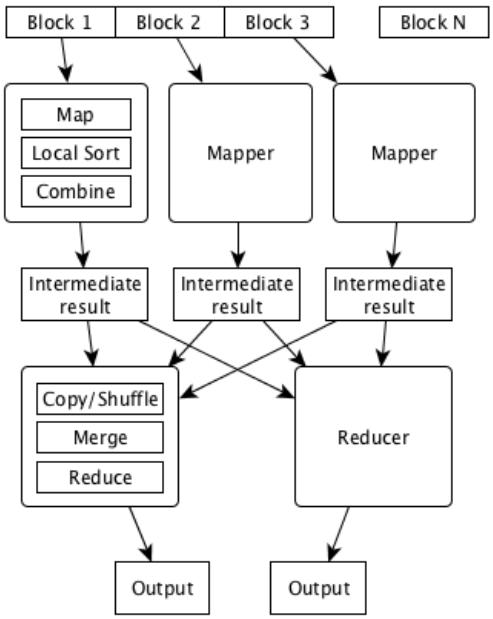

Figure 6.: Hadoop MapReduce architecture.

```
map(String key, String value):
  // key: document name
  // value: document contents
  for each word w in value:
    EmitIntermediate(w, "1");

reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
  int result = 0;
  for each v in values:
    result += ParseInt(v);
  Emit(AsString(result));
```

Figure 7.: Pseudocode representing a words counting implementation in map-reduce.

The main advantages of using MapReduce are its simplicity and ease of use, being storage independent (can work with different storage layers), its fault tolerance and providing high-scalability. On the other hand, there are some pitalls, such as: the lack of a high-level language, being schema-free and index-free, lack of maturity and the fact that operations not being always optimized for I/O efficiency. Lee et al. (2012).

2.3.2 *Real Time Analytics*

In the spectrum of analytics two extremes can be identified. On one end of the spectrum there is batch analytical applications, which are used for complex, long-running analyses. Generally, these have slower response times (hours or days) and lower requirements for availability. Hadoop-based workloads are an example of batch analytical applications. On the other end of the spectrum sit real-time analytical applications. Real-time can be considered from the point of view of the data or from the point of view of the end-user. The earlier translates into the ability of processing data as it arrives, making it possible to aggregate data and extract trends about the actual situation of the system (streaming analytics). The former refers to the ability to process data with low latency (processing huge amount of data with the results being available for the end user almost in real-time) making it possible, for example, to to provide recommendations for an user on a website based on its history or to do unpredictable, ad hoc queries against large data sets (online analytics).

Regarding stream processing the main problems are related to: Sampling Filtering, Correlation, Estimating Cardinality, Estimating Quantiles, Estimating Moments, Finding Frequent Elements, Counting Inversions, Finding Subsequences, Path Analysis, Anomaly Detection Temporal Pattern Analysis, Data Prediction, Clustering, Graph analysis, Basic Counting and Significant Counting. The main applications are A/B testing, set membership, fraud detection, network analysis, traffic analysis, web graph analysis, sensor networks and medical imaging (Kejariwal et al. (2015)).

According to Kejariwal et al. (2015) these are the most well-known streaming open source tools:

S4 Real-time analytics with a key-value based programming model and support for scheduling/message passing and fault tolerance.

STORM The most popular and widely adopted real-time analytics platform developed at Twitter.

MILLWHEEL Google's proprietary realtime analytics framework thats provides exact once semantics.

SAMZA Framework for topology-less real-time analytics that emphasizes sharing between groups.

AKKA Toolkit for writing distributed, concurrent and fault tolerant applications.

SPARK Does both offline and online analysis using the same code and same system.

FLINK Fuses offline and online analysis using traditional RDBMS techniques.

PULSAR Does real-time analytics using SQL.

HERON Storm re-imagined with emphasis on higher scalability and better debuggability.

Online analytics, on the other hand, are designed to provide lighter-weight analytics very quickly. The requirements of this kind of analytics are low latency and high availability. In the Big Data era, OLAP (on-line analytical processing Chaudhuri and Dayal (1997)) and traditional ETL processes are too expensive. Particularly, the heterogeneity of the data sources difficults the definition of rigid schemas, making model-driven insight difficult. In this paradigm analytics are needed in near real time in order to support operational applications and their users. This includes applications from social networking news feeds to analytics, from real-time ad servers to complex CRM applications.

2.3.3 *MongoDB Aggregation Framework*

MongoDB is actually more than a data storage engine, as it also provides native data processing tools: MapReduce[19] and the Aggregation pipeline[20]. Both the aggregation pipeline and map-reduce can operate on a sharded collection (partitioned over many machines, horizontal scaling). These are powerful tools for performing analytics and statistical analysis in real-time, which is useful for ad-hoc querying, pre-aggregated reports, and more. MongoDB provides a rich set of aggregation operations that process data records and return computed results, using this operations in the data layer simplifies application code and limits resource requirements. The documentation of MongoDB provides a comparison of the different options of aggregation commands[21].

The Aggregation pipeline (introduced in MongoDB 2.2) is based on the concept of data processing pipelines (analogous to the unix pipeline). The documents are processed in a multi-stage pipeline that produces the aggregated results. Each stage transforms the documents as they pass through the pipeline. Output of first operator will be fed as input to the second operator and so on. Despite, being limited to the operators and expressions supported, the aggregation pipeline can add computed fields, create new virtual sub-objects, and extract sub-fields into the top-level of results by using the *project*[22] pipeline operator.

Follwing the pipeline architecture pattern, expressions can only operate on the current document in the pipeline and cannot refer to data from other documents: expression operations provide in-memory transformation of documents. Expressions are stateless and are only evaluated when seen by the aggregation process with one exception: accumulator expressions. The accumulators, used in the *group*[23] stage of the pipeline, maintain their state (e.g. totals, maximums, minimums, and related data) as documents progress through

19 https://docs.mongodb.org/manual/core/map-reduce/
20 https://docs.mongodb.org/manual/core/aggregation-pipeline/
21 https://docs.mongodb.org/manual/reference/aggregation-commands-comparison/
22 https://docs.mongodb.org/manual/reference/operator/aggregation/project/#pipe._S_project
23 https://docs.mongodb.org/manual/reference/operator/aggregation/group/#pipe._S_group

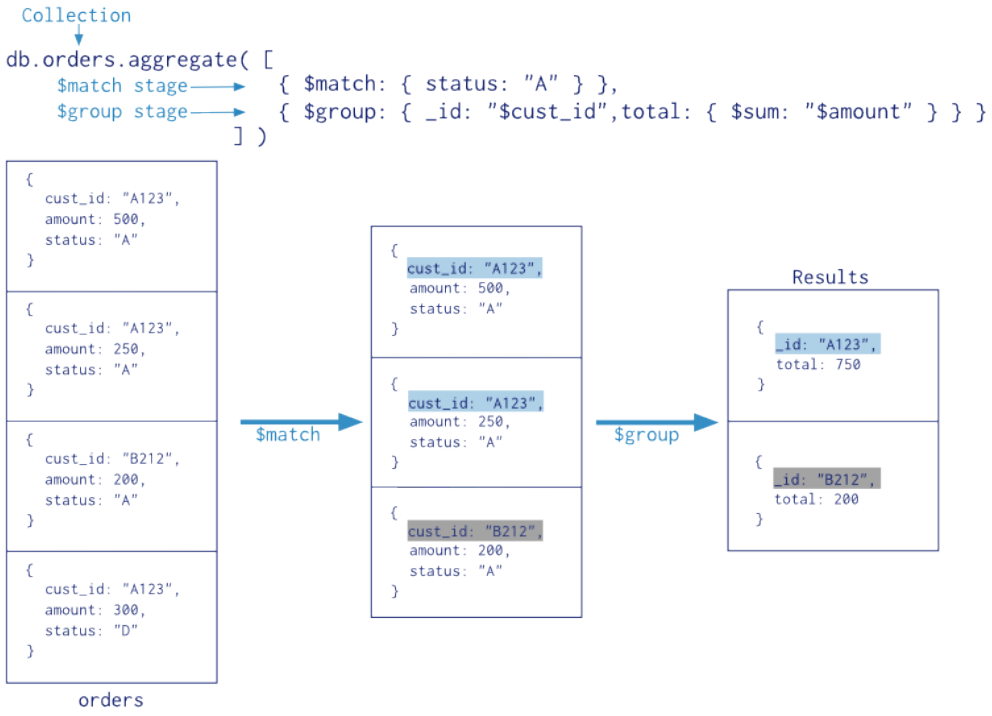

Figure 8.: MongoDB Aggregation Pipeline example.

the pipeline. In version 3.2 (the most recent) some accumulators are available in the *project* stage, but it this situation they do not maintain their state across documents.

2.4 MACHINE LEARNING

In this section, an introduction to the current state of machine learning will be provided. This review will follow a top-down approach. The basic concepts of learning will be introduced, and further in the section an overview of deep neural networks (the main theoretical topic driving machine learning research) will be presented, essentialy from a user perspective. The goal here is to provide insight on how the current machine learning techniques are located in the big data scene, what to expect from them in the near future and how could they help to provide real-time intelligence.

2.4.1 *Introduction to Learning*

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E (Mitchell (1997)). From this formal definition of machine learning, a generalization can be made categorizing such systems as systems that automatically learn

programs from data (Domingos (2012)). As the data volumes grow rapidly this premise becomes more and more attractive, providing alternative to manually constructing the desired programs. Among other domains Machine learning is used in Web search, spam filters, recommender systems, ad placement, credit scoring, fraud detection, stock trading, drug design, among others.

Generally, learning algorithms consist of combinations of just three components. For each of the components the list of options is very large resulting in a variety of machine learning algorithms that is in the order of magnitude of the thousands. The three components are described below (Domingos (2012)):

REPRESENTATION A classifier must be represented in some formal language that the computer can handle. Conversely, choosing a representation for a learner is equivalent to choosing the set of classifiers that it can possibly learn. This set is called the hypothesis space of the learner. The crucial question at this stage is how to represent the input, i.e., what features to use.

EVALUATION An evaluation function (also called objective function or scoring function) is needed to distinguish good classifiers from bad ones. Examples of evaluation functions are: accuracy/error rate, precision and recall, squared error, and likelihood.

OPTIMIZATION a method to search among the classifiers in the language for the highest-scoring one. The choice of optimization technique is key to the efficiency of the learner, and also helps determine the classifier produced if the evaluation function has more than one optimum. The optimization methods are can be combinatorial (greedy search, beam search, branch-and-bound) or continuous (gradient descent, quasi-newton methods, linear and quadratic programming).

Many different types of machine learning exist, such as clustering, classification, regression and density estimation. There is a fundamental difference on the types of algorithms that is related to goals of the learning process. In order to illustrate these differences, the definitions of clustering (unsupervised learning) and classification (supervised learning) are hereby presented (Bagirov et al. (2003)).

Clustering names the process of identification of subsets of the data that are similar between each other. Intuitively, a subset usually corresponds to points that are more similar to each other than they are to points from another cluster. Points in the same cluster are given the same label. Clustering is carried out in an **unsupervised** way by trying to find subsets of points that are similar without having a predefined notion of the labels.

Classification, on the other hand, involves the **supervised** assignment of data points to predefined and known classes. It is the most mature and widely used type of machine learning. In this case, there is a collection of classes with labels and the goal is to label a new observation or data point as belonging to one or more of the classes. The known classes of examples constitute a training set and are used to learn a description of the classes (determined by some a priori knowledge about the dataset). The trained artifact can then be used to assign new examples to classes.

Another definition that is relevant in this context is the concept of reinforcement learning, that is much more focused on goal-directed learning from interaction than are other approaches to machine learning. Reinforcement learning is a formal mathematical framework in which an agent manipulates its environment through a series of actions, and in response to each action, receives a reward value. An agent stores its knowledge about how to choose reward-maximizing actions in a mapping form agent-internal states to actions. In essence, the agent's "task" is to maximize reward over time. Good task performance is precisely and mathematically defined by the reward values (McCallum (1996)).

The goal of these kind of algorithms is to obtain a generalization, however no matter how much data is available, data alone is not enough. Every learner must embody some knowledge or assumptions beyond the data it's given in order to generalize beyond it. This was formalized by Wolpert in his famous "no free lunch" theorems, according to which no learner can beat random guessing over all possible functions to be learned (Wolpert (1996)).

The catch here is the fact that the functions to be learned in the real world are not drawn uniformly from the set of all mathematically possible functions. In fact, very general assumptions are often enough to do very well, and this is a large part of why machine learning has been so successful.

The main problems associated with learning algorithms are the possibility of overfitting over the training data and the "curse" of dimensionality Bellman (1961).

Overfitting it comes in many forms that are not immediately obvious. When a learner outputs a classifier that fits all the training data but fails on most of the data from the test dataset, it has overfit. One way to understand overfitting is by decomposing generalization error into bias and variance (see figure 9). Bias is a learner's tendency to consistently learn the same wrong thing. Variance is the tendency to learn random things irrespective of the real signal. It's easy to avoid overfitting (variance) by falling into the opposite error of underfitting (bias). Simultaneously avoiding both requires learning a perfect classifier, and short of knowing it in advance there is no single technique that will always do best (no free lunch). Generalizing correctly becomes exponentially harder as the dimensionality (number of features) of the examples grows, because a fixed-size training set covers a very small fraction of the input space. Fortunately, there is an effect that partly counteracts the curse as in most applications examples are not spread uniformly throughout the instance space,

but are concentrated on or near a lower-dimensional manifold. Learners can implicitly take advantage of this lower effective dimension, or algorithms for explicitly reducing the dimensionality can be used.

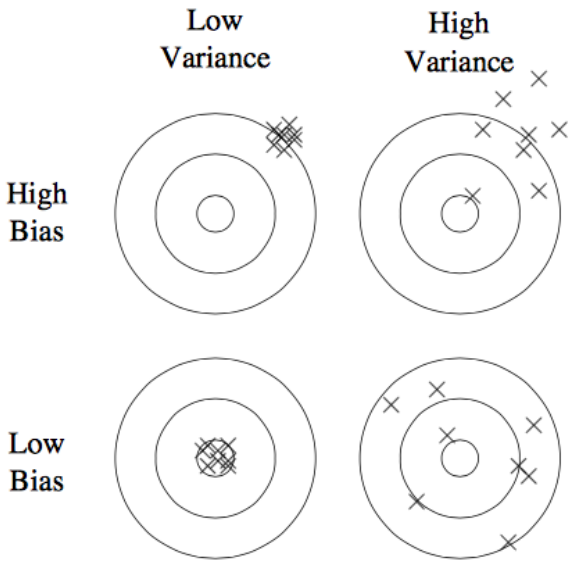

Figure 9.: Bias and variance in dart-throwing (Domingos (2012)).

In the Big Data context, data mining techniques and machine learning algorithms have been very useful in order to make use of complex data, bringing exciting opportunities. For example, researchers have successfully used Twitter to detect events such as earthquakes and major social activities, with nearly online speed and very high accuracy. In addition, the knowledge of people's queries to search engines also enables a new early warning system for detecting fast spreading flu outbreaks (Wu et al. (2014)).

2.4.2 *Deep Neural Network Architecutres*

The recent vast research activities in neural classification have established that neural networks are a promising alternative to various conventional classification methods. The advantage of neural networks lies in four theoretical aspects.

- Neural networks are data driven self-adaptive methods in that they can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model.
- They are universal functional approximators, meaning that neural networks can approximate any function with arbitrary accuracy.

- Neural networks are nonlinear models, which makes them flexible in modeling real world complex relationships.
- Neural networks are able to estimate the posterior probabilities, which provides the basis for establishing classification rule and performing statistical analysis.

