Master's Degree in Informatics Engineering

Final Dissertation

Observing and Controlling Performance in Microservices

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Abstract

Microservice based software architecture are growing in usage and one type of data generated to keep history of the work performed by this kind of systems is called tracing data. Tracing can be used to help Development and Operations (DevOps) perceive problems such as latency and request work-flow in their systems. Diving into this data is difficult due to its complexity, plethora of information and lack of tools. Hence, it gets hard for DevOps to analyse the system behaviour in order to find faulty services using tracing data. The most common and general tools existing nowadays for this kind of data, are aiming only for a more human-readable data visualisation to relieve the effort of the DevOps when searching for issues in their systems, however these tools do not provide good ways to filter this kind of data neither perform any kind of tracing data analysis and therefore, they do not automate the task of searching for any issue presented in the system, which stands for a big problem because they rely in the system administrators to do it manually. In this thesis is present a possible solution for this problem, capable of use tracing data to extract metrics of the services dependency graph, namely the number of incoming and outgoing calls in each service and their corresponding average response time, with the purpose of detecting any faulty service presented in the system and identifying them in a specific time-frame. Also, a possible solution for quality tracing analysis is covered checking for quality of tracing structure against OpenTracing specification and checking time coverage of tracing for specific services. Regarding the approach to solve the presented problem, we have relied in the implementation of some prototype tools to process tracing data and performed experiments using the metrics extracted from tracing data provided by Huawei. With this proposed solution, we expect that solutions for tracing data analysis start to appear and be integrated in tools that exist nowadays for distributed tracing systems.

Keywords

Microservices, Cloud Computing, Observability, Monitoring, Tracing.

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Resumo

A arquitetura de software baseada em micro-serviços está a crescer em uso e um dos tipos de dados gerados para manter o histórico do trabalho executado por este tipo de sistemas é denominado de tracing. Mergulhar nestes dados é díficil devido à sua complexidade, abundância e falta de ferramentas. Consequentemente, é díficil para os DevOps de analisarem o comportamento dos sistemas e encontrar serviços defeituosos usando tracing. Hoje em dia, as ferramentas mais gerais e comuns que existem para processar este tipo de dados, visam apenas apresentar a informação de uma forma mais clara, aliviando assim o esforço dos DevOps ao pesquisar por problemas existentes nos sistemas, no entanto estas ferramentas não fornecem bons filtros para este tipo de dados, nem formas de executar análises dos dados e, assim sendo, não automatizam o processo de procura por problemas presentes no sistema, o que gera um grande problema porque recaem nos utilizadores para o fazer manualmente. Nesta tese é apresentada uma possivel solução para este problema, capaz de utilizar dados de tracing para extrair metricas do grafo de dependências dos serviços, nomeadamente o número de chamadas de entrada e saída em cada serviço e os tempos de resposta coorepondentes, com o propósito de detectar qualquer serviço defeituoso presente no sistema e identificar as falhas em espaços temporais especificos. Além disto, é apresentada também uma possivel solução para uma análise da qualidade do tracing com foco em verificar a qualidade da estrutura do tracing face à especificação do OpenTracing e a cobertura do tracing a nível temporal para serviços especificos. A abordagem que seguimos para resolver o problema apresentado foi implementar ferramentas protótipo para processar dados de tracing de modo a executar experiências com as métricas extraidas do tracing fornecido pela Huawei. Com esta proposta de solução, esperamos que soluções para processar e analisar tracing comecem a surgir e a serem integradas em ferramentas de sistemas distribuidos.

Palavras-Chave

Micro-serviços, Computação na nuvem, Observabilidade, Monitorização, Tracing.

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Acknowledgements

This work would not be possible to be accomplished without effort, help and support from my family, fellows and colleagues. Thus, in this section I would like to give my sincere thanks to all of them.

Starting by giving thanks to my mother and to my whole family, who have supported me through this entire and long journey, and who always gave and will always give me some of the most important and beautiful things in life, love and friendship.

In second place, I would like to thank all people that were involved directly in this project. To my supervisor, Professor Filipe Araújo, who contributed with his vast wisdom and experience, to my co-supervisor, Professor Jorge Cardoso, who contributed with is vision and guidance about the main road we should take and to Engineer Jaime Correia, who "breathes" these kind of topics through him and helped a lot with is enormous knowledge and enthusiasm.

In third place, I would like to thank Department of Informatics Engineering and the Centre for Informatics and Systems, both from the University of Coimbra, for allowing and provide the resources and facilities to to be carried out this project.

In fourth place, to the Foundation for Science and Technology (FCT), for financing this project facilitating its accomplishment, to Huawei, for providing tracing data, core for this whole research, and to Portugal National Distributed Computing Infrastructure (INCD) for providing hardware to run experiments.

And finally, my sincere thanks to everyone that I have not mentioned and contributed to everything that I am today.

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Chapter 1

Introduction

This document presents the *Master Thesis* in *Informatics Engineering* of the student *André Pascoal Bento* during the school year of 2018/2019, taking place in the *Department of Informatics Engineering (DEI)* of the *University of Coimbra*.

1.1 Context

In today's world, software systems tend to become more distributed as time move on, resulting in new approaches that lead to new solutions and new patterns of developing software. One way to solve this is to develop systems that have their components decoupled, creating software with "small pieces" connected to each other that encapsulate and provide a specific function in the larger service. This way of developing software is called Microservices and has become mainstream in the enterprise software development industry [1]. However, with this kind of approach, the systems complexity is increased as a whole because with more "small pieces", more connections are needed and with this more problems related to latency and requests become harder to detect, analyse and correct [2].

To keep a history of the work performed by this kind of systems, multiple techniques like monitoring [3], logging [4] and tracing [5] are adopted. Monitoring consists on measuring some aspects like, e.g., Central Processing Unit (CPU) usage, hard drive usage and network latency of the entire system or of some specific node in a distributed system. Logging provides an overview to a discrete, event-triggered log. Finally, tracing is much similar to logging, however the focus is registering the flow of execution of the program through several system modules and boundaries. Lastly, distributed tracing, shares the focus on preserving causality relationships, however, is geared towards the modern distributed environments, where state is partitioned over multiple, threads, processes, machines and even geographical locations. This last one is better explained in Subsection 3.1.3 - Distributed Tracing. There are multiple approaches to gather information of this kind of systems, each with its benefits and disadvantages.

The main problem with this nowadays is that there are not many implemented tools for processing tracing data and none for performing analysis of this type of data. For monitoring it tend to be easier, because data is represented in charts and diagrams, however for logging and tracing it gets harder to manually analyse the data due to multiple factors like its complexity, plethora and increasing quantity of information. There are some visualisation tools for the Development and Operations (DevOps) to use, like the ones presented in Subsection 3.2.1 - Distributed Tracing Tools, however none of them gets

to the point of performing the analysis of the system using tracing, has they tend to be developed only for visualisation and display of tracing data in a more human readable way. Nevertheless, this is critical information about the system behaviour, and thus there is the need for performing automatic tracing analysis.

1.2 Motivation

The motivation behind this work resides in exploring and develop ways to perform tracing analysis in microservice based systems. The analysis of this kind of systems tend to be very complex and hard to perform due to their properties and characteristics, as it is explained in Subsection 3.1.1 - Microservices, and to the type of data to be analysed, presented in Subsections 3.1.3 - Distributed Tracing and **??** - **??**.

DevOps teams have lots of problems when they need to identify and understand problems with this systems. They usually detect the problems when the client complains about the quality of service, and after that DevOps dive in monitoring metrics like, e.g, CPU usage, usage, hard drive usage and network latency, and then in distributed tracing data visualisations and logs to find some explanation to what is causing the reported problem. This involves a very hard and tedious work of look-up through lots of data that represents the history of work performed by the system and, in most cases, this tedious work reveals like a big "find a needle in the haystack" problem. Some times, DevOps can only perceive problems in some services and end up "killing" and rebooting these services which is wrong, however, due to lack of time and difficulty in identifying anomalous services precisely this is the best known approach.

Problems regarding the system operation are more common in distributed systems and their identification must be simplified. This need of simplification comes from the exponential increase in the amount of data needed to retain information and the increasing difficulty in manually managing distributed infrastructures. The work presented in this thesis, aims to perform a research around these needs and focus on presenting some solutions and methods to perform tracing analysis.

1.3 Goals

The main goals for this thesis consists on the main points exposed bellow:

1. Search for existing technology and methodologies used to help DevOps teams in their current daily work, with the objective of gathering the best practices about handling tracing data. Also, we aim to understand how these systems are used, what are their advantages and disadvantages to better know how we can use them to design and produce a possible solution capable of performing tracing analysis. From this we expect to learn the state of the field for this research, covering the core concepts related work and technologies, presented in Chapter 3 - State of the Art.
2. Perform a research about the main needs of DevOps teams, to better understand what are their biggest concerns that lead to their approaches when performing pinpointing of microservices based systems problems. Relate these approaches with related work in the area, with the objective of understanding what other companies and groups have done in the field of automatic tracing analysis. The processes used to tackle this type of data, their main difficulties and conclusions provide a

better insight about the problem. From this we expected to have our research objectives clearly defined and a compilation of questions to be evaluated and answered, presented in Chapter **??** - **??**.

3. Reason about all the gathered information, design and produce a possible solution that provides a different approach to perform tracing analysis. From this we expect first to propose a possible solution, presented in Chapter **??**. The we implement it using state of the art technologies, feed it with tracing data provided by Huawei and collect results, presented in Chapter **??** - **??**. Finally, we provide conclusions to this research work in the last Chapter **??** - **??**.

1.4 Research Contributions

From the work presented on this thesis, the following research contributions were made:

- Andre Bento, Jaime Correia, Ricardo Filipe, Filipe Araujo and Jorge Cardoso. On the Limits of Automated Analysis of OpenTracing. International Symposium on Network Computing and Applications (IEEE NCA 2019) (The paper is waiting review).

1.5 Document Structure

This section presents the document structure in this report, with a brief explanation of the contents in every section. The current document contains a total of seven chapters, including this one, Chapter 1 - Introduction. The remaining six of them are presented as follows:

- In Chapter 2 - Methodology are presented the elements involved in this work, with their contributions, has well as the work plan, with "foreseen" and "real" work plans comparison and analysis.
- In Chapter 3 - State of the Art the current state of the field for this kind of problem is presented. This chapter is divided in three sections. The first one, Section 3.1 - Concepts introduces the reader to the core concepts to know as a requirement for a full understanding of the topics discussed in this thesis. The second, Section 3.2 - Technologies presents the result of a research for current technologies, that are able to help solving this problem and produce a proposed solution to be implemented. Finally, Section 3.3 - Related Work presents the reader to related researches produced in the field of distributed tracing data handling.
- In Chapter **??** - **??** we present how we tackled this problem, the main difficulties that were found and the objectives involved to solve the issues that are presented. Also, in this chapter, a compilation of questions are presented and evaluated with some reasoning about possible ways to answer them.
- In Chapter **??** - **??** a possible solution for the presented problem is exposed and explained in detail. This chapter is divided in four sections. The first one, Section **??** - **??**, expose the functional requirements with their corresponding priority levels and a brief explanation to every single one of them. The second one, Section **??** - **??**, contains the gathered non-functional requirements that were used to

build the solution architecture. The third one, Section **??** - **??**, presents the defined technical restrictions for this project. The last one, Section **??** - **??**, presents the possible solution architecture using some representational diagrams, and ends with an analysis and validation to check if the presented architecture meets up the restrictions involved in the architectural drivers.

- In Chapter **??** - **??**, the implementation process of the possible solution is presented with detail. This chapter is divided in three main sections covering the whole implementation process, from the input data set through the pair of components presented in the previous chapter. The first one, Section **??** - **??**, the tracing data set provided by Huawei to be used as the core data for research is exposed with some detail. Second, in Section **??** - **??** we present the possible solution for the first component, namely "Graphy OpenTracing processor (OTP)", that processes and extracts metrics from tracing data. The final Section **??** - **??** presents the possible solution for the second component, namely "Data Analyser", that handles data produced by the first component and produces the analysis reports. Also, in the last two sections presented, the used algorithms and methods in the implementations are properly detailed and explained.

- In Chapter **??** - **??**, the gathered results, corresponding analysis and limitations of tracing data are presented. This chapter is divided in three main sections. The first one, Section **??** - **??**, the results regarding the gathered observations on the extracted metrics of anomalous service detection are presented and explained. Second, in Section **??** - **??** the results obtained from the quality analysis methods applied to the tracing data set are presented and explained. The final Section **??** - **??** we present the limitations felted when designing a solution to process tracing data, more precisely OpenTracing data.

- Last, in Chapter **??** - **??**, the main conclusions for this research work are presented. The chapter is divided in three main sections. First, Section **??** - **??**, a reflection about the implemented tools, methods produced and the open paths from this research are exposed. Also a reflection of the main difficulties felted with this research regarding the handling of tracing data are presented. Second, Section **??** - **??**, the future work that can be addressed considering this work is properly explained taking into consideration what is said in the previous section. Finally, Section **??** - **??**, the state of answers for the selected questions defined in this research are discussed.

Next, Chapter 2 - Methodology, the elements involved in this work, their contributions and work plans for this research project are presented.

Chapter 2

Methodology

The methodology of work carried out in this research project is presented in this chapter. First, every member involved will be mentioned as well as their individual contribution for the project. Second, the adopted approach and organisation process of the collaborators involved will be explained. Finally, the work plan as well as the work performed, including the foreseen and real work plans for the whole year of work are presented and discussed.

The main people involved in this project were myself, André Pascoal Bento, student at the Master course of Informatics Engineering at Department of Informatics Engineering (DEI), who carried out the investigation and development of the project. In second, Prof. Filipe Araújo, assistant professor at the University of Coimbra, who contributed with his vast knowledge and guidance on topics about distributed systems and cloud computing. In third, Prof. Jorge Cardoso, Chief Architect for Intelligent CloudOps at Huawei Technologies, who contributed with his vision, great contact with the topics addressed in this work and with the tracing data set from Huawei Cloud Platform [6]. In fourth, Eng. Jaime Correia, doctoral student at DEI, who contributed with his vast technical knowledge regarding the topics of tracing and monitoring microservices. In Sixth, Eng. Ricardo Filipe, doctoral student at DEI, who contributed, like the ones mentioned before, with peer review of the produced paper for the International Symposium on Network Computing and Applications (IEEE NCA 2019).

This work stands for an investigation and was mainly an exploratory work, therefore, no development methodology was adopted. Meetings were scheduled to happen every two weeks. In these meetings, every participant element in the project joined with the objective of discussing the work carried out in the last two weeks and define the new course of research. In the first semester, topics like published papers, state of the art, analysis of related work and a proposition of solution were the main focus. In the second semester, two more colleagues joined the whole project (DataScience4NP). One of them with a project somehow related to this research. They started participating in meetings and this contributed with a wider discussion of ideas. In these meeting, the main topics covered were: implementation of the proposed solution, research for algorithms and methods for trace processing and analysis of gathered data. In the end, these meetings were more than enough to keep the productivity and good work.

Total time spent in each semester, by week, were sixteen (16) hours for the first semester and forty (40) hours for the second one. In the end, it was spent a total of three-hundred and four (304) hours for the first semester, starting in 11.09.2018 and ending in 21.01.2019 (19 weeks $*$ 16 hours per week). For the second semester, eight-hundred and forty (840)

hours were spent, starting in 04.02.2019 and ending in 28.06.2019 (21 weeks $*$ 40 hours per week).

Before starting this research project, there was a work plan defined for two semesters presented in the proposition. For record, these plans are presented in Figure 2.1.

For purposes of analysis and comparison with the proposed work plan, the real work plan carried out in the first semester is presented in Figure 2.2.

As we can see in Figures 2.1 and 2.2, the proposed work for the first semester has suffered some changes, when comparing it to the real work plan. Task 1 - Study the state of the art(...), was branched in two, 1 - Project Contextualisation and Background and 2 - State of the Art, however, these last ones tocked more time to accomplish due to lack of work in the field of trace processing and trace analysis, core topics for this thesis. Task 2 - Integrate the existing work was replaced by task 3 - Prototyping and Technologies Hands-On due to redirections in the work course. This redirection was done due to interest increase in testing state of the art technologies, allowing us to get a better visualisation of the data provided by Huawei and enhancing our investigation work. The remaining tasks took almost the predicted time to accomplish.

For the second semester, an "expected" work plan was defined with respect to the proposed work, presented in Figure 2.1, and the state of the research at the time. The expected work plan can be visualized in Figure 2.3. This Figure contains the expected (Grey) and real (Blue) work for the second semester.

Three main changes were made over time in the work plan. The first one involved a reduction in task 1 - Metrics collector tool. When the solution was being implemented and the prototype was capable to extract a set of metrics, we decided to stop the implementation process to analyse the research questions. Second, this analysis lead to an emergence of ideas, "2 - Restructuring research questions',' and thus a project redirection. Tests were removed from planning and the project followed with the objective of producing the data analyser, "3 - Data Analyser tool", and with it, answer two main questions regarding anomalous services and quality of tracing. Third, the introduction of a new task, "4 - Write paper to NCA 2019", covering the work presented in this thesis.

These Figures have been created by an open-source tool called GanttProject [7] that produce Gantt charts, a kind of diagram used to illustrate the progress of the different stages of a project.

Next, Chapter 3 - State of the Art, the state of the field is covered with core concepts, technologies and related work.

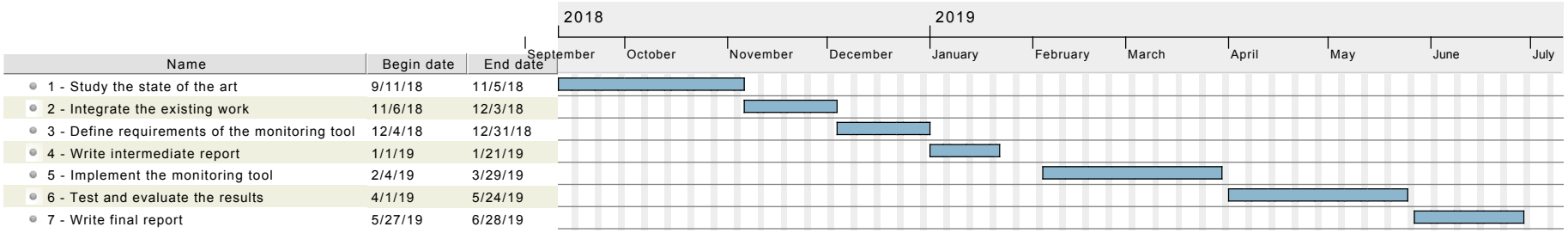

Figure 2.1: Proposed work plan for first and second semesters.

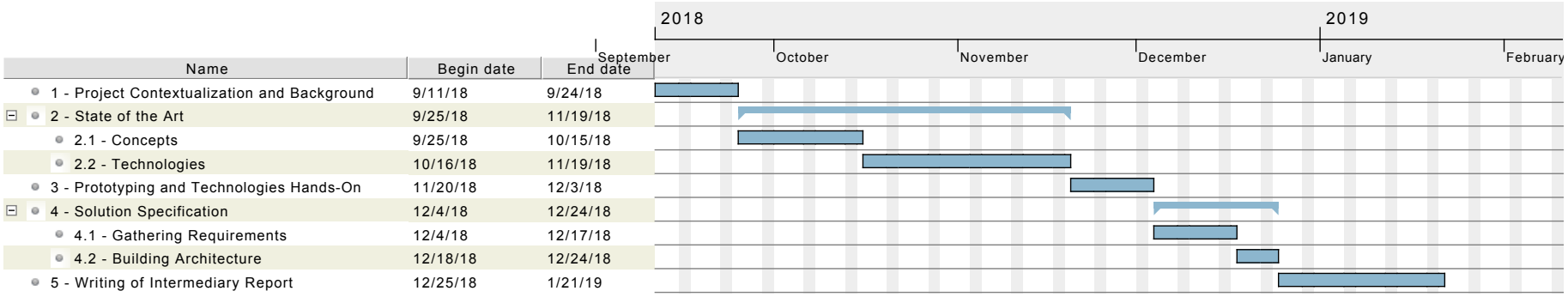

Figure 2.2: Real work plan for first semester.

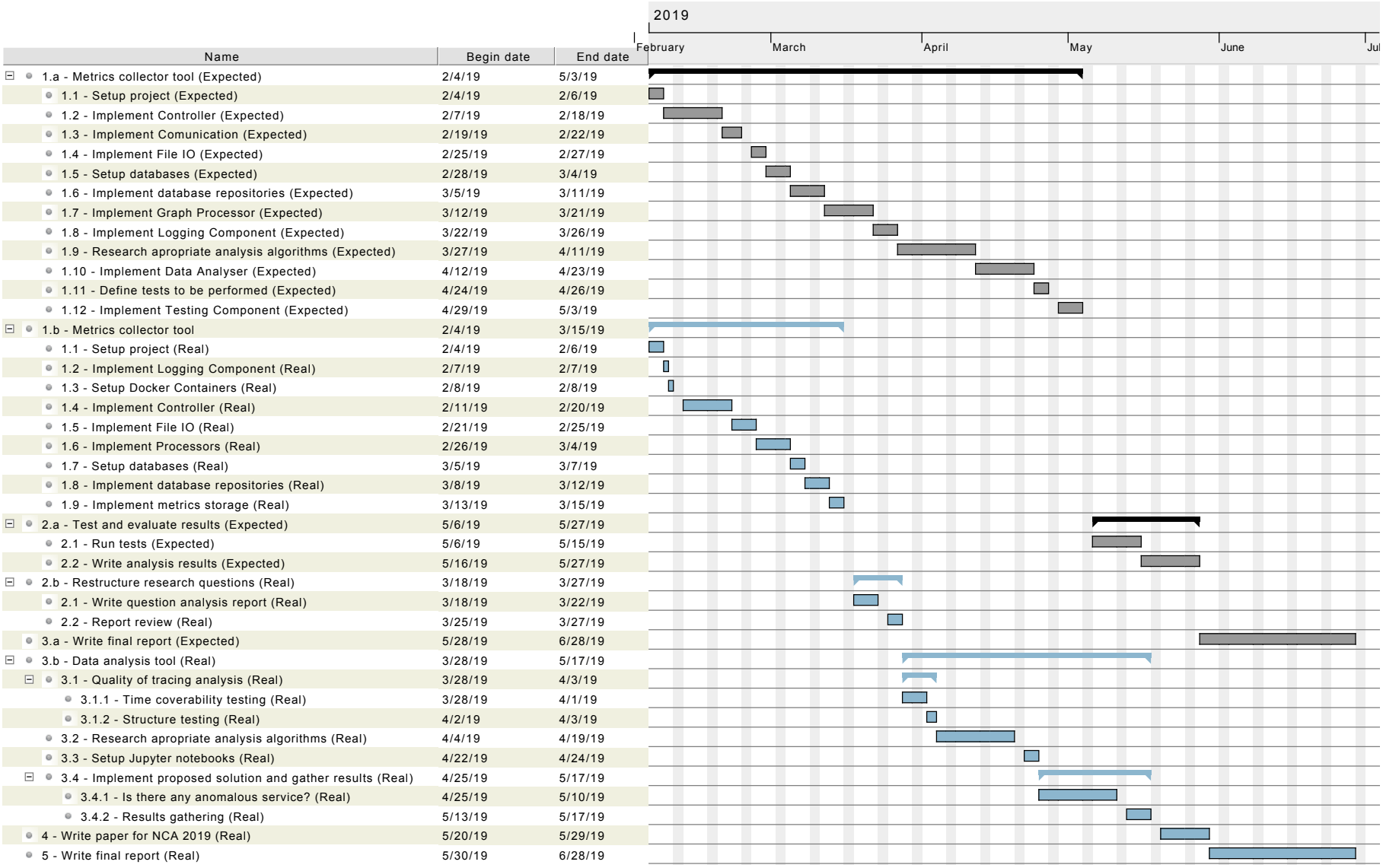

Figure 2.3: Real and expected work plans for second semester.

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Chapter 3

State of the Art

In this Chapter, we discuss the core concepts regarding the project, the most modern technology for the purpose today and related work in the area. All the information presented results from work of research through published articles, knowledge exchange and web searching.

First, the main purpose of Section 3.1 - Concepts is to introduce and provide a brief explanation about the core concepts to the reader. Second, Section 3.2 - Technologies, all the relevant technologies are analysed and discussed. In the final Section 3.3 - Related Work, published articles and posts of related work are presented and possible research directions are discussed.

3.1 Concepts

The following concepts represents the baseline to understand the work related to this research project. First an explanation of higher level of concepts that composes the title of this thesis are presented in Subsections 3.1.1 and 3.1.2. The following Subsections 3.1.3 to 3.1.5, aim to cover topics related to previous concepts: Distributed Tracing, Graphs and Time Series.

3.1.1 Microservices

The term "micro web services" was first used by Dr. Peter Rogers during a conference on cloud computing in 2005, and evolved later on to "Microservices" at an event for software architects in 2011, where the term was used to describe a style of architecture that many attendees were experimenting with at the time. Netflix and Amazon were among the early pioneers of microservices [8].

Microservices is "an architectural style that structures an application as a collection of loosely coupled services, which implement business capabilities" [1], [9].

This style of software development has a very long history and has being introduced and evolving due to software engineering achievements in the later years regarding cloud distributed computing infrastructures, Application Programming Interface (API) improvements, agile development methodologies and the emergence of the recent phenomenon of containerized applications. "A container is a standard unit of software that packages up code and all its dependencies so the application runs quickly and reliably from one

computing environment to another, communicating with others through an API" [10].

In Microservices, services are small, specifically calibrated to perform a single function, also each service is designed to be autonomous, resilient, minimal and composable. This framework brings a culture of rapid iteration, automation, testing, and continuous deployment, enabling teams to create products and deploy code exponentially faster than ever before [11].

Until the rising of Microservices based architecture, the Monolithic architectural style was the most used. This style has a the particularity of produce software composed all in one piece. All features are bundled, packaged and deployed in a single tier application using a single code base.

Figure 3.1 aims to give a comparison between both architectural styles, Monolithic and Microservices, and provide an insight about the differences between them.

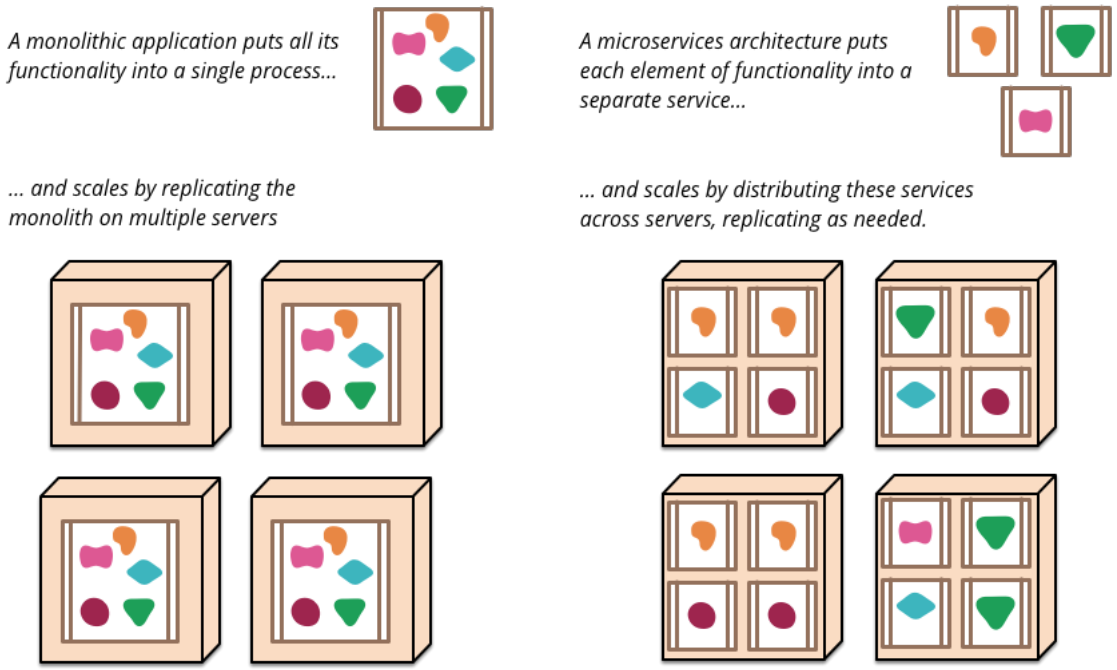

Figure 3.1: Monolithic and Microservices architectural styles [12].

Both styles presented have their own advantages and disadvantages. To briefly present some of them, two examples are provided, one for each architectural style. First example: if one team needs to develop a single process system, e.g., e-Commerce application, that authorizes customer, takes an order, check products inventory, authorize payment and ships ordered products. The best alternative is to use Monolithic architecture, because they can develop every feature in a single software package due to the application simplicity, however, if the client starts to demand hard changes and additional features in the solution, the code base may tend to increase into "out of control", leading to more challenging and time consuming changes. Second example, if one team needs to develop a complex and huge service that needs to scale, e.g., Video streaming service, the best alternative is to use Microservices architecture, because they can tackle the problem of complexity by decomposing the application into a set of manageable small services which are much faster to develop and test by individual organized teams, and thus, it will be easier to maintain the code base due to decoupling, however, it will be harder to monitor

and manage the entire platform due to additional complexity associated with distributed systems.

Taking into consideration this increasing difficulty in monitoring and managing large Microservice based platforms, one must be aware and observe system behaviour to be able to control it. Therefore, in the next Subsection 3.1.2, the core concept of Observability and Controlling Performance is explained.

3.1.2 Observability and Controlling Performance

This Subsection aims to provide an introduction to some theory concepts about Observability and Performance Controlling, regarding distributed software systems.

Observability is a meaningfully extension of the word observing. Observing is "to be or become aware of, especially through careful and directed attention; to notice' '[13]. The term Observability comes from the world of engineering and control theory. Observability is not a new term in the industry, however it has gain more focus in the last years due to Development and Operations (DevOps) raising. It means by definition "to measure of how well internal states of a system can be inferred from knowledge of its external outputs" [14]. Therefore, if our good old software systems and applications do not adequately externalize their state, then even the best monitoring can fall short.

Controlling in control systems is "to manage the behaviour of a certain system" [15]. Controlling and Observability are dual aspects of the same problem [14], as we need to have information to infer state and be able take action. E.g., When observing an exponential increase in the Central Processing Unit (CPU) load, the system scales horizontally invoking more machines and spreading the work between them to easy handle the work. This is a clear and simple example that conjugates the terms presented, we have: values that are observed "Observability" and action that leads to system control "Controlling Performance".

When we want to understand the working and behaviour of a system, we need to watch it very closely and pay special attention to all details and information it provides. Microservice based systems produce multiple types of information if instrumented. These type of information are the ones mentioned in Chapter 1: Monitoring, Tracing and Logging. In this thesis, the goal is to use tracing data thus, this type of produced information is the one to focus.

In the next Subsection 3.1.3 - Distributed Tracing, the type of data mentioned before is presented and explained in detail.

3.1.3 Distributed Tracing

Distributed tracing [16] is a method that comes from traditional tracing, but in this case acts in a distributed system at the work-flow level. It is used to profile and monitor applications, especially those built using microservice architectures and, in the end, it can be used to help DevOps teams pinpoint where failures occur and what causes system problems.

From this concept, standards emerged, like the best-known OpenTracing [17]. The OpenTracing standard, follows the model proposed by Fonseca *et al.* [18], which defines traces as a tree of spans, which represent scopes or units of work (i.e., thread, function, service) and follows their executing through the system.

OpenTracing uses dynamic, fixed-width metadata to propagate causality between spans, meaning that each span has a *TraceID* common to all spans of that trace, as well as a *SpanID* and *ParentID* that are used to represent parent/child relationships between them [19].

The standard defines the format for spans and the semantic [20], [21] conventions for their content / annotations.

Figure 3.2 provides a clear insight about how spans are related to time and with each other.

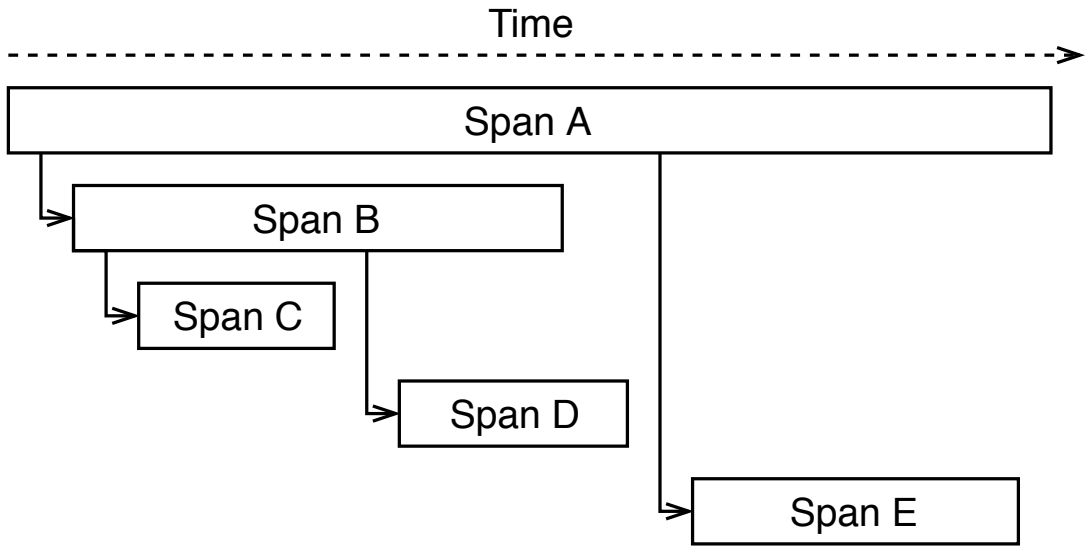

Figure 3.2: Sample trace over time.

In Figure 3.2 there are a group of five spans spread through time that represents a trace. A trace is a group of spans that share the same *TraceID*. A trace is a representation of a data/execution path in the system. A span represents the logical unit of work in the system. A trace can also be a span, if there is only one span presented in the trace. One span can cause another.

Causality relationship between spans can be observed in Figure 3.2, where "Span A" causes "Span B" and "Span E", moreover, "Span B" causes "Span C" and "Span D". From this we say that "Span A" is parent of "Span B" and "Span E". Likewise, "Span B" and "Span E" are children of "Span A". In this case, "Span A" does not have a parent, it is an "orphan span" and therefore, is the root span and the origin of this whole trace. Spans carry with them metadata like e.g., *SpanID* and *ParentID*, that allows to infer this relationships.

Disposition of spans over time is another clear fact that can be observed from the representation in Figure 3.2. Spans have a begin and an end in time. This causes them to have a duration. Spans are spread through time, however they usually stay inside parent boundaries, this means that the duration of a parent span always covers durations of their children. Considering a parent and a child spans, if they are related, the parent span always start before child span, also, the parent span always end after child span. Note that nothing prevents multiple spans to start in the same exact moment. Span also carry with them metadata like e.g., *Timestamp* and *Duration*, that allows to infer their position in time and when they end.

An example of a span can be an Hypertext Transfer Protocol (HTTP) call or a Remote Procedure Call (RPC) call. We may think of the following cases to define each operation inherent to each box presented in Figure 3.2: A - "Get user info", B - "Fetch user data from database", C - "Connect to MySQL server", D - "Can't connect to MySQL server" and E - "Send error result to client".

In the data model specification, the creators of OpenTracing say that: "with a couple of spans, we might be able to generate a span tree and model a directed graph of a portion of the system" [17]. This is due to the causal relationships they represent. Figure 3.3 provides an example of a span tree.

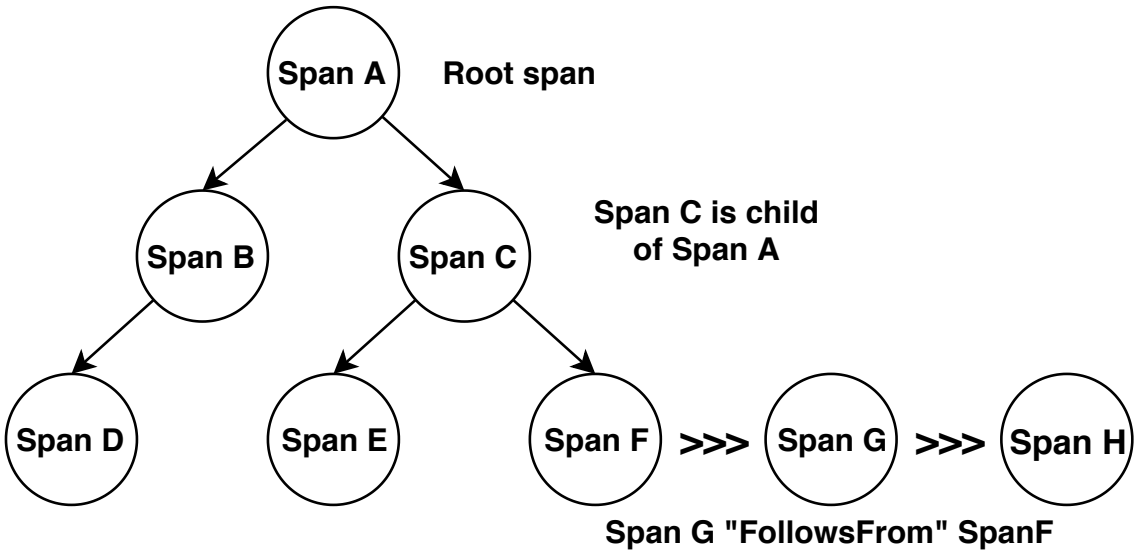

Figure 3.3: Span Tree example.

Figure 3.3 contains a span tree representation with a trace containing eight spans. As said before,every span must be a child of some other span, unless it is the root span, this is very clear in a span tree visualization with the usage of the root node. With this causal relationship, a path through the system can be retrieved. For example, if for example every span processes in a different endpoint represented by letters presented in the span tree, one may generate the request path: A —> B —> D. This means that our hypothetical request passed through machine A, B and D, or if it were services, the request passed from service A, to B and finally to D. From this, we can generate the dependency graph of the system (explained in the Subsection 3.1.4 - Graphs).

This type of data is extracted as trace files or streamed over transfer protocols like e.g., HTTP, from technologies like Kubernetes [22], OpenStack [23], and other cloud or distributed management system technologies that implements some kind of system or code instrumentation using, for example, OpenTracing [24] or OpenCensus [25]. Tracing contains some vital system details as they are the result of system instrumentation and therefore, this data can be used as a resource to provide observability over the distributed system.

As said before, from the causality relationship between spans we can generate a dependency graph of the system. The next Subsection 3.1.4 - Graphs aims to provide a clear understand of this concept and how they relate with distributed tracing.

3.1.4 Graphs

From distributed tracing we can be able to extract the system dependency graph from a representative set of traces. To introduce the concept of Graph, "A Graph is a set of vertices and a collection of directed edges that each connects an ordered pair of vertices" [26].

Taking the very common sense of the term and to provide notation, a graph, G, is an ordered pair $G = (V, E)$, where V are the vertices/nodes and E are the edges.

Graphs are defined by:

- Node: Are the entities in the graph. They can hold any number of attributes (key-value pairs) called properties. Nodes can be tagged with labels, representing their different roles in a domain. Node labels may also serve to attach metadata (such as index or constraint information) to certain nodes;
- Edge (or Relationships): provide directed, named, semantically-relevant connections between two node entities;
- Property: can be any kind of metadata attached to a certain Node or a certain Edge.

Also, there are multiple types of graphs, they can be:

1. Undirected-Graph: the set of edges without orientation between a pair of nodes;
2. Directed-Graph: the set of edges have one and only one direction between a pair of nodes;
3. Multi-Directed-Graph: multiple edges have more than one connection between a pair of nodes that represents the same relationship.

Figure 3.4 gives us a simple visual representation of what a graph really is for a more clear understanding.

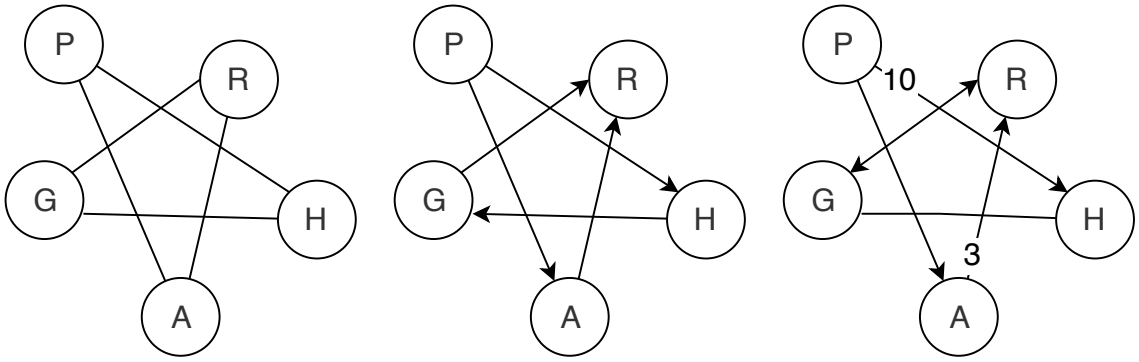

Figure 3.4: Graphs types.

In Figure 3.4 three identical graphs are presented and each one is composed by five nodes, however, they are not equal because each one has it own type. They belong respectively to each type enumerated above. From left to right, the first graph is a Undirected-Graph, the second one is a Directed-Graph and the last one is a Multi-Directed-Graph.

The last graph has some numbers in some edges. Every graph can have this annotations. These can provide some information about the connection between the pair of nodes. For example, in distributed systems context, if this graph represents our system dependency graph, and nodes H and P hypothetical services, the edge between them could represent calls between these two service and the notation number the number of calls with respect to the edge direction. Therefore, in this case, we would have 10 requests from incoming from P to H.

Figure 3.5 provides a clear insight about service dependency graphs.

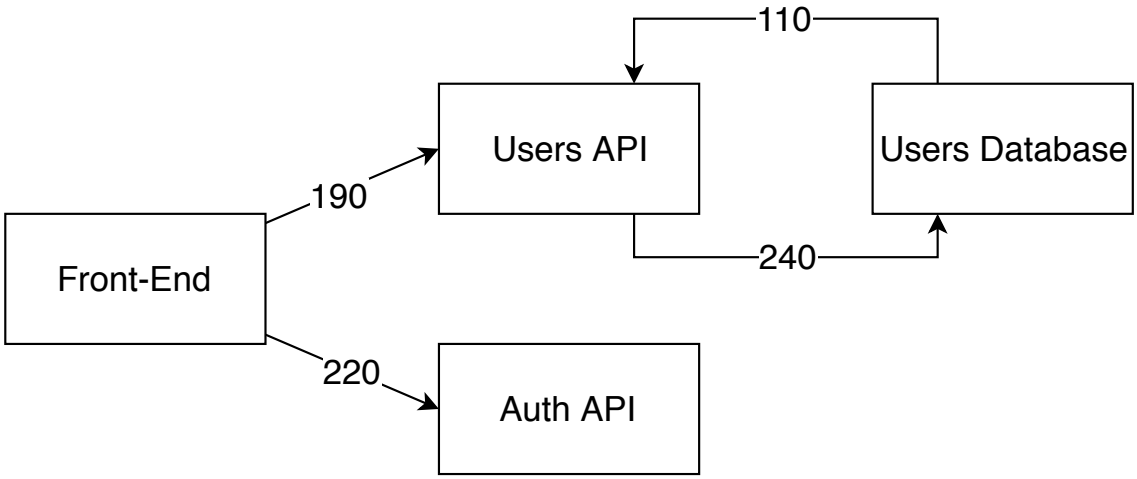

Figure 3.5: Service dependency graph.

In Figure 3.5, a representation of a service dependency graph is provided. Service dependency graphs are graphs of type Multi-Directed-Graph, because they have multiple edges with more than one direction between a pair of services(Nodes). In this representation, there are multiple services involved, each inside a box. The edges between boxes (Nodes), indicate the number of calls that each pair of services invoked, e.g., "Users API" called "Users Database" 240 times. These dependency graphs gives the state of the system in a given time interval. This can be useful to study the changes in the morphology of the system, e.g., a service disappeared and a set of new ones appeared. Other interesting study could be the variation in the amount of call between services.

Graphs are a way to model and extract information from tracing data. Another interesting approach could be to extract metrics in time from tracing because traces and spans are spread in time, and they have information about the state of the system at a given instant. The next Subsection 3.1.5 - Time Series provides an introduction to a data representation model.

3.1.5 Time Series

Time-Series are a way of representing data as a time-indexed series of values. This kind of data is often arise when monitoring systems, industrial processes, tracking corporate business metrics or sensor measurements. Figure 3.6 provides a visual example of this way of data representation.

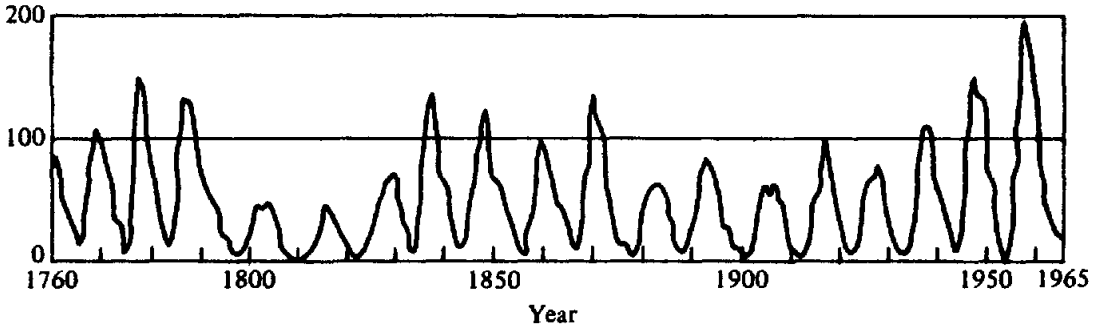

Figure 3.6: Time series: Annual mean sunspot numbers for 1760-1965 [27].

In Figure 3.6, Brillinger *D.* [27] presents a visual representation of a time-series as a collection of values in time. These values are measurements of sunspot means gathered from 1960-1965. In this case, measurements come from natural origin, however, one can perform observations of e.g., CPU load, system uptime / downtime and network latency.

As these processes are not random, autocorrelation can be exploited to extract insight from the data, such as predict patterns or detect anomalies. Therefore, time-series data can be analysed to detect anomalies present in the system. One way to do this is to look for outliers [28] in the multidimensional feature set. Anomaly detection in time series data is a data mining process used to determine types of anomalies found in a data set and to determine details about their occurrences. Anomaly detection methods are particularly interesting for our data set since it would be impossible to manually tag the set of interesting anomalous points. Figure 3.7 provides a simple visual representation of anomaly detection in time series data.

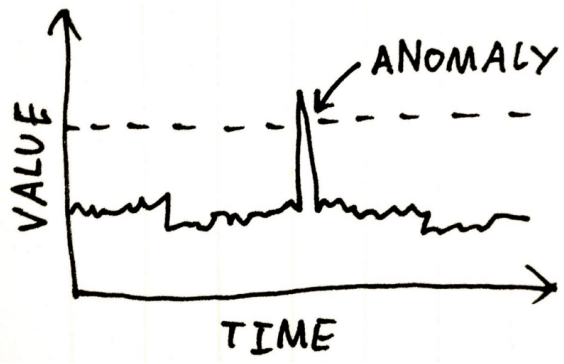

Figure 3.7: Anomaly detection in Time Series [29].

In Figure 3.7, there is a clear spike in values from this time series measurements. This can be declared an outlier because it is a strange value considering the range of remaining measurements and therefore, it is considered an anomaly. In this example, anomaly detection is easy to perform by a Human, however, in mostly cases nowadays, due to great variation of values and plethora of information that can be gathered, perform this detection manually is impracticable, thus automatic anomaly detection using Machine Learning techniques are used nowadays.

Anomaly detection in time series data is a data mining process used to determine types of anomalies found in a data set and to determine details about their occurrences. This auto anomaly detection method has lots of usage due to the impossible work of tag

manually the interesting set of anomalous points. Auto anomaly detection has a wide range of applications such as fraud detection, system health monitoring, fault detection, event detection systems in sensor networks, and so on.

After explaining the core concepts, foundations for the work presented in this thesis, to the reader, technologies capable of handling this types of information are presented and discussed in next Section 3.2 - Technologies.

3.2 Technologies

In this section are presented technologies and tools capable of handling the types of information discussed in the previous Section 3.1 - Concepts.

The main tools covered are: 3.2.1 - Distributed Tracing Tools, for distributed tracing data handling, 3.2.2 - Graph Manipulation and Processing Tools and 3.2.3 - Graph Database Tools, for graph processing and storage, and 3.2.4 - Time-Series Database Tools, for time series value storage.

3.2.1 Distributed Tracing Tools

This Subsection presents the most used and known distributed tracing tools. These tools are mainly oriented for tracing distributed systems like microservices-based applications. What they do is to fetch or receive trace data from this kind of complex systems, treat the information, and then present it to the user using charts and diagrams in order to explore the data in a more human-readable way. One of the best features presented in this tools, is the possibility to perform queries on the tracing (e.g., by trace id and by time-frame). Table 3.1 presents the most well-known open source tracing tools.

In Table 3.1, we can see that these two tools are very similar. Both are open source projects, allow docker containerization and provide a browser ui to simplify user interaction. Jaeger was created by Uber and the design was based on Zipkin, however, it does not provide much more features. The best feature that was released for Jaeger in the past year was the capability of perform trace comparison, where the user can select a pair of traces and compare them in terms of structure. This is a good effort in additional features, but it is short in versatility because we can only compare a pair of traces in a “sea” of thousands, or even millions.

These tools aim to collect trace information and provide a user interface with some query capabilities for DevOps to use. However they are always focused on span and trace lookup and presentation, and do not provide a more interesting analysis of the system, for example to determine if there is any problem related to some microservice presented in the system. This kind of work falls into the user, DevOps, as they need to perform the tedious work of investigation and analyse the tracing with the objective of find anything wrong with them.

This kind of tools can be a good starting point for the problem that we face, because they already do some work for us like grouping the data generated by the system and provide a good representation for them.

In next Subsection 3.2.2, graph manipulation and processing tools are presented and discussed.

Table 3.1: Distributed tracing tools comparison.

	Jaeger [30]	Zipkin [31]
Brief description	Released as open source by Uber Technologies and is used for monitoring and troubleshooting microservices-based distributed systems. Was inspired by Zipkin.	Helps gather timing data needed to troubleshoot latency problems in microservice architectures and manages both the collection and lookup of this data. Zipkin's design is based on the Google Dapper paper.
Pros	OpenSource; Docker-ready; Collector interface is compatible with Zipkin protocol; Dynamic sampling rate; Browser UI.	OpenSource; Docker-ready; Allows lots of span transport ways (HTTP, Kafka, Scribe, AMQP); Browser UI.
Cons	Only supports two span transport ways (Thrift and HTTP).	Fixed sampling rate.
Analysis	Dependency graph view; Trace comparison (End 2018).	Dependency graph view.
Used by	Red Hat; Symantec; Uber.	AirBnb; IBM; Lightstep.

3.2.2 Graph Manipulation and Processing Tools

Distributed tracing is a type of data produced by Microservice based architectures. This type of data is composed by traces and spans. With a set of related spans, a service dependency graph can be produced. This dependency graph is a Multi-Directed-Graph, as presented in Subsection 3.1.4. Therefore, with this data at our disposal, there is the need of a graph manipulation and processing tool.

In this Subsection, graph manipulation

CONTINUE FROM HERE!!!

