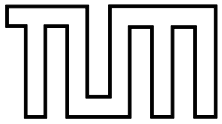

Department of Informatics
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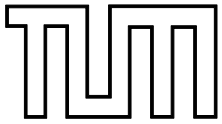
Master's Thesis in Information Systems

Using Distributed Traces for Anomaly Detection

Lukas Daniel Steigerwald



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Master's Thesis in Information Systems

Using Distributed Traces for Anomaly Detection

Verwendung von Distributed Traces zur Erkennung von Anomalien

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I confirm that this master's thesis is my own work and I have documented all sources and materials used.

Garching, 11.10.2017 Lukas Steigerwald

Abstract

Performance of web applications and a smooth user experience are key for today's online business. Even small increases in response times impact a user's experience on a web page what leads to lower conversion rates. So anomalous behavior of a company's web applications can negatively impact their revenue. At the same time, more and more web applications are provided through a large number of interacting services across different machines. This is the reason, why companies are employing distributed tracing to track the way the requests take through different services while they are processed.

In this thesis a prototype is implemented that is able to detect anomalies based on distributed tracing data. The anomalies that are targeted by the anomaly detection are application errors, violations of defined thresholds and increased response times compared to the normal behavior of a service. This is achieved by running three different anomaly detection algorithms, implemented based on Apache Spark, in parallel on the incoming data from distributed tracing.

The reported anomalies are then processed by a second module that is based on Apache Spark. It sets the anomalies into a context, that represents the dependencies among the services, that reported them. This context is used to prioritize the reported anomalies that are seen to be the root cause of the set of anomalies.

The evaluation on a small-scale demo application shows, that the targeted anomalies can be detected by the prototype. This means, that it is possible to perform anomaly detection and root cause analysis based on distributed tracing data.

Keywords: Anomaly Detection, Root Cause Analysis, Distributed Traces, Microservices, Apache Spark, Apache Kafka, Spring Cloud Sleuth

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List of Abbreviations

ARIMA *Autoregressive Integrated Moving Average*

EBS *Enterprise Service Bus*

FN *False Negative*
FP *False Positive*

JVM *Java Virtual Machine*

LOF *Local Outlier Factor*
LSTM *Long Short Term Memory*

RDD *Resilient Distributed Dataset*

SOA *Service Oriented Architecture*

TN *True Negative*
TP *True Positive*

1 Introduction

The goal of this thesis is to implement a prototype that is able to detect anomalies based on information from distributed tracing. This chapter explains the motivation behind this topic and specifies the problem statement and the research questions of this work.

1.1 Motivation

This chapter shows the motivation behind this thesis. It explains, why anomaly detection based on distributed tracing is relevant and why its results should be enhanced by a root cause analysis to provide even more value.

1.1.1 Increasing complexity of applications

In the age of digital transformation, it is vital for a company to react to emerging trends quickly. Therefore, a reduced time to market for new features of a company's web application is important. To cope with this requirement for fast development, a lot of companies use microservice architectures. [1]

This architectural style keeps the single service application small and independent from other services. However, services have to communicate with each other to fulfil tasks. This means, that while a single service has a relatively simple code base, the overall complexity of the distributed system can get very high. As an example: At LinkedIn, there are more than 400 services on thousands of machines in operation [2].

1.1.2 Performance matters

At the same time, another important point has to be considered for companies that rely on web applications: Users of web applications usually wait for their request to be processed, before moving on. If the processing time takes too long, due to anomalous behavior of the application that impacts performance, this can result in a bad customer experience. And a customer that is not happy with a service, is less likely to spend money on it. This is the reason, why long response times can directly impact the revenue of the business operating the web application. [3]

This is as well supported by findings of big players in the online world, that are described below. Google, Amazon and the Mozilla Firefox project shared their experiences, how increased response times of their offered services impacted customer behavior.

Google ran an experiment, where they asked a test group of users how many search results they would like to see per page. As they asked for more results per page, they were provided with 30 results per page. However, instead of improved usage, Google observed a drop of 20% in traffic. What they did not take into account was, that by increasing the number of displayed search results, the page load time increased by half a second and this impacted the customer satisfaction more than delivering on their wish for more results on each page. [4]

In another experiment, Amazon did A/B testing on incrementing the page load speed in steps of 100ms. They found out, that even those small delays resulted in drops in revenue. [4] There are claims, that 100ms increases in response time caused a drop of 1% in revenue. [5, 6]

At Mozilla Firefox, they discovered that a simplified download page for the browser, resulted in an increased conversion rate of people looking at the page and downloading in the end. They tested their hypothesis, that this increase came through a faster page load time. By running further tests, they recognized that an increase in page load time by one second resulted in a 2.7% decrease in conversions. [7]

Those three cases show that the performance of web applications does matter when it comes to business success. Providing the customer with a fluid user experience throughout his visit to the online presence is key. Therefore, it is important to have system monitoring in place and use the gathered information to detect anomalous behavior as early as possible, that could decrease the user satisfaction.

The business impacting nature of anomalies requires operators of a system to fix them as fast as possible. However, in a complex microservices environment, another factor complicates this task. Anomalies caused by a single service can propagate to other services, that rely on that anomalous service [2]. Therefore, a monitoring system should not only report anomalous behaving services, but also needs to perform a root cause analysis on the detected anomalies. This analysis, that includes information about the dependencies of the services among each other, can help to prioritize the right services, where to search for those anomalies.

1.1.3 Distributed tracing is important for companies

In order to understand the behavior of a micro services application, it is important to be able to track requests across several machines and services, as well as being able to discover and analyze performance issues that might occur while the application is running [8]. By instrumenting the microservices with distributed tracing, this information can be collected.

The relevance of distributed tracing is underlined by the companies, that are actively working on solutions in this field. Google engineers published a paper [8] on the distributed tracing

instrumentation that was in use at Google. This paper provided the theoretical foundation, that is implemented today by popular open source instrumentations. Based on the Google paper, Twitter developed their own distributed tracing instrumentation and called it Zipkin. It was open sourced in 2012 [9] and is now a popular open source framework for distributed tracing.

Other companies are talking about their use of distributed tracing on their tech blogs. Yelp contributed to the Zipkin instrumentation for Python services by sharing their developments with the open source community [10]. Pinterest contributed their tracing pipeline "Pintrace" for Zipkin [11]. And Uber recently open sourced their own distributed tracing implementation "Jaeger" [12]. This is the result of them starting from a Zipkin instrumentation and then evolving the system, until they ended up with their own solution, that fits their needs [13].

This shows, that distributed tracing is playing an important role in a world of microservices and distributed web applications. Therefore, it can be assumed, that distributed tracing data will be widely available in the future providing valuable insights for monitoring the performance of a system and the path a request takes while it is processed.

1.2 Problem Statement

Based on the motivation outlined in chapter 1.1, the goal of this thesis is to create a prototype that should be able to serve two purposes: The first one is to detect anomalies and the second one is to perform a root cause analysis to enhance the results.

The anomaly detection must be able to observe the data that is generated by a demo application that is instrumented with a distributed tracing solution for anomalous behavior – especially for user impacting anomalies like increased response times or application errors. The only source of information that is used by the algorithms should be distributed tracing data.

The root cause analysis has the task to set the reported anomalies in the context of service dependencies that can be seen as a possible way of anomaly propagation. The context information should be created based on distributed tracing information as well.

This results in the following four research questions, that will be answered in this thesis:

RQ1: What is a valid architecture for supporting anomaly detection and root cause analysis in a service oriented and distributed environment?

RQ2: What are features required to detect performance anomalies?

RQ3: Which algorithms for anomaly detection are suitable for the chosen environment?

RQ4: How can a root-cause analysis be performed based on the discovered anomalies and the component dependencies?

1.3 Outline

The thesis is structured as follows: Chapter 2 will provide background information on the relevant topics for this thesis. It will cover the topics of microservices, distributed tracing, anomaly detection and root cause analysis.

Chapter 3 is about the design of the prototype. The design decisions for the anomaly detection and root cause analysis pipeline will be outlined. Then the architecture of the prototype will be explained. At the end of the chapter, the key technologies Spring Cloud Sleuth, Apache Spark and Apache Kafka are described in more detail.

Chapter 4 covers the anomaly detection. Feature extraction, the targeted anomalies and the selection of the detection algorithms are described. Next the implementation is described with challenges and an overview of the detection pipeline and detailed descriptions of the parts of the anomaly detection process.

Chapter 5 gives insights into the root cause analysis. After describing the challenges for this part of the prototype, detailed information about the implementation is provided.

Chapter 6 is about the evaluation of the prototype. The description of the monitored demo application is followed by the evaluation setup, including the way anomalies are injected amd the measurement metrics that are used. The tests, which were performed for the evaluation are pointed out and the results are presented and analyzed.

Chapter 7 wraps up this thesis. The general findings that were made during the design, development and the evaluation of the prototype are summarized, the limitations are identified and the thesis concludes with suggestions for future work.

2 Background

This chapter provides some background on the relevant topics for this work. It will start with explaining microservices, followed by distributed tracing, anomaly detection and root cause analysis.

2.1 Microservices

The term microservices was born by a group of software architects who needed an appropriate name for an architectural style they were starting to explore in 2012. This approach is all about independent components that communicate with each other through messages [14]. In this chapter first the characteristics of a Microservices Architecture will be outlined. Afterwards it will be differentiated from monolithic and Service Oriented Architecture approaches. Finally challenges and applications in companies will be pointed out.

2.1.1 Characteristics of Microservices

In 2014, Martin Fowler and James Lewis published an article [14] online, that is frequently cited when the definition of microservices is concerned and on which this chapter about the characteristics of microservices is based.

In this article characteristics of a microservice architecture are defined. It is component based, which means each service can be replaced and upgraded without impacting the other services. Best practices propose an architecture, in which services do not share memory and databases and therefore have to communicate through remote calls. A huge advantage of those components is, that if you get more requests than you can handle on a specific machine, it is possible to start another one with an instance of this service – and not an instance of the whole application. This enables good scalability, especially in cloud environments. Furthermore, several instances of the same service can be run in parallel to have some redundancy in the case of service failures. This results in a greater reliability of the microservices application as a whole.

The communication principle is “smart services and dumb pipes”. This means that all the logic is inside the services and they communicate through simple and lightweight ways without logic. The common technologies for this communication are HTTP request/response and lightweight message queues.

As you have independent components that communicate through well-defined interfaces, it is not necessary that every service runs the same technology stack, as long as the used

technology supports the communication standards. This enables developers to choose the best tools for the job.

A service should be oriented on business capabilities instead of technological layers. Instead of having separate teams for database, business logic and the user interface, cross functional teams with all these skill sets will implement whole user stories. The development team should build and run their component. This is often called a DevOps approach, which means that the responsibility of the developer does not end with the development of the application but also includes operation and maintenance.

The orientation on business capabilities leads to another characteristic of microservices. When defining the size and the functionalities of a service, it should be considered that it can be replaced or upgraded without affecting other services. This results in an application environment, where services can be easily maintained and upgraded. Furthermore, it allows for a fast and efficient way of implementing changes.

The characteristics of microservice architectures, that are described above, result in a large number of different applications that have to be tested and deployed. Therefore, microservice architectures are supported by a high degree of automation. Continuous Integration and Continuous Deployment practices are important, so that it does not matter whether just a single application or a large number of applications need to be tested and deployed.

2.1.2 Differentiation from Monolithic Applications

The characteristics described previously, distinguish a microservice architecture from monolithic applications. “A monolithic software application is a software application composed of modules that are not independent from the application to which they belong.”[15] This is a very common approach to application development up until now.

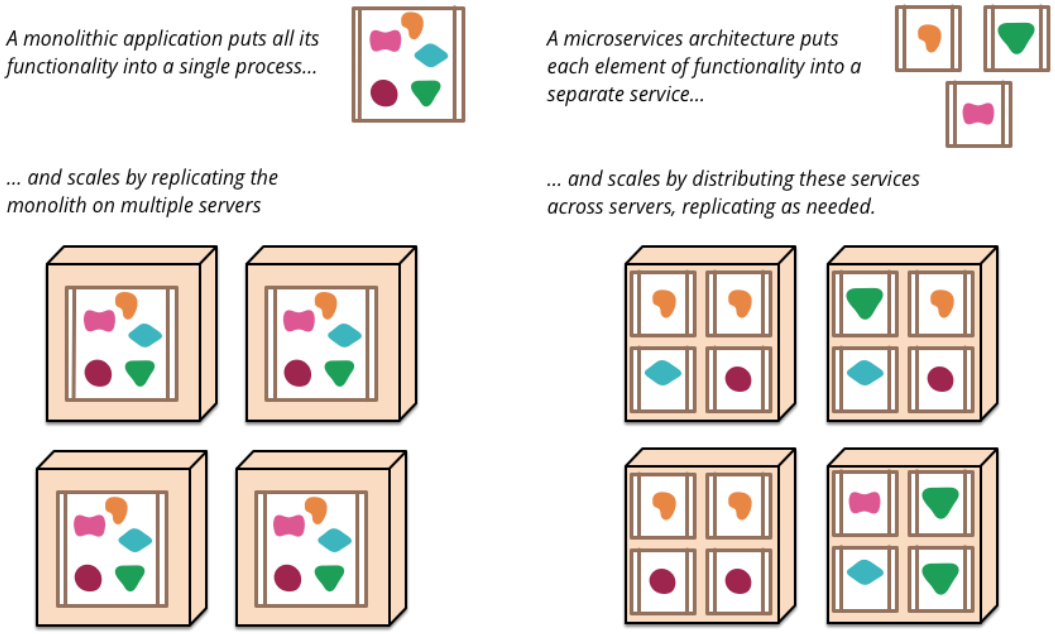

Figure 1: Differences in scaling between monoliths and microservices [14]

A Monolith shares memory and databases and is able to communicate through method calls instead of messages. However, if you need to scale a monolithic application you cannot do this on the service level as you can do with microservices, but you have to replicate the whole monolith on another server. This is shown in Figure 1. Hence, this does not allow to scale as flexible and efficient as in a microservice architecture. In addition, in a monolithic application it is necessary to stick with a technology stack that is previously defined. Additionally, in the case of an application update the whole applications needs to be recompiled and rebooted and not only the affected service.

2.1.3 Differentiation from Service Oriented Architecture (SOA)

"SOA is focused on creating a design style, technology, and process framework that will allow enterprises to develop, interconnect, and maintain enterprise applications and services efficiently and cost-effectively."[16] This characterization of the goals of SOA from Papazoglou and van den Heuvel show the focus of SOA towards making the functionalities of enterprise applications accessible as services.

One difference between Microservices and SOA are the completely different approaches about how the structure of the application is looked at. For Microservices it is important to have the component based and independent internal structure. In contrast, SOA just looks at providing an integrated view of the underlying services to the outer world. For SOA it is not important how the application or applications that deliver those services are built. [17]

Another differentiation of microservice architecture from SOA is the messaging approach “smart endpoints and dumb pipes”. In contrast SOA often use an Enterprise Service Bus (EBS) for communication. An EBS has internal routing logic for communication. This contradicts the approach microservices take. There the smart logic is only inside the services itself. [18]

2.1.4 Challenges for Microservice Architectures

Communication through messages is more expensive than method calls. Therefore, the communication between services has to be optimized to the right level of granularity to enable a high performance of the services. [14]

One challenge in microservice architectures is to handle failures gracefully. As each and every service could go offline at any time, other services must be able to deal with such a situation. Additionally, it is very important to detect those outages as fast as possible and recover them [14]. However, the detection of anomalies is not an easy task, because microservice architectures tend to change frequently. Therefore, calculating a baseline from normal behavior to compare incoming data points against, is difficult [17].

As each functionality should be encapsulated in a separate microservice application, there are a lot of applications to manage in a project. Enabling development, testing and deployment to production for a large number of services requires a high degree of automation. Continuous Integration with testing automation and a pipeline for Continuous Deployment are needed to keep up with changes.[14]

2.1.5 Application in Practice

Microservice applications enable a company to react to changing business requirements in an agile way. Additionally, they can be scaled very well, depending on the business needs. Technical debt that has been accrued by companies in the past, prevents them from flexibly adapting and scaling their applications. This is a reason why microservice architectures find popularity in practice, supporting a new and flexible way forward. [19]

One of the early adopters of microservices in large scale was Netflix and the team around Adrian Cockcroft. He migrated the companies monolithic application to an architecture with hundreds of services that produce the streaming experience of the users today. [20]

Another big company that communicates openly about their migration to microservices is Soundcloud. They state that switching to this architecture style enabled them to adopt their development in a way, which decreases the effort of developing new services, set up telemetry, testing and deployment of their applications. [21]

2.2 Distributed Tracing

In an application environment, where requests are processed by different services, it is no longer enough to just look at the latency of the initial request. This might be enough to identify that a problem exists, however there is no information on where this problem is located. Using distributed tracing, information will be available that at least contains the begin and end of each unit of work and where it was executed. This gives insight into the structure of the application for a developer or operator – even if no deep knowledge about a system is given or the system is changing frequently. With this information at hand, it is easier to identify the root cause of a problem. [8]

When it comes to distributed tracing, the paper that is frequently cited as the basic idea for current implementations is the work of Sigelman et al [8]. This paper describes Dapper, the distributed tracing instrumentation that was in place at Google, when the paper was written. One of the popular open source implementations for distributed tracing, OpenZipkin [22], state that it is based on the Dapper paper. Compared to similar publications on the topic of distributed tracing that are published without long production experience[23–25], the Dapper publication includes insights and learnings from operating the system at a large scale.

The principal of the Dapper approach [8] is to instrument a commonly used library for communication to track all incoming and outgoing requests and report them to a central instance that aggregates the traces. This enables the instrumentation of an application without the need of developers adhering to certain annotations. Every step that has to be done repeatedly and manually could be forgotten which would impact the reliability of the instrumentation. Furthermore, the less effort is required from the developers to integrate the tracing into their application, the better the acceptance for distributed tracing will be.

Another publication on this topic is X-Trace [25]. In this concept, meta data is added to a request to make it identifiable. This paper focuses on the possibility to track a request through different administration domains (e.g. an Internet Service Provider and an Web Application Provider) and on different protocol layers. The idea is that everyone can extract a trace for the domain they are responsible for without sharing secrets with other domain owners. The common identifier across all those domains gives the possibility to cooperate and communicate with each other if need be. This approach requires to instrument all involved clients and devices to include the metadata and to modify protocols to carry the meta data, if they do not already have a possibility to do so.

Magpie [24] is another approach to distributed tracing. It uses a black box approach for instrumenting the application to generate log files. Then an offline algorithm is used to derive performance anomalies from an aggregated log. Pinpoint [23] is taking a similar approach to Magpie, however focuses more on detecting faults.

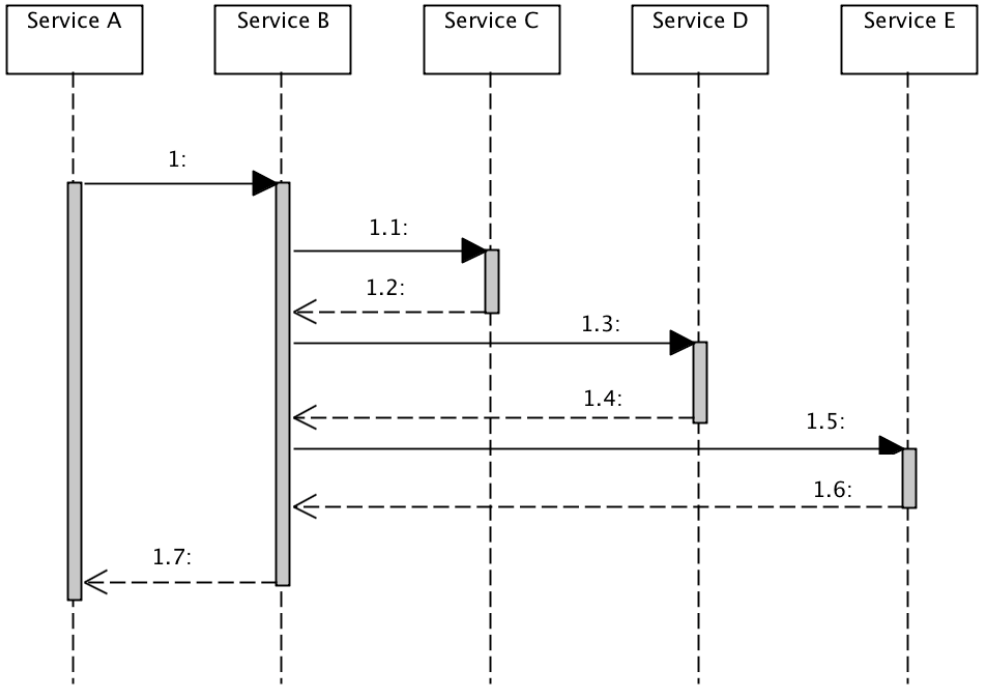

Figure 2: Example Call Hierarchy

Figure 2 shows an example how a distributed call could look like. While the original call was made to the service A, in the background services B-E are involved in processing the request, before a result is returned.

Based on the Dapper paper [8], the terms of spans and traces have been coined. A **span** represents a basic unit of work. This could be for example an HTTP request, that is sent from the client to the server, processed on the server and the response returned to the client. When looking at Figure 3, each execution will be represented by a span. A span has a begin and an end timestamp. It has an Span ID and a Trace ID as reference to the trace it belongs to. Each span, except the root of a trace, has a reference to its parent. And furthermore, the endpoint, that generated the span can be identified. A **trace** is the tree of spans that are required to serve a request. It starts at the border of the instrumented application, includes all calls to instrumented services, that are needed for processing the request, and finishes once the request leaves the instrumented application again. Those terms have found their way into the terminology of open source implementations like OpenZipkin [22].

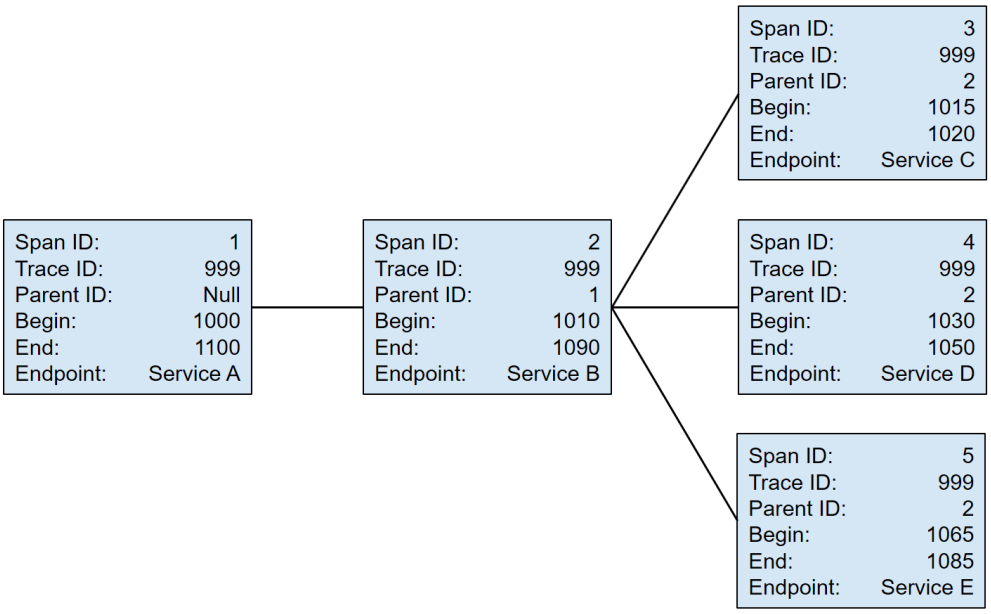

Figure 3: Simplified trace tree resulting from Figure 2

A widely used and open source implementation of Dapper [8] is OpenZipkin [22]. Originally developed and open sourced by Twitter [9], it is now used by known companies such as Pinterest [11] and Yelp [10]. Furthermore Uber recently open sourced their distributed tracing framework Jaeger [12], that originated on OpenZipkin and then was modified to fit the specific needs at Uber [13].

2.3 Anomaly Detection

The following section will focus on the topic of anomaly detection. First it will be explained what anomalies are. Then metrics for anomaly detection are summarized. Afterwards possible failure scenarios that result in anomalies are pointed out. And finally challenges and application fields of anomaly detection are described.

2.3.1 What are anomalies?

A very early definition of an anomaly – in this case called outlier – is Hawkins definition from 1980: An outlier is “an observation which deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism”[26].

Bovenzi et al[27] define an anomaly as “changes in the variable characterizing the behavior of the system caused by specific and non-random factors”.

Anomaly detection in literature comes often in the context of failure prediction. Another term that is frequently used is outlier detection. To define a more precise language for different types of anomalies in time series data, the three categories defined by Laptev et al [28] will be used in this thesis:

- An **Outlier** is a single data point in a time series. Its value deviates significantly from the value that is expected at this point.
- A **Changepoint** is a point in a time series that marks the border where afterwards the behavior of a time series is significantly different than before that point
- An **anomalous time series** deviates in its behavior significantly from others in a set of time series that are expected to display similar behavior.

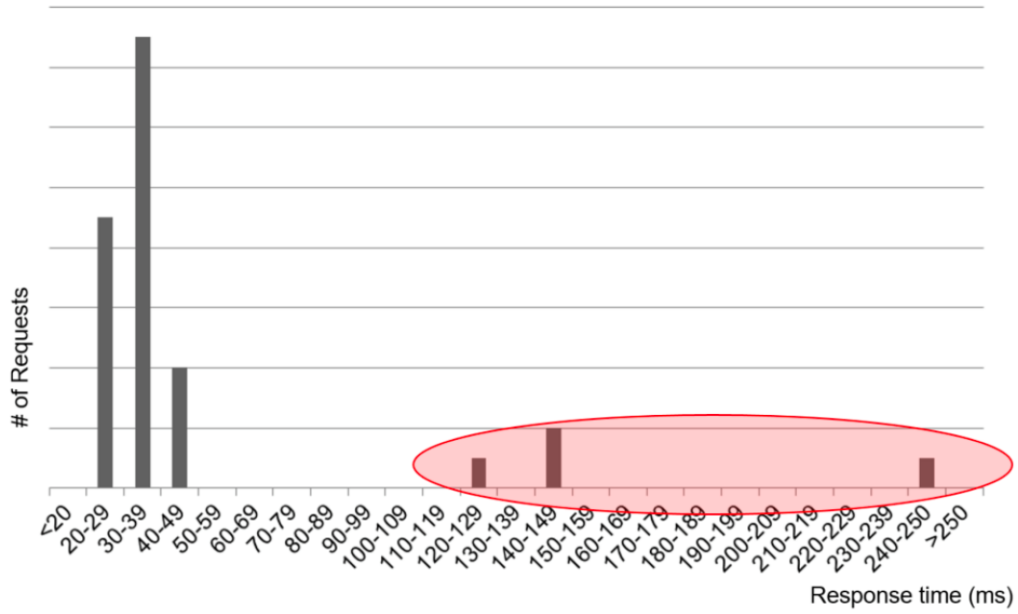

Figure 4: Artificial distribution of requests in regard to their duration to illustrate outliers. Outliers in red circle.

Figure 4 illustrates how outliers can look like in a data set. It shows the distribution of the number of requests in relation to their response time. The majority of the requests took between 20ms and 50ms. The few requests further to the right with response times that are higher than 120ms are deviating from what is usually expected. These requests would be considered as outliers regarding their response time.

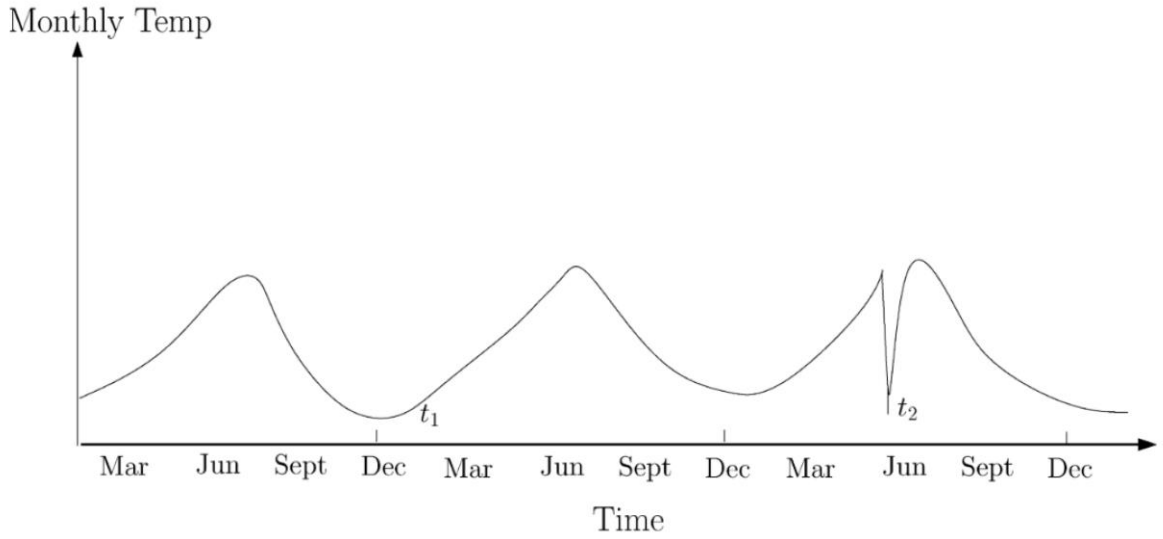

Figure 5:Time series with temperature data for three years with an anomaly at t_2 [29]

In Figure 5 the temperature values over three consecutive years are shown. When comparing the third year against the two previous years, the temperature drop in June of the third year (t_2) is noticeable. When regarding each year of this graph as a time series and comparing them, then the third year has a significant deviation from the other two. Therefore, the temperature data for the third year is considered as an anomalous time series compared to the years before.

Most work on anomaly detection focuses on outliers as single data points [28, 30–32]. However, there are as well papers that define anomalies as anomalous time series [27, 28]. For changepoints there was only the example in [28] in the body of reviewed literature.

2.3.2 Metrics to observe for Anomaly Detection

In this thesis two categories of anomalies will be distinguished: **Failures** and **performance degradations**.

Failures are the category of the two that is easier to detect. Avizienis et al [33] describe the failure of a service in the following way: “A service failure […] is an event that occurs when the delivered service deviates from correct service.”
In the case of deviations from expected service behavior, applications issue error codes or throw exceptions. In the case of http requests that are frequently used in micro service architectures for communication between services, status codes are sent with every response that can be monitored for anomalies.

Performance degradations are more challenging to detect, as they need to be derived from changing performance metrics of the monitored system.

Metric	**References**
Response time	[17, 34–40]
CPU utilization	[17, 36, 39, 41, 42]
Throughput (requests/minute)	[34, 35, 38, 40, 43]
Memory utilization	[17, 36]
I/O operations	[36]
Service reachability	[42]
Data throughput	[39]

Table 1: Performance Metrics in Micro Service Literature

Table 1 shows the performance metrics found in microservice literature. The most common one is the response time of the service. CPU utilization and request throughput are also mentioned frequently. Metrics like Memory utilization, I/O operations, service reachability and data throughput did only appear in two or less papers.

With the scope of papers extended to literature about anomalies in the context of application performance management [30, 32, 44–47], response time and CPU are as popular as in the microservice environment. Request throughput is less frequently mentioned, but present as well. A metric that is mentioned frequently that had no big emphasis in the work on microservices is memory usage. [44] and [32] make use of the monitoring systems of virtual machines and use the variety of metrics that are offered. [45] add database related metrics to the catalogue of monitored metrics. [47] use the ratio of succeeding and failing requests as a metric for discovering anomalies.

2.3.3 Failure Scenarios

Avizienis et al [33] suggest three categories of failures: Failures regarding the delivered content, the timing of the content delivery and both combined. Services that take **longer than expected to respond** fall into the timing category. Whereas a service that is **halted**, does not change its external state at all. This is a combined problem of timing and content. [27] add a service **crash** as an unexpected termination due to an exception at runtime.

In this thesis, we consider three possible failure scenarios:

- The service crashes due to a runtime exception
- The service does not return and the request times out eventually
- The service has an increased response time compared to normal operation

Memory leak is mentioned as a typical example of a failure scenario by Pitakrat et al [47] and is also mentioned as a failure scenario by Lan et al [48]. They describe the pattern of this scenario as follows: The heap utilization and the memory utilization are increasing in a linear way. Once a certain threshold is passed, garbage collection kicks in heavily and increases CPU utilization more and more. This results in poor performance of the application when serving requests, with the result of increased response time.

Another failure scenario example described by Pitakrat et al [47] are failing requests. They state that if the rate of succeeding requests falls below a certain threshold they consider this as an anomaly. Furthermore, they are pointing out a scenario of system overload, where the system cannot handle all the incoming requests in time. This might either result in increased response times or into failing requests.

2.3.4 Anomaly Detection Algorithms

When reviewing literature, different approaches to algorithms for anomaly detection can be found. Two major categories are **machine learning** approaches and **statistical** approaches [44]. The machine learning approaches can further be separated into **supervised** and **unsupervised** learning [32]. For supervised learning, there is a data set with labels for each data point with the category (e.g. anomaly or normal behavior) it should be classified later on. For unsupervised learning, you only get a set of data points without any additional knowledge - it might contain normal data points as well as anomalies.

Outliers (as defined in chapter 2.3.1) can be either derived as exceeding an absolute value that was previously defined (e.g. in a Service Level Agreement) or by exceeding a threshold above a certain calculated baseline [45]. Those thresholds can be either **static** or **adaptive** [27]. Furthermore, you can do those predictions **offline** or **online**. This means either a data set is collected and then processed offline in batches to determine whether those data points are anomalies or not – or the predictions are performed online, once a data point arrives.

In the following, approaches to anomaly detection are explained, which will be considered when selecting the algorithms for the prototype.

Clustering Based

One approach for anomaly detection is based on Clustering Algorithms [30, 44, 49]. In this approach, first an arbitrary, but usually predefined number of cluster centers is calculated for

the data set. A commonly used algorithm for this step is KMeans Clustering [50]. The assumption is, that the training set contains a set of normal data points. Then the distance between each of the training set data points and its nearest cluster center is calculated. Those distances are used to specify a value, that will be used as a threshold. If a data point is further away from the nearest cluster center than this value, it is regarded as an outlier.

Computing the cluster centers and the thresholds can be very expensive, however for predicting on incoming data points the computational effort is low. To predict whether an incoming data point is an anomaly or not, it is enough to find the closest cluster center and calculate the distance to it. Then this distance is compared to the threshold. If it is smaller, the incoming data point is normal, otherwise it is classified as an anomaly.

Distance Based

The next approach is based on the number of neighbors within a specified distance to a certain point in a dataset [48, 51, 52]. Those outliers are called distance based outliers and they are defined as follows: “For the given positive parameters: k and R, an object o in data set D is a DB(k, R, D)-outlier if the number of objects which lie within the distance of R from o is less than k.”[51]

Due to this definition, the state of such an object can change, when new points are added. If an object has already enough objects in its neighborhood, when it is inserted into the data set, it can be regarded as a save inlier. It will never become an outlier, as long as no objects are removed from the data set. However, when we look at an object that is originally an anomaly, when it was entered to the data set, due to not enough neighbors within the specified distance, this one could become normal eventually. If enough incoming objects are in the neighborhood of the anomalous object, it will eventually fulfil the requirements and can then be classified as normal.

When you are only interested in whether an incoming data points will be an anomaly or not, this algorithm has no training time. The only thing necessary is the availability of the set of already recorded data points. However, all data points have to be kept available during the prediction phase and all the neighbors of incoming objects, that lie within the distance border, have to be identified each time. This means, that more calculations have to be performed at prediction time compared to the clustering based approach.

In order to improve the suitability of the original algorithm for online anomaly detection scenarios, Lan et al [48] designed an approximation of the algorithm, to increase its performance. They divide the object space into cells and only keep the object count per cell. When a new object arrives, they check first whether in the cell it belongs into, the object count is high enough to classify it as normal. If not, they add up the counts of the surrounding

cells, until they either reach the required object count, or they reach the cells that are further away than the specified distance.

Density based / local

Another approach to detect outliers in a set of data points is the Local Outlier Factor (LOF), introduced by Breunig et al [53]. This approach assigns a degree of "outlierness", the LOF, by comparing the density of the neighborhood of a data point with the density of its neighbors' neighborhoods. This is done by calculating the distance to the k-th closest neighbor (k-distance) from the point that is evaluated. Then the same is done for those k neighbors.

The LOF is calculated by dividing the k-distance of the evaluated point p by the average of the k neighbors' k-distances. With this calculated LOF for every point in the data set a ranking can be created or all data points with a LOF above a certain threshold can be considered as outliers. An intriguing feature of this algorithm is, that depending on how large k is set, it is capable of handling multiple clusters with different densities in the data set and still come up with good results for local outliers, even if the densities of those clusters vary greatly.

Calculating the LOF requires the whole data set to be present and requires a recalculation of the LOF values for each data point, once new data is inserted. As this algorithm was designed for offline use, this was not an issue. However, for online anomaly detection usages this must be considered. Furthermore, this algorithm does not need any labeled training set, so it is a unsupervised approach.

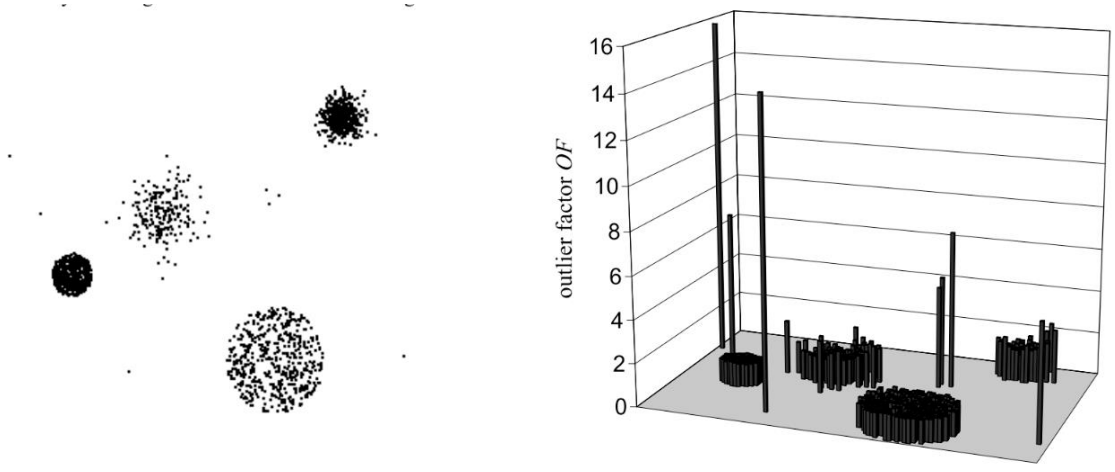

Figure 6: Outlier-factors for points in a sample dataset [53]

Figure 6 shows an example how LOF works. On the left side, you see the distribution of the data points. They are grouped into mainly 4 clusters with several outliers in between. On the

right side you see the same distribution, but with an added third dimension. This dimension represents the calculated outlier score. The higher the column, the more the data point is seen as an outlier.

Time series modelling

Laptev et al [28] suggest a framework for anomaly detection where they model time series based on historic data and give a predicted value for a certain point in time. If the measured value at this point in time deviates from the predicted value by a larger amount than a predefined threshold, this data point is regarded as an outlier.

Their suggestions for algorithms to model the time series include ARIMA [54], Exponential Smoothing [55], Kalman Filter [56] and State Space Models [57]. Pitakrat et al also use ARIMA to forecast time series in their work [47].

Time series distribution

Solaimani et al [44] present a statistical approach to detect anomalous time series. For a predefined time window, they categorize the values into a fixed number of bins. This distribution is then compared against historical distributions using Goodness of Fit of Pearson's Chi Square method. If the incoming time series deviates significantly from a defined number of previously observed normal time series, it will be classified as anomaly.

This approach is comparing time series against each other. It is not possible to define a single outlier, but it points out a whole anomalous time series. This means, that this algorithm tries to figure out, whether the occurrence of values that follow after each other over a certain amount of time is distributed equally or not.

Pattern based

Watanabe et al [58] propose an approach to anomaly prediction based on message patterns. Their algorithm does create a dictionary of patterns that might be the indicator of system failures. When a new set of data comes in, it is compared against the pattern dictionary. Then a failure probability is calculated based on the known patterns. If this probability is above a certain threshold, a warning is issued.

Mdini et al [59] take the pattern approach from the other side. They define a normal pattern, based on a training set. Then they compare the incoming data against this base pattern. If the incoming data deviates too much from the normal pattern, it will be regarded as an anomaly.

Neural Networks

Malhotra et al [60] chose Neural Networks to detect anomalous sequences in time series. Specifically, they use Long Short Term Memory (LSTM) Neural Networks. Those Neural

Networks have a long term memory, that allows for discovering long term correlations in a sequence. The Neural network is trained with a training set of sequences. Based on a validation set, the trained model is used to calculate error vectors that are modelled towards a Gaussian distribution. This distribution is then used to calculate a likelihood to observe a certain error vector at a certain point in a sequence. If this likelihood drops below a certain value, this part of a sequence is regarded anomalous.

By using this approach, they showed that they can train a model with normal behavior and then detect sequences in a time series that do not match this normal behavior. They claim that the advantage over other methods to predict anomalous time series sequences is, that this approach does not need a specified sequence length or any preprocessing.

2.3.5 Challenges of Anomaly Detection for System Monitoring

Monitoring a micro service application to detect anomalies provides several challenges. The task of an online monitoring application is to detect the occurring anomalies in real time [27]. Furthermore, it should be considered that a system that raises too many false alarms will likely be turned off by the operator [61]. Therefore, a reliable detection algorithm that supports online prediction is very important.

In a frequently changing application environment, like an evolving microservice application, it is essential that the anomaly detection model is adapting frequently [47]. When the state of the system at run time starts to deviate heavily from the state of the system, the detection model was trained on, the accuracy of detecting anomalies decreases [27]. Therefore, it is important to apply algorithms that cope with changing environments.

2.3.6 Application Fields of Anomaly Detection

Besides application monitoring, anomaly detection is used in many different areas. Popular applications are in the fields of Intrusion Detection and Fraud Detection. Additionally, Sensor Networks, Image Processing and Text Processing are areas where different kinds of anomaly detection can be applied. [29]

2.4 Root Cause Analysis

In large scale distributed systems, it can be a huge effort to figure out the service that is causing the observed anomalies. If a distributed application provides a large number of services with a number of endpoints on each, there are a lot of locations, where a service

could actually behave anomalous. If the root cause for an anomaly, that was observed at one of those endpoints, should be discovered, it gets even more complex, as services call each other during the processing of their requests.[2]

Enhancing an anomaly detection system with information on services causing the detected set of anomalies, can be of great use to pin down and solve the problems in a system as fast as possible. This can be crucial, as appearing anomalies can really impact the business results of a company, if it degrades the customer experience.

One possible approach is to take the architecture and the propagation of errors into account to improve the anomaly prediction results [47]. Error propagation means, that when a specific service A delivers an incorrect result to service B that was calling it, service B will continue its calculation with the incorrect result and therefore deliver incorrect results as well [33, 47]. Even though service A and B will both deliver wrong results, the root cause of those deviations is in service A. This means, that anomalies would be observed on both service A and B, but service B is actually working correctly – just using the anomalous input from A.

The same propagation chain can happen for performance issues. If one service takes longer to process a request than usual, this decrease in performance will be affecting all services that rely on it.

Cortellessa et al [62] propose a modelling approach to improve the reliability of component based systems during development. Based on the error propagation probability among components, they draw conclusions of the reliability of the system. This approach tries to discover possible root causes for errors at the time of system design and development and mitigate their impact as far as possible.

Knowledge about root causes is of interest in a lot of different domains. Weng et al [63] propose a solution for public cloud providers with multiple tenants, that shows root causes that could either be a bug in a service itself or propagations from other tenants. Zasadzinski et al [64] apply root cause analysis to the domain of the Internet of Things. And Gonzalez et al [65] use root cause analysis in a network operation setting. All those fields of application have in common, that a large amount of monitored devices or services are present and a manual identification of the root cause from a set of anomalies is not feasible.

3 Solution Architecture

In the following, the process behind designing the architecture of the prototype will be described. The architecture of the prototype is shown and afterwards, the key technologies are explained in more detail.

3.1 Anomaly detection and root cause analysis pipeline design

The goal is to detect anomalies based on distributed tracing information. The specific anomalies that should be detected are:

1. Increased response time compared to a learned baseline
2. Violations of a defined threshold
3. Errors

Furthermore, the detected anomalies should be set into the context of the architecture to determine which reported anomalies are really coming from an anomalous service and which ones are only suffering from error propagations.

The process can be described in the following five stages that are displayed in Figure 7.

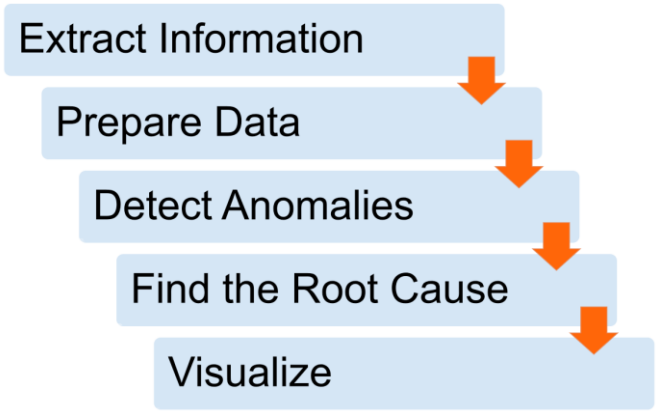

Figure 7: Five Stage of the Anomaly and Root Cause Discovery Process

In the first stage, the data is extracted from the application through distributed tracing and made available for later stages. Then the data is prepared to match the needs of the anomaly detection algorithms. Those algorithms detect anomalies from the information, as soon as it gets available – this means the data is streamed and processed online. Afterwards, the detected anomalies are processed by the root cause analysis, to prioritize all anomalies that are most likely root causes of a set of anomalies and deprioritize those that are caused by anomaly propagation.

The prototype covers all these stages. However, the focus of this thesis is on preparing the data, detecting anomalies and set them into a service dependency context to identify the root cause of an anomaly. Data extraction must deliver the required features and visualization should provide a basic overview of a previously modelled request to the monitored application.

As this prototype is foreseen as the foundation for further research, to set it up for future use and changes is essential. As already foreseeable, the system should be capable of evolving over time to match changes in the direction of future research. A modular approach is the way to go.

First and foremost, the models and algorithms for anomaly detection have to be exchangeable. Even running different algorithms in parallel and still make good use of the results should be possible. To achieve this, asynchronous message queues will be used for the communication of distributed tracing, anomaly detection and root cause analysis. As parallel running algorithms might all report the same request as anomalous, the root cause analysis must be capable of identifying and merging those duplicates.

The other modular part should be the whole pipeline itself. Using a different instrumentation to gather the distributed tracing, or deciding on a different approach to get the dependency information for the root cause analysis should be possible without impacting the other parts. As long as the message format stays the same, the modules should be exchangeable.

3.2 Architecture Overview

The architecture of the prototype and the choices of technologies to implement this pipeline is shown in Figure 8 and is explained in the following. The main technologies will be described in more detail in the next chapter.

The instrumentation of the application will be done based on Spring Cloud Sleuth. The basic setup will be enhanced by some custom coded extensions to get access to additional information that is useful for anomaly detection.

The distributed tracing data will be written to a Kafka topic in JSON format. This is where the anomaly detection module, that is based on Apache Spark, collects its data from. The data is extracted from Kafka and used in the different algorithms for anomaly detection, that run within the module. Each of those algorithms is independent. It may or may not have a training

phase where it could access the whole historical data that is stored in Kafka at training time. Each algorithm has a detection phase, when it looks at the incoming data points and evaluates whether the data point is an anomaly or not. Each of the algorithms writes its detected anomalies to a common anomaly topic in Kafka. Duplicates could occur, if the same data point is reported by multiple algorithms.

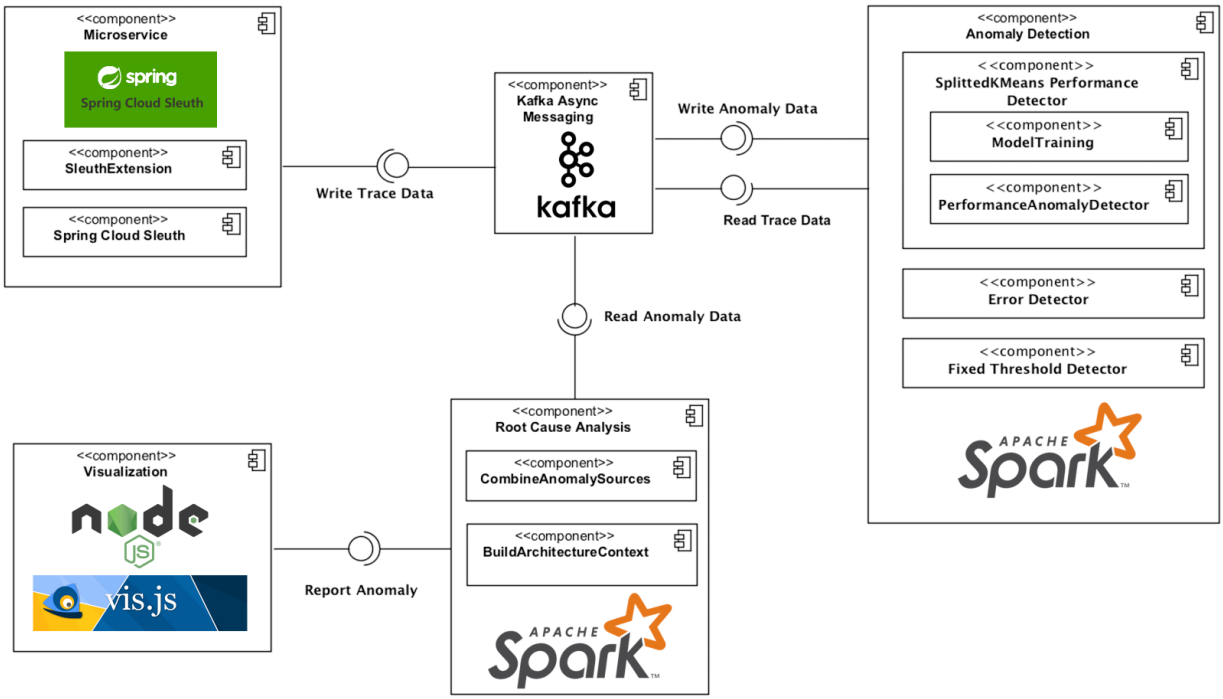

Figure 8: Architecture Overview

The second module based on Apache Spark is the root cause analysis. It reads the detected anomalous data points from Kafka and has the goal to report the root cause for a set of anomalies. This is done by setting the reported anomalies into a context, representing how anomalies are propagated among the services.

Finally, a simple visualization is implemented to help presenting the results of the system in a more human readable way. However, as another thesis in this research project deals with the specific topic of an intelligent user interface, this thesis will keep the visualization minimal.

3.3 Main Technologies

The following chapter describes the most important technologies that are used for the prototype. Spring Cloud Sleuth is used for distributed tracing. Apache Spark provides the

foundation for the anomaly detection and root cause analysis. Apache Kafka is the asynchronous messaging queue that is used for the communication between the modules.

3.3.1 Spring Cloud Sleuth

Spring Cloud Sleuth [66] is a distributed tracing framework for Spring Cloud Applications. The demo application to be monitored(see chapter 6.1 for closer description) is already instrumented with OpenZipkin [22]. Hence, it was already clear, that this would be used for the distributed tracing.

The only decision that had to be made was at which level to pull the data. OpenZipkin relies on the distributed traces, that are generated by Spring Cloud Sleuth. This framework is the convenient and easy way to setup OpenZipkin for Spring Cloud applications by simply adding a set of maven dependencies. One possibility was to read the traces from the database that is kept by the Zipkin server. The other option is to get the data directly from the same message queue, the Zipkin server reads the data from. The options of usable message queues are Apache Kafka [67] and RabbitMQ [68]. As the goal of this prototype is performing online anomaly detection, the message queue approach with plain Spring Cloud Sleuth is chosen as the way to go. It promises to get the data without any postprocessing and as fast as possible.

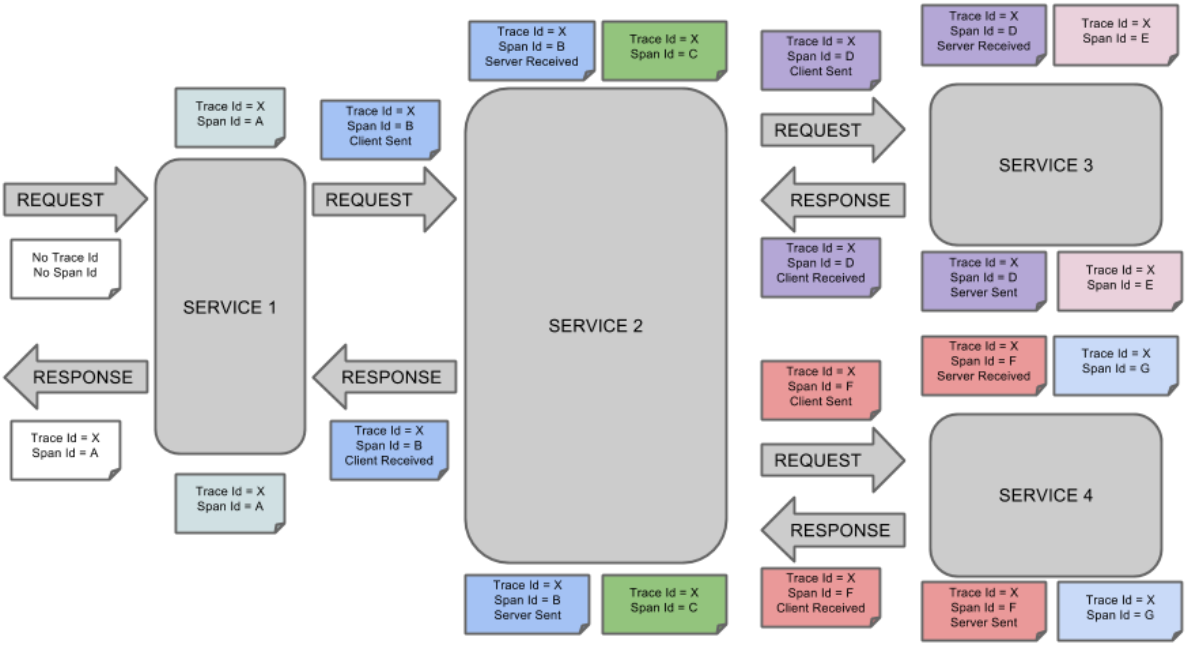

Figure 9: Span Creation in Spring Cloud Sleuth – a single color indicates a single span [66]

Spring Cloud Sleuths terminology is heavily oriented towards the terminology of the Dapper paper [8]. They use the terms trace and span as described in chapter 2.2 and have only small deviations from the data format used by OpenZipkin. Figure 9 illustrates the way how the

spans of a trace are recorded. A common color indicates which information belongs together as a span in the sense of the definition in the Dapper paper. However, when looking for example at the blue spans with the Span ID = B, it already shows a difficulty. The one part of the span is recorded in one service and the other part in another service.

An instrumented service will collect spans for a certain amount of time and then it reports a JSON representation of a Spans object to the message queue. The reported object is illustrated in Figure 10. It is a holder object for one Host object and a collection of Span objects. The Host object contains the information about the service that collected all the spans. The collection of Span objects contains all the recorded spans. However, with spans being recorded on both, the requesting and the processing service, it is either necessary to merge those spans, or to see it as a possibility to have more detailed information available.

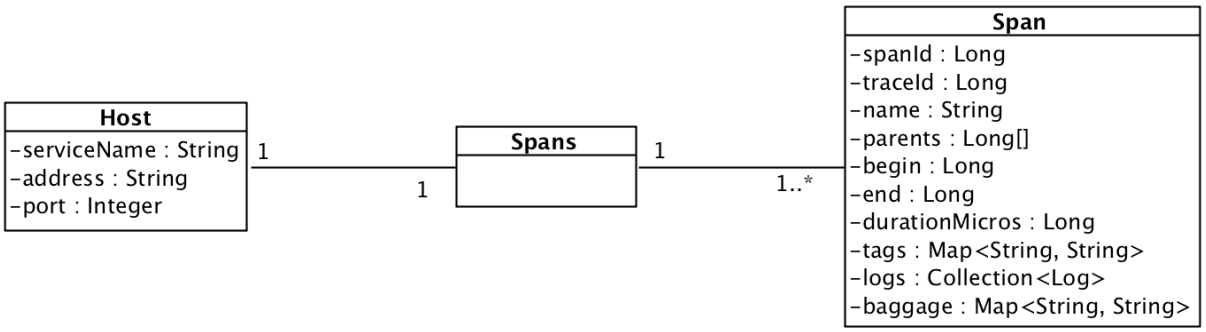

Figure 10: UML representation of Spans Object as used by Spring Cloud Sleuth

To keep control of the generated amount of traces, especially in a production environment, the sampling rate can be adjusted. This means a parameter can be set, that tells Spring Cloud Sleuth which percentage of the observed requests should be actually reported. This is necessary to avoid the generation of more data than the amount that can be handled and stored by the system.

3.3.2 Apache Spark

Apache Spark [69] is an unified framework for distributed data processing. The project was started in 2009 at the University of California in Berkeley. It has since become the most active open source project for big data with over 1000 contributors. Apache Spark is deployed in more than 1000 companies. [70] It is used in a lot of current academic research projects on streaming and anomaly detection topics like [44, 71–74].

Apache Spark supports multiple programming languages to create applications. Those languages are Java, Scala and Python. The main abstraction of data in Spark application are

RDDs (Resilient Distributed Datasets). They are collections of objects that can be distributed across multiple clusters for fast parallel processing of tasks. The basic operations to transform the data are map, filter and group by operations.

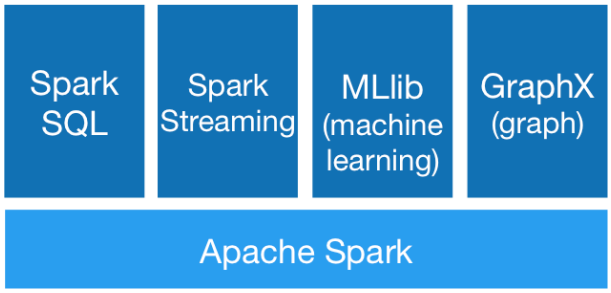

Figure 11: Apache Spark Extension Libraries [69]

To extend the base functionality of Apache Spark, that mainly targets the batch processing of large data sets, different libraries are included into the project, as shown in Figure 11. Spark SQL enables the user to use SQL queries on RDDs as another way to access structured data. Spark MLlib [75] contains a set of machine learning algorithms, that are leveraging the Spark framework for fast processing and that can be easily integrated in Spark Applications and GraphX [76] adds functionality to efficiently work with graphs.

The last of the four extension libraries is Spark Streaming [77]. It enables distributed stream processing and manipulation. This is achieved by processing incoming data in mini batches as shown in Figure 12. This means that Spark Streaming collects incoming data for a predefined window of time that can be adjusted depending on the latency requirements of the system. Those mini batches are then processed by the Spark Engine.

Figure 12: Stream Processing in Spark Streaming [77]

Even though Apache Spark aims at being a framework that can be used as a general approach to many problems in the domain of big data processing, it can keep up in performance with frameworks that are specialized in a certain niche. For the problem in this thesis, streaming and machine learning are of highest interest. Figure 13 shows an aggregation of the results of two sources of performance evaluations of Apache Spark.

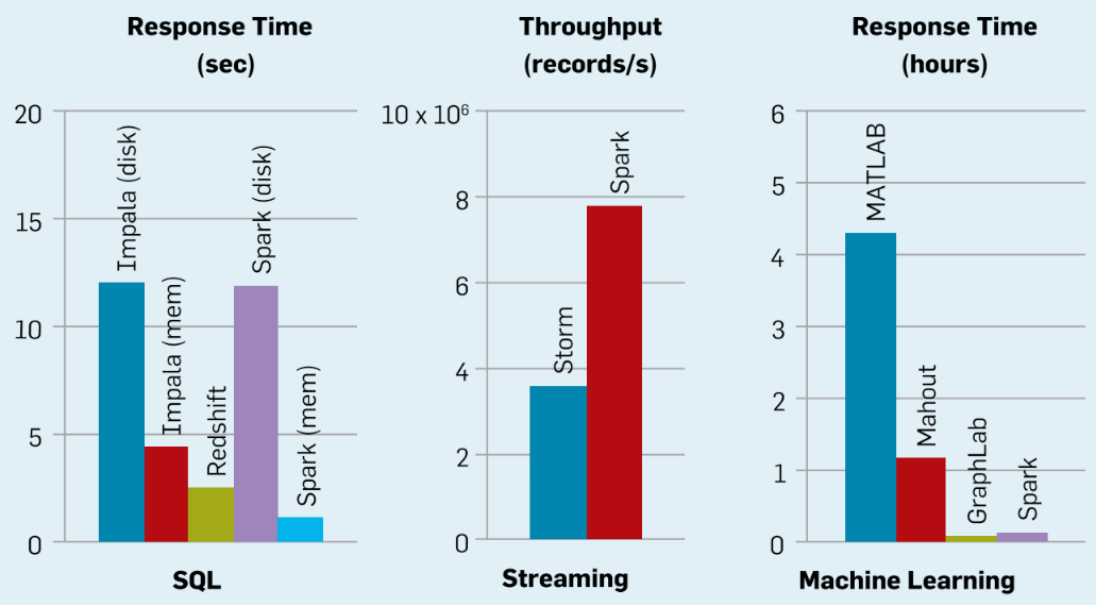

Figure 13: Comparing the performance of Spark with specialized systems for SQL, streaming and Machine Learning [70] (based on [78] and [71])

Zaharia [78] compared Apache Spark against Apache Storm [79], an open source project that specializes in stream processing. In his results Apache Spark processed the tasks at least twice as fast as Apache Storm. And Sparks et al [71] evaluated the performance of their machine learning applications against other frame works for their task at hand. They show that their solution outperforms MATLAB and Mahout and lies only behind GraphLab that is highly specialized for the measured task.

With streaming and a set of implemented machine learning algorithms, Apache Spark has the tools to do the job that is required from the prototype – namely detecting anomalies from an input stream of data. With the promising results from different performance tests against other frameworks that could be also applied in these scenarios, it leads to the conclusion, to be a good choice for the task. Additionally, it offers a wide variety of additional tools for Big Data tasks, which allows to adapt flexibly to future challenges.

3.3.3 Apache Kafka

The reason to use Apache Kafka [80] is due to the constraints that derive from the selection of Apache Spark and Spring Cloud Sleuth as described in the chapters before. Spring Cloud Sleuth supports output to either Apache Kafka or to RabbitMQ [68]. On the other hand Spark Streaming provides built in support to read from Apache Kafka [81], while the support for RabbitMQ is only available through third party libraries. Furthermore, Apache Kafka offers the possibility of storing data in addition to act as a messaging queue. Even on the blog of Pivotal, the company supporting RabbitMQ, Apache Kafka is mentioned as a good choice for

scenarios where a “stream from A to B without complex routing, with maximal throughput” [82] is required. And this is exactly what is needed for this prototype. Therefore, Apache Kafka is chosen as tool for the job of asynchronous messaging.

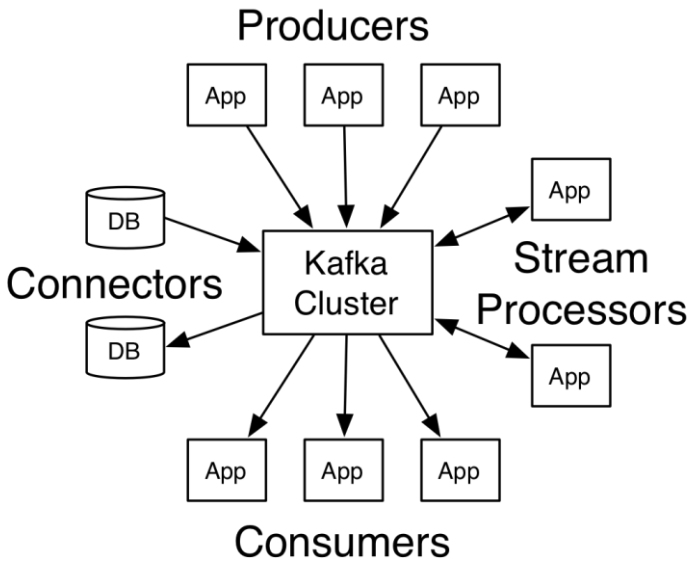

Figure 14: Apache Kafka Architecture [80]

Apache Kafka acts as a publish/subscribe messaging queue while on the same time storing the data and keeping it available based on a setup retention policy. The most important roles in the Kafka architecture are producers, brokers and consumers. As shown in Figure 14, applications that act as **producers**, send data to the Kafka Cluster. The cluster acts as **broker**, that administrates the different **topics**. A topic is the destination, where the producer writes its messages to and where the **consumers** can subscribe to, to receive all the new incoming messages. A consumer that subscribes to a topic can decide to first receive all messages, that are currently stored in the topic or not to receive the historical messages and just read the new incoming messages. To ensure that no data is lost due to the failure of a node in the Kafka Cluster, the topics can be replicated among the nodes.

4 Anomaly Detection

When looking at the detection of anomalies there are the three scenarios described in chapter 2.3.3 that the prototype should be able to detect. First, **errors** have to be detected. In this case the monitored application does not process the request as expected, but returns an error code or an exception. The second case are **timeouts**. A request is sent to the application but there is never a response returned and eventually the application throws a timeout exception. And finally, the prototype has to detect **performance problems**. This is the case when the application does not process the requests as fast as it usually does.

In the following chapter, it will be explained which parameters can be collected with the distributed tracing instrumentation. Afterwards the selection of the algorithms for the prototype is explained. And finally, the implementation will be described.

4.1 Feature Extraction

In chapter 2.3.2 common metrics were collected that have been used in current research to identify anomalies. Namely those are response time, CPU utilization, memory utilization and throughput in requests per minute.

As described earlier, Spring Cloud Sleuth [66] is used to instrument the microservices and extract information about requests. The only metric that is implemented by default is the response time. More precisely the **duration** of the span that is representing a request.

By customizing the framework, **CPU utilization average over the last minute** and **heap memory utilization** of the Java Virtual Machine (JVM) are added to the extracted parameters. Those changes are based on monitoring possibilities from inside the JVM and do only require developers to add a few lines of code once they set up a microservice in a single place. Listing 1 shows all that needs to be done on each service in the configuration class. After injecting a BeanFactory and the Spring Cloud Sleuth Tracer, three beans have to be registered. Those beans are imported through a maven dependency. After set-up, no more additional code is required, for the distributed tracing instrumentation to work. This keeps the implementation effort minimal and is ensuring that the instrumentation cannot be forgotten during the application development process. Furthermore, it is easy to instrument an already existing application, without the need to modify a lot of code.

```
@Configuration
public class MvcConfig extends WebMvcConfigurerAdapter {
	Tracer tracer;

	@Autowired
	BeanFactory beanFactory;

	Tracer tracer() {
		if (this.tracer == null) {
			this.tracer = this.beanFactory.getBean(Tracer.class);
		}
		return this.tracer;
	}

	@Bean
	public CustomTraceHandlerInterceptor customTraceHandlerInterceptor(BeanFactory
	beanFactory) {
		return new CustomTraceHandlerInterceptor(beanFactory, tracer());
	}

	@Bean
	public SpanAdjuster customSpanAdjuster() {
		return new CustomSpanAdjuster();
	}

	@Bean
	CustomFilter customFilter() {
		return new CustomFilter(tracer());
	}
}
```

Listing 1: Once required Code per Service to implement the enhanced tracing instrumentation

On top of the metrics suggested in literature, Spring Cloud Sleuth offers some more features to look at. There is some useful information to map the request to specific method calls on a specific instance of a service. This information includes the **request's URI**, **service-name** and **IP address** and **port** of the service host.

For http requests, that are an important means of communication for microservices, there is further information available. The **HTTP method** and **HTTP status** are reported by Spring Cloud Sleuth. Furthermore, in case of an error, an additional **error tag** is set once in a trace, reporting the error message of the exception thrown. If the reported span is no http request, but representing a request that is processed by a controller, the **controller class name** and **method name** are available.

Finally, each span has its unique **Span ID** and a **Trace ID** that identifies the trace, to which the span belongs to. This information can be used to aggregate spans on trace level or to identify specific spans e.g. in the case of anomalous behavior.

Depending on the algorithm those features summarized in Table 2 can be used, if required.

Identification Features	Performance Features	Error Features
Span ID Trace ID Service name Request URL IP address Port HTTP method Controller class Controller method	Span Duration CPU utilization (average over last minute) JVM Heap Utilization	HTTP status Error tag

Table 2: Available Features

4.2 Target Anomalies

This prototype is designed to detect the following three types of anomalies:

- Errors and Exceptions
- Violations of fixed thresholds (e.g. for CPU or Heap utilization)
- Increased response time of requests compared to a calculated baseline

An Error is the deviation of the state of a service from its expected state [33]. Usually this results in an exception or in a reported error code. In a perfect world, an application that reaches production should be tried and tested to find all possible sources of errors and eliminate them. But in the case some source of error finds its way into production, the anomaly detection system should be able to detect unhandled exceptions and recognize status codes that are not expected.

Fixed thresholds are especially useful with monitoring every metric that is measured as a percentage. From the available metrics recorded by the distributed tracing instrumentation and outlined in Table 2 earlier, those are the CPU utilization and heap utilization.

The third type of anomalies is the increased response time compared to a baseline. As explained in the motivation for this thesis (Chapter 1.1), increased response times can have a negative impact on the success of a business running a web application. Therefore, a baseline should be established. Increased response time anomalies will be all requests, that exceed the calculated base value by more than a certain threshold.

With detecting those types of anomalies, it is possible to detect the failure scenarios, that were described in chapter 2.3.3:

- The service crashes due to a runtime exception
- The service does not return and the request times out eventually
- The service has an increased response time compared to normal operation

The first scenario will cause an error or an exception, that is one of the defined anomalies above. By detecting those, this scenario is covered.

In the monitored system, a request that takes too long, will cause the system to throw a timeout exception. Hence, this failure scenario is as well covered by the error detection. If another system handles a timeout by returning a request with a very long request duration, this would be covered by the detection of increased response times. The only case that cannot be detected by the system, is a case where nothing is reported. If there is no reported span to predict on, the system will not be able to detect anything.

To illustrate the usefulness of the Fixed Threshold monitoring, the memory leak scenario, that was mentioned as an example for a failure in chapter 2.3.3, will be used. In this scenario CPU usage usually increases, when the JVM heap utilization is above a certain threshold. This is due to the fact that in this case the garbage collector activity is increasing heavily [47]. If a system operator knows, where this heap threshold for his system is, he can set this threshold and will be informed, once a certain service enters such a critical zone. Furthermore, fixed thresholds could be used to monitor compliance to negotiated service level agreements.

4.3 Algorithm Selection

In the following, the selection of the algorithms for detecting the three types of anomalies that were pointed out in the previous section is explained. The approaches, that are considered for this selection were described in chapter 2.3.4.

Monitoring for errors and timeouts does not require any machine learning or statistical algorithm in the use case at hand. When an exception is thrown, Spring Cloud Sleuth attaches an error tag to the current span. Furthermore, spans for HTTP requests get a tag with the http status that is returned. Therefore, filtering for spans with error tags or an HTTP status of 500 (Internal Server Error) will result in a stream of spans where requests have either timed out – then a timeout exception is thrown – or have provoked an unhandled exception in the application. This is comparable to the pattern based approach. However, no learning is in place. Just a pattern, that is known to be anomalous, will be detected.

When monitoring for performance anomalies, the three metrics JVM memory utilization, CPU utilization and request duration are available from the instrumentation. To make best use of the available information those metrics can be treated differently.

The JVM memory utilization is a metric that can be used as early indicator that something could go wrong. As garbage collection kicks in more frequently, when heap space is running out [47], it is beneficial to set up an anomaly warning, when heap space utilization exceeds a certain threshold.

As the CPU utilization is reported as a percentage, the easiest way to report anomalies is by defining a fixed threshold that is regarded as being an anomaly and compare the incoming values of this metric against this threshold.

Compared to memory and CPU utilization the threshold for the duration is trickier to define. As the expected duration varies from endpoint to endpoint, a predefined threshold is not an option. It is necessary to derive a baseline and an acceptable threshold from normal behavior data of the system and use that to detect anomalies.

As the system aims to do online anomaly detection, it is paramount, that the algorithms will be capable of processing incoming data points very fast to deliver results in a timely manner and to be able to handle a large amount of incoming data. In addition, it has to be considered, that each endpoint behaves differently. Therefore, it is likely, that it could be necessary to store a trained model for each endpoint to detect the anomalies. This requires the algorithm to store the information that is needed for each endpoint in a way that is as minimal as possible.

To ensure fast and well-fitting implementation, it would be very beneficial to have support for the chosen algorithm through Spark MLlib. It would be beneficial to have a sufficient amount of documentation, to get started fast.

As the system is designed in a way, that multiple algorithms can be run in parallel. This means, that new algorithms can be placed alongside the originally implemented algorithms or

replace them entirely. As the system is designed to evolve during further research, the selected algorithm does not have to be perfect – but it has to be capable of performing the task of detecting increased response times effectively.

Furthermore, the algorithm has to detect outliers. As the root cause analysis implementation (described in chapter 5.2) is based on the assumption, that the anomalies are predicted on span level. Therefore, it is not possible to use an algorithm that detects anomalous time series, as then the information on span level that are needed for the root cause analysis would be lost.

The density based approach using LOF can be ruled out, as it is not efficient during prediction. This counts as well for the exact distance based approach. The cell based version should be efficient enough, however there is no implementation available in the collection of MLlib algorithms and no popular third party library.

The time series distribution approach is only working for detecting anomalous time series. This means, that it will be difficult to identify the required anomalous spans for the root cause analysis.

This leaves an approach based on time series modelling or on clustering. For the first one, there is no support in Spark MLlib directly and the third party library [83], that is pointed to in different communities, is no longer under active development and has only few documentation and examples. For clustering however, there is an implementation of the popular KMeans algorithm available directly in MLlib. This approach has furthermore the advantage, that after the training phase, anomaly detection is very efficient and the only information that has to be stored for each endpoint are the coordinates of the calculated cluster centers and the threshold distance. Hence, the algorithm in the prototype for detecting increased response times will be developed based on clustering.

4.4 Implementation

The following chapter describes the implementation of the anomaly detection process of the prototype. It will start with describing the faced challenges. The overview of the anomaly detection pipeline follows, before the different parts of the anomaly detection process are broken down in more detail.

4.4.1 Challenges

The first challenge that must be addressed is the fact, that there is no information about the monitored system available up front. As the anomaly detection should work with any

application, that implements the distributed tracing information, the only available knowledge up front is the behavior of Spring Cloud Sleuth in presence of certain events.

The next requirement for the system is to detect anomalies in real time. This means, that the data has to be categorized as normal or not, as soon as it is available. Calculating a baseline however, is acceptable to be performed before starting the anomaly detection.

Furthermore, this prototype is restricted to only use data available from distributed tracing. In literature, often hardware sensors are used to gather for example CPU information. The developed prototype is restricted to work with the information that is available from using Spring Cloud Sleuth. Out of the box that would only be information on the duration of a span and the information to locate the appropriate service and method, where this span was reported. However, as described in section 4.1, by using the customization option of Spring Cloud Sleuth, additional instrumentations have been implemented to gather information on JVM heap utilization and the average CPU utilization over the last minute.

Finally, the module for anomaly detection must support the modular approach that was set when designing the system. This requires asynchronous communication to the distributed tracing information before and the root cause analysis after it in the pipeline using Kafka topics. Furthermore, the algorithms used for anomaly detection should be implemented in a way, that multiple algorithms can run in parallel and implementing a new algorithm to add to the pipeline should be easily feasible.

4.4.2 Pipeline Overview

The basic concept to implement the detection of the three anomaly types described above, is shown in Figure 15. A commonly used module is implemented for extracting the information from Kafka – the basic process is equal for all three algorithms. The anomaly reporting is similar for all algorithms as well – in the end all anomalies have to be reported to the same Kafka topic in a predefined and common format.

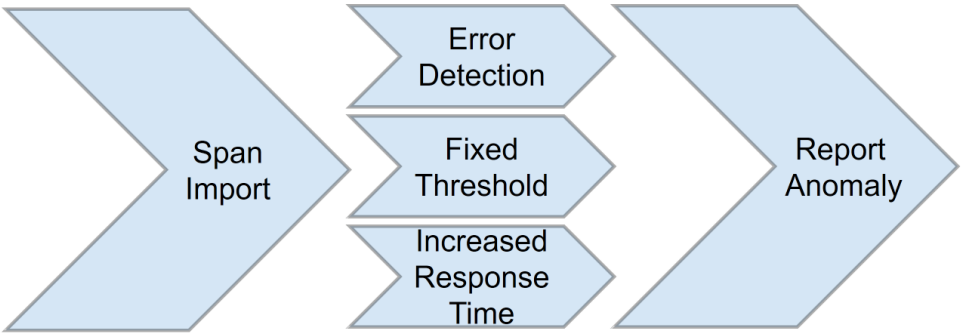

Figure 15: Anomaly Detection Pipeline Concept

The application is developed in a way, that an arbitrary number of anomaly detection algorithms can be installed and run in parallel. They could try to detect similar anomalies or completely different ones – as long as they do it based on the spans, the import provides. Interpreting those reported anomalous spans is then the task of the root cause analysis.

In the following, the single steps of the anomaly detection pipeline will be explained in more detail.

4.4.3 Data Import

Before any of the anomaly detection algorithms can start their individual processing, the Spark Application needs access to the data that has been reported by the distributed tracing instrumentation and is stored in Kafka by the Spring Cloud Sleuth instrumentation. The topic contains JSON representation of the Spring Cloud Sleuth Spans object, as shown in Figure 10 in chapter 3.3.1. It is a container for information about a set of reported spans and the service and endpoint, that did report them. The JSON representation is preceded by additional header information.

The most interesting information is found in the Span objects. Especially the duration and the tags, that represent attributes that can be set to a span, will be used by the anomaly detection algorithms. The IDs, name and host information will serve as a way to identify and group the requests, that are represented by those spans, by the endpoints they were reported by. An endpoint is the combination of host, service and method. It identifies the location, where a span was created.

To create the initial stream with the input from the Kafka topic, Apache Spark Streaming, which is used for the implementation of the anomaly detection, makes use of a connector library [81]. After the stream is opened, it can be manipulated with mapping and filter operations.
In a first step, the header information is removed, so the remainder only contains the JSON. Afterwards the JSON is converted into Spring Cloud Sleuth's Spans object for easier processing.

However, as the anomalies will be detected on span level, they must be extracted from the list inside the Spans object. After extracting the single Span objects, they are mapped together with the corresponding Host object as a tuple. This is done to retain the host information throughout the anomaly detection process. The resulting tuple stream is the basis on which each of the algorithms, that are described in the following chapters 4.4.4 - 4.4.6 will start their stream manipulations and calculations.

4.4.4 Error Detection

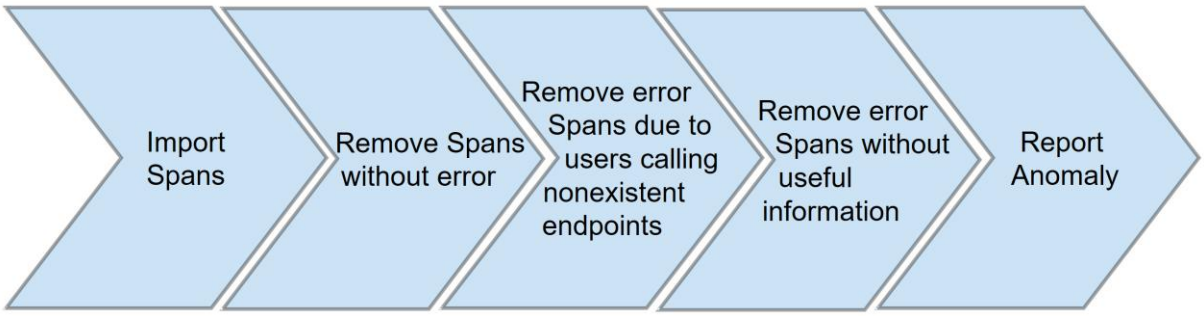

Figure 16: Error Detection Process

The Error detection is performed as displayed in Figure 16. It is a filtering procedure on the input stream of spans that is given to the algorithm. It makes use of the HTTP status code and the error tag that Spring Cloud Sleuth records. In the end, the remaining spans are considered as anomalies.

In a first step, all spans that have a status code, that is defined as normal, and that also have an empty error tag, are removed. In the prototype, the status codes considered as normal are 200 (ok) and 201(created). However, this list could be extended, if this is required.

In a next step, all spans with a status code of 404 (not found) are eliminated. In the system under test, this status code was only issued if a user requests an endpoint that was not existing in the system. This would inflate the reported anomalies if a lot of users are mistyping URLs. When services internally request other services that should be available, but are currently not active, a status code 500 (internal server error) will be reported. This is very convenient to separate those cases. However, if a system admin decides, that it is important to be informed about users requesting non-existent endpoints, it would be possible to remove this filter without impacting anything else.

The next step is required to counter some effects that happen, when an exception is handled by the framework. Instead of stopping the trace at the span, for which the exception was reported, error handling classes are called thereafter. This causes the trace to not end with the relevant span, but would include the generic framework error handling calls as well. To prevent those additional spans, a behavior in recording those errors by Spring Cloud Sleuth can be used. In all the observed scenarios, each thrown error would have only a single span that includes an error tag – and this span is exactly where the exception appeared. It can happen, that an exception in one service would cause another exception in a calling service – e.g. when it would expect a result with status 200 (ok) but receives 500(internal server error). Such an exception would not be filtered out, as it has its own error message. Finding out

which of the exceptions in one trace is the relevant root cause, will be the task of the root cause analysis.

To get rid of the superficial spans, the last filter step for the error detection is to eliminate all spans with a status code of 400(bad request) and 500(internal server error) that do not have an error tag. In the system under test, those cases behaved both similar as described. Filtering out the spans without error tag did not result in losing any of the exceptions, but improved the ability to report the relevant anomalies.

The spans that remain after filtering will then be reported as anomalous spans to be processed by the root cause analysis. It was a deliberate decision to not only take the spans with status code 400 and 500 and perform the last described step on them, but to go the way as described. This gives the possibility to detect cases that are not yet known but might appear in a different system. If filtering only for the known errors, those new cases would never come to attention.

4.4.5 Fixed Threshold Detection

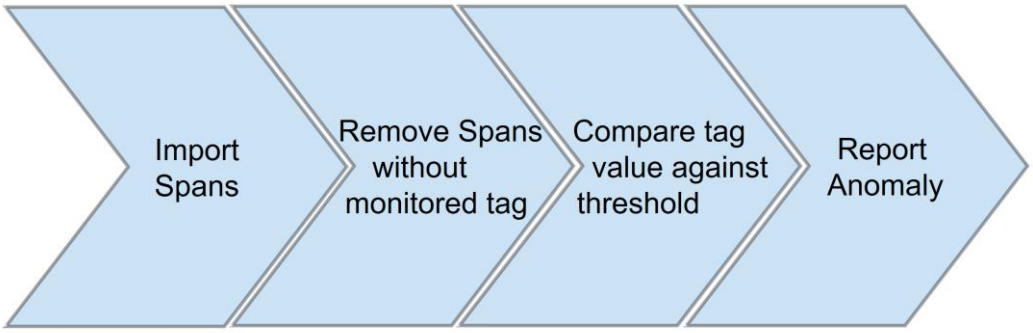

Figure 17: Fixed Threshold Detection Process

This anomaly detection module is very straight forward. It can be set up multiple times in parallel with different settings. It can be specified which of the spans' information tags to monitor – this means which metric, that was collected by the distributed tracing instrumentation should be monitored – and what the threshold should be, that has to be exceeded, so the span is seen as an anomaly. Furthermore, it can be specified, whether the monitored tag is expected to be present on every span or whether it could be available only on some spans.

If the tag is marked as not present on every span, the first step is to remove every span that does not have the monitored tag attached to it. In the case the tag should be present in every span, spans without the tag will be reported as anomalies.

After this filter step, the value from the tag will be extracted. This value is then compared to the threshold that was defined previously. If the value exceeds the threshold, the span will be reported as an anomalous span for further processing by the root cause analysis.

4.4.6 Splitted KMeans – Increased Response Time Detection

The most complex algorithm for anomaly detection in this prototype is the one to detect increased response times. This algorithm has a training phase, once it is started to create a baseline and a threshold. Then the anomaly detection phase kicks in, where the result from the training phase is used to detect anomalies in the stream of incoming spans.

Training phase

For the training phase, a set of historic data is needed. In this case Kafka's storage functionality is very useful. Kafka stores all the data of a topic based on a defined retention policy. When a new client starts to read from a topic it has two possibilities. The first is to receive everything that is written to that topic after the client subscribed. The other one – the one that is used to get the training data - is the possibility to read all the data that has already been written to the topic in the past, and then to continue reading the new data as it arrives. The historic data set is used to calculate the base line and the threshold in the training phase.

While importing the training set, the application gathers a distinct list of all endpoint identifiers. These identifiers include the following information:

- service name
- host IP address and port
- endpoint URI extracted from name of span
- http method or controller class name

All this information is available from the default instrumentation that is provided by Spring Cloud Sleuth. By using this information, a set of all endpoints is created that have already reported a span at the time of training. Endpoints that have never reported a span before, cannot be detected by the algorithm and will not be monitored in the detection phase.

In the next processing step the data set is split into multiple sub sets – one for each of the identified endpoints. As it can be assumed that each service call will have a different behavior, this step does make sense – it provides the foundation for defining a baseline on endpoint level, without relying on a machine learning algorithm to figure out the right segmentation with the features available to it. This allows to reduce the number of features in the later training step for each of the models. Each entry contains the data set and information on the scaling factor, if any scaling has been applied to the features.

For each of the sub sets a base value and a threshold will be calculated. For this prototype the duration of a span is the only feature, that is included for the training, as adding other features did not improve the results of the anomaly detection. To take into account that the training set could already contain some outliers, the application gets rid of the 0.1% of the data, that has the highest duration values. By removing those extreme values, the final result of the base line calculation is less biased by potentially extremely large outliers. The less extreme the largest values are away from most of the values, the less impact this step will have on the final results. If a larger percentage is chosen, it could happen that too many large values will be removed – this could impact the baseline to be calculated too strict, what would lead to an increased number of false positives during the prediction phase. The value of 0.1% has proven as good fit during the development of this prototype, but might have to be adjusted in other cases.

This data set will now be used to train a KMeans model with k=1 for a single cluster center. This is done by using the KMeans implementation of Apache Spark's MLlib [84]. A single cluster center is chosen, as each model will be for a specific endpoint. And one endpoint is expected to have a single normal behavior. The cluster center of this model will be the reference value for the anomaly detection. For the prototype, the cluster will be trained using only the duration of the spans as feature. Adding other features from the available set of features that is provided by the Springe Cloud Sleuth instrumentation, did not improve the performance of the algorithm. As the only goal of this algorithm is to detect changes on the duration, this is expected. Especially as most of the other relevant information is about separating the endpoints from each other – and this step is done before running the KMeans clustering. However, as the KMeans algorithm accepts vectors of any length as input, it would be easy to modify the application to use multiple features for clustering.

In addition to the reference value, a threshold is needed. It represents the distance from the reference point, that is acceptable. Only if the distance will be above the threshold, an anomaly will be reported. At the end of the model training, the distances of each point in the training set to the reference value will be calculated. Based on those distances, five values will be provided for the anomaly detection phase to choose from as a threshold:

- The maximum distance
- The median distance
- The average distance
- The 95^{th} percentile of distances
- The 99^{th} percentile of distances

For the prototype, the 99^{th} percentile is used as threshold, because it showed to be a good tradeoff between reducing the number of false positives, while still retaining the capability of

detecting increased response times. Depending on the distribution of the values of the training set and the monitored data, the use of another selection criteria for the threshold could be necessary.

At the end of the training phase there is a reference value and a threshold for every identified endpoint. As this is the only information that is needed for the anomaly detection phase, it does not matter how much data needs to be processed to get those values and how long the initial setup takes. Once the information is available, the anomaly detection can start.

Detection phase
With the training phase completed, the online anomaly detection can start. The main goal of this phase is to evaluate incoming spans as they are reported, whether they are deviating from the expected norm.

This calculation is pretty straight forward. For each incoming span, the endpoint identifier is calculated. This identifier is then used to identify the right reference value and threshold to compare it against. If the distance between the incoming span and the reference point is greater than the threshold, the span will be considered as an anomaly and reported as an anomalous span for further processing by the root cause analysis.

If an incoming span has an endpoint identifier that has not yet been seen, this span will be ignored. The reason behind this approach is, that with how the model is generated, there is no guarantee that every available endpoint will be covered. To prevent a large number of false alarms, those endpoints will remain unchecked, until a model exists for them. The next time, the models are recalculated, the information about the new endpoint will be added and a model will be calculated from the values that have been collected in the meantime. This makes sure, that the model can adapt to a changing environment, even though no prior knowledge about the system is available.

In the current implementation of the prototype, it is required to restart the whole system to update the underlying KMeans models. However, as the only information that is required for the anomaly detection is the map that lists reference value and threshold for each available endpoint, this map could be calculated out of band and swapped in the running prediction algorithm while it is running.

4.4.7 Anomaly Reporting

Once a span has been identified to be anomalous, it has to be reported to a new Kafka topic. This is where the root cause analysis will fetch the anomalous spans it uses as input.

Therefore, all detectors have to use the same JSON format and write the detected anomalies to the same topic. The chosen format is displayed in Listing 2.

```
{
"endpointIdentifier": "service@host:port/uri:::methodName",
  "spanId": "1234567890",
  "traceId": "0987654321",
  "anomalyDescriptor": "splittedKMeans",
  "begin": "100000000",
  "end": "200000000",
  "parentId": "5432167890"
}
```

Listing 2: JSON format of reported anomalies

The reported JSON is a simplified representation of a span. It only contains the information that is needed for the root cause analysis. This means all tags and duration information, that were important for the anomaly detection itself are now dropped, as the root cause analysis knows that all the reported spans are anomalous and therefore does not need this information anymore. Trace Id, begin and end, as well as the parent ID are kept. Furthermore, the span ID is reported with a defined String concatenated to it, if the reported span has a controller class and method set. This enables unique IDs for the next stage, while still keeping the two parts of a span separated, that are recorded on the client service that is requesting and the server service, that is processing the request. As the same span can be reported by different detection algorithms, a descriptor is added. This gives information later in the process which algorithm reported the span as anomalous. Furthermore, additional useful information can be added to the descriptor. For reported errors, the error message is added to the descriptor to give as much information as possible to the person in charge of resolving the problem.

As it is very costly to instantiate a Kafka producer, that is needed to write to a topic from within an application, it is necessary to reuse it, once created, as long as possible. When using a new producer for every reported anomalous span, the performance of the application suffers heavily.

If newly implemented anomaly detection algorithms keep the output format like described in Listing 2, they can be integrated easily into the pipeline by running in parallel to the existing algorithms and their results will be included in the root cause analysis. This is one of the properties of the application, that enables the prototype to be extended easily in the future.

5 Root Cause Analysis

The root cause analysis aims on reducing the number of reported anomalous spans from the anomaly detection stage as far as possible. The main goal is to set those spans in the context of the dependencies the services have amongst each other. This context can then be used to prioritize the anomaly that is the root cause of a set of anomalies, while lowering the priority for every other anomaly. This will finally result in a more manageable amount of information for the system operator.

5.1 Challenges

The challenges, that were described for the anomaly detection in section 4.4.1, apply to the root cause analysis stage as well. For this prototype, there is still no information about the structure of the monitored application. The root cause analysis has to be performed online and based only on the information from distributed tracing. Furthermore, the modular approach should continue through this module.

Especially the last point does impact the root cause analysis. The input for this stage are the reported anomalous spans from the different detection algorithms. As they are running in parallel, there is a possibility, that some spans are reported multiple times – they could potentially be anomalous for multiple or all of the detection algorithms. While the anomaly detection stage can assume, that each span is reported exactly once, this is no longer true for the root cause analysis.

And finally, the biggest challenge for this stage is to reduce the amount of information, an operator has to look through when searching for the root cause of an anomaly. This means, the returned information of this stage must be as minimal as possible, without losing the most important information – that is the existence of an anomaly and the specific endpoint that is most likely causing it. Therefore, at the end of the root cause analysis a set of endpoints has to be reported, that is seen as causing the anomalous spans that were reported by the anomaly detection.

5.2 Implementation

The implementation of the root cause analysis consists of two steps. In the first step, the data is imported from Kafka and prepared for further processing. The second step aims on setting

the spans into a dependency context and derive the root cause of a set of anomalies in that way.

5.2.1 Data preparation

The main goal of this step is to read the data from Kafka, deal with the problem of spans that have been reported as anomaly multiple times and provide the remaining data in a format that can be used for further processing. This is similar to the import of data in the chapter 4.4.3 for the anomaly detection.

The information that is available at this stage is defined by the reporting format of the anomaly detection algorithms:

- Span ID and Trace ID
- Identifier for the endpoint that created the span
- Timestamp of begin and end of the span
- Custom anomaly descriptor
- Parent ID if the span has a parent

To merge spans that have been reported by multiple algorithms, Apache Spark Streaming's way of processing incoming data in mini batches, is useful. With the assumption, that all the reported instances of the same span will arrive at approximately the same time, they are all in the same mini batch. For each iteration of the mini batch process, the spans are grouped by their span IDs. Then they are reduced to a single span by concatenating the anomaly descriptors and by keeping the information they have in common as it is.

Figure 18: Reducing anomalous spans that have been reported by multiple detectors

At the end of this stage, the stream of anomalies only contains one entry per unique span, even if it was reported by multiple algorithms at the same time. The next step of the root cause analysis can assume that it will find each anomalous span exactly once.

5.2.2 Root Cause Identification

The initial situation of anomaly reporting, before the root cause analysis is performed, is shown in Figure 19. The effects of the anomalous behavior in service E, propagated its effects to services A and B as well. Therefore, the spans of services A and B were reported as anomalies together with the ones of service E, even though there is nothing anomalous happening in those services, that is not due to the propagation effects from service E. As services A and B are healthy, even though they show anomalous behavior, for someone who wants to solve the problem, they are false positives – they are reported as anomalies, but are not the right place to investigate when the goal is to fix the problem.

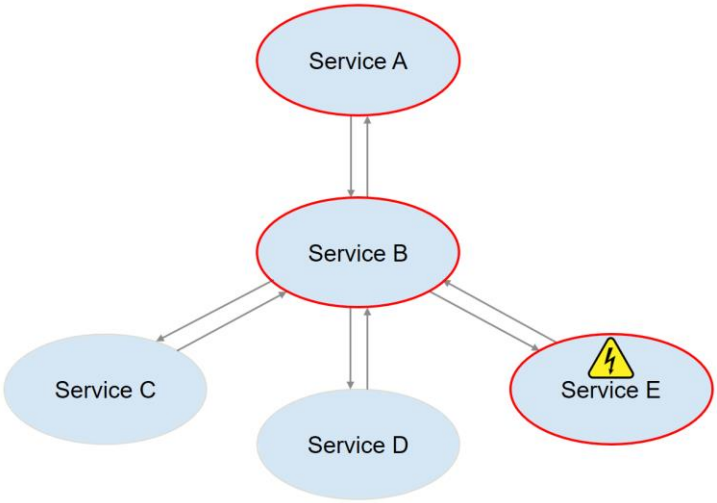

Figure 19: Error Propagation – The propagation effects of the anomaly in service E causes the anomaly detectors to report anomalies (red circles) for services A and B as well.

To reduce the amount of those false positives the goal of this stage is to find contextual information from the reported anomalous spans' information and use it to highlight the root cause of a set of anomalies – and deprioritize the reported anomalous spans, that are most likely only influenced by anomaly propagation.

When having a look at the available information, that was described earlier in section 5.2.1, some information appears to be useful and some not. In the following this information will be analyzed with regards of their usefulness to create a dependency context.

The span ID does not deliver any useful information. As it is a randomly generated number, there is no information contained that might give a hint on the order of the spans, with regards to this ID.

The endpoint identifier and the anomaly descriptor contain information that is useful, once the root cause is identified to give information, where this root cause is located in the application. However, for deriving the dependencies among the different services and spans, this information does not add value.

The trace ID however, is delivering valuable information. A trace is a collection of spans that were created, while a single request was executed. Every span of the same trace is executed to serve the same original request. This means, that if an anomaly that is detected inside this trace does have propagation effects, those other anomalous spans in the same trace are most likely affected. Hence, the trace ID can be used to group spans together that belong to the same request.

The parent ID is only of limited use at this stage of the process. In theory, the parent ID would be a great way to establish the relations of the spans of a trace among each other. However, the problem is, that this does only work reliably if the whole trace is available. In this stage, this is not guaranteed. The root cause analysis can only work with the spans of a trace that have been reported by the anomaly detection stage. This could be a whole trace, but it can happen as well, that some spans are missing and therefore no closed chain of parent child relationships exists. Where the parent ID works as a mean to establish the dependency relationships among those spans, it can be used. However, there needs to be a fallback mechanism in place, where the chain is broken.

The last values that are available from the reported anomalous spans are the timestamps that mark the begin and end of each of the spans. These can help to build the dependency structure. This is due to how those spans are created. Each one is created, once the request reaches its associated endpoint and closes when the endpoint has finished processing the request.

In a microservices environment that communicates via http requests, there is usually a http request that calls an endpoint and at this endpoint a controller class is taking care of this request. This controller itself can either process the request by its own, call other endpoints through http requests or process the task in another class. No matter where you are in this process, a span is started, once the request reaches the endpoint and ends once it has finished its task for the request. Therefore, assumptions can be made about the relationship of timestamps of parent spans and their children.

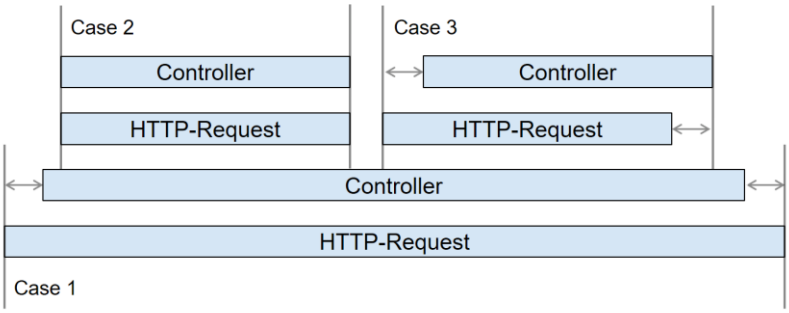

Figure 20: How the relationship between begin and end timestamp of spans can appear

A span starts, once the request reaches its associated endpoint. Furthermore, a parent calls the endpoint of the child. Therefore, the begin of the child has to be later than the begin of the parent. The inverse counts for the end. When a span ends the moment, the request has finished to be processed on its associated endpoint and the parent waits for the response of the child, the end timestamp of the parent has to be later than the one of the child. This is illustrated as “Case 1” in Figure 20.

However, besides this expected case, two other cases have been observed, when monitoring the data generated by the demo application. “Case 2” is likely a result of executing all services of the monitored application on the same machine. Due to the missing network latency there were traces, where the begin of parent and child or their end or even both had the identical timestamp. When network latency comes into play, this case should be observed less frequently, if not disappearing at all.

“Case 3” is very counter intuitive. With the assumptions described for “Case 1” it should never happen, that the end of the child is later than the end of the parent. However, those cases occurred rarely. When those cases were observed, it usually was a difference by a few microseconds.

With knowledge about those relationships it is now possible to design an algorithm that can reconstruct the structure of the trace, without the need for the complete set of spans. To achieve this, a data structure is created that will help to build the dependency tree and then report the root cause endpoint and the endpoints that might be affected by it. This data structure is called Anomaly and is shown in Figure 21. It serves as a storage for the information of each reported anomalous span and provides a way to build the trace structure at the same time. Once the structure is built through the insert() method that is explained in the next paragraph, the remaining methods are used to retrieve the root causes and warnings for reporting.

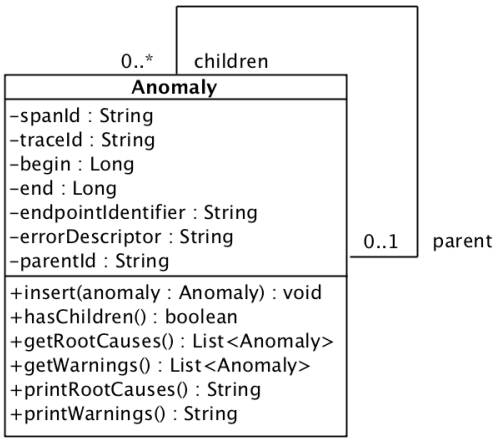

Figure 21: UML class diagram of the root cause analysis data structure "Anomaly"

As the data structure is designed to rebuild the dependency structure of a trace, the prepared anomalous spans have to be grouped by their trace IDs. Then they must be brought into the order in which they originally started. This is done by sorting first by the begin timestamp and then by the end timestamp. However, this step is the weak point of this algorithm when looking at "Case 2" from Figure 20. In the case that the begin and end of two spans are identical, the order of those two spans could be mixed up. However, as in some cases a http request span and its corresponding span for processing in the controller class share the same span ID, the span ID of the controller spans gets the ending "mvc" attached, when they are reported from the anomaly detection algorithms. This means that in some of the cases the spans can be brought into the right order reliably, even though their begin and end are identical. Identifying a way to improve the sorting further would make the root cause analysis more robust against this issue.

After sorting, the anomalous spans are converted into Anomaly objects. The Anomaly object with the earliest beginning is the root and all the other Anomaly objects of the trace are inserted into the root by calling its insert function. The Scala implementation of the insert method is shown in Listing 3. It is a recursive function. The inserted anomaly is compared against the children of the anomaly it is inserted into. If its parent ID matches the ID of a child, or its begin and end are within the begin and end of one, it will be inserted into it. If none of those conditions apply, it will be added to the list of children of the anomaly where it was inserted into. In this way, the inserted anomaly will go further down the trace tree, until it does either not match the insert conditions, or there are no anomalies left to insert it into. In the last case, it will be a new leave in the tree of anomalies.

```
def insert(anomaly: Anomaly): Unit = {
 var inserted = false
 for (child <- children) {
        if (anomaly.parentId==this.spanId
        ||(anomaly.begin > child.begin && anomaly.end <= child.end)
        ||anomaly.begin >= child.begin && anomaly.end < child.end) {
                if (!inserted) {
                child.insert(anomaly)
                inserted = true}
        }
 }
 if (!inserted) {
        children.append(anomaly)
         anomaly.parent = this
 }
}
```

Listing 3: Anomaly insert method (Scala)

Once the tree is created, the method getRootCauses will return a list of all anomaly objects that are leave nodes in the anomaly tree. Those are the anomalies, where the associated endpoints are most likely the root cause for the set of anomalies. By calling the getWarnings method on each of those root causes, a list of all endpoints that lie on the path to the root of the anomaly tree are returned. Those are the reported anomalous endpoints that are likely to be the result of the anomaly propagation from the issue at the root cause endpoint. The endpoint identifiers and error descriptors of the root causes are persisted in a database together with the endpoint identifiers of their warnings. This information is then available for the final visualization step.

5.2.3 Warning elimination

During the visualization, one more step is performed that enhances the result of the root cause analysis. As the whole root cause analysis is based on mini batch processing that contains all spans of a trace, it can happen that some of the spans are missing, as they slipped into another mini batch. If those missing spans are containing the root causes, another endpoint identifier will be written to the data base as the identified root cause, that would be just a warning, when the trace would have been processed as a whole. Therefore, all anomalies are deprioritized to a warning, if they appear in the set of warnings of another root cause. This means, they will never be lost completely, just in case they happen to be a real anomaly – but they are assigned a lower priority in the reporting. This enables the person in charge of chasing down the root cause of an anomaly to start with the high priority anomalies and later transition to the lower priority warnings, if still necessary.

After applying the steps of the root cause analysis and the warning elimination to the anomalies that were reported from the different detection algorithms, a more differentiated view on the problem is possible. In Figure 19, that represented the result after just the anomaly detection stage, all the propagated anomalies were reported as anomalies. The reporting after the root cause analysis and warning elimination looks different. As illustrated in Figure 22, now the anomalies that were reported in services that rely on the anomalous service E, are reported as warnings and only service E is reported as anomaly.

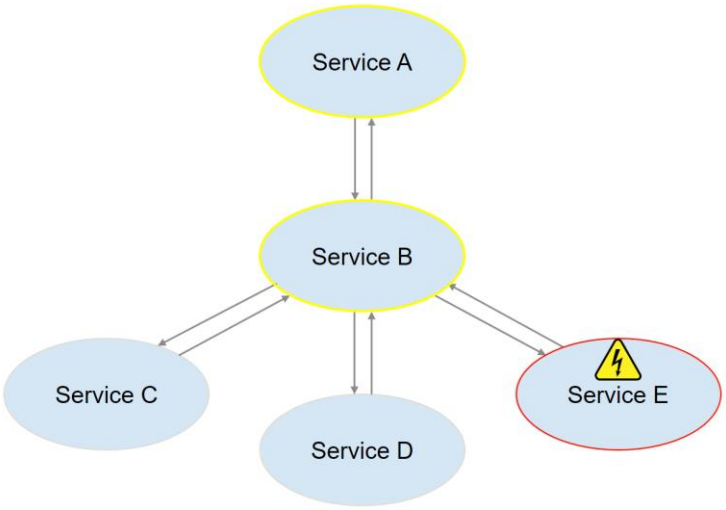

Figure 22: Differentiated reporting of anomalies (red circle) and warnings (yellow circle)

6 Evaluation

This chapter will point out how the prototype was evaluated. First the monitored system will be described. Then it will be explained how the anomalies were injected into the system. Finally, the tests and results will be described.

6.1 Monitored system

The monitored application is a small-scale micro service application. It serves the business case of a user who wants to book a journey. First the user decides which of the three available providers he wants to use to book his journey. When the provider is selected, the user enters the starting point and the destination of his journey and then gets possible connections, depending on the offers of the chosen provider. Once the decision is made, which of those connections to take, it can be booked.

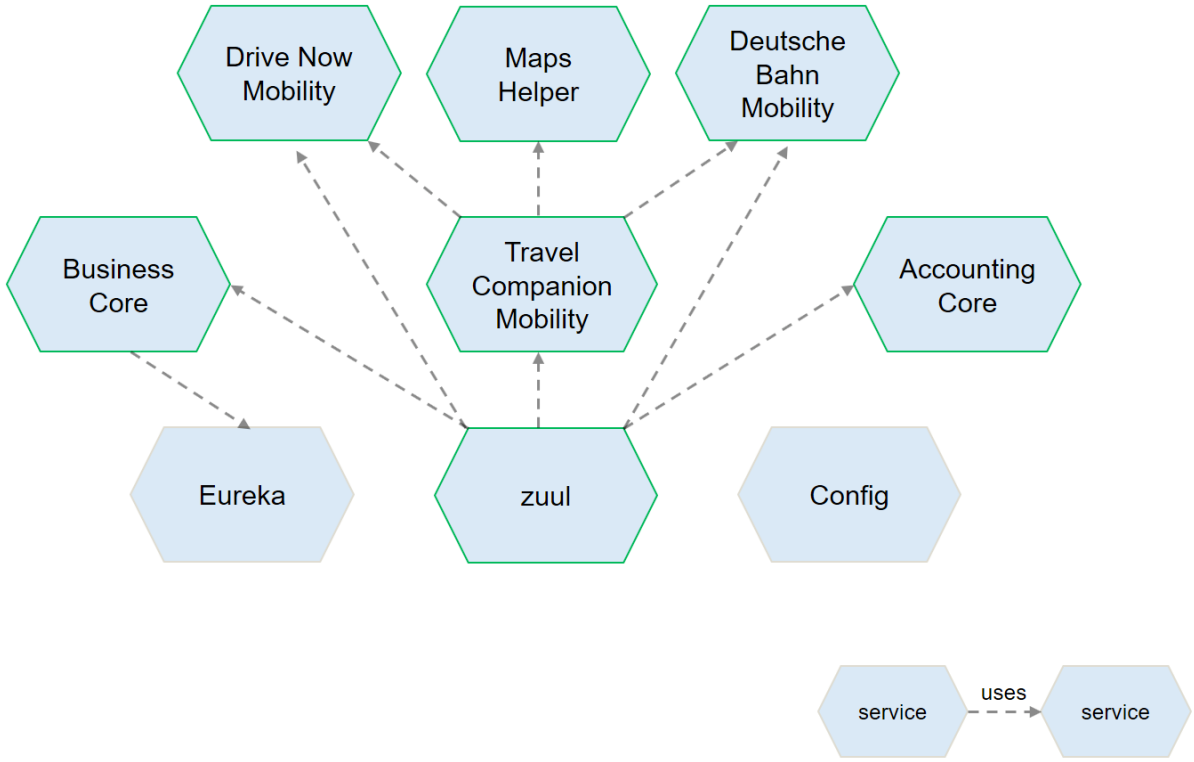

Figure 23: Service dependencies of the monitored application during operation. Services that are instrumented for distributed tracing have got a green border.

The application consists of nine services, as can be seen in Figure 23. Seven of those services are instrumented for distributed tracing. Those are the services with green borders. The bottom three services are technical services, while the other six services serve the business case. The communication among those services is done through HTTP requests. In the following, it will be briefly described, what the purpose of each of those services is.

Starting with the technical services, the Eureka service is responsible for locating the available services and making this information available to the other services in the application. It offers the possibility to other services, to query, which services are currently available in the micro service application.

The configuration service is a central instance, that is holding all the configuration information for each service. At startup, each service retrieves its configuration from this service. This enables a centralized configuration management.

The last of the three technical services, and the only one that is instrumented with distributed tracing, is the zuul service. It is responsible for routing of requests and for authentication. In the case of this application, the requests will all be made to the port zuul is running on. Zuul then takes care to forward the requests to the proper port for the requested service. Additionally, during this process it makes sure, the user that is requesting the service is authenticated and authorized.

The first service a user interacts with, when booking a journey, is the Business Core service. It queries the Eureka service for the currently available mobility services and provides a list of links to the user, who can choose, which of the mobility services to use. Only the services that are currently up and running will be presented to the user.

The three mobility services all work similar. They accept a starting point and a destination and then provide a set of possible connections to the user. The Deutsche Bahn Mobility service and the Drive Now Mobility service both pull the requests directly from a database. However, the Travel Companion Mobility service requests the possible connections from both the other mobility services and furthermore adds some distance information based on calculations of the Maps Helper service. Therefore, the request to the Travel Companion Mobility service is the most complex request in terms of involved services.

The last service of this micro services application is the Accounting Core service. It is responsible of writing the booked connection of the user to the database.

6.2 Evaluation Setup

To evaluate the ability of the prototype to detect the anomalies defined in section 4.2, first the monitored application is instrumented to enable the injection of those types of anomalies and a training set is generated. This is the preparation before the tests to evaluate the prototype can be performed.

As instrumenting the application for anomaly injection is a manual task, the evaluation will be restricted to a single request that will be executed repeatedly. As in the previous chapter described, the request to the Travel Companion Mobility service includes the most calls to other services – exactly what is useful for this evaluation. The involved services can be seen in Figure 24. The path of the request is shown in red. It enters the system through a request to the zuul service. To serve the request the Travel Companion Mobility Service, the Drive Now Mobility service, the Deutsche Bahn Mobility service and the Maps Helper service are involved. The high number of involved services is the reason why this request will be selected for the evaluation.

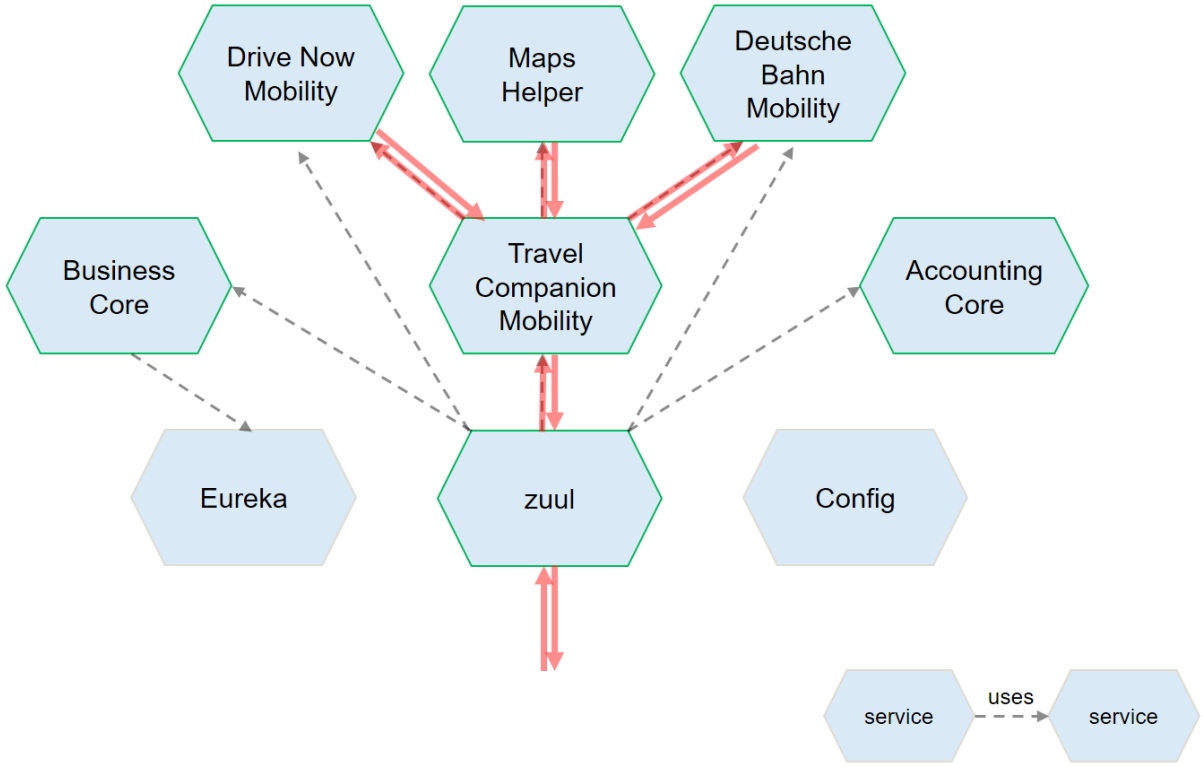

Figure 24: Flow of the monitored request (red arrows)

6.2.1 Anomaly Injections

The information, whether an anomaly should be injected into a request or not, should be added on the request level. This means, depending on parameters in the request, the anomaly should appear or not. To achieve this, for all requests (see Figure 24), a new parameter will be added. This parameter is a string that carries the information whether an anomaly should be triggered and if yes, where and which kind.

The code required for the option to inject a delay of 100 ms is shown in Listing 4. If the info parameter contains the sub string “maps-100msDelay”, the program flow enters the conditional statement and is halted for 100 ms. If the info parameter does not contain this text, nothing happens and the application proceeds as normal. By checking whether the string contains the trigger and not using the equals method, it is possible to inject multiple anomalies for the same request. Analogous to the injection of 100 ms delays, there are measures in place to inject delays of 25 ms, 50 ms and 200 ms in all services. In the Maps Helper service, there are additional measures in place for injecting delays of 5 ms and 10 ms.

```
if (info.contains("maps-100msDelay")) {
        try {
                Thread.sleep(100);
        } catch (InterruptedException e) {
                e.printStackTrace();
        }
}
```

Listing 4: Code snippet for injecting a 100ms delay in the controller class

Injecting an uncaught exception, as shown in Listing 5, works exactly the same way as the delay. The only difference is, that instead of halting the process, a sequence of operations is executed that always will cause a NullPointerException to be thrown.

```
if (info.contains("maps -nullpointer")) {
        String nullPointer = null;
        nullPointer.charAt(5);
}
```

Listing 5: Code snippet for injecting an uncaught exception (NullPointerExcdption) in the controller class

The delay and the exception can be implemented directly into the controller classes, as those anomalies can be simulated easily with the possibilities Java provides. Those events will be recorded by the Spring Cloud Sleuth instrumentation and are then sent to the anomaly detection algorithm.

Injecting an anomaly, that violates a fixed threshold for a monitored attribute is not possible from inside the controller classes. The attributes that are monitored by the prototype are the JVM heap utilization and the average of the CPU utilization over the last minute. Both of those values are difficult to manipulate reliably from within the controller class.

However, there is another location where the anomaly can be injected reliably. This is inside the distributed tracing extension, that was implemented to add information about heap utilization and CPU utilization to the reported spans. In this place, the code snippet shown in Listing 6 is inserted. By reading information from the HTTP request, it is possible to identify the URI of the request that is currently processed. Furthermore, as the tracer, that is taking care of creating the spans of the distributed tracing instrumentation, is available at this location in the application, the parameter with the info about the anomaly injection can be accessed.

```
String requestUri = httpRequest.getRequestURI();
String infoParam = tracer.getCurrentSpan().tags().getOrDefault("servlet.param.info", "not set");

if (infoParam.contains("maps-highCPU") && requestUri.equals("/maps-helper-service/distance")) {
        tracer.addTag("cpu.system.utilizationAvgLastMinute", "99");
}
```

Listing 6: Code snippet to inject a high CPU utilization value inside the distributed tracing extension

If the info parameter contains the required string and the URI does match, the CPU utilization tag will be overwritten with a value of 99. As the anomaly detection algorithm will only read the value, this is sufficient to inject an anomaly that will trigger the violation of a fixed threshold on the CPU utilization without the need to really impact the CPU.

6.2.2 Test set generation

To train the Splitted KMeans algorithm for the detection of increased response times, a set of historical data has to be available. To create this set, a large number of requests has to be sent to the application and recorded by the Spring Cloud Sleuth instrumentation. The recorded data will be stored in a Kafka topic and is then available for training the Splitted KMeans algorithm, when the anomaly detection is started.

To have a consistent way of sending the requests throughout the whole evaluation, JMeter [85] will be used to send the requests. JMeter is a software that is designed for performance testing of applications. There are different possibilities to configure a request and send it repeatedly. Furthermore, there are ways to record the results of the sent requests.

To generate the training set, JMeter is set up to run requests against the Travel Companion Mobility Service through the zuul service. This will result in the request flow that was

illustrated in Figure 24 earlier. The requests are sent by 5 parallel processes. Each request sent will generate 9 spans.

For all tests, the requests are sent with JMeter, using the same five parallel processes. All anomalies are injected into the Maps Helper service. However, every other service would work as well.

6.2.3 Evaluation metrics

The prototype will be evaluated using the metrics precision, recall and the F-score (also called F-measure or F_1 score). Those metrics are commonly used for evaluating anomaly detection algorithms [47, 58, 86].

	True Anomaly	No Anomaly	Sum
Anomaly predicted	True Positive (TP)	False Positive(FP)	Predicted Anomalies
No anomaly predicted	False Negative(FN)	True Negative(TN)	Predicted Normals
Sum	Anomalies	Normals	Total

Table 3: Contingency table based on [86]

Those metrics are based on the contingency table that is used to categorize predictions and that is shown in Table 3. In this approach, each prediction gets one of four categories. If a real anomaly is detected, this is seen as a **true positive (TP)**. If the detection algorithm reports a normal data point as anomalous, this is a **false positive (FP)**. If an anomaly is missed by the detection algorithm, this is a **false negative (FN)**. And finally, a normal data point that is not reported as an anomaly is a **true negative (TN)**.

$$recall = \frac{TP}{TP + FN}$$

Listing 7: Formula for calculating recall

The metric recall is calculated with the formula displayed in Listing 7. It is the ratio between the detected anomalies – predicted anomalies that are actual anomalies – and the total number of occurred anomalies. This means, recall is an indicator, which percentage of the occurring anomalies is detected by the algorithm.

$$precision = \frac{TP}{TP + FP}$$

Listing 8: Formula for calculating precision

The metric precision is calculated with the formula displayed in Listing 8. It is the ratio between the detected anomalies and the number of reported anomalies. This metric is an indicator for how reliable a data point that is reported as an anomaly by the algorithm is really an anomaly.

$$F\text{-}score = \frac{2 \cdot precision \cdot recall}{precision + recall}$$

Listing 9: Formula for calculating the F-score based on precision and recall

To improve precision, the false positives have to be reduced. On the other hand, to improve recall, the false negatives have to be reduced. As usually the improvement of one of those metrics results in a worse result for the other, the F-Score was introduced as a quality measure that takes the harmonic mean of precision and recall. For equal weights on precision and recall, as it will be used for the evaluation, the formula is shown in Listing 9. This metric goes back on a suggestion of van Rijsbergen [87].

6.2.4 Measurement points

To get the most information out of the test, the required metrics are calculated on three different stages of the prototype for each test. First the results that come out from the anomaly detection stage are observed. This means, the raw performance of the anomaly detection algorithms in this setting can be evaluated, before any enhancing processing is performed on the detected anomalies. This stage is called "**anomaly detection**" in the result tables.

Then the results after applying the basic root cause analysis are evaluated. This gives an insight how the root cause analysis works and what the calculated context is able to give as improvement to the process of detecting meaningful anomalies. This stage is called "**root cause analysis**" in the result tables.

And finally, the results after removing anomalies that have been reported as warnings before, is analyzed. This step is removing the mistakenly reported anomalies, that resulted from a trace being processed over more than one mini batch. This stage is called "**warning elimination**" in the result tables.

6.3 Prototype Evaluation

In a first set of tests, the whole prototype is evaluated for its capabilities to detect errors, increased response times and violations of a fixed threshold. This is tested by running the algorithms in parallel. The focus of this set of tests is on the behavior of the system as a whole. The training set contains 20,000 requests.

6.3.1 Performed tests

To evaluate the capability of the prototype to detect the anomalies defined in chapter 4.2, five tests are performed. Before running the test, all three algorithms, described in chapters 4.4.4, 4.4.5 and 4.4.6, are started to run in parallel.

For the first test, 500 requests without any injected anomalies are sent to the monitored application. This test tries to figure out, how many false positives will be issued by the application, when no anomalies are present.

The next two tests are targeted towards the capability of detecting increased response times. For the second test, delays of 100 milliseconds are injected and a total number of 100 requests is sent. The third test is similar to the second one, with the difference, that the injected delays are only lasting for 50 milliseconds. The normal duration of the request, the delays were injected into was about 7ms.

The fourth test is about detecting uncaught exceptions. To evaluate the performance of the error detection algorithm, 100 requests are sent with injected NullPointerExceptions.

And finally, the fifth test targets the capabilities of detecting the violation of fixed thresholds. The fixed threshold detector is set up to monitor the CPU utilization average over the last minute and raise an alarm if the value gets above 98%. To test the detector, 100 requests are sent with an injected CPU utilization average of 99%:

During all tests, the complete set of detectors was running. This means, that at any stage of the evaluation all sensors could potentially detect an anomaly. So, even though all the tests are targeted at specific detectors, it can happen, that another detector will report false positives.

6.3.2 Results

Each request generates nine spans, which are examined by the anomaly detection algorithms, whether they are anomalous or normal. In case an anomaly is injected, exactly one of those nine spans is anomalous per request. The other spans are normal.

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	0	22	0	-	0	-
Root Cause Analysis	0	7	0	-	0	-
Warning elimination	0	7	0	-	0	-

Table 4: Result of Test 1 – 500 requests with no injected anomalies

As the preprocessing and training of the Splitted KMeans algorithm was aimed at a low false positive rate, a low rate is expected. Those 500 requests generate 4500 spans that are predicted on by the prototype. Compared to this, the result of Test 1 (Table 4) shows a false positive rate of 0.02%. As precision and recall require anomalies to be present to give meaningful values, those measures are not applicable for this test. This is the reason, why Table 4 lacks those metrics.

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	100	400	0	1	0.2	0.333
Root Cause Analysis	100	75	0	1	0.571	0.727
Warning elimination	100	0	0	1	1	1

Table 5: Result of Test 2 – 100 requests with an injected 100ms delay

The result of the second test (Table 5) shows the reason for the different stages of the anomaly detection process. During the anomaly detection stage, all the true anomalies are reported together with 400 other anomalies. This is due to the fact, that 4 of the processing steps that are represented as spans of the request trace depend on the one processing step that got the 100ms delay injected. Due to the propagation of this delay, all those other steps in the process were reported as anomalies.

After the root cause analysis, the number of false positives is already reduced, which results in an improved precision metric. After the warning elimination stage, all false positives are gone. This is an indicator, that those 75 reported anomalies from the root cause analysis are caused by traces where one part has been processed in another mini batch process than the other. However, the warning elimination stage took care of the problem, as intended.

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	100	110	0	1	0.476	0.645
Root Cause Analysis	95	9	5	0.95	0.913	0.931
Warning elimination	95	3	5	0.95	0.969	0.960

Table 6: Result of Test 3 – 100 requests with an injected 50ms delay

The result of Test 3 (Table 6) shows issues, the prototype can run into. While the anomaly detection is able to identify all of the injected anomalies, five of those are lost after the root cause analysis was performed. This is due to the fact, that the root cause analysis relies on sorting the anomalous spans into the order in which they appeared, before processing them. In the case begin and end are identical, it can happen that the order is mixed up and therefore the wrong anomalies are reported.

As those wrong predictions will be eliminated in the warning elimination, the remaining false positives are due to false positive predictions in services that do not depend on the anomalous service. This issue can only be addressed by increasing the threshold of the Splitted KMeans predictor.

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	100	178	0	1	0.360	0.529
Root Cause Analysis	100	34	0	1	0.746	0.855
Warning elimination	100	15	0	1	0.870	0.930

Table 7: Result of Test 4 – 100 requests with injected NullPointerException

Test 4 (Table 7) shows that all of the injected exceptions are detected. The propagated errors are eliminated by the root cause analysis. The remaining false positives are false reports by the Splitted KMeans algorithm.

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	100	0	0	1	1	1
Root Cause Analysis	100	0	0	1	1	1
Warning elimination	100	0	0	1	1	1

Table 8: Result of Test 5 – 100 requests with a high CPU utilization value injected

The result of Test 5 (Table 8) shows no propagated errors and no false positives. Therefore, the last two stages would not even be needed.

In total, the prototype detected 395 of the 400 injected anomalies (98.75%). Over all the 900 requests and the resulting 8100 generated spans, there was a total of 25 spans that were reported as false positives, that remained after the last stage of the detection process. This is a false positive rate of 0.3%.

	Test 2	Test 3	Test 4	Test 5	Tests 1-5
Anomaly detection	0.333	0.645	0.529	1	0.530
Root Cause Analysis	0.727	0.931	0.855	1	0.859
Warning elimination	1	0.960	0.930	1	0.963

Table 9: F-Score Overview for the prototype tests, with all algorithms running

When analyzing the F-score results of the different tests and stages in Table 9, those numbers suggest, that all of the stages of the anomaly detection process add value to the final result. Throughout all tests, including an aggregation of tests 1-5, the F-score increases from stage to stage. The aggregation is the result of adding up the values in the contingency table of each test and then calculating the F-score based on the resulting values for true positives, false positives and false negatives. When comparing test 2 and test 3, that were the 100ms and 50ms injections, the numbers suggest, that the larger the anomaly and therefore the higher the probability to detect propagated anomalies, the more value the root cause analysis and the warning elimination provide. When looking at test 5, where no false positives were recorded, the root cause analysis and the warning elimination do not provide additional value.

6.4 Splitted KMeans Algorithm Evaluation

A second set of tests is run to evaluate the performance of the Splitted KMeans algorithm for the detection of the increased response times in isolation from the other algorithms. The set of tests is aimed towards evaluating the general performance of the algorithm on a different training set from the first one and to figure out, how small the delays that are injected as anomalies can be, before the algorithm is not able to detect them anymore. The training set contains 20,000 requests.

6.4.1 Performed tests

The performed tests are similar to the tests that were run before. First a set of 500 requests without injected anomalies is run. This is done for the same purpose as before – detecting false positives when there are no anomalies present.
Afterwards, increased response times will be injected into the requests. This set of tests aims at discovering what the lowest injected latency is that the algorithm can detect reliably. Additionally, the general performance of the algorithm and the following processing stages is analyzed. Therefore, tests were performed with lowering the injected delays more and more, until the algorithm would not detect them anymore. That resulted in five tests with injected anomalies of 100ms, 50ms, 25ms, 10ms and 5ms.

6.4.2 Results

The following tables show the results for the performed tests. The meaning of the results is discussed after the tables, to set the results into context. Same as in the first round of tests, each request generates 9 spans, which are examined by the anomaly detection. In case an anomaly is injected, exactly one of those spans is anomalous. All the other spans are normal.

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	0	18	0	-	0	-
Root Cause Analysis	0	12	0	-	0	-
Warning elimination	0	8	0	-	0	-

Table 10: Result of Test 6 – 500 requests without injected anomalies

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	100	428	0	1	0.189	0.318
Root Cause Analysis	99	85	1	0.99	0.538	0.697
Warning elimination	99	18	1	0.99	0.846	0.912

Table 11: Result of Test 7 – 100 requests with an injected 100ms delay

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	100	112	0	1	0.472	0.641
Root Cause Analysis	98	33	2	0.98	0.748	0.848
Warning elimination	98	5	2	0.98	0.951	0.966

Table 12: Result of Test 8 – 100 requests with an injected 50ms delay

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	100	101	0	1	0.498	0.664
Root Cause Analysis	95	49	5	0.95	0.660	0.779
Warning elimination	95	1	5	0.95	0.990	0.969

Table 13: Result of Test 9 – 100 requests with an injected 25ms delay

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	100	33	0	1	0.752	0.858
Root Cause Analysis	91	11	9	0.91	0.892	0.901
Warning elimination	91	10	9	0.91	0.901	0.905

Table 14: Result of Test 10 – 100 requests with an injected 10ms delay

	True Positives	False Positives	False Negatives	Recall	Precision	F-Score
Anomaly detection	5	32	95	0.05	0.135	0.073
Root Cause Analysis	5	20	95	0.05	0.2	0.080
Warning elimination	5	16	95	0.05	0.238	0.083

Table 15: Result of Test 11 – 100 requests with an injected 5ms delay

When looking at the test results in Table 10 - Table 15, the injected delay, that could not be detected by the algorithm anymore are 5 ms. While 10 ms were still detected with a high success rate, 5ms were not detected reliably with a recall of only 0.05, compared to 0.91 and higher for the tests 7-10.

This behavior can be explained, when looking at the parameters that resulted from the training of the model for the endpoint, in which the delays were injected. The cluster center, that is taken as a reference value, was set to 4.5 ms. And the 99^{th} percentile of the distances of all points in the training set to that point was 7.8 ms. This means, that delays, that are below this threshold cannot be detected reliably anymore. By checking the trained thresholds for each of the predictors it is possible to give a rough statement, which delays can be detected and when the algorithm starts to struggle.

The other finding of this test is, that the lower the injected delay, the higher is the number of lost anomalies from the anomaly detection stage to the root cause analysis. The Splitted KMeans algorithm itself, was able to reliably detect all the inserted anomalies, until they were

below the detection threshold, as explained earlier. However, the root cause analysis started to struggle. This correlation could be incidental. During the development of the prototype, the only reason, why the root cause analysis lost a reported span, that was really anomalous, was the case, when the reported anomalous spans of a trace could not be sorted by their begin and end timestamps unambiguously.

	Test 7 (100ms)	Test 8 (50ms)	Test 9 (25ms)	Test 10 (10ms)	Test 11 (5ms)	Tests 6-10	Tests 6-11
Anomaly detection	0.318	0.641	0.664	0.858	0.073	0.536	0.497
Root Cause Analysis	0.697	0.848	0.779	0.901	0.080	0.787	0.707
Warning elimination	0.912	0.966	0.969	0.905	0.083	0.928	0.820

Table 16: F-Score Overview for the Splitted KMeans Tests

Table 16 shows the overview of the F-scores for all the tests. Furthermore, the F-scores for aggregations of tests 6-10 and 6-11 are included. Same as for the first round of tests, those aggregations are the result of adding up the values in the contingency table of each test and then calculating the F-score based on the resulting values for true positives, false positives and false negatives. Tests 6-10 exclude test 11, as this was the case, where the anomaly detection could not detect the injected delays anymore, due to the calculated threshold.

The F-Scores for this set of tests show again, that the three stages of the prototype, each adds value to the quality of the final result. Even though the recall dropped this time from anomaly detection to root cause analysis for every test, the improved precision caused the F-score to increase. Furthermore, the tests show, that the improvements that are caused by root cause analysis and warning elimination is higher for the long delays, that are more likely to be detected as propagated anomalies in other services.

7 Conclusion

The final chapter of this thesis will wrap things up. Findings and limitations will be pointed out and perspectives for future work will be suggested.

7.1 Findings

The first finding of the thesis is, that it is possible to detect anomalies by just using information from distributed tracing. The three implemented algorithms were able to detect all the anomalies that were targeted, namely error, fixed threshold violations and increased response time compared to the normal behavior of a service.

The evaluation of the prototype (see Chapter 6), with all algorithms running in parallel, showed that the algorithms work together effectively. Besides the high detection rate of the injected anomalies of 98.75%, the false positive rate, when no anomalies were injected was at 0.2%. The separate evaluation of the Splitted KMeans algorithms that is used to detect performance anomalies, showed that the algorithm detects anomalies reliably until the delay gets lower than the calculated threshold. By examining the thresholds, that result for each endpoint after the training phase, assumptions can be made, which delays will be detected and which will be missed.

Furthermore, the prototype is capable of recreating the dependency context from a set of spans that have been reported as anomalous, in all cases where the anomalous spans can be brought into the order in which they were created by the attached timestamps. It is not necessary that the whole trace with all spans and an unbroken chain of parent and child relationships is present. Information that is available from distributed tracing is enough for the task. This is useful in suggesting the endpoint, the anomalous span that is furthest down the call hierarchy to be the most likely root cause for the set of anomalies.

The whole prototype is designed in a way, that it can be changed easily in the future. The distributed tracing instrumentation, the anomaly detection and the root cause analysis are connected through asynchronous messaging. This means, as long as the messaging formats are not changed, each of those modules can be replaced. Furthermore, the prototype is designed, so that multiple anomaly detection algorithms can be run in parallel. This means, that in the case a new type of anomalies should be detected, a new algorithm can be written and then plugged in besides the already available algorithms. Or if an existing algorithm is not performing as intended, it can be removed without impacting the other algorithms running in parallel.

Finally, the whole prototype is built on open source frameworks with scalability in mind. Especially Apache Spark and Apache Kafka are able to run in cluster mode. This means, the processing power of the system can be increased by running the application on a cluster to meet the need of processing more data in a production scenario with a larger number of services and endpoints.

7.2 Limitations

Besides all the positive results of this thesis, the work has its limitations. Those will be described in the following.

The first limitation that came up during the extension of the tracing instrumentation, was the fact, that system level metrics are hard to fetch from inside of Java applications. With relying on APIs of the JVM to access system level metrics, the amount of metrics that is available is limited by those. Furthermore, it can be very expensive to gather this information. When adding CPU metrics to the tracing information, the first approach was to take the current utilization. This required a continuous processing effort by the instrumentation extension. The CPU utilization average over the last minute, that is provided by the JVM, is not as precise, but does not need the ongoing processing. Therefore, it was used for the instrumentation instead, to keep the impact on the instrumented application as low as possible.

The next limitation of this work is about the root cause analysis. The root cause analysis as it is implemented does only work, if anomalies are reported as outliers – this means as anomalous spans. This has the consequence, that all algorithms that only work by detecting anomalous time series instead of outliers, are not working in this prototype.

Furthermore, the root cause analysis, that is only using distributed tracing information, is performed in the context of a trace and the anomalous spans that have been reported for it by the anomaly detection algorithms. This is the context this algorithm has available. There is no other reference data, which the results can be compared against, or where results that might appear off, could be corrected with. This is especially relevant, as the algorithm for creating the dependency context among the reported anomalous spans, relies on bringing those spans into the order they were started. However, in some rare cases this order is ambiguous what results in impacting the reported anomalies and warnings.

Another limitation of the current approach are asynchronous requests. Especially “fire and forget” requests, like writing to a database without waiting for a confirmation, is currently not covered by the implementation of the root cause analysis.

The last limitation concerns the scope of the evaluation of the prototype. The evaluation was performed against a demo application that ran on the same local machine with all the services.

In a production environment, the services would run on different machines and the number of requests and endpoints to monitor would be much larger. As no data from production or a production application to monitor was available, the system could not be tested in large scale.

7.3 Suggestions for future work

The first suggestions for future work is to improve the evaluation of the system. Getting access to a data set from a production environment, or even instrumenting a microservice application that is running in production would give a lot of insight into the capabilities of the prototype. By now, the scaling capability has not been verified – the application was designed on frameworks, that allow for running them on a cluster for scaling – however, there is no proof yet.

The next suggestion would be the improvement of the root cause analysis. By relaxing the requirement to getting all information from the spans at hand, it could be possible to include externally calculated information on the service and endpoint dependencies into the algorithm. This would have three big advantages. First this would be a reliable source of information, that will know the dependencies for sure – even if some information inside a trace gets mixed up or behaves unexpectedly. Second, it would make it easier to handle asynchronous requests properly. The third advantage is, that the availability of the dependencies would enable the prototype to use algorithms that do predict on time series data, as no trace context would be needed anymore and it would be sufficient to identify the endpoint that is behaving anomalous. This could be achieved by integrating this prototype, with another prototype from this research group that is targeted at discovering microservice structures and dependencies based on distributed tracing.

Another topic where further work could be focused to is the tracing instrumentation. This thesis only touched briefly on the topic of including further metrics into the reported spans. By analyzing thoroughly, which metrics could be obtained during the tracing process and how much resources would be needed to get them, would benefit the anomaly detection with providing a greater number of features to choose from. Furthermore, it would be interesting to see how applications that cannot be instrumented with Spring Cloud Sleuth – as they are e.g. no Java applications – can be instrumented, to provide a matching messaging format to be included into the anomaly detection and root cause analysis process.

Finally, the last suggestion regards the visualization of the results. The visualization that is provided by this prototype does only work for the request that was used in the evaluation phase. A proper visualization would have to deal with displaying a large amount of services,

as microservice applications can get very complex. Furthermore, it would need to display the reported anomalies in a way that is easy to understand by the operator and provides as much information as is necessary. As other work in this research group focuses at exactly this topic, an integration with this project would be very beneficial.

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