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Bachelor Thesis

My Bachelor Thesis

Submitted by

Marcel Pascal Stolin

32168

born at 03.04.1993 in Kamen

Written at

Fraunhofer-Institut für Produktionstechnik und Automatisierung IPA

and

Stuttgart Media University

First Examiner:	Prof. Walter Kriha
Second Examiner:	Prof. Dr.-Ing. Marco Huber
Supervisor:	M.Sc. Christoph Hennebold

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Zusammenfassung

Hier kommt eine deutschsprachige Zusammenfassung hin.

Abstract

Abstract in English.

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Notation

Konventionen

x	Skalar
$\underline{x}$	Spaltenvektor
$\boldsymbol{x}, \underline{\boldsymbol{x}}$	Zufallsvariable/-vektor
$\hat{x}, \hat{\underline{x}}$	Mittelwert/-vektor
$x^*, \underline{x}^*$	Optimaler Wert/Vektor
$x_{0:k}, \underline{x}_{0:k}$	Folge von Werten $(x_0, x_1, \ldots, x_k)$ / Vektoren $(\underline{x}_0, \underline{x}_1, \ldots, \underline{x}_k)$
$\mathbf{A}$	Matrizen
$\mathcal{A}$	Mengen
$\preceq, \prec$	schwache/strenge Präferenzrelation
$\mathbb{R}$	Reelle Zahlen
$\mathbb{N}$	Natürliche Zahlen
■	Ende eines Beispiels
□	Ende eines Beweises

Operatoren

$\mathbf{A}^{\mathrm{T}}$	Matrixtransposition
$\mathbf{A}^{-1}$	Matrixinversion
$\lvert\mathbf{A}\rvert$	Determinante einer Matrix
$\lvert\mathcal{A}\rvert$	Kardinalität der Menge $\mathcal{A}$
$\mathrm{pot}(\mathcal{A})$	Potenzmenge von $\mathcal{A}$
$\mathrm{E}\{\cdot\}$	Erwartungswertoperator
$\mathcal{O}(g)$	O-Kalkül entsprechend der Landau-Notation bei welcher beispielsweise $f(x) \in \mathcal{O}(g(x))$ besagt, dass die Funktion $f(x)$ die Komplexität $\mathcal{O}(g(x))$ besitzt

Spezielle Funktionen

$\Pr(\mathcal{E})$	Wahrscheinlichkeitsmaß, welches die Wahrscheinlichkeit angibt, dass Ereignis $\mathcal{E}$ eintritt
$p(\underline{x})$	(Wahrscheinlichkeits-)Dichtefunktion für kontinuierliche $\underline{x}$

	und Zähldichte für diskrete $\underline{x}$
$p(\underline{x}\|\underline{y})$	Bedingte Dichtefunktion
$P(\underline{x})$	(Wahrscheinlichkeits-)Verteilungsfunktion
$\mathrm{erf}(x)$	Gauß'sche Fehlerfunktion
$\exp(x)$	Exponentialfunktion e^x
$\mathcal{N}(\underline{x};\underline{\hat{x}},\mathbf{C}_x)$	Gaußdichte, d. h. Dichtefunktion eines normalverteilten Zufallsvektors $\underline{\boldsymbol{x}}$ mit Mittelwertvektor $\underline{\hat{x}}$ und Kovarianzmatrix $\mathbf{C}_x$

Chapter 1

Introduction

In this chapter the concepts of distributed computing, GPU acceleration, auto-scaling, and automated deployment pipeline will be introduced. Next, the research objective and the research questions as well as the problem statement of this thesis will be described. Finally, the structure of this thesis is being explained.