Considering that we have data to be processed and manipulated, we have to be sure that we can handle it for analysis. For this purpose, and knowing that the data is a representation and an abstraction of a graph, we needed to study the frameworks available this task. Table 3.2 presents the main technologies available at the time for graph manipulation and processing.

Table 3.2: Graph manipulation and processing tools comparison.

	Apache Giraph [32]	Ligra [33]	NetworkX [34]
Description	An iterative graph processing system built for high scalability. Currently used at Facebook to analyse the social graph formed by users and their relationships.	A library collection for graph creation, analysis and manipulation of networks.	A Python package for the creation, manipulation, and study of structure, dynamics, and functions of complex networks.
Licence [35]	Free Apache 2.	MIT.	BSD - New License.
Supported languages	Java and Scala.	C and C++.	Python.
Pros	Distributed and very scalable; Excellent performance – Process one trillion edges using 200 modest machines in 4 minutes.	Handles very large graphs; Exploit large memory and multi-core CPU – Vertically scalable.	Good support and very easy to install with Python; Lots of graph algorithms already implemented and tested.
Cons	Uses "Think-Like-a-Vertex" programming model that often forces into using sub-optimal algorithms, thus is quite limited and sacrifices performance for scaling out; Unable to perform many complex graph analysis tasks because it primarily supports Bulk synchronous parallel.	Lack of documentation and therefore, very hard to use; Does not have many usage in the community.	Not scalable (single-machine); High learning curve due to the maturity of the project; Begins to slow down when processing high amount of data – 400.000+ nodes.

With the information presented in the previous table, we can have a notion that this three frameworks don't work and perform in the same level in many ways.

One thing to consider when comparing them is the scalability and performance that each can provide, for instance, in this component the first one, Apache Giraph is the winner since it is implemented with the distributed systems paradigm in mind and can scale to multiple-machines to get the job done in no time, considering high amounts of

data. In other way, we have the third framework, called NetworkX, that is different from the previous as it works in a single-machine and doesn't have the ability to scale to multiple-machines. This can be a very problematic feature if we are dealing with very high amounts of data and we have to process it in short amounts of time. The last framework, called Ligra, works in a single-machine environment like the previous one, but it can scale vertically as it has the benefit of use and exploit multi-core CPU's.

The second, and also most important thing to consider, is the support and quantity of implemented graph algorithms in the framework, and in this field the tables turned, and the NetworkX has a lot of advantage as it have lots of implemented graph algorithms defined and studied in graph and networking theory. The remaining frameworks don't have very support either because they don't have it documented or because the implementation and architecture that where considered don't allow to implement it.

For a more clear insight of the position of the presented technologies in the previous table, we have the figure 3.8.

With the presented figure, our perception of what we might choose when considering this tools is more clear, but we have always some trade offs we cannot avoid. The best approach, and if it's possible, is to consider the usage of an hybrid environment where Giraph and NetworkX coexist one with another, as one fills the gaps of the other, but always taking into consideration that a bottleneck will occur between them **graph˙frameworks˙performance˙evaluation** and that there are almost none implementation where they coexist **graph˙frameworks˙performance˙evaluation** because of their disparity.

3.2.3 Graph Database Tools

This data can be modelled as information. After having a Graph instantiated we may be able to store it. For this type of information, there are specific ways of storing it. For example, we can store graphs in a Graph Database (GDB). A GDB is "a database that uses graph structures for semantic queries with nodes, edges and properties to represent and store data"[37].

Manipulating and process graph data is not enough, we need to store this data somewhere, and to do this we need a GDB. The results of the research for the best graph databases tools available are presented in the table 3.3.

As we can notice by the data provided by the presented table, the state of the art about graph databases is not very good. The offers are very limited and all of them lack something when we start to see them in detail. The interest in this databases is increasing as graph technology tend to have many use cases and solve lots of problems nowadays.

Facebook detains the most powerful and robust system for this purpose, but as it is the base of their business because they need to perform large operations in their huge social graph in reduced times, it is a proprietary technology and is only referenced in some articles [39].

The remaining two tools, are very supported by the community because of their license and demand, however based on the stars and forks of their repositories, Neo4J is more well received by the community and tends to become more popular. It doesn't implement horizontal scalability by design and this can be a risk when using it in systems with scalabilty in mind, but there are some authors that report they were able to perform implementations and surpass the scalability issue, however with many snags[42]. ArangoDB supports

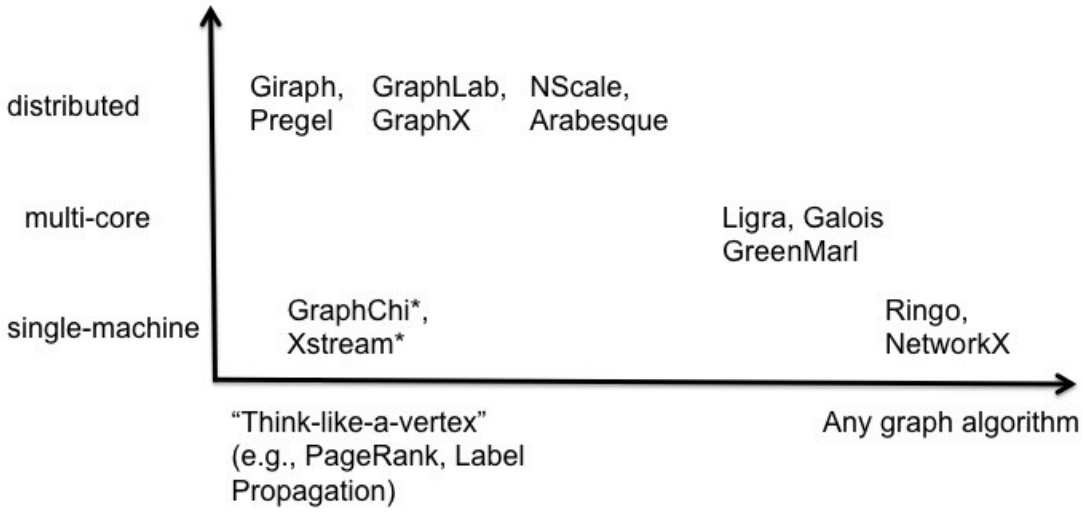

Figure 3.8: Graph manipulation tools comparison, regarding scalability and graph algorithms [36].

scalability by default as we can see in the figure 3.9[43], but it has a very hard query language with a high learning curve inherent to it, and it is payed to use some special features like SmartGraphs storage[44] that improves the writing of graph in distributed databases.

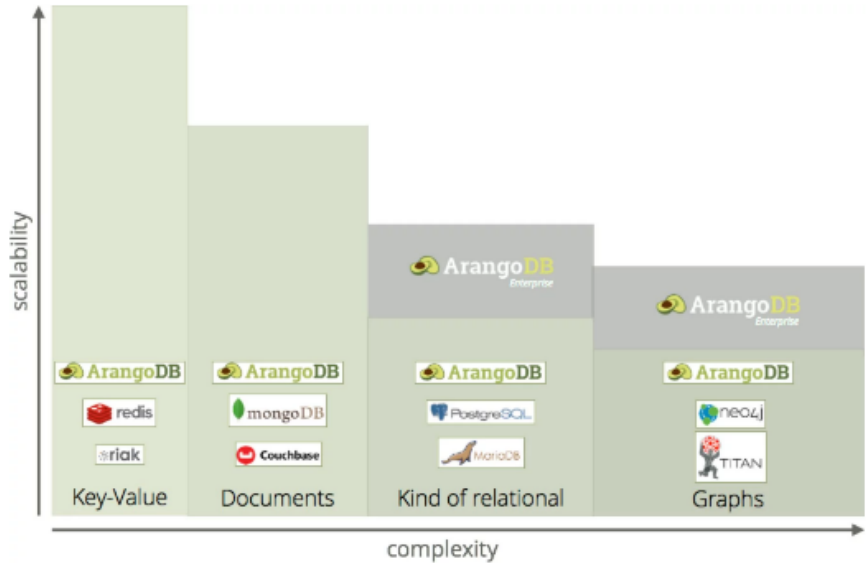

Figure 3.9: ArangoDB vs. Neo4J scalability over complexity.

3.2.4 Time-Series Database Tools

CHECK THIS!!!

A Time Series Database (TSDB) is "is a database optimised for time-stamped or time series data like arrays of numbers indexed by time (a date time or a date time range)"[45].

This kind of databases are natively implemented using specialised database algorithms

to enhance it's performance and efficiency due to the widely variance of access possible. The way this databases use to work on efficiency is to treat time as a discrete quantity rather than as a continuous mathematical dimension. Usually a TSDB allows operations like create, enumerate, update, organise and destroy various time series entries.

The TSDB and the GDB, presented in this subsection and in the subsection before respectively, are at the time, the most wanted and fastest growing kind of databases due to their use cases in the trending fields of Cloud and Distributed based Systems and in the *Internet of Things (IoT)*. The figure 3.10 presents the growing of this databases in the last two years. As we can see in the figure presented, the TSDB and GDB are distancing from the remaining databases in terms of popularity starting from the same spot in December

Table 3.3: Graph databases comparison.

Name	ArangoDB [38]	Facebook TAO [39]	Neo4J [40]
Description	It's a NoSQL database developed by ArangoDB Inc. that uses a proper query language to access the database.	TAO, "The Associations and Objects", is a proprietary database, developed by Facebook, that stores all the data related to the users in the social network.	It's the most popular open source graph database. Has been developed by Neo4J Inc. and is completely open to the community.
Licence	Free Apache 2	Proprietary	GPLv3 CE
Supported languages	C++ Go Java JavaScript Python Scala	—	Java JavaScript Python Scala
Pros	Multi data-type support (key/value, documents, graphs). Allows the combination of different data access patterns in a single query. Supports cluster deployment.	Very fast(=100ms latency). Accepts millions of calls per second. Distributed.	Supports ACID(Atomicity, Consistency, Isolation, Durability)[41]. High-availability. Has a visual node-link graph explorer. REST API interface. Most popular open source graph database.
Cons	Needed to learn a new query language called AQL(Arango Query Language). High learning curve. Has paid version with high price tag.	Not accessible to use.	Can't be distributed (It needs to be vertically scaled).

of 2016. The predictions are that this databases will not stop increasing popularity, until this kind of systems described before start losing it too.

CHECK THIS!!!

As we intend to extract useful data from span trees and graphs, we need to store it somewhere. We already know that the spans and trace data are directly related with time based information, explained in the subsection **??** - **??**, so the best way to store the gathered or calculated information from them is in a TSDB.

The figure 3.11 present the ranking of the TSDB at the current time[47].

The table 3.4 exposes a comparison between the two top databases presented in the ranking, the *InfluxDb* and *OpenTSDB*, two very well known databases in the world of TSDB, in order to understand the advantages and disadvantages of each one.

Table 3.4: Time-series databases comparison.

Name	InfluxDB [48]	OpenTSDB [49]
Description	It is an open-source time series database developed by InfluxData written in Go and optimised for fast, high-availability storage and retrieval of time series data in fields such as operations monitoring, application metrics, Internet of Things sensor data, and real-time analytics.	It is a distributed, scalable Time Series Database (TSDB) written on top of HBase. OpenTSDB was written to address a common need: store, index and serve metrics collected from computer systems (network gear, operating systems, applications) at a large scale, and make this data easily accessible and graphable.
Licence	MIT	GPL
Supported languages	Erlang Go Java JavaScript Lisp Python R Scala	Erlang Go Java Python R Ruby
Pros	Scalable in the enterprise version. Outstanding high performance. Accepts data via HTTP, TCP, and UDP protocols. SQL like query language. Allows real-time analytics.	It's massively scalable. Great for large amounts of time-based events or logs. Accepst data via HTTP and TCP access protocols. Good platform for future analytical research into particular aggregations on event/log data. Doesn't have paid version.
Cons	Enterprise high price tag. Clustering support only available in the enterprise version.	Expensive to try. Not a good choice for general-purpose application data.

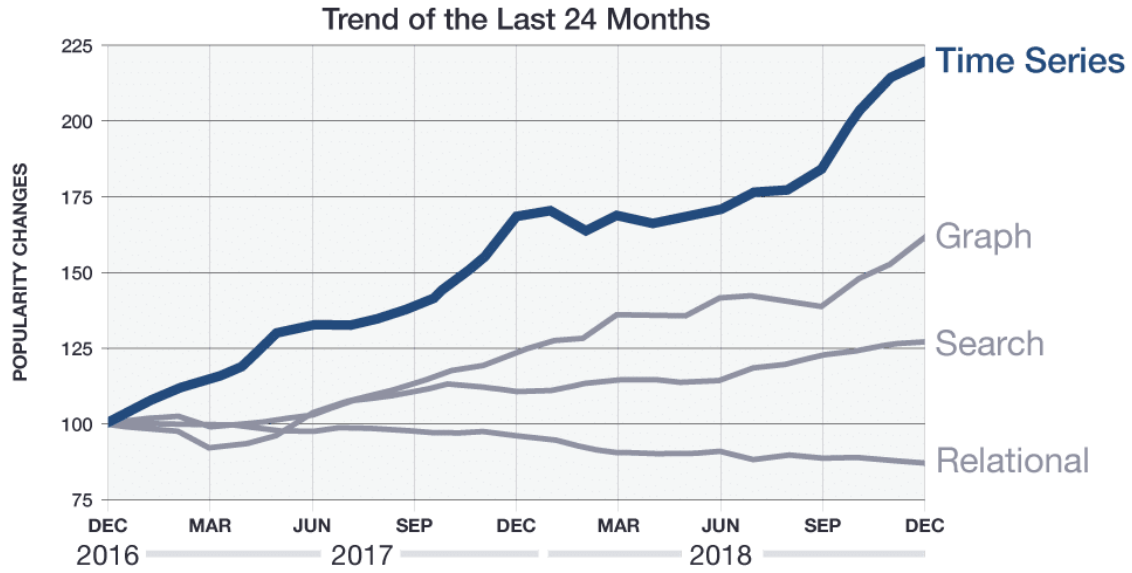

Figure 3.10: Fastest Growing Databases.[46]

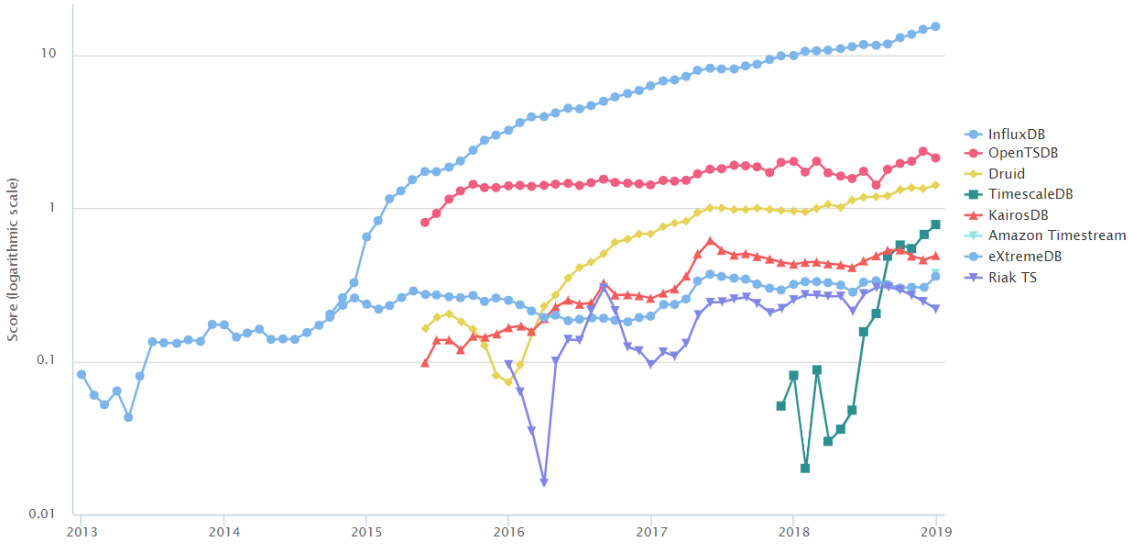

Figure 3.11: TSDBs ranking from 2013 to 2019.

Based on the information presented in the referenced table, we can notice that this two databases are very similar on what they offer like the access protocols and scalability capabilities. In the point of licence, both are open source, however the first one, InfluxDB, has an enterprise paid version that is not very well exposed in its documentations and much people don't even notice it, contrarily to OpenTSDB which is completely free. The enterprise version of InfluxDB provides clustering support, high availability and scalability[50], features that OpenTSDB offer for free, however in terms of performance, InfluxDB outperforms OpenTSDB in almost every benchmark by a far distance as we can see in the figures **??** and **??**.

3.3 Related Work

In this section are presented three section of the existing related work for tracing data analysis. After explaining each one, a brief reflection is made to note some directions of research for this project.

3.3.1 Mastering AIOps

// TODO: Explain what is done and how is done.

[51]

3.3.2 Anomaly Detection using Zipkin Tracing Data

// TODO: Explain what is done and how is done.

[52]

Wei Lee was contacted by email to understand better their research focus, however without success because no answer was given.

3.3.3 Analysing distributed trace data

// TODO: Explain what is done and how is done.

[53]

3.3.4 Research possible directions

// TODO: Make a brief reflection about the related work.

After providing the state of the art for this research to the reader, next Chapter **??** - **??** will cover the objectives of this research, the approach used to tackle the problem and the compiled research questions.

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