A standard neural network (NN) consists of many simple, connected processors called neurons, each producing a sequence of real-valued activations. Input neurons get activated through sensors perceiving the environment (x, y and z), other neurons get activated through weighted connections (α values) from previously active neurons (as it is shown on figure 10).

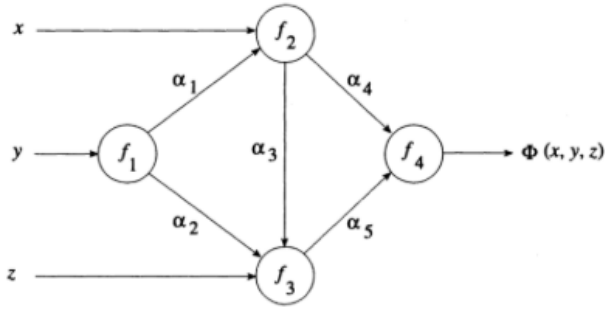

Figure 10.: Functional model of an artificial neural network (Rojas (2013)).

Learning or credit assignment is about finding weights (α values) that make the network exhibit desired behavior. Depending on the problem and how the neurons are connected, such behavior may require long causal chains of computational stages, where each stage transforms the aggregate activation of the network (Schmidhuber (2015)). Therefore, in any model of artficial neural networks there are three elements that are particularly important (Rojas (2013)): the structure of the nodes, the topology of the network and the learning algorithm used to find the weights of the network.

In recent years, **deep artificial neural networks** (including recurrent ones) have won numerous contests in pattern recognition and machine learning. Training of deep neural networks with many layers had been found to be difficult in practice by the late 1980s (Sec. 5.6), and had become an explicit research subject by the early 1990s. However since 2000s, deep learning have finally attracted wide-spread attention, mainly by outperforming alternative machine learning methods such as kernel machines in numerous important applications. In fact, since 2009, supervised deep NNs have won many official international pattern recognition competitions, achieving the first superhuman visual pattern recognition results in limited domains (Rojas (2013)).

These type of architectures are more efficient for representing certain classes of functions, particularly those involved in visual recognition. A deep architecture trades space for time

(or breadth for depth), more layers (more sequential computation), but less hardware (less parallel computation), LeCun et al. (2015).

2.4.3 *Popular Frameworks and Libraries*

Given the current success of deep learning techniques on machine learning tasks, its use has become more widespread. In this subsection the goal is to show some examples of popular frameworks and libraries that support deep learning, particularly deep neural networks. The list of available frameworks includes, but is not limited to, Caffe, DeepLearning4J, deepmat, Eblearn, Neon, PyLearn, TensorFlow, Theano, Torch. Different frameworks try to optimize different aspects of training or deployment of a deep learning algorithm (Bahrampour et al. (2015)).

TensorFlow is an interface for expressing machine learn- ing algorithms, and an implementation for executing such algorithms. A computation expressed using TensorFlow can be executed with little or no change on a wide variety of hetero- geneous systems, ranging from mobile devices such as phones and tablets up to large-scale distributed systems of hundreds of machines and thousands of computational devices such as GPU cards. The system is flexible and can be used to express a wide variety of algorithms, including training and inference algorithms for deep neural network models, and it has been used for conducting research and for deploying machine learning systems into production across more than a dozen areas of computer science and other fields, including speech recognition, computer vision, robotics, information retrieval, natural language processing, geographic information extraction, and computational drug discovery (Abadi et al. (2016)).

Theano is a framework in the Python programming language for defining, optimizing and evaluating expressions involving high-level operations on tensors. Theano offers most of NumPy's functionality, but adds automatic symbolic differentiation, GPU support, and faster expression evaluation. Theano is a general mathematical tool, but it was developed with the goal of facilitating research in deep learning (Bergstra et al. (2011)).

DeepSpark is a distributed and parallel deep learning framework that simultaneously exploits Apache Spark for large-scale distributed data management and Caffe for GPU-based acceleration. DeepSpark directly accepts Caffe input specifications, providing seamless compatibility with existing designs and network structures (Kim et al. (2016)).

H2O[24] is a open source math engine for big data that computes parallel distributed machine learning algorithms. It is distributed as an R package. H2O supports a number of standard statistical models, such as GLM, K-means, and Random Forest. H2O is nurturing a grassroots movement of physicists, mathematicians, and computer scientists to herald the

24 http://www.h2o.ai

new wave of discovery with data science by collaborating closely with academic researchers and Industrial data scientists Arora et al. (2015).

2.5 RELATED PROJECTS

In this section will be presented current projects from different domains that share some of the technical challenges with the defined goal project of this dissertation.

2.5.1 *Financial Services - MetLife*[25]

MetLife is an insurance company that has more than 100 million clients as individuals. Its new subsystem called "The Wall" was in production across MetLife's call centers. The Wall collects vast amounts of structured and unstructured information from MetLife's more than 70 different administrative systems. When a customer calls MetLife to ask about a claim, add a new baby to a policy, or dig into coverage details, the customer representatives use the Wall to pull up every bit of information they need in seconds – name, address, policies, and life events. The challenges here are related to data variety and velocity (on ad-ho queries). Right now, MetLife is creating a real-time analytical system that predicts customer attrition rates, prompting customer reps to offer alternative products or promotions. Additionally MetLife is considering adding social data and data from mobile apps into The Wall to gain an even better understanding of customers.

2.5.2 *Government - The City of Chicago*

Event capture and analysis, crime data management and analytics, citizen engagement platforms, entity catalog and healthcare record management are some of the use cases for Goverment that require Big Data capabilities. An example of a stakeholder for such use cases is The City of Chicago[26]. WindyGrid (from the city of Chicago) is a system that it pulls together seven million different pieces of data from city departments every day, and powers the users with analytics (with visual maps), giving managers insights in real time on city operations. Roadwork updates, trash pickup delays, 911 health emergencies, 311 complaints about noise, public tweets about the minutia of the city's workings, bus locations along their route, traffic light patterns, are collected and are integrated into a real-time geospatial platform. This platform enables the identification of unexpected correlations and potential issues before they develop into bigger problems, and helps coordinate responses among departments to everything from marathons to major snowstorms.

25 http://global.metlife.com
26 https://www.mongodb.com/customers/city-of-chicago

2.5.3 *High Tech - Expedia*[27]

With its new feature (Scratchpad) Expedia, a travel shopping company, automates the note-taking process, intelligently remembers searches, and automates the search for the lowest prices (in real-time). The challenges in this project have to do with the fact that suppliers constantly change inventory and pricing information, creating a huge volume of highly variable data. After putting ""Scratchpad" into production and seeing heavy customer use and feedback, the Expedia team radically changed the schema structure three times. Most relational databases can't keep up with this sort of experimental approach. Only an approach with NoSQL could serve the purposes of this project.

2.5.4 *Retail - Otto* [28]

OTTO is Germany's top online retailer for fashion and lifestyle goods. The company turns over more than €2B per year and has more than two million daily site visitors and offers products from over 5,000 brands. Each of product has a different set of attributes (such as name, color, size) and its price and availability are dynamic, and need to be constantly refreshed to maintain competitive advantage. This results in loading new two million catalog updates per day. Having high variety and high velocity of data Otto had to develop a new approach. The solution is a system that uses MongoDB as the data store.

2.6 SUMMARY

Big data is an evolving field of study. Despite this fact, there are permanent challenges that need to be addressed. In this chapter we analyzed the main stages of the data pipeline from data generation to analytics. The techniques that are most used were introduced as well as some challenges that arise from the Big Data landscape. High-velocity arriving data, big in volume, and heterogeneity are particularly addressed since they are the main data requirements for real-time analytics. In Figure 11 a tree represents the set of concepts that were presented. In this figure MongoDB and MongoDB Aggregation Framework, as well as data mining are the highlighted topic since they will be object of a deeper study during this work.

27 https://www.expedia.com
28 https://www.otto.de

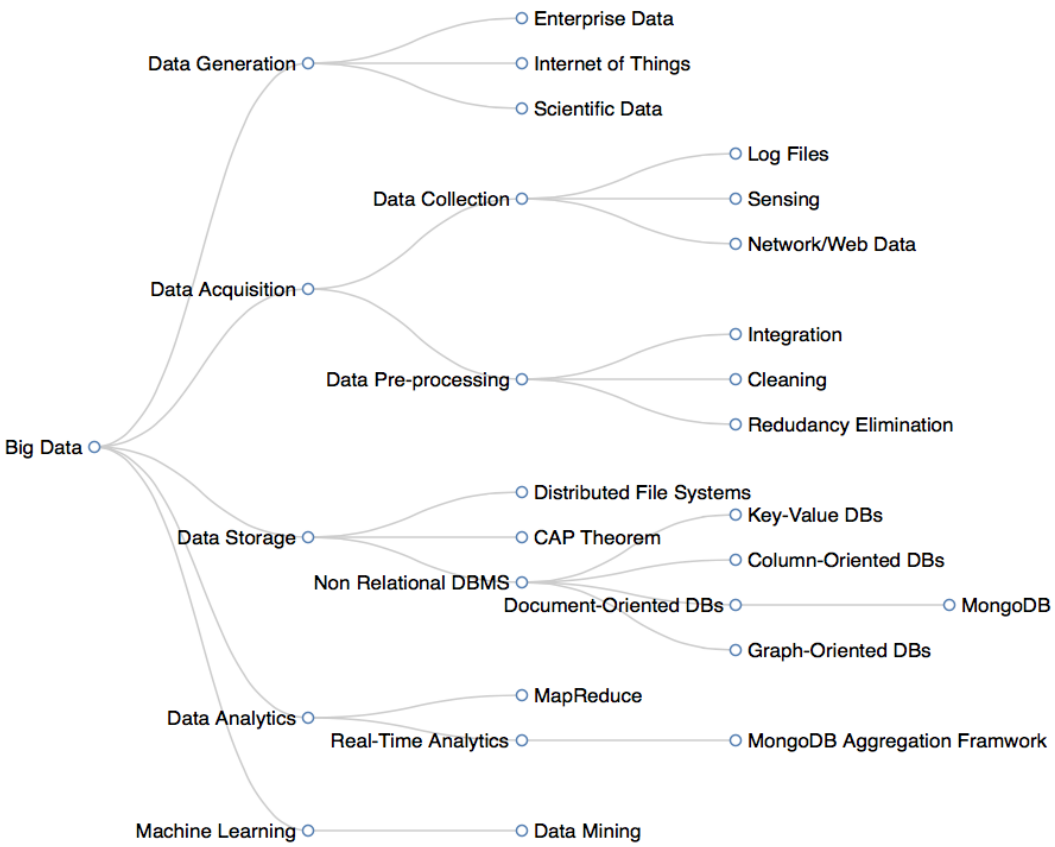

Figure 11.: Overview of the concepts presented in chapter 2.

3

THE PROBLEM AND ITS CHALLENGES

With the advent of the Internet of Things the number of devices that are connected is increasing every day. Consequently, the number of interactions that can generate data is growing as well. Humans tend to show their personality or their state through their actions, even in an unconscious way. Facial expressions and body language, for example, have been known as a gateway for feelings that result in intentions. The resultant actions can be traced to a certain behavior. Therefore, it is safe to assume that a human behavior can be outlined even if the person does not want to explicitly share that information.

The interaction with computers and other technological devices can provide dataset containing records that are relative to unconscious behaviors. The rhythm at which a person types on a keyboard or the movement of the mouse changes when the individual becomes fatigued or under severe stress, as it was established in Pimenta et al. (2013); Carneiro et al. (2012). Moreover, the interaction with smartphones can also provide analogous patterns from diverse sources including a touchscreen (that provides information about touches, their intensities, their area or their duration), gyroscopes, accelerometers, among others.

Gathering metrics on people's behaviours and providing tools for visualization, particularly real time analytics, enables decision making and data-driven actions concerning well-being of individuals (Carneiro et al. (2016)). The trend for data collection regarding sensing on humans is growing and the perspective is for this trend to keep strong, giving the expected growth of IoT (Internet of Things). Furthermore, Big Data tools and techniques enable for this to be done at a large scale without compromising performance and availability.

According to Pimenta et al. (2013), by recording the data from the keyboard and mouse movements it is possible to metrics that enable the prediction of fatigue levels. In this paper the authors introduce a monitoring system for mental fatigue. The system works in a non-invasive way, by analysing a set of features that are acquired from the individual's regular use of a computer (namely from the mouse and the computer). The mental fatigue is quantified by a classifier. By going through a prior learning phase on historical data, the system learns on how to classify the fatigue of an individual user.

Particularly, the following features are considered Pimenta et al. (2013):

KEYDOWN TIME time spent between the key down and the key up events;

ERRORS PER KEY PRESSED number of times the backspace key is pressed, versus the keys pressed;

MOUSE VELOCITY velocity at which the cursor travels;

MOUSE ACCELERATION acceleration of the mouse at a given time;

TIME BETWEEN KEYS time spent between each two keys pressed;

TOTAL EXCESS OF DISTANCE excess of distance travelled by the pointer when considering two consecutive clicks;

AVERAGE EXCESS OF DISTANCE average of the distance excess travelled by the pointer when considering two consecutive clicks;

DOUBLE CLICK SPEED speed of the double click;

NUMBER OF DOUBLE CLICKS number of double clicks in a time frame;

DISTANCE WHILE CLICKING distance travelled by the mouse while dragging objects;

SIGNED SUM OF ANGLES how much the pointer "turned" left or right during its travel;

ABSOLUTE SUM OF ANGLES how much the pointer "turned" during its travel, in absolute terms;

SUM OF DISTANCES BETWEEN PATH AND STRAIGHT LINE considering two consecutive clicks, it measures the distance between all the points of the path travelled by the mouse, and the closest point in a straight line (that represents the shortest path) between the coordinates of the two clicks;

AVERAGE DISTANCE BETWEEN PATH AND STRAIGHT LINE the same as above, but provides an average value of the distance to the straight line;

TIME BETWEEN CLICKS time spent between each two clicks.

By evaluating the mental performance, a sense of the plain use of cognitive skills by an individual can be acquired, and with this information optimize the productivity of an individual while carrying sensitive tasks. This approach also takes a step forward on the development of intelligent working environments, that can take actions on the insights obtained from workers' behaviours and improve the quality of life and their performance on tasks in which they are engaged.

The potential of applying this system in large scale is enormous and Performetric (in development since the August of 2015) is a company that works in order to do so. The

platform developed by Performetric aims to bring the fatigue classifier to big companies in order to improve its overall performance and the well-being of its employees. In order to achieve its objective, the system needs the data engineering that will enable the system to manage massive amounts of data while being able to deal with the variety of possible inputs (other than mouse and keyboard, the possibility to acquire data from). The system must be able to be train the classifiers on large subsets of data and to handle the analytical needs in order to provide the desired insight. The two needs expressed in the last sentence are crucial to the success of the business, and form the main requirements that are to be handled in the present work.

3.1 SYSTEM ARCHITECTURE

In this section, the initial architecture of the system will be presented as it will provide a way to ease the reasoning about the data problems. The relevant views as well as design decisions behind that lead to the implementation will be justified. According to Clements et al. (2002), a software architecture for a system is the structure or structures of the system, which comprise elements, their externally-visible behavior, and the relationships among them. To document the architecture of a system, is a matter of documenting the relevant views and adding documentation that applies to more than one view. Regarding the scope of this work, the reader will be presented the data model (the decisions regarding data storage and management), the structure of components (the overview over the different packages of software that are produced in Performetric), the fatigue classifier (more details regarding the practical implementation of the matter that was introduced in the beginning of this chapter) and a deployment view (the system from a system engineer's point of view, the topology of software components on the physical layer, as well as the physical connections between these components).

3.1.1 *Data Model*

In this subsection the data model will be introduced, as well as some decisions that lead the development of the product.

Entity-Relationships diagram

This diagrams basically show data entities and their relationships, and is useful in this particular case since is agnostic regarding the logical data model (e.g relational model, NoSQL). Among other practical purposes, the data model serves as the blueprint for the physical database, helps implementation of the data access layer of the system, and has strong impact on performance and modifiability. The following E-R (figure 12), shows the

main entities in the system from the data engineer point of view, some entities referring to the operationality of the apps were excluded (session and login data, for example) for clarity purposes.

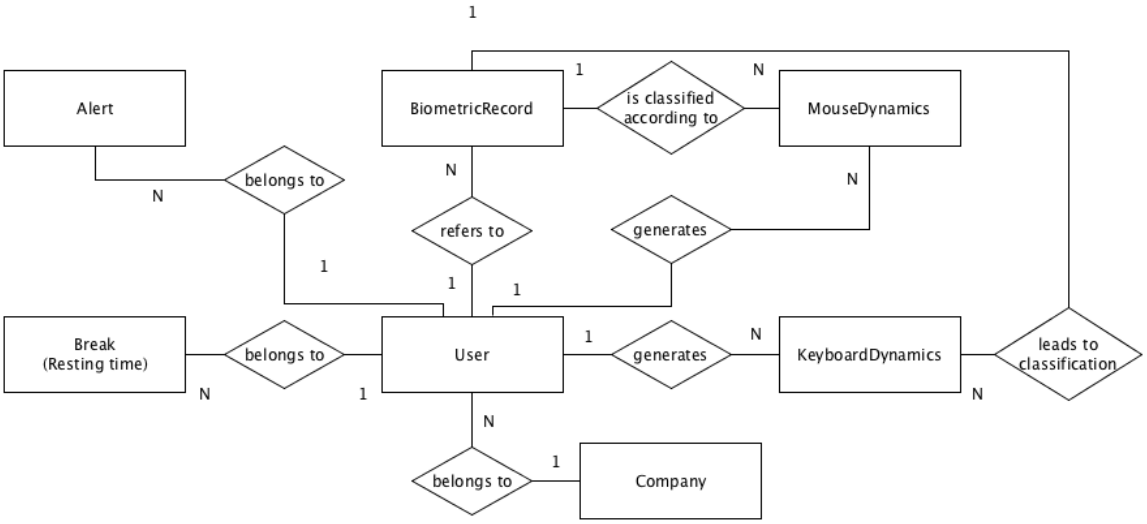

Figure 12.: Conceptual Diagram of the Data Model (according to Chen (1976)).

The diagram is self explanatory regarding the relationships between entities, however some details must be clarified regarding the entities themselves. As it is shown in figure 12, the User is the central entity of the diagram. This entity contains all the attributes that describe the user (personal info such age, sex and attributes regarding the machine). A user is associated with a company (and with a team within a company) and contains data related to the fatigue alerts (issued when a user fatigue level goes beyond the defined threshold) and break times (recorded when a user takes a break in the 30 minutes after a fatigue alert). The MouseDynamics and KeyboardDynamics entities represent the data generated by the user interaction with the mouse and keyboard, respectively. The data in the previous entities is pre-processed and then is applied to the classifier, generating a BiometricRecord that contains the fatigue level average calculated in 5 minutes intervals.

Storage Decisions

The decision regarding the database management system present in this system is major as the database will be under intense write operations loads and is also the basis for analytical purposes. As it was presented in the literature review chapter, conventional databases are limited regarding flexibility (capacity to deal with semi-structured or unstructured data) issues. Also, the relational model shortcomings on scalability frequently cause bottlenecks on big data projects. Having this in mind, and the requirement of a document-oriented database imposed by the development team, there was a last factor that determined the

decision. According to the comparison presented on Chapter 2, MongoDB is the best option regarding read-performance, reliability, consistency and durability, and these criteria were considered as they relate to the analytical capabilities of a database management system.

3.1.2 *System Components*

The following diagram has the goal of showing the different modules that constitute the Performetric software. The software product follows the layered architecture pattern. Within each layer, functionality is related by a common role or responsibility. Communication between layers is explicit and loosely coupled. The diagram in figure 13 represents strict layering (Bass et al. (2012)), meaning that components in one layer can interact only with components direct below it. Inside each layer the software is divided in modules according to its functionality. The division in modules is made according to the loose coupling, high cohesion principle Bass et al. (2012).

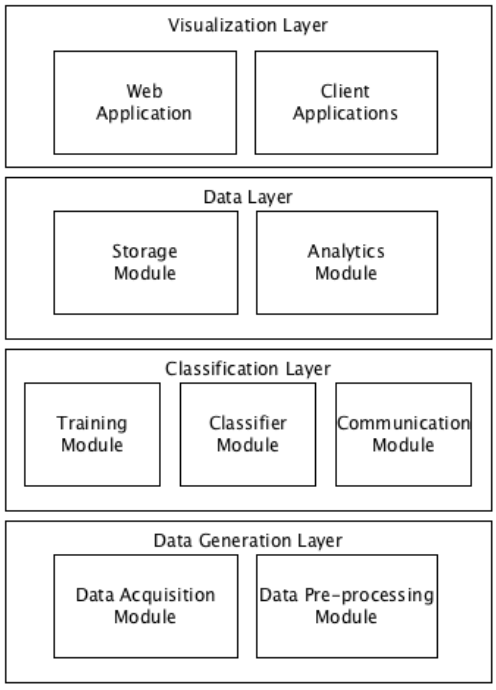

Figure 13.: The deplyment view (showing the layered architecture).

The first implemented layer was the data generation layer. The raw data is generated in the devices, then pre-processed (applying redundancy elimination techniques such as data aggregation and measurements) and stored locally whenever possible (as in smartphones and personal computers) in a SQLite database. The names of the modules in this layer

are self-explanatory, and relate directly to the implemented software packages (currently implemented in Objective-C on OSX, and C# on Windows).

The classification layer contains all the software related to the mental fatigue prediction. This layer contains three modules, being the training and the classifier module the implementation of the learning system and the communication module related to the network API with which the other modules communicate. The classifier is implemented in the R language[1].

The analytics and storage module form the data layer. These modules handle the persistence of the data and querying that serve the analytical use cases. Both these modules and the and the web application are developed in Java. The database system is MongoDB and the aggregations are done in the logic of the application (i.e. outside the database system). The communication across the web are done through a RESTful [2] API.

Client and web applications allow the users to track the mental fatigue across the teams through personalized dashboards. The fatigue alerts are issued in the client applications and allow the users to consult personal informations (as opposed to the web applications where team selection is the most specific filter available).

3.1.3 *Deployment View*

The Deployment view focuses on the physical environment in which the system is intended to run, including the hardware environment your system needs, and the mapping of your software elements to the runtime environment that will execute them. In this work the presentation of this view is relevant as it allows the reasoning about how changes on the physical devices selection can impact in the system as a whole.

As it is shown in figure 14 the deployment of the system is done across three sets of computing devices. The data generating devices, namely smartphones (running Android or iOS), wearable devices (activity trackers) and personal computers run the software that belongs to the data generation layer (see figure 13). The data is synchronized with the web servers in the cloud (namely the Microsoft Azure IaaS). The communication between applications is made over the network over HTTPS. The set of cloud servers is constituted by a server running a database, a server running the classification layer and a server where the J2EE application is running. The data can be visualized in the client machines through OS specific applications (for Microsoft Windows or OSX) or via a web browser.

1 https://www.r-project.org
2 http://docs.oracle.com/javaee/6/tutorial/doc/gijqy.html

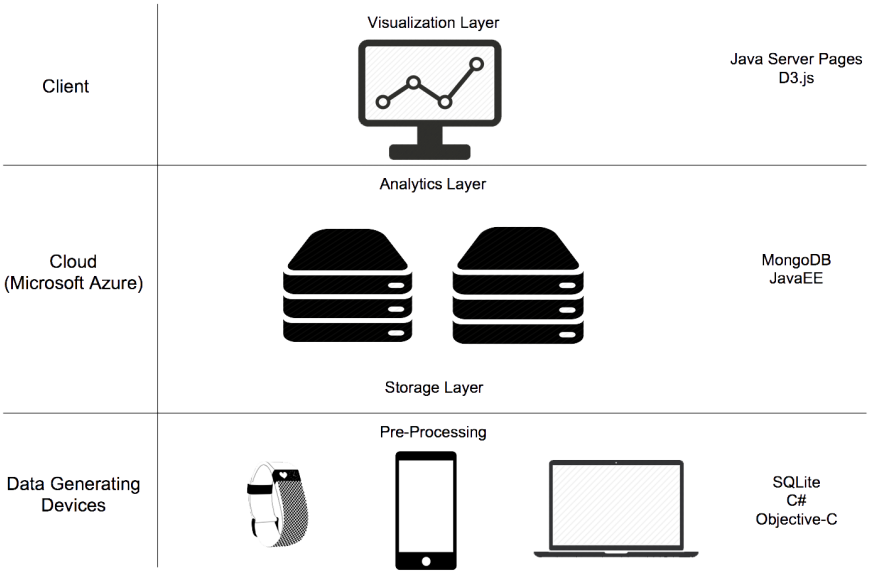

Figure 14.: The deployment view (showing the devices that take part in the system).

3.2 RATE OF DATA GENERATION AND GROWTH PROJECTION

The captured records related to the fatigue status contain fifteen values (represented as doubles) that are a result of applying data redudancy techniques (i.e. aggregation of collected data by calculating values such as mean and variance on the very frequently collected values) that are not exposed here since they is a restriction by the company, and such details do not provide useful information in this context, and additionally contain a timestamp. Therefore, each record needs (15 times 8 bytes, the MongoDB double size plus 8 bytes relative to the timestamp, and 8 bytes relative to two keys that refer the task and user) 136 bytes of storage space. These records are produced every five minutes for each user of the system. As a user is expected to be around eight hours per day (13056 bytes, 12.75 Kbytes) interacting with its desktop/laptop a prediction about the data volumes that need real time processing can be made (see table 2).

	1 user	**100 users**	**10000 users**	**1000000 users**
5 minutes	136 bytes	13.28 Kbs	1.297 MBs	129.7 MBs
1 day	12.75 KBs	1.245 MBs	124.5 MBs	12.159 GBs
1 week	89.25 KBs	8.716 MBs	871.6 MBs	85.115 GBs
1 month	382.5 KBs	37.354 MBs	3.648 GBs	364.8 GBs
1 year	4.545 MBs	454.5 MBs	44.382 GBs	4.438 TBs

Table 2.: Data growth projections.

These estimates numbers are according to the growth prediction of the company for the upcoming years. As it is shown on the table the data volumes are hitting numbers in the orders of terabytes, and this is the main drive for design and implementation of big data handling mechanisms. Together with the engineers at Performetric the topics presented in the next subsections were identified as the sources of possible future bottlenecks. These are precisely the topics that are in analysis in this work, from a data engineer perspective.

3.2.1 *Data Analytics*

The trigger that alerted Performetric's development team for the need of mechanisms for handling large volumes of data appeared when the response time for the analytics queries was getting beyond the acceptable for the web application. Having this in mind, the queries that need to be optimized are divided in two sets. The following set of queries, returns a single double value:

LAST HOUR FATIGUE AVERAGE Given an user, company or team identifier, calculate the average fatigue status across the values obtained in the last hour.

LAST BUT ONE HOUR FATIGUE AVERAGE Given an user, company or team identifier, calculate the average fatigue status across the values obtained in the penultimate hour.

CURRENT DAY FATIGUE AVERAGE Given an user, company or team identifier, calculate the average fatigue status across the values obtained in the current day.

LAST DAY FATIGUE AVERAGE Given an user, company or team identifier, calculate the average fatigue status across the values obtained in the last day.

CURRENT WEEK FATIGUE AVERAGE Given an user, company or team identifier, calculate the average fatigue status across the values obtained in the current week.

LAST WEEK FATIGUE AVERAGE Given an user, company or team identifier, calculate the average fatigue status across the values obtained in the last week.

CURRENT MONTH FATIGUE AVERAGE Given an user, company or team identifier, calculate the average fatigue status across the values obtained in the current month.

LAST MONTH FATIGUE AVERAGE Given an user, company or team identifier, calculate the average fatigue status across the values obtained in the last month.

The following set of queries, returns an array of double values:

MONTH FATIGUE AVERAGE GIVEN A YEAR Given an user, company or team identifier, calculate the average fatigue status for each month in a given year.

DAY FATIGUE AVERAGE GIVEN A MONTH Given an user, company or team identifier, calculate the average fatigue status for each day in a given month.

DAY FATIGUE AVERAGE GIVEN A WEEK Given an user, company or team identifier, calculate the average fatigue status for each day in a given week.

3.2.2 *Data Insertion*

On the period of time when the of the data requirements were gathered there was no evidence of performance issues regarding the writing operations. However, as it is shown in table 2, the rate of data generation can be identified as a potential issue on the system's performance. As the number of users increases the number of records that have to be stored in the period of five minutes increases linearly. Table shows an estimative based of the possible growth on the number of users:

	1 user	**100 users**	**10000 users**	**1000000 users**
Number of Records (5 minutes)	1	100	10000	1000000
Size of Data	136 bytes	13.28 KBs	1.297 MBs	129.7 MBs

Table 3.: Data growth projections.

Table 26 shows an estimative based of the possible growth on the number of users, and according to these estimates, at one million number of users the same number of records must be inserted in 5 minutes, in average. Although the optimization of the data writing operations is out of the scope of this dissertation's work plans, some hints on how to handle insertions can be exposed.

By having, for example, a queue (such as RabbitMQ) assuring a constant flow of records the value of 3334 records (1000000 records in 300 seconds) per second can be obtained as the minimum required write throughput.

MongoDB provides a method for storing data across multiple machines (horizontal scaling) denominated sharding (see figure 15). MongoDB uses sharding to support deployments with very large data sets and high throughput operations, and the documentation presents the scaling as being linear in both write and read operations throughput. Sharding reduces the number of operations each shard handles. Each shard processes fewer operations as the cluster grows.

A sharded cluster consists of shards, config servers and client instances. Each shard is either a single mongo daemon (mongod) instance or a replica set. Each config server is a mongod instance that holds metadata about the cluster. The metadata maps chunks or collection portions to shards. The mongos instances route the reads and writes from client applications to the shards. Applications do not access the shards directly.

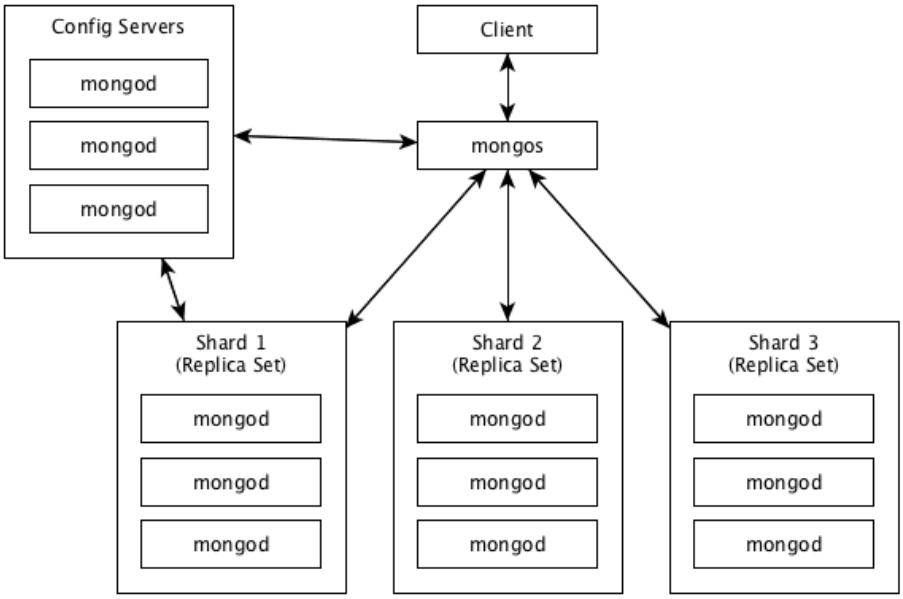

Figure 15.: A representation of a sharded deployment in MongoDB.