1.1 Distributed Computing

Machine Learning and Big Data projects consist of a combination of extract-transform-load (ETL) pipelines and compute intensive algorithms to create meaningful information from large datasets [Vad18]. Because of its computing intensive nature, Big Data is mostly processed in parallel on distributed hardware. Both concepts of distributed computing and parallel processing follow a divide-and-conquer principle [KBE16]. Distributed computing is achieved by forming a cluster of multiple machines with commodity hardware to utilize their resources to solve highly complex problems [GOKB16]. To process Big Data in parallel, a larger task will be divided into smaller sub-tasks that run concurrently. In general, one of the two following approaches can be used to achieve parallel processing [KBE16]:

- Task Parallelism: This approach refers to enabling parallelization by dividing a task into multiple sub-tasks. Each sub-task performs a different algorithm with its own copy of the same data in parallel. The result is created by joining the output of all sub-tasks together [KBE16].
- Data Parallelism: This approach is achieved by dividing a dataset into a series of smaller sub-datasets to process each sub-dataset in parallel. The sub-datasets are processed using the same algorithm across different nodes. The final output is joined together from each sub-dataset [KBE16].

Various tools and frameworks such as MapReduce, Apache Hadoop and Apache Spark have been created to facilitate distributed computing. The

MapReduce[DG04] framework gives the opportunity to solve massive complex problems in parallel on a cluster of single machines. Apache Hadoop[1] is an ecosystem platform for distributed computing. It contributes to create a cluster to process massive amounts of data in parallel by implementing the MapReduce processing framework [KBE16]. Implementing data pipelines with MapReduce requires to chain multiple MapReduce jobs together. This causes a huge amount of writing and reading operation to the disk with bad impact on the overall performance. Another framework called Apache Spark was developed to simplify writing and executing parallel applications at scale while keeping the benefits of MapReduce's scalability and fault-tolerant data processing. Apache Spark provides a performance improve of 10x in iterative Machine Learning algorithms over MapReduce [ZCF+10] and has evolved as a replacement for MapReduce as the distributed computing framework of choice.

1.2 Computing Acceleration with GPUs

Distributed computing frameworks like Apache Spark perform applications on a huge amount of CPU cores to enable parallelism. A CPU is build of multiple cores which are optimized for sequential serial processing. Performing computationally intensive applications on an Apache Spark cluster, consumes a huge amount of CPU cycles with negative impact on the overall performance [PYNY15]. To handle the complexity of Big Data applications, from executing Machine Learning algorithms or training Deep Learning models, an option of distributed computing clusters is to scale-up individual nodes. Scaling-up is limited by resource capacity and can be become uneconomically at a specific point. To perform computationally complex applications with better performance, Graphical Process Units (GPUs) have become first class citizens in modern data centers. The architecture of a GPU consists of a large amount of smaller and more efficient cores which are suitable for data-parallel data processing (handling multiple tasks simultaneously) [YSH+16]. In general, GPUs process data at a much faster rate than CPUs are capable. Apache Spark applications have a data-parallel nature. Therefore, enabling Apache Spark to leverage GPUs to perform complex ML algorithms on big datasets can have a huge positive impact on the performance [YSH+16].

1.3 Auto-Scaling

Adjusting the resources in a computing environment is not an easy task. To do it manually, a system administrator needs a deep knowledge about the environment and has to watch performance spikes regularly. This is a resource wasting process. In an optimal way, an automized process would watch the

1 Apache Hadoop - `https://hadoop.apache.org/` (Accessed: 2020-01-08)

computing environment, analyse performance metrics and automatically add or remove resources to optimize the performance and cost of running. This process is called auto-scaling.

Hiring experts to manually watching an application and scaling an computing environment is a waste of resources. An *Auto-Scaler* takes care of watching the environment by adding and removing resources to adapt to the computing needs. The *Auto-Scaler* can be configured to take care of optimal resource allocation and keep the cost of running at low point.

There exist two different scaling approaches to scale resources in a computing environment: Vertical-scaling and horizontal-scaling. Vertical scaling refers to adjusting the hardware resources of an individual node in the environment. Hardware adjustments can include adding (scale-up) or removing (scale-down) resources like memory or CPU cores [Wil12]. By adding more powerful resources to a node, a node can take more throughput and perform more specialized tasks [LT15]. Adjusting the nodes in a computing environment is referred as horizontal scaling [Wil12]. Increasing the number of nodes in an environment, increases the overall computing capacity and additionally, the workload can be distributed across all nodes [Wil12, LT15]. It is important to note, that both approaches are not exclusive from each other and a computing environment can be designed to combine both approaches [Wil12]. Vertical scaling is limited by the maximum hardware capacity. Furthermore, a point can be reached where more powerful hardware resources become unaffordable or are not available [LT11]. Therefore, horizontal scaling is the preferred approach to enable auto-scaling.