To provide high availability and data consistency, in a production sharded cluster, each shard should be a replica set. As argued in MongoDB documentation, the implementation of this system in the early stages of the application is considered premature optimization and may even degrade performance, however it is on the roadmap of the company.

3.2.3 *Classifier Training*

The learning algorithm is the core of Performetric system (Pimenta et al. (2016)). The project started by asking whatever it would be possible to use the data resulting from interactions of an user with his machine peripherals (mouse and keyboard) in order to predict the fatigue level (on a scale of 1 to 7). Using a supervised learning algorithm, based on an artificial neural network, was an early decision that led to a classifier that showed satisfactory results.

Given the set of documents that contain the characterization of human-computer interactions, the goal of the learning system is to improve the classifier accuracy on the task of classifying the Fatigue Levels associated with new records. In order to do so, Performetric uses the vanilla implementation of R neural networks, whose parameters have been optimized, using for that purpose a set of already labeled records.

As the flow of data obtained from the users interaction is constant, there is an opportunity for continuously improving the results of the classification task. However, the increasing of

data volumes and the rate of data arrival itself bring challenges regarding the performance of the learning system.

The requirements regarding this topic state that there must exist a different neural network for each activity (the activity parameter on each document describes what kind of task the user is performing based on the current opened application) and that the cycle for training the networks must be less than a week (meaning that the data generated during a week must be fed to the learning system at the end of the week).

3.3 SUMMARY

After analysing the existent architecture of Performetric's software system, the focus of where the optimization should be done has been identified. The ability of doing low-level analytics operations and the ability to scale the capacity of the learning system are the key topics that must be addressed in the system. Along the big data requirements, this chapter provides a documentation for the architecture of the system that can be useful since there was no such artifact at the moment that this work started.

4

CASE STUDIES

During the development of this work some experiments were made. For each of the data stages presented on section 3.2, alternative versions of the implementations were designed, implemented and evaluated. The rationale behind each of the main decisions regarding design and implementation of the system are hereby documented.

Roughly, half of this chapter is focused on the optimization of the analytical capabilities of the system. The reading throughput is studied and optimized using the capabilities of the Mongo Aggregation Framework and a caching system. The remainder of the chapter is about performance optimization of the classifier learning system, particularly exploring the use of a different neural networks implementation.

4.1 EXPERIMENTAL SETUP AND ENHANCEMENTS DISCUSSION

This section introduces the reader to the hypothetical improvements tested in the experiments. The proposed upgrades to Performetric's data architecture are hereby presented and discussed.

4.1.1 *MongoDB Aggregation Framework*

As it was presented in subsection 2.3.3, MongoDB provides two power tools for performing analytics and statistical analysis in real-time. While MapReduce, through custom JavaScript functions, provides greater flexibility, it is less efficient and more complex that the aggregation pipeline[1]. These were the main factors that determined the usage of the aggregation pipeline over the MapReduce.

The pipeline uses native operations within MongoDB and, according to the documentation, it makes its use more efficient than external function calls. The most basic pipeline stages (stage operators in the documentation) provide filters that operate like queries and document transformations that modify the form of the output document. For a simple

1 https://docs.mongodb.org/manual/aggregation/

count grouped by some attribute value there is an operator called *$group*. This is the exact analog of GROUP BY in SQL where a new document with *_id* field indicating what field we are grouping by is created. The most common operator to use before (and frequently after) *$group* is *$match* - this is exactly like the find method and it enables the aggregation of only a matching subset of the documents, or to exclude some documents from the result. Some examples of *$group* operators (expression operators in the documentation) are *$sum*, *$avg*, *$max* and *$min*, whose name is self-explanatory.

Another example of pipeline operator is the *$sort* which performs the operation indicated by its name (sorts the set of documents according to the value(s) of a set of fields), along with it there are also *$skip* and *$limit* (which removes, respectively, the set of first and last documents indicated by the value passed as an argument). There is another powerful pipeline operator called *$project* which enables the inclusion/exclusion of certain fields, and the creation of new fields based on values in existing fields. For example, math operators can be used to add together values of several fields before finding out the average, and string operators can be used to create a new field that is a concatenation of some existing fields.

The introduced operators, despite being a scratch on the surface of what can be done with aggregations, enable the creation of powerful queries, such as the ones presented on this work. A more detailed view over the set of operators can is shown on MongoDB documentation [2].

Query Development

The set of developed queries follows two types of structure that are represented on figures 16 and 17. The difference lays in the presence of a *$project* stage that is only necessary for the type of queries returning an array of values.

On both structures, the first stage is a *$match* that removes the documents with values of *_id* (that contains an embedded timestamp of its creation time) outside the interval limits specified as parameters. Additionally, the *$match* stage filters the documents according to the specified set of username and/or company name and/or team name. On the queries that return a single value the second (and last) stage is an instance of a *$group* operator that uses the *$avg* operation in order to calculate the average value of the *FatigueStatus* for each of the matched entities (users, companies and/or teams).

As for the queries that return arrays as results (structure represented in figure 17) there is an additional stage on the pipeline. The *$project* stage occurs after the *$match*, and has the function of adding a label that has the value of the date in the desired level of granularity. In the given an example the value of the label is name of the month, as the goal is to calculate the average value for each month in given a year. The last stage of the pipeline

2 https://docs.mongodb.com/v3.0/reference/operator/aggregation/

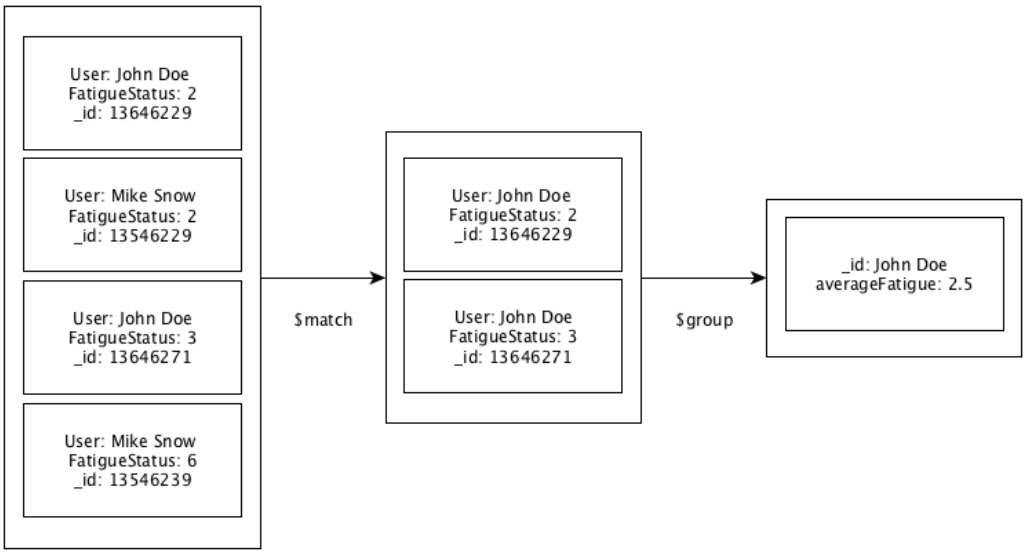

Figure 16.: Example of an aggregation pipeline (includes 2 stages).

(*$group*) uses the*$avg* operation in order to calculate the average value grouping by each of the values of the label given on the *$project* stage. The piece of pseudocode shown in figure 18 represents an example of an implementation of using a simple query to retrieve all the documents that match both the desired time interval and the entity passed as an argument (in this case the company name). In this case, the calculation of the mean value is done on application side, instead of being done on the DBMS.

On the example shown in figure 19 the query is made using the *aggregate* method, whose result contains the desired value (the average of the FatigueStatus values), since it is calculated on the MongoDB side. The *match* and *group* objects relate respectively to the *$match* and *$project* stages on the aggregation pipeline. The referred objects are then attached on a list that is sent through the MongoDB client.

Case Operator

The implementation of the queries on the Mongo Aggregation Framework required some work regarding the ability to group records by intervals in the domain of a specific attribute. In order to do so, an additional stage on the pipeline needed to be implemented (*$project*), enabling the creation of a new attribute with the value referring the interval in which the original records belong. Mongo Aggregate Framework, however, does not provide an operator such as the *switch* operator Kernighan et al. (1988).

By defining a Java function (see figure 20) that recursively creates chained *if* statements where the conditions check if a certain value is within the specified range, we can replicate the behavior of a switch statement that checks for values within intervals. The defined

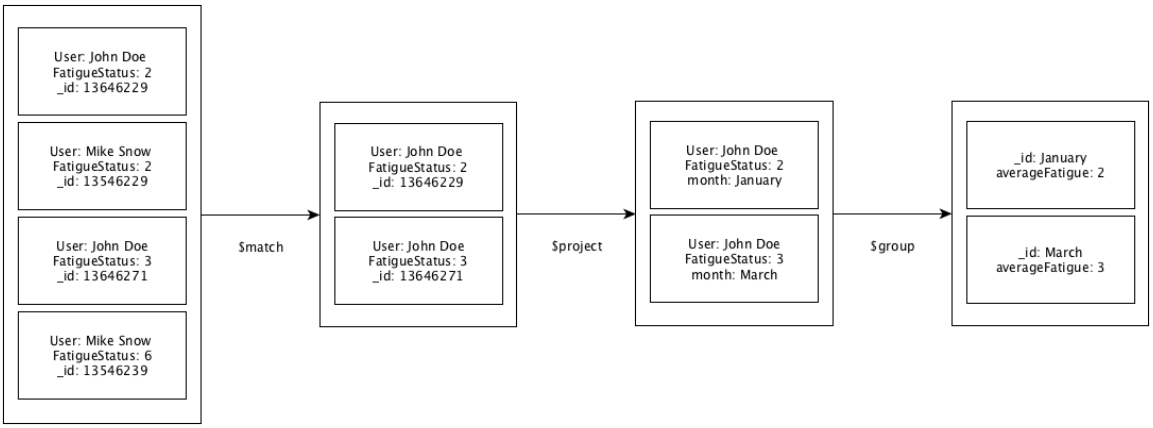

Figure 17.: Example of an aggregation pipeline (includes 3 stages).

```
Double averageFatigueByCompanyCurrentMonth(String company, String timezone) {

    Date date = TimeConverter.getMonthInit(new Date(), timezone)
    Query<FatigueStatus> query  = dataAccessObject.createQuery()
    q.field("_id").greaterThanOrEq(new ObjectId(date));
    q.field("company").equal(company)

    List<FatigueStatus> records = q.asList()

    return records.mean()
}
```

Figure 18.: Pseudocode representing the implementation of a simple MongoDB query.

function has as arguments, a list (containing the limits of the filter intervals) and an integer that specifies the current (on each recursive step) interval conditions being defined.

MongoDB and Storage Engines

To improve writing performance several MongoDB features may be took into account when customizing the operating system in the servers that form the replica sets (Tugores and Colet (2013)). One of the first considerations is that MongoDB uses write ahead logging to an on-disk journal to guarantee write operation durability and to provide crash resiliency. If the filesystem does not implement journaling and mongod exits unexpectedly the data can be in an inconsistent state. To avoid this issue *ext4* can be used since it implements journaling. Besides choosing a convenient filesystem, writing speed can be increased by mounting the file system where the database is located with the option noatime (Zadok

```
Double averageFatigueByCompany(String company, Date init, Date end) {

    BasicDBList list = new BasicDBList()
    list.add(new BasicDBObject("company", company))
    list.add(new BasicDBObject("_id", new BasicDBObject("$gt", new ObjectId(
        init)))
    list.add(new BasicDBObject("_id", new BasicDBObject("$lt", new ObjectId(
        end)))

    BasicDBObject match = new BasicDBObject("$match", new BasicDBObject("$and"
        , list))
    BasicDBObject group = new BasicDBObject("$group", new BasicDBObject("_id",
         "$company")
        .append("avg", new BasicDBObject("$avg", "$FatigueLevel")))

    List<BasicDBObject> pipeline = new ArrayList<>()
    pipeline.add(match)
    pipeline.add(group)

    Document output = collection.aggregate(pipeline).first()
    return output.getDouble("avg")
}
```

Figure 19.: Pseudocode representing the implementation of a MongoDB aggregation framework query.

et al. (2015)) avoiding the logging of the record of the last time the file has been accessed or modified.

Another aspect in the data architecture that must be addressed is related to the storage engines of the DBMS. As the there is no longer a universal database storage technology capable of powering every type of application built by the business, MongoDB provides pluggable storage engines, namely WiredTiger and MMAPv1. Multiple storage engines can co-exist within a single MongoDB replica set, making it easy to evaluate and migrate engines. Running multiple storage engines within a replica set can also simplify the process of managing the data lifecycle. This approach significantly reduces developer and operational complexity compared to running multiple databases. Therefore, users can leverage the same MongoDB query language, data model, scaling, security and operational tooling across different applications, each powered by different pluggable MongoDB storage engines. WiredTiger (default storage engine starting in MongoDB 3.2) provides significant benefits in the areas of lower storage costs, greater hardware utilization, and more predictable performance [3] and, consequently should be used in this system.

3 https://docs.mongodb.org/manual/core/storage-engines/

```
Condition switch (List dates) {
    Condition condition = new Condition()

    if (dates.size() > 1) {

        Interval interval = new Interval("$_id", first(dates), second(dates))
        condition.if = interval
        condition.then = first(dates)
        Condition elseCondition = switch(tail(dates))
        condition.else = elseCondition

    } else {

        condition.if = "true"
        condition.then = "Out of bounds."

    }
    return condition
}
```

Figure 20.: Pseudocode representing the implementation of the *case* operator.

4.1.2 *Caching the queries' results with EhCache*

Additionally to the improvement of the queries' running time, there was the opportunity for optimization on application side. The proposed solution was to include a cache for the queries' results. A cache can be generally defined as a collection of temporary data that either duplicates data located elsewhere or is the result of a computation. Data that is already in the cache can be repeatedly accessed with minimal costs in terms of time and resources. Reducing the response time while also reducing server load were the main goals of this development stage.

During the analysis of the system there was the opportunity to check the web platform (the data visualization layer) logs, and this enabled the inference of some insights on its usage. This was the main factor that drove the design of the caching system.

The built cache is part of the Java application (installed using Maven) and was built using the Ehcache [4]. Alongside with being the most widely-used java cache it is open source, it supports in-process/out-process (and mixed), and has a Java type-safe API (Ehcache v3). From the provided data (web application logs) the observed number of users regularly logging on the web application was around one hundred. As it is suggested in ehc the Pareto's law makes a sufficient approach to guess the cache sizes. By defining cache sizes as around 20% of the total query requests (by the Pareto's law) 80% of the results from the queries are expected to be a cache hit (when a data element is requested from cache

4 http://www.ehcache.org

and the element exists for the given key). For each cache, there is a similar amount of the storage allocated off the heap (not subject to garbage collection). These act as a second level cache (slower response time than first level), that were idealized as useful for values that are seldom used.

Therefore, by calculating the total number of different queries in a defined amount of time a guess can be done on how big should be the cache sizes on this early stage of the application. Hereupon, there was a final parameter that needed to be tuned on the caches, the time-to-live (expiration time) of the saved records. According to this, there were defined two types of caches: the first save the results from queries that need refresh every five minutes (such as current hour, current day, current month), and the second save results from queries that have no expiry time (records are refreshed using a last recently used policy). For each of the two types there are two caches: one for single value results and other for arrays.

An example of the usage of the cache is shown in figure 21 the method. The *cache* element is an instance of a singleton object where the caches are defined and initialized.

```
public double averageFatigueByCompanyCurrentMonth(String company, String tz) {
    Date initDate = TimeConverter.initMonthDateTz(new Date(), tz);
    String init = initDate.getTime().toHexString();
    CacheElement cacheElement = new CacheElement(company, initDate.getYear(),
        initDate.getMonth());

    if (cache.getDoubleCacheCurrent(cacheElement) != null) {
        return cache.getDoubleCacheCurrent(cacheElement);
    }

    Double avg = averageFatigueByCompany(company, init);
    cache.putDoubleCacheCurrent(cacheElement, avg);
    return avg;
}
```

Figure 21.: Example of usage of the defined cache (Java code).

4.1.3 *H2O Package*

The setup presented on chapter 3 includes a learning algorithm. In order to optimize performance and according to what was presented o section 2.4, there was an opportunity for experimenting with different machine learning libraries in order to improve the classifier training performance.

Hereupon, and given the Performetic's team expertise using the R programming language and respective environment, there was the preference on using the H2O package

(previously introduced) in order to reach the desired goals. Thus, the only change on the software, regarding the deployed version of Performetric's system, was made in the code respective to the training of the classifier.

For this experimental procedure the number of rows in the provided dataset is 10000. The dataset was initially split in two, generating the training dataset (by including 75% of the original rows, randomly selected) and the testing dataset (by including the remaining 25% of the original rows). This was the selected option for results validation, in opposition to, for example, cross-validation.

The H2O packages features a deep neural network API that enable the easy deployment of a classifier based on this kind of algorithms. The R code respective to the definition of the neural network is shown on figure 22.

```
predictors <- c( 'Performance.KDTMean', 'Performance.MAMean', 'Performance.
    MVMean', 'Performance.TBCMean', 'Performance.DDCMean', 'Performance.
    DMSLean', 'Performance.AEDMean', 'Performance.ADMSLMean')

net <- h2o.deeplearning(
  training_frame=trainset,
  x=predictors,
  y='FatigueLevel',
  activation="Rectifier",
  hidden = c(40,25),
  epochs = 500
)
```

Figure 22.: Example of usage of neural networks with H2O (R code).

The *training_frame*, *x* and *y* parameters refer to the selection of the dataset, the naming of the features and the definition of the label feature, respectively. As for the rest of the parameters:

ACTIVATION A string indicating the activation function to use. Must be either "Tanh", "TanhWithDropout", "Rectifier", "RectifierWithDropout", "Maxout", or "MaxoutWithDropout"

HIDDEN The schema of the hidden layers in the neural network.

EPOCHS How many times the dataset should be iterated (streamed).

These parameters have been optimized using the grid search hyper-parameter tuning included in H2O. The machine where the tests were run has the same specifications as the machines that were used in the experiments regarding query optimization (see subsection 4.2.1). As for the results, beyond the running time, were recorded the values for the root-

mean-square deviation (rmse), the mean square error (sme), the percent bias (pbias) and the variance (var).

4.2 TESTING SETUP

This section introduces the reader to the setup used in order to test the proposed upgrades to Performetric's data architecture.

4.2.1 *Physical Setup*

The testing setup used in this experiment is similar to what is present in the Performetric's system. A java application containing the benchmarks runs in an isolated machine (in Microsoft Azure), and a connection is made with another machine that contains MongoDB's replica set primary member. Each of the machines present in the replica set (and the client, aswell), are part Microsoft Azure Infrastructure as a Service (IaaS) solution. The specifications are equal in each of the machines, and are the following: 3.5 GB of RAM, a primary storage disk with the capacity of 50 GB (solid-state drive) and two 500 GB mechanical disks as secondary storage.

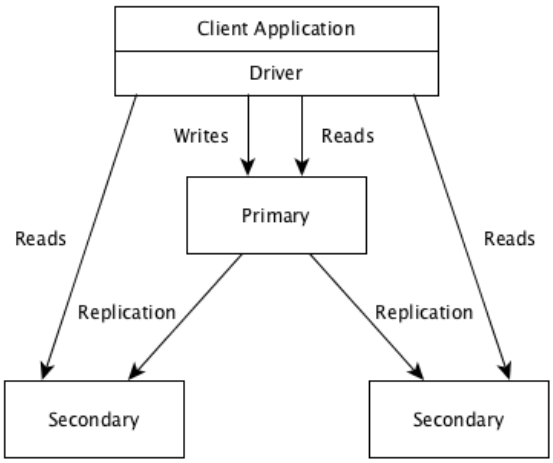

Figure 23.: MongoDB replica set topology.

Database replication with MongoDB adds redundancy, helps to ensure high availability and increases read capacity. Regarding these attributes MongoDB provides master-slave replication and replica sets [5]. Nowadays, replica sets are recommended for most use cases. The standard (and minimum) number of replicas in a set is three (see figure 23). One being the primary (the only one with writes allowed), and two secondaries, since an odd

5 https://docs.mongodb.org/manual/replication/

number of members ensures that the replica set is always able to elect a primary. Whenever, the primary becomes unavailable, an election is triggered selecting one of the remaining secondaries as the new primary (see figure 24). The setup used in this experiment includes a three-member replica set.

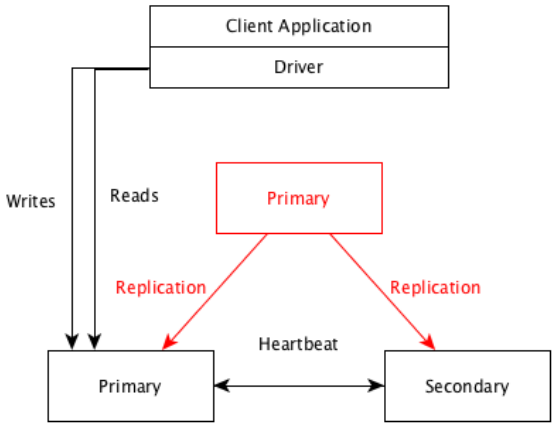

Figure 24.: MongoDB replica set topology (after primary member becomes unavailable).

Each of the machines in the presented set runs a LTS version of Ubuntu (14.04) and are part of the same network (an option provided by Microsoft Azure), have MongoDB 3.0 version and have the Java SE Development Kit 8 (JDK 8) installed.

4.2.2 *Data Collection*

In order to make accurate measurements that may lead to an effective analysis of the time elapsed during the data processing, a set of benchmarks was setup using the JMH - Java Microbenchmark Harness toolkit. For a the set of methods defined in the QueryListInterface interface, three classes were coded containing, respectively, the code related to the existing solution, the solution using Mongo Aggregation Framework, and the solution that saves results of a query in a cache. An example of usage of JMH is provided in figure 25.

The mode and the precision (different orders of magnitude, such as nanoseconds, microseconds, milliseconds and seconds) of the measurements can be specified for each benchmark. In the presented example the time unit is nanoseconds and the mode is SimpleTime. The set of modes available in JMH are presented below:

THROUGHPUT Measures the number of operations per second, meaning the number of times per second your benchmark method could be executed.

AVERAGE TIME Measures the average time it takes for the benchmark method to execute (a single execution).

SAMPLE TIME Measures how long time it takes for the benchmark method to execute, including max, min time etc.

SINGLE SHOT TIME Measures how long time a single benchmark method execution takes to run. This is good to test how it performs under a cold start (no JVM warm up).

ALL Measures all of the above.

Regarding this study case, the used modes are: Throughput, AverageTime. Both Throughput and AverageTime modes were ran because, despite being reciprocal, provide useful information on this context. The option for these Modes over SingleShot and SimpleTime was made due the consistency. Benchmarks ran over bigger periods of time are more likely to minimize the effect of different conditions for analogous queries.

At a benchmark level (all threads sharing the same instance), states are defined (using the @State annotation) and contain the setup of the benchmark (driver initialization and database connection). Each of the benchmark methods in a bench has access to the respective state (passed as a parameter) and, thus, the setup is only done once in each fork.

The output produced by running the Java ARchive (.jar) file is similar to what is presented in figure 26. For each defined benchmark a referent to a measurement is ran twenty times (10 warmup iterations, and 10 recorder iterations) for each of the ten forks (making up 200 measurements in total). By warming up, the effects of caching warming up on the database are expected to be mitigated.

```
@State(Scope.Benchmark)
public static class BenchmarkState {
    QueryListInterface q = new MongoAggregateImpl();
}

@Benchmark
@BenchmarkMode({Mode.SampleTime})
@OutputTimeUnit(TimeUnit.NANOSECONDS)
public double averageFatigueByCompanyLastHour(BenchmarkState state) {
    return state.q.averageFatigueByCompanyLastHour("Performetric");
}
```

Figure 25.: Example of JMH usage (Java code).

Data Treatment

Regarding data treatment and presentation little effort was required since the output was delivered in a readable format. A simple AWK script (see figure 27) in order to filter out

```
# Run progress: 0.81% complete, ETA 13:20:38
# Fork: 10 of 10
# Warmup Iteration   1: 2016-03-11 16:15:55 INFO  cluster:71 - Cluster created
     with settings {hosts=[maindb.cloudapp.net:27017], mode=SINGLE,
    requiredClusterType=UNKNOWN, serverSelectionTimeout='30000 ms',
    maxWaitQueueSize=60000}
# Warmup Iteration   1: 0.610 ops/s
# Warmup Iteration   2: 7.437 ops/s
# Warmup Iteration   3: 8.531 ops/s
# Warmup Iteration   4: 8.361 ops/s
# Warmup Iteration   5: 8.977 ops/s
# Warmup Iteration   6: 9.627 ops/s
# Warmup Iteration   7: 9.429 ops/s
# Warmup Iteration   8: 9.436 ops/s
# Warmup Iteration   9: 9.577 ops/s
# Warmup Iteration  10: 9.509 ops/s
Iteration   1: 9.827 ops/s
Iteration   2: 10.092 ops/s
Iteration   3: 9.908 ops/s
Iteration   4: 9.930 ops/s
Iteration   5: 9.557 ops/s
Iteration   6: 9.976 ops/s
Iteration   7: 9.467 ops/s
Iteration   8: 9.792 ops/s
Iteration   9: 9.709 ops/s
Iteration  10: 10.036 ops/s
```

Figure 26.: Example of output generated by JMH benchmarks.

the summarized results. Additionally the features provided by Sublime Text enabled the conversion of the data to LaTeXtables and diagrams.

```
{
    if ($0 ~ "# Benchmark mode:") print $0;
    if ($0 ~ "# Benchmark:") print $0;
    if ($0 ~ "Result:") print $0;
    if ($0 ~ "Statistics:") print $0;
    if ($0 ~ "Confidence interval") print $0 "\n";
}
```

Figure 27.: Piece of AWK code used for parsing the output generated by JMH.

4.3 RESULTS

In this section the results obtained are shown to the reader. In each subsection, the performance results of different parts of the system are presented. Whenever it is appropriate a comparison between the existing and proposed solution is shown.

4.3.1 *Data Aggregation*

In the following set of figures, the results of the tests ran on the queries (see subsection 3.2.1 for the list of queries) are plotted. As it was mentioned on subsection 4.2.2 the chosen modes were Throughput and Average Time. The thorughput is measured over a period of one second, as for the average time is calculated based on a set of 200 samples for each benchmark.

For each of the queries, the average times and the measured throughput of the current implementation are shown side-by-side with the results of the implementation that uses MongoDB aggregate. The goal is to provide insight on how the performance changed after the proposed enhancements. For each graph, the respective values can be consulted on Appendix A in sections related to each of the topics in this subsection. The results of queries for which the granularity of the time filter is the hour are shown on section A.5. This set of plots shows that results are fairly similar and were isolated because the intervals are much smaller than the others (day, week, month).

In the figures 28 and 29 are shown the results of the benchmarks ran on the queries that filter the results by a company name. Each of the queries in this set returns a double value resulting of the filtering the Fatigue Status collection by a time interval (specified in labels presented on the charts) and subsequent calculation the respective average value. The first pair of charts (see figure 28) shows the results for the queries for open intervals (filters data only by the beginning of the interval). As for figure 29 is shows the results for queries where the filtered documents are inside a closed interval (between the beginning and end of the respective time span).

The same presentation pattern is followed for the queries that filter the Fatigue Status collection by team name (see figures 30 and 31) and by user name (see figures 32 and 33).

Company Queries Execution Performance

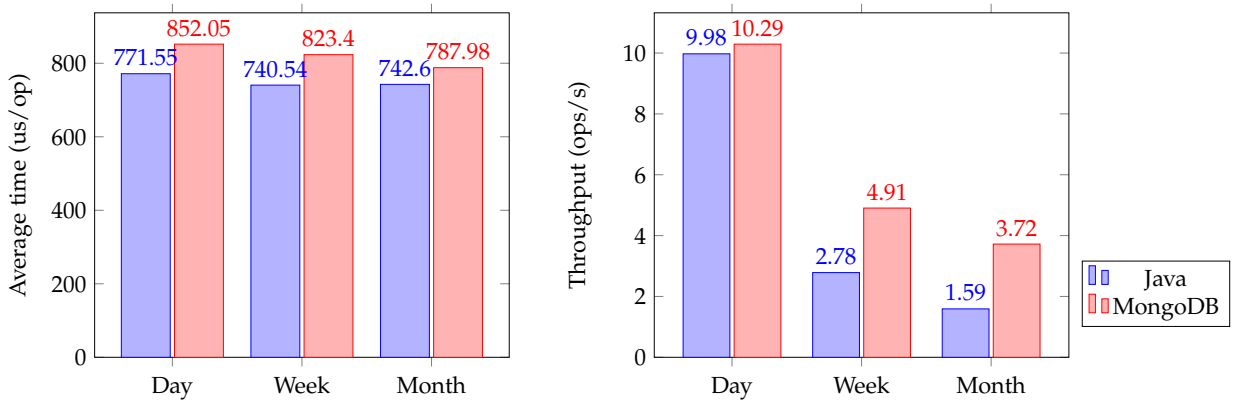

Figure 28.: Comparison between Java and MongoDB aggregation framework implementations (queries about a specific company name) for a current time interval (see subsection 3.2.1).

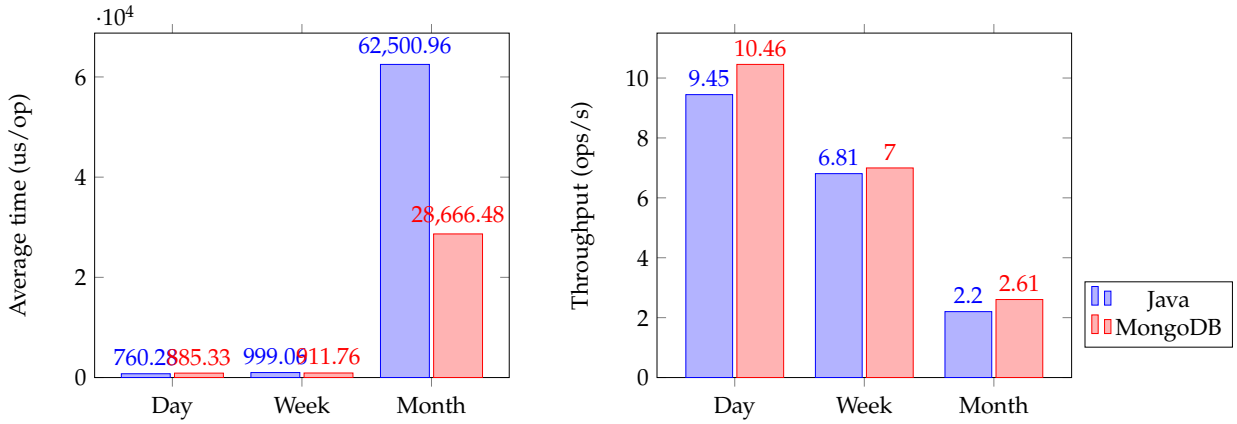

Figure 29.: Comparison between Java and MongoDB aggregation framework implementations (queries about a specific company name) for a past time interval (see subsection 3.2.1).

Team Queries Execution Performance

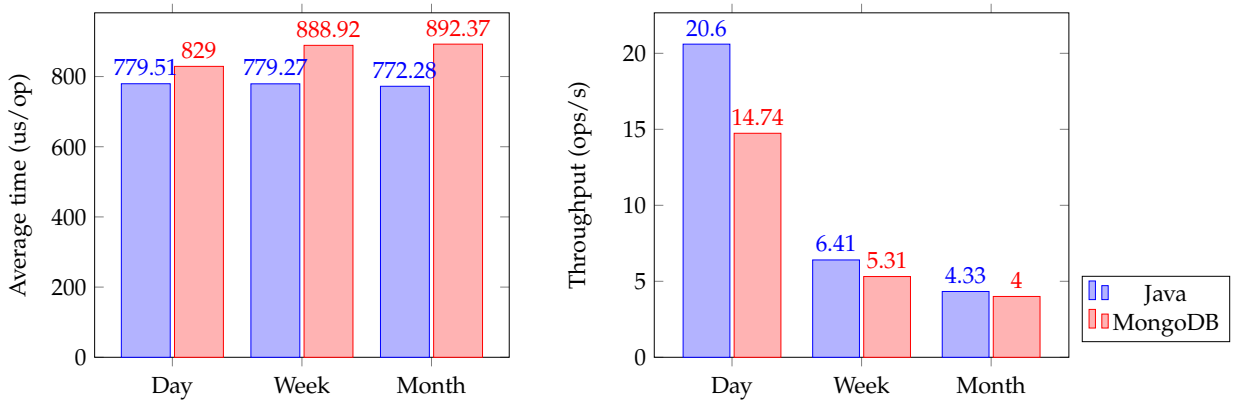

Figure 30.: Comparison between Java and MongoDB aggregation framework implementations (queries about a specific team name) for a current time interval (see subsection 3.2.1).

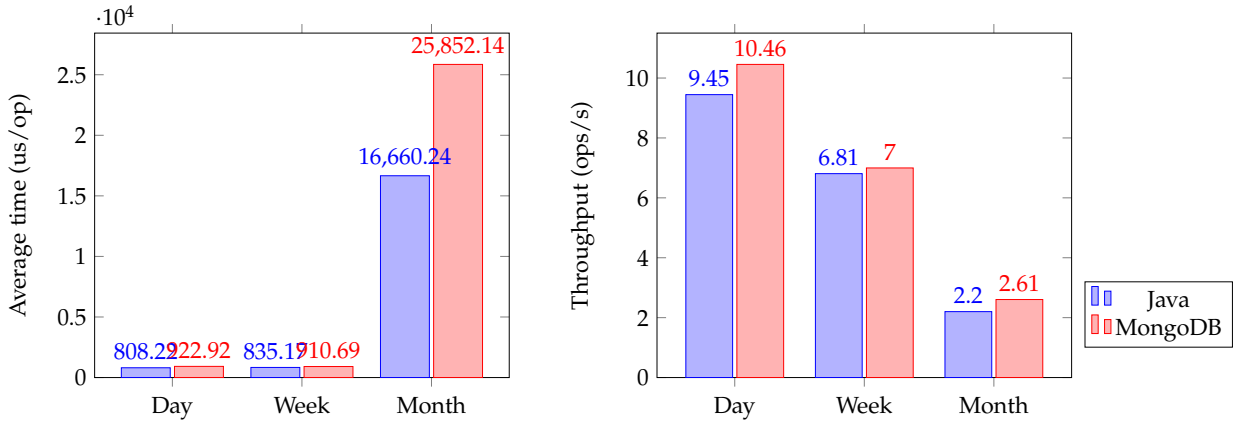

Figure 31.: Comparison between Java and MongoDB aggregation framework implementations (queries about a specific team name) for a past time interval (see subsection 3.2.1).

User Queries Execution Performance

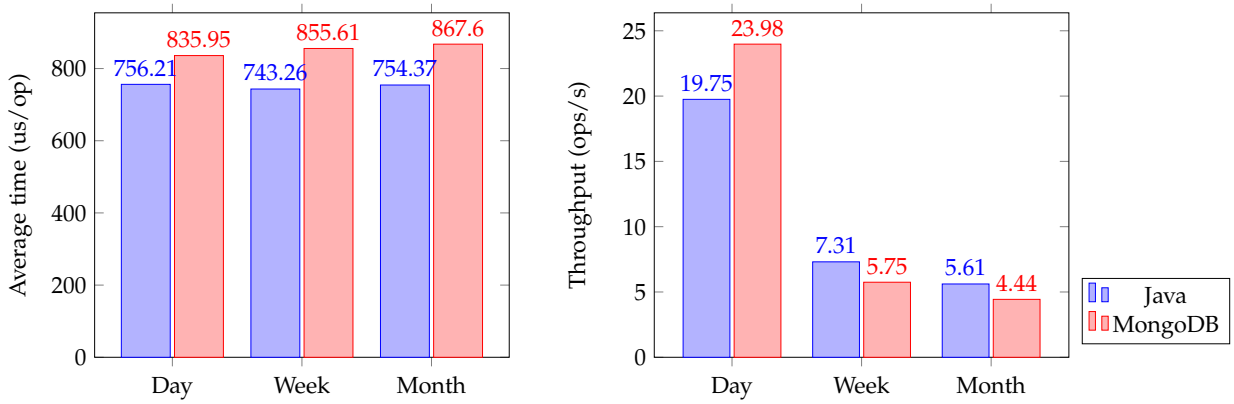

Figure 32.: Comparison between Java and MongoDB aggregation framework implementations (queries about a specific user name) for a current time interval (see subsection 3.2.1).

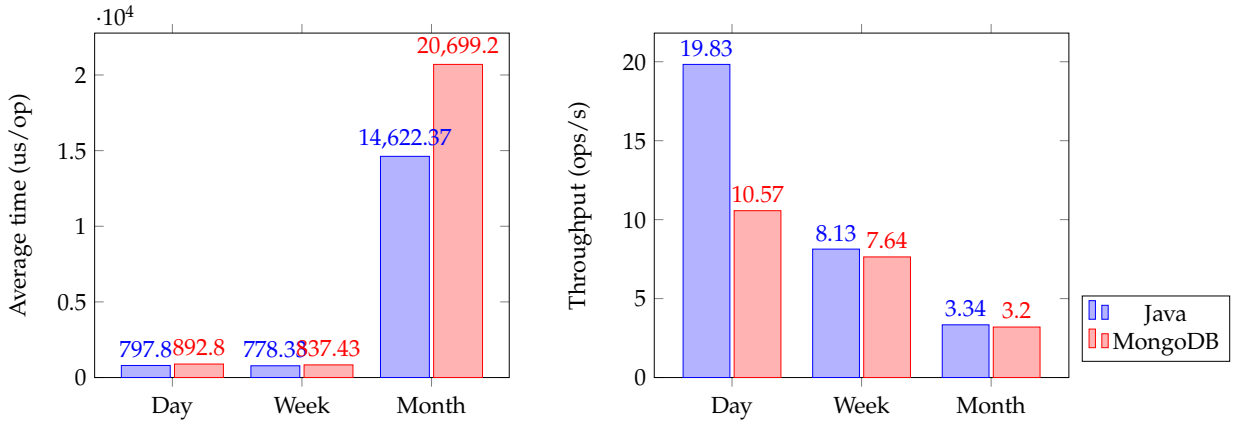

Figure 33.: Comparison between Java and MongoDB aggregation framework implementations (queries about a specific user name) for a past time interval (see subsection 3.2.1).

Group By Queries Execution Performance

Each of the following pair of charts refers to a set of queries that groups the Fatigue Status by time intervals, according to the granularity specified by the labels in the charts. This set of queries follows the structure presented on figure 17 and each one returns arrays of doubles.

The values associated with the label *Day* refer to the queries that calculate the average value for each hour given a day and an entity (user, team and/or company names). As

for the values associated with the label *Week*, they refer to the queries that calculate the average value for each day given a week and a year and an entity (user, team and/or company names). The values associated with the label *Month* refer to the queries that calculate the average value for each day given a month and an entity (user, team and/or company names).

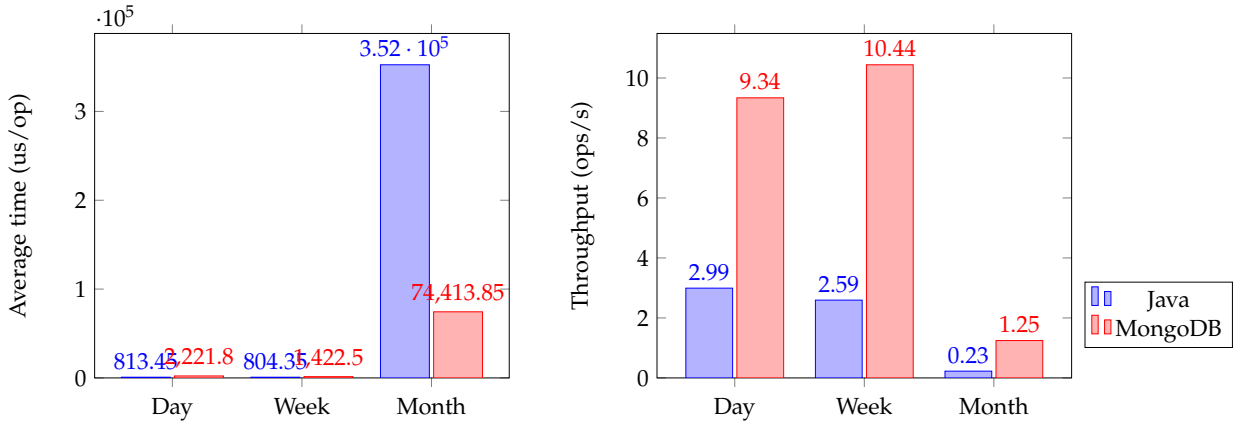

Figure 34.: Comparison between Java and MongoDB aggregation framework implementations (queries about a specific company name).

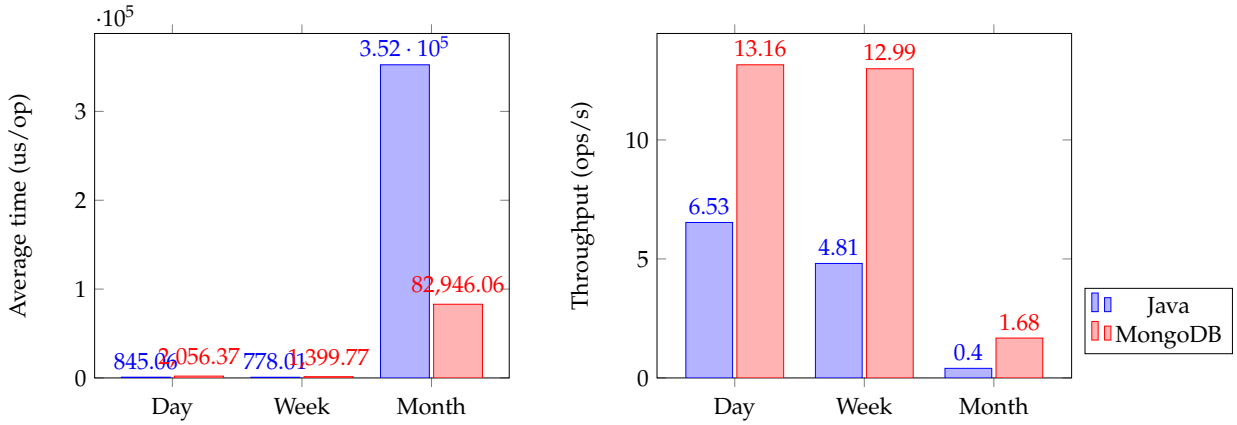

Figure 35.: Comparison between Java and MongoDB aggregation framework implementations (queries about a specific team name).

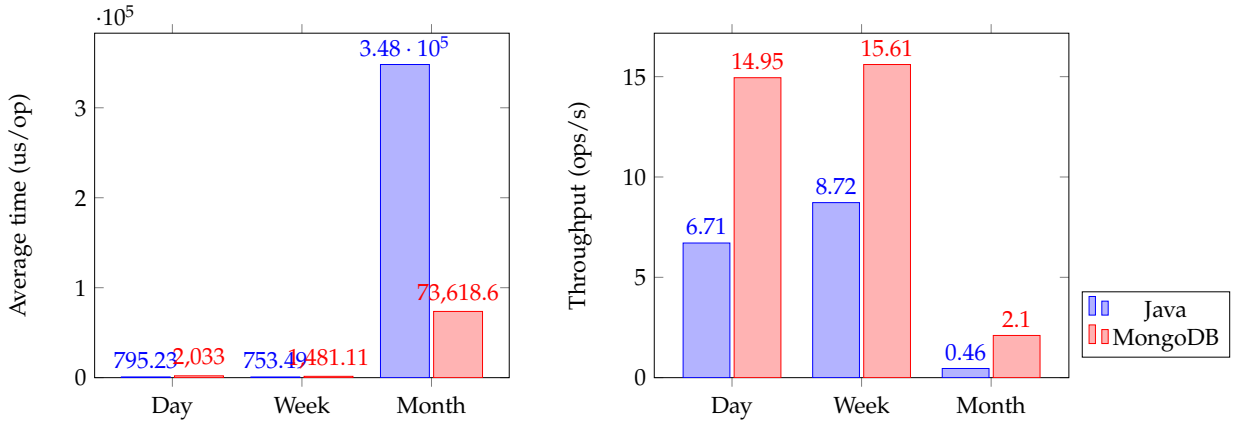

Figure 36.: Comparison between Java and MongoDB aggregation framework implementations (queries about a specific user name).

Cache Performance

The results of the performance evaluation on the Cache can be examined in section A.6. As it would be expected the results are not on the same order of magnitude of the ones presented in section the previous sections. As can be observed the results of the average time for accessing the cache in the mounted setup are around the microseconds per operation, which is considerably less than the running time of the queries. As for the throughput it is roughly around the 1e5 operations per second, which (as expected) is much higher than the throughput obtained when running the queries, independently of the usage of the MongoDB Aggregation Framework.

The set of queries in which the time interval is one or two hours before the time when the request is made are excluded form this set of results as its caching is unnecessary since this values are frequently updated and cached on client applications.

4.3.2 *Data Classification*

The following table (see table 4) shows the results obtained in the experiment involving the classifier training. The set of values for the four selected metrics (the root-mean-square deviation, the mean square error, the percent bias and the variance) are shown side-by-side, as well as the training time, for each of the implementations (R *neuralnet* package, and *h2o* package).

The values under *NeuralNet Package* column refer to the optimized parameters, obtained by Performetric. These values were obtained through GridSearch (Bergstra and Bengio (2012)). The parameters optimized were: the configuration of the two hidden layers in the

network (the obtained value was 40 nodes on the first hidden layer and 25 nodes in the second hidden layer), the threshold for the partial derivatives of the error function (on the stopping criteria, the obtained value was 0.01) and the maximum steps for the training of the neural network (another stopping criteria, the obtained value was 2e09).

	NeuralNet Package	**H2O implementation**
RMSE	2.067289212	1.48904
MSE	4.273684685	2.21724
PBIAS (%)	-6.4	11.9
VAR	0.8397328191	-0.01441812
Time (seconds)	232.39	24.825

Table 4.: Classifier training results.

4.4 SUMMARY

This chapter introduces the reader to the setup used in the experiments. The important and unique aspects of the setup are described. Additionally, the testing methodology is presented along with the obtained results. Some additional details are included in order to give helpful hints to those who work with this or similar systems in the future.

The decisions behind the proposed enhancements are hereby introduced and justified. The results are presented in a coeherent form, enabling a simple comparision between the current solutions and the proposed upgrades. All the results that may introduce noise in the analysis are sent to the appendixes and refered in this chapter.

5

RESULT ANALYSIS AND DISCUSSION

In this chapter the results obtained in the experiments presented on the previous chapter will be analyzed. Whenever possible, conclusions and explanations about the observations will be provided. Each section refers to each of the different experiments. For each topic the results are discussed and criticized, and whenever possible conclusions are inferred.

5.1 DATA AGGREGATION

For analysis purposes, this part of the results can be divided in three parts: the performance results for the simpler queries (whose pipeline consists in two stages, see figure 16 on chapter 4), the performance results for more complex queries (whose pipeline consists in two stages, see figure 17 on chapter 4) and the performance results for the caching system.

5.1.1 *Simple queries results analysis*

The set of figures that include the ones from figure 28 to figure 33, is related to this type of queries.

As it can be seen (and as it would be expected) there are similarities on the graphs that plot the average time (per day, week and month) for the company, team and user for a current time interval. It is shown an increase in the average time on the order of the 100 microseconds (from around 700 microseconds average to around 800 microseconds).

As for the respective throughput, the values for the Mongo Aggregate are very similar in the three graphs, and there is a trend (except in the company queries) that shows a decrease in the throughput values (that is consistent with the average time values).

Regarding the graphs for past intervals, the values of both the average times and the throughput are consistent for the implementation that uses the Mongo Aggregate. As for the values for the Java implementation are not consistent across company, team and user plots, the task of drawing conclusions becomes more difficult. There is no clear trend, but

generally, the results are worse than in the Java implementation (bigger average response times, and smaller throughput values).

Behind the incoherence on the values, may be the fact that the Java implementation may not follow the same structure across similar methods, as opposed to what happens in the Mongo Aggregate implementation. Another possible reason, is that the overhead of using the Mongo Aggregate may do not pay off for queries of this complexity (relatively simple) and its benefits may not be shown in this setup. The obtained results are measured for the whole operation, the only way for comparing the performance between the two implementations.

Despite having benefits, as the amount of data that is transferred between machines in the Mongo Aggregate implementation is smaller (computations are made on the DBMS, in opposition to the Java implementation), there are no evidences that the proposed implementation would perform better in this case.

5.1.2 *Complex queries results analysis*

The set of figures that include the ones from figure 34 to figure 36, is related to this type of queries.

The results are very similar across company, team and user. There is a general trend for the improvement of the performance, both the average times and the respective throughput, in the Mongo Aggregate implementation (in opposition to the Java implementation).

It must be noted, though, that as the granularity of the time interval increases the benefits grow bigger. The relative improvements (the proportion between the previous and the recent implementations results) are higher in the month than the ones observed in the week, and in turn, the relative improvements in the week results are higher that ones observed in the day.

The benefits of using Mongo Aggregation Framework for this type of queries are tangible. Thus, it should be implemented on Performetric's system.

5.1.3 *Caching queries results analysis*

As it was noted in the subsection 4.3.1 the average times of accessing the caches are smaller (in several orders of magnitude) and the throughput is much higher. Implementing a cache in this system must be done at this level (as opposed to a cache for the web pages, for example) as, for example, a decision agent may consult data that has already been summarized, from another machine.

Despite increasing the complexity on the application development, the decision of integrating the cache in the Performetric system should be made, as the benefits are evident.

5.2 DATA CLASSIFICATION

This experiment led to a comparison between the performance in both speed and accuracy between a R native implementation and the implementation provided by H2O. Each of the statistical measure is computed between the values obtained by the respective classifier and the values that were expected (values range from 1 to 7, accoring to the mental fatigue scale created in about 1979 by Dr. William F. Storm and Captain Layne P. Perelli of the Crew Performance Branch of the USAF School of Aerospace Medicine, Brooks AFB, San Antonio, Texas, Samn and Perelli (1982)). The obtained results are shown on table 4.

The value obtained for the root-mean-square deviation (RMSE) decreased relatively to the previous implementation (2.0673 to 1.4890, as it is expected the mean square error - MSE - value also decreased, 4.2736 to 2.2172). This parameter gives the standard deviation of the model prediction error. A smaller value indicates a better model performance.

The percent bias (PBIAS) measures the average tendency of the simulated values to be larger or smaller than their observed ones. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate overestimation bias, whereas negative values indicate model underestimation bias (the results are given in percentage). The value obtained for the R implementation is better (-6.4) than the obtained on the H2O implementation (11.9).

The variance measures how far each number in the set is from the mean. A variance value of zero indicates that all values within the set are identical. A large variance indicates that numbers in the set are far from the mean and each other, while a small variance indicates the opposite. In this case, as the variance values vary from 0.8397328191 to -0.01441812, it can be observed that the there was an improvement in this measure. The difference between the obtained and expected results is smaller for each record, generally, in the H2O implementation.

The speed of the training is the measure where the results are more clear. The training on R implementation ran on 232.39 seconds, and the H2O implementation ran on 24.825 seconds, which means a value around ten times smaller.

As it is commonly referred in data mining literature, more data could mean more reliable results. Another way to make the results be more reliable is to use cross-validation instead of traditional validation for assessing the results.

By experimenting with deeper configurations of the neural networks (which H2O supports), it may be possible to improve the accuracy of the model. Although it can be argued against the improvement of the performance of the classifier, there is a clear improvement on speed of the training. The training speed is vital to the system, and the main focus in this work, so it can be said it there was an improvement, regarding the defined goals.

5.3 PROJECT EXECUTION OVERVIEW

Regarding what was initially planned the way the development of this project went suffered some deviations. The study of ways to improve the classifier was not in the initial plans for this thesis, but as it is such a big concert on this architecture it was imperative that it was addressed.

As it can be noted there were no tests on possible optimizations regarding data insertion, however the techniques for doing so are well described on MongoDB documentation and its benefits are proven (and as it was previously presented, when applied on early stages of the application may even degrade performance).

Despite not all the results being positive (as it is addressed in subsection 5.1.1) the set of tested hypotheses provide helpful insights on how the system can be improved.

6

CONCLUSION

This final chapter has the objective of providing a comprehensive synthesis of all the work that has been accomplished along with the findings that were drawn from the results obtained. Additionally, some insight will be given into the future work that could be done in the pursuit of better results.

6.1 WORK SYNTHESIS

Keeping a performing system in a cutting edge field as it is Performetric's, is an hard task. The crossing between Big Data, Machine Learning and Internet of Things field has brings lots of opportunities and challenges, that are addressed everyday in both academic and industrial environments. However, the presented work is a step forward in what it is expected to be a successful large-scale software solution for providing monitoring on mental fatigue and, ultimately, wellness. By tackling some issues on the data architecture of the company some contributions have been made, and hopefully can be replicated in similar contexts.

The first achieved goal of this work was to carry a study on Big Data (and document it as a state-of-the-art), this helped to frame the problem. The next step was to produce the architecture documentation for the Performetric system. This enabled the gathering of the contextual needs. The development of the testing setup, the prototypes and the measuring mechanisms, was a goal that was achieved. The development of this task led to the arising of artifacts (queries' code, the caching system code, the H2O code) that may be included in the deployed system. The analysis of the obtained results makes this contribution mare valuable, as the results are expected to be replicated in similar contexts.

As an additional result, from this work resulted the following publication: Araújo D., Pimenta A., Carneiro D., Novais P., Providing Wellness Services Using Real Time Analytics, Ambient Intelligence- Software and Applications – 7th International Symposium on Ambient Intelligence (ISAmI 2016), Springer - Advances in Intelligent Systems and Computing,

Lindgren H. et al. (eds), Vol 476, ISSN 2194-5357, ISBN 9783319401133, pp 167-175, 2016. http://dx.doi.org/10.1007/978-3-319-40114-0_19.

6.2 Prospect for future work

Despite reaching successfully all the defined goals, this study is not nearly over. The opportunities to experiment with the system and for tuning it are huge. There are some suggested improvements that may be followed in order to increase the system performance and robustness. The first suggestion presented in section 3.2.2 of using a sharded cluster and a messaging queue in order to handle data insertion and increase availability.

The study on the classifier training was limited and mainly focused on speed of the training. However, there are many opportunities for optimization in this topic. The deployment of a continuous learning system should be on the roadmap. Additionally, the emerging of deep learning frameworks such as the ones presented in the literature review section of this document should not be neglected.

On the other hand, there are unexplored opportunities that share the context with Performetric, namely the use of different non-intrusive devices (such as wrist trackers or smartphones), that may constitute interesting challenges on the tasks of data-handling.

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A

QUERIES RESPONSE TIMES

A.1 COMPANY QUERIES EXECUTION PERFORMANCE

Benchmark	**Score**	**Units**
CompanyCurrentDay	9.975 ± 0.052	ops/s
CompanyCurrentMonth	1.591 ± 0.032	ops/s
CompanyCurrentWeek	2.784 ± 0.061	ops/s
CompanyLastDay	8.671 ± 0.057	ops/s
CompanyLastMonth	0.639 ± 0.014	ops/s
CompanyLastWeek	2.631 ± 0.070	ops/s

Table 5.: Throughput of a set of queries where data is filtered by company name (Java implementation).

Benchmark	**Score**	**Units**
CompanyCurrentDay	10.293 ± 0.069	ops/s
CompanyCurrentMonth	3.721 ± 0.050	ops/s
CompanyCurrentWeek	4.905 ± 0.053	ops/s
CompanyLastDay	9.990 ± 0.067	ops/s
CompanyLastMonth	2.315 ± 0.035	ops/s
CompanyLastWeek	6.425 ± 0.069	ops/s

Table 6.: Throughput of a set of queries where data is filtered by company name (MongoDB Agg. implementation).

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
CompanyCurrentDay	771.549 ±(99.9%) 14.112	603.327	921.557	59.753
CompanyCurrentMonth	742.598 ±(99.9%) 11.250	640.712	1011.391	47.635
CompanyCurrentWeek	740.535 ±(99.9%) 10.273	595.665	913.820	43.496
CompanyLastDay	760.279 ±(99.9%) 29.092	602.494	2310.215	123.175
CompanyLastMonth	62500.964 ±(99.9%) 984.787	58862.535	85299.133	4169.651
CompanyLastWeek	999.057 ±(99.9%) 170.117	652.962	4100.092	720.285

Table 7.: Average time of a set of queries where data is filtered by company name (Java implementation).

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
CompanyCurrentDay	852.049 ±(99.9%) 17.191	706.908	1135.263	72.788
CompanyCurrentMonth	787.979 ±(99.9%) 13.394	681.094	1212.313	56.712
CompanyCurrentWeek	823.395 ±(99.9%) 22.952	688.795	1226.201	97.178
CompanyLastDay	885.331 ±(99.9%) 27.845	735.971	1488.011	117.896
CompanyLastMonth	28666.483 ±(99.9%) 507.855	25315.333	36950.971	2150.289
CompanyLastWeek	911.761 ±(99.9%) 27.459	732.330	1327.129	116.262

Table 8.: Average time of a set of queries where data is filtered by company name (MongoDB Agg. implementation).

A.2 Team Queries Execution Performance

Benchmark	Score	Units
GroupNameCurrentDay	0.604 ± 0.098	ops/s
GroupNameCurrentMonth	4.330 ± 0.052	ops/s
GroupNameCurrentWeek	6.405 ± 0.064	ops/s
GroupNameLastDay	9.446 ± 0.557	ops/s
GroupNameLastMonth	2.201 ± 0.041	ops/s
GroupNameLastWeek	6.808 ± 0.055	ops/s

Table 9.: Throughput of a set of queries where data is filtered by group name (Java implementation).

Benchmark	Score	Units
GroupNameCurrentDay	14.739 ± 1.502	ops/s
GroupNameCurrentMonth	4.002 ± 0.058	ops/s
GroupNameCurrentWeek	5.313 ± 0.066	ops/s
GroupNameLastDay	10.455 ± 0.058	ops/s
GroupNameLastMonth	2.605 ± 0.042	ops/s
GroupNameLastWeek	6.998 ± 0.080	ops/s

Table 10.: Throughput of a set of queries where data is filtered by group name (MongoDB Agg. implementation).

GroupNameCurrentDay	779.511 ±(99.9%) 9.683	659.377	897.758	40.998
GroupNameCurrentMonth	772.275 ±(99.9%) 16.694	659.918	1289.849	70.682
GroupNameCurrentWeek	779.273 ±(99.9%) 11.840	680.202	933.347	50.132
GroupNameLastDay	808.216 ±(99.9%) 15.566	645.108	1093.238	65.906
GroupNameLastMonth	16660.244 ±(99.9%) 311.775	13984.496	19804.006	1320.074
GroupNameLastWeek	835.166 ±(99.9%) 25.407	641.138	1365.381	107.577

Table 11.: Average of a set of queries where data is filtered by group name (Java implementation).

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
GroupNameCurrentDay	829.000 ±(99.9%) 17.060	707.294	1163.682	72.232
GroupNameCurrentMonth	892.367 ±(99.9%) 23.951	737.097	1299.380	101.409
GroupNameCurrentWeek	888.923 ±(99.9%) 27.011	734.344	1327.092	114.366
GroupNameLastDay	922.916 ±(99.9%) 31.660	742.063	1455.796	134.052
GroupNameLastMonth	25852.141 ±(99.9%) 424.129	22983.086	32425.929	1795.787
GroupNameLastWeek	910.689 ±(99.9%) 25.250	751.257	1302.503	106.910

Table 12.: Average of a set of queries where data is filtered by group name (MongoDB Agg. implementation).

A.3 USER QUERIES EXECUTION PERFORMANCE

Benchmark	Score	Units
UserCurrentDay	9.750 ± 0.756	ops/s
UserCurrentMonth	5.613 ± 0.049	ops/s
UserCurrentWeek	7.308 ± 0.053	ops/s
UserLastDay	9.831 ± 0.125	ops/s
UserLastMonth	3.339 ± 0.049	ops/s
UserLastWeek	8.134 ± 0.052	ops/s

Table 13.: Throughput of a set of queries where data is filtered by user name (Java implementation).

Benchmark	Score	Units
UserCurrentDay	23.978 ± 0.036	ops/s
UserCurrentMonth	4.435 ± 0.056	ops/s
UserCurrentWeek	5.747 ± 0.064	ops/s
UserLastDay	10.567 ± 0.050	ops/s
UserLastMonth	3.199 ± 0.044	ops/s
UserLastWeek	7.639 ± 0.076	ops/s

Table 14.: Throughput of a set of queries where data is filtered by company name (MongoDB Agg. implementation).

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
UserCurrentDay	756.206 ±(99.9%) 15.410	634.606	1275.504	65.246
UserCurrentMonth	754.370 ±(99.9%) 13.324	639.476	951.447	56.415
UserCurrentWeek	743.263 ±(99.9%) 13.061	555.086	900.639	55.300
UserLastDay	797.804 ±(99.9%) 15.327	664.254	992.808	64.894
UserLastMonth	14622.372 ±(99.9%) 268.548	12554.240	17914.857	1137.050
UserLastWeek	778.330 ±(99.9%) 19.516	625.987	1462.678	82.630

Table 15.: Average time of a set of queries where data is filtered by company name (Java implementation).

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
UserCurrentDay	835.948 ±(99.9%) 17.722	712.882	1232.402	75.038
UserCurrentMonth	867.603 ±(99.9%) 25.314	702.406	1297.521	107.183
UserCurrentWeek	855.609 ±(99.9%) 22.953	717.561	1293.853	97.183
UserLastDay	892.796 ±(99.9%) 21.068	720.555	1320.240	89.203
UserLastMonth	20699.202 ±(99.9%) 222.759	19138.772	23870.581	943.175
UserLastWeek	837.432 ±(99.9%) 13.810	680.984	1168.042	58.472

Table 16.: Average time of a set of queries where data is filtered by company name (MongoDB Agg. implementation).

A.4 GROUP BY QUERIES EXECUTION PERFORMANCE

Benchmark	Score	Units
CompanyPerDay	2.993 ± 0.083	ops/s
CompanyPerMonth	0.226 ± 0.004	ops/s
CompanyPerWeek	2.594 ± 0.048	ops/s
GroupNamePerDay	6.532 ± 0.086	ops/s
GroupNamePerMonth	0.403 ± 0.005	ops/s
GroupNamePerWeek	4.810 ± 0.360	ops/s
UserPerDay	6.710 ± 0.115	ops/s
UserPerMonth	0.457 ± 0.006	ops/s
UserPerWeek	8.723 ± 0.047	ops/s

Table 17.: Throughput of a set of queries where data is grouped by time intervals according to labels (Java implementation).

A.4. Group By Queries Execution Performance

Benchmark	Score	Units
CompanyPerDay	9.338 ± 0.128	ops/s
CompanyPerMonth	1.246 ± 0.021	ops/s
CompanyPerWeek	10.440 ± 0.130	ops/s
GroupNamePerDay	13.157 ± 0.161	ops/s
GroupNamePerMonth	1.675 ± 0.029	ops/s
GroupNamePerWeek	12.990 ± 0.153	ops/s
UserPerDay	14.948 ± 0.165	ops/s
UserPerMonth	2.103 ± 0.026	ops/s
UserPerWeek	15.605 ± 0.142	ops/s

Table 18.: Throughput of a set of queries where data is grouped by time intervals according to labels (MongoDB Agg. implementation).

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
CompanyPerDay	813.448 ±(99.9%) 11.933	701.000	976.712	50.524
CompanyPerMonth	352493.366 ±(99.9%) 4320.757	318465.225	419011.867	18294.357
CompanyPerWeek	804.345 ±(99.9%) 10.171	697.690	939.670	43.064
GroupNamePerDay	845.059 ±(99.9%) 20.042	666.387	1109.565	84.860
GroupNamePerMonth	352465.745 ±(99.9%) 4998.579	316902.750	510857.850	21164.295
GroupNamePerWeek	778.012 ±(99.9%) 13.378	657.581	978.461	56.641
UserPerDay	795.227 ±(99.9%) 13.973	638.799	966.371	59.164
UserPerMonth	348103.005 ±(99.9%) 3648.443	318337.050	410099.000	15447.734
UserPerWeek	753.491 ±(99.9%) 14.892	625.584	975.965	63.054

Table 19.: Average times of a set of queries where data is grouped by time intervals according to labels (Java implementation).

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
CompanyPerDay	2221.799 ±(99.9%) 61.884	1832.736	3117.538	262.020
CompanyPerMonth	74413.845 ±(99.9%) 1269.111	64171.963	90991.182	5373.498
CompanyPerWeek	1422.495 ±(99.9%) 20.929	1206.646	1809.806	88.614
GroupNamePerDay	2056.374 ±(99.9%) 39.204	1781.787	2918.718	165.994
GroupNamePerMonth	82946.057 ±(99.9%) 979.325	74655.943	95033.436	4146.524
GroupNamePerWeek	1399.766 ±(99.9%) 18.665	1247.340	1855.286	79.029
UserPerDay	2032.995 ±(99.9%) 34.468	1780.784	2589.290	145.939
UserPerMonth	73618.597 ±(99.9%) 1096.248	64414.500	87095.525	4641.584
UserPerWeek	1481.112 ±(99.9%) 21.514	1302.670	2030.167	91.091

Table 20.: Average times of a set of queries where data is grouped by time intervals according to labels (MongoDB Agg. implementation).

A.5 HOURLY QUERIES EXECUTION PERFORMANCE

Benchmark	Score	Units
CompanyCurrentHour	12.082 ± 0.017	ops/s
CompanyLastHour	12.067 ± 0.017	ops/s
GroupNameCurrentHour	23.940 ± 0.038	ops/s
GroupNameLastHour	23.821 ± 0.035	ops/s
UserCurrentHour	24.116 ± 0.033	ops/s
UserLastHour	12.094 ± 0.017	ops/s

Table 21.: Throughput of a set of queries where the retrived data is from last 2 hours (Java implementation).

Benchmark	Score	Units
CompanyCurrentHour	23.920 ± 0.037	ops/s
CompanyLastHour	23.977 ± 0.035	ops/s
GroupNameCurrentHour	23.933 ± 0.039	ops/s
GroupNameLastHour	23.935 ± 0.037	ops/s
UserCurrentHour	24.171 ± 0.038	ops/s
UserLastHour	24.172 ± 0.031	ops/s

Table 22.: Throughput of a set of queries where the retrived data is from last 2 hours (MongoDB Agg. implementation).

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
CompanyCurrentHour	853.403 ±(99.9%) 19.983	709.416	1183.326	84.610
CompanyLastHour	893.152 ±(99.9%) 21.714	744.736	1292.683	91.937
GroupNameCurrentHour	824.774 ±(99.9%) 14.903	726.444	1071.436	63.102
GroupNameLastHour	895.235 ±(99.9%) 20.644	730.778	1256.505	87.410
UserCurrentHour	857.884 ±(99.9%) 20.291	693.011	1311.317	85.912
UserLastHour	840.488 ±(99.9%) 18.173	716.033	1128.712	76.947

Table 23.: Average time of a set of queries where the retrived data is from last 2 hours (Java implementation).

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
CompanyCurrentHour	705.383 ±(99.9%) 10.749	605.392	926.571	45.510
CompanyLastHour	741.466 ±(99.9%) 11.812	602.365	887.552	50.014
GroupNameCurrentHour	743.669 ±(99.9%) 11.460	596.499	1032.145	48.521
GroupNameLastHour	770.045 ±(99.9%) 15.568	655.979	1125.733	65.917
UserCurrentHour	731.622 ±(99.9%) 12.349	606.549	1007.288	52.288
UserLastHour	759.463 ±(99.9%) 11.363	647.483	1023.656	48.113

Table 24.: Average time of a set of queries where the retrived data is from last 2 hours (MongoDB Agg. implementation).

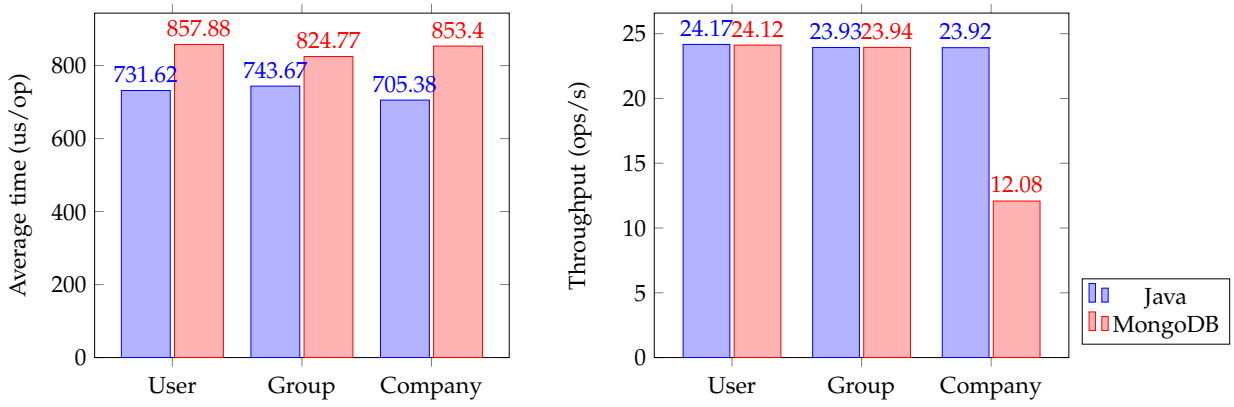

Figure 37.: Comparison between previous and MongoDB aggregation framework implementations (query about data generated in the current hour).

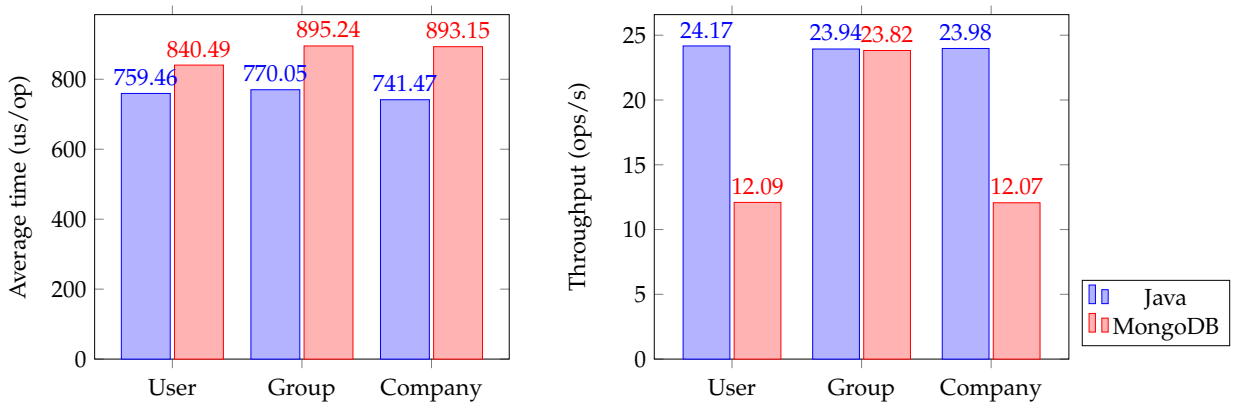

Figure 38.: Comparison between previous and MongoDB aggregation framework implementations (query about data generated in the last hour).

A.6 CACHE PERFORMANCE

Benchmark	Score	Units
averageFatigueByCompanyCurrentDay	278191.387 ± 2294.399	ops/s
averageFatigueByCompanyCurrentMonth	274568.827 ± 2156.977	ops/s
averageFatigueByCompanyCurrentWeek	575351.164 ± 5679.002	ops/s
averageFatigueByCompanyLastDay	265446.917 ± 2487.687	ops/s
averageFatigueByCompanyLastMonth	163570.197 ± 1501.222	ops/s
averageFatigueByCompanyLastWeek	540436.522 ± 4600.465	ops/s
averageFatigueByCompanyPerDay	704741.790 ± 7183.195	ops/s
averageFatigueByCompanyPerMonth	712551.957 ± 6524.740	ops/s
averageFatigueByCompanyPerWeek	512515.627 ± 4648.135	ops/s
averageFatigueByGroupNameCurrentDay	277079.455 ± 2445.997	ops/s
averageFatigueByGroupNameCurrentMonth	273284.238 ± 2271.772	ops/s
averageFatigueByGroupNameCurrentWeek	585269.922 ± 4445.416	ops/s
averageFatigueByGroupNameLastDay	268957.629 ± 2328.898	ops/s
averageFatigueByGroupNameLastMonth	163267.525 ± 1711.443	ops/s
averageFatigueByGroupNameLastWeek	542771.273 ± 4150.717	ops/s
averageFatigueByGroupNamePerDay	706460.643 ± 5901.613	ops/s
averageFatigueByGroupNamePerMonth	717570.553 ± 5572.612	ops/s
averageFatigueByGroupNamePerWeek	511308.593 ± 4566.637	ops/s
averageFatigueByUserCurrentDay	274687.748 ± 2480.478	ops/s
averageFatigueByUserCurrentMonth	275349.263 ± 2344.364	ops/s
averageFatigueByUserCurrentWeek	584568.297 ± 4814.899	ops/s
averageFatigueByUserLastDay	266133.762 ± 2431.766	ops/s
averageFatigueByUserLastMonth	163464.781 ± 1457.564	ops/s
averageFatigueByUserLastWeek	544447.907 ± 4334.425	ops/s
averageFatigueByUserPerDay	708642.074 ± 5533.543	ops/s
averageFatigueByUserPerMonth	713253.697 ± 5509.457	ops/s
averageFatigueByUserPerWeek	511827.517 ± 4689.561	ops/s

Table 25.: Throughput of the set of queries using the Cache system.

Benchmark	Average time (us/op)	Min time	Max time	St. Deviation
CompanyCurrentDay	3.430 ±(99.9%) 0.023	3.293	4.101	0.096
CompanyCurrentMonth	3.493 ±(99.9%) 0.022	3.346	3.859	0.092
CompanyCurrentWeek	1.648 ±(99.9%) 0.016	1.554	2.196	0.067
CompanyLastDay	3.609 ±(99.9%) 0.030	3.386	4.341	0.126
CompanyLastMonth	5.868 ±(99.9%) 0.052	5.474	6.953	0.221
CompanyLastWeek	1.761 ±(99.9%) 0.013	1.676	2.075	0.057
CompanyPerDay	1.348 ±(99.9%) 0.011	1.275	1.593	0.048
CompanyPerMonth	1.326 ±(99.9%) 0.010	1.267	1.493	0.043
CompanyPerWeek	1.856 ±(99.9%) 0.013	1.776	2.162	0.054
GroupNameCurrentDay	3.429 ±(99.9%) 0.024	3.250	4.092	0.103
GroupNameCurrentMonth	3.553 ±(99.9%) 0.084	3.338	7.193	0.354
GroupNameCurrentWeek	1.633 ±(99.9%) 0.010	1.567	1.821	0.042
GroupNameLastDay	3.591 ±(99.9%) 0.022	3.407	4.021	0.091
GroupNameLastMonth	5.893 ±(99.9%) 0.053	5.503	7.838	0.226
GroupNameLastWeek	1.764 ±(99.9%) 0.014	1.683	2.166	0.058
GroupNamePerDay	1.344 ±(99.9%) 0.010	1.285	1.489	0.042
GroupNamePerMonth	1.327 ±(99.9%) 0.009	1.265	1.529	0.040
GroupNamePerWeek	1.855 ±(99.9%) 0.017	1.772	2.360	0.071
UserCurrentDay	3.496 ±(99.9%) 0.035	3.264	4.694	0.147
UserCurrentMonth	3.511 ±(99.9%) 0.024	3.353	4.134	0.100
UserCurrentWeek	1.621 ±(99.9%) 0.010	1.554	1.921	0.041
UserLastDay	3.598 ±(99.9%) 0.024	3.419	3.986	0.103
UserLastMonth	5.849 ±(99.9%) 0.048	5.470	7.074	0.203
UserLastWeek	1.760 ±(99.9%) 0.011	1.690	1.895	0.048
UserPerDay	1.331 ±(99.9%) 0.010	1.278	1.574	0.041
UserPerMonth	1.330 ±(99.9%) 0.007	1.269	1.426	0.029
UserPerWeek	1.846 ±(99.9%) 0.010	1.772	2.038	0.041

Table 26.: Average time of the set of queries using the Cache system.