1.4 Automated Deployment Pipeline

TODO: Eher automated software deployment nennen, dann warum das nötig ist und dann auf die pipeline eingehen.

Building, testing and releasing software manually is a time-consuming and error-prone process. To overcome this issue, a pattern called deployment pipeline automates the build, test, deploy, and release processes of an application development cycle. The concept of deployment pipelines is based on automation scripts which will be performed on every change on an applications source code, environment, data or configuration files [FH10]. A fully automated deployment pipeline has many improvements over deploying applications manually:

- Makes every process until release visible to all developers [FH10]
- Errors can be identified and resolved at an early stage [FH10]
- The ability to deploy and release any version of an application to any environment [FH10]
- A non automated deployment process is not repeatable and reliable [FH10]
- The automation scripts can serve as documentation [FH10]

- If an application has been deployed manually, there is no guarantee that the documentation has been followed [FH10]

The automated deployment pipeline is based on the Continuous Integration (CI) process. Furthermore, the deployment pipeline is the logical implementation of CI [FH10].

1.5 Research Objective and Research Questions

The thesis work will be implemented at the Center for Cyber Cognitive Intelligence at the Fraunhofer IPA[2]. At the IPA, developers train ML models on Docker container running on a NVIDIA DGX[3] workstation. To optimize the training of ML applications, developers combine CPU and GPU resources only limited. Therefore a prototype of an Apache Spark cluster prototype has to be implemented which has the ability to automatically allocate resources according to the computing needs to scale its performance.

The following three research question will be investigated to implemented the mentioned prototype:

- RQ1: Is it possible to scale the number of Apache Spark Worker in accordance to performance utilization?
- RQ2: How can Apache Spark be extended to accelerate application execution with GPU support?
- RQ3: Is it possible to automate the deployment process of applications to a running Apache Spark cluster?

The first research question searches for concepts to create a self-adapting computing environment. To answer this question, state-of-the-art computing architectures have to be investigated. Monitoring tools to collect performance metrics need to evaluated. Additionally, tools which enable fast deployment of computing units. Furthermore, a suitable scaling approach has to be investigated.

The main goal of the second research question is to enable Apache Spark to perform algorithms with GPU acceleration included. Therefore, a concept needs to be investigated to extend Apache Spark to use GPUs for suitable algorithms in addition to the available CPUs.

2 Fraunhofer Institute for Manufacturing Engineering and Automation IPA - `https://www.ipa.fraunhofer.de/` (Accessed: 2021-01-07)

3 The Universal System for AI Infrastructure - `https://www.nvidia.com/en-us/data-center/dgx-a100/` (Accessed: 2020-01-09)

The last research question has a more applied nature. Automating the development cycle of an application is a well investigated topic. The IPA is using a platform called GitLab (will be introduced in Section 4.6) which provides an API to build automated pipelines. To answer this research question, GitLabs functionality will be investigated to find a solution that fits the need of this project work.

1.6 Problem Statement

Given the previously introduced research questions and the research objective, this thesis work will provide a solution to the following three problem statements:

1. Developers at the Fraunhofer IPA perform ML model training on several Docker containers running on a DGX with limited usage of available GPUs. Apache Spark can be used to optimize the model training by distributing the workload. Additionally, the Apache Cluster should be aware about available GPUs to accelerate the model training.

2. To enable GPU acceleration for Apache Spark alone is not sufficient to increase the performance. At some point, an Apache Spark Worker can reach the limit of its available computing resources. If this point is reached, the environment should automatically scale the number of Apache Spark worker to distribute the workload.

3. To perform an Apache Spark application to the cluster, developers have to submit the application manually. With an automated deployment pipeline, developers can submit an application by pushing changes to the code base. Additionally, a deployment pipeline will contribute to the reliability of executing applications and reduces the development time.

1.7 Thesis Structure

TODO: Chapter 9

Chapter 2 provides the theoretical foundation about concepts which have been introduced in this chapter. Chapter 3 focuses on related work which provides solutions to solve the given problems of this thesis introduced in Section 1.6. In Chapter 4 all used technologies to implement the objective of this thesis are being introduced. Afterwards in Chapter 5, a conceptual design of a dynamic computing environment and an automated deployment pipeline is being described. Chapter 6 contains the implementation of the computing environment and how the deployment pipeline is being used to automate the deployment of applications to the computing environment. In Chapter 7 the results of the implementation are being presented and analysed. Chapter 8 introduces further work, which has been discovered during the work of this thesis, as well as improvements for the implementation. Finally Chapter 9 ...

Chapter 2

Theoretical Foundation

This chapter provides the theoretical foundation to understand concepts that will be used in this thesis. First, the concept of Scalability will be described. Second, the theory behind a deployment pipeline is explained. Third, the concept of autonomic computing is introduced. Fourth, the theory of measuring system performance is explained. Lastly, the concept of monitoring is being described.

2.1 Scalability

Scalability defines the ability of a computing system to handle an increasing amount of load [Far17]. The limit of scalability is reached, when a computing system is not able to serve the requests of its concurrent users [Wil12]. Different approaches exist to increase the scalability of a system. The two main approaches are vertical scaling and horizontal scaling.

2.1.1 Horizontal Scaling

Horizontal scaling is accomplished by adding nodes to the computing environment to increase the overall capacity. Each node typically adds the equal amount of computing capacity (e.g. amount of memory) [Wil12]. By increasing the number of nodes in a computing environment, the workload can be distributed more efficiently across all nodes to handle and balance an increasing workload [Wil12, LT15].

Scaling a computing environment horizontally is limited by the efficiency of each added node. The horizontal scaling approach is more efficient with the simplicity of homogeneous nodes. Homogeneous nodes add the same amount of computing power to the system and are able to perform the same work and response as other nodes. With homogeneous nodes, creating strategies for capacity planning, load balancing, and auto-scaling is more efficient. In an environment with different types of nodes, creating these strategies is more complex due to the need of context [Wil12].

2.1.2 Vertical Scaling

Vertical scaling refers to increasing the overall capacity by improving the computing power with additional hardware of individual nodes (e.g. adding memory, increasing number of CPU cores) [Wil12].

If additional hardware has to be added to a system, it is not guaranteed that more powerful hardware is available or affordable. Therefore, vertical scaling is limited by of available hardware. Additionally, changing physical hardware of a running system can require a downtime. For most system a downtime should be avoided because it will interrupt important services running on the system [Wil12].

2.2 Deployment Pipeline

A deployment pipeline is an implementation of the process of getting software from source code to production. It is based on the concept of Continuous Integration (CI). The process involves building, testing and deploying software through automated scripts [FH10].

2.2.1 Continuous Integration

Continuous Integration is a development practice where each change on a primary code base is validated by automated scripts. This ensures that errors are detected and fixed in an early development stage [DMA07]. The CI process is responsible for building and testing the software to guarantee that it is in a releasable state at all time [Ros17]. CI contributes with the following advantages to the development life cycle of an application:

- Reduce risks: The CI process runs tests and validates the software on each change. Errors are detected in an early stage and can be fixed immediately [DMA07].
- Reduce manual processes: The CI process will perform every time a commit has being made to the code base. Each run is processed the exact same way every time. Therefore, no human intervention is needed to start the process which saves time and cost [DMA07].
- Generate deployable software: If an error occurs during a CI run, developers will be informed and fixes can be applied immediately. This ensures that the software is in a deployable state at all times [DMA07].

2.2.2 Requirements of a Continuous Integration Process

The implementation of a CI process is based on several requirements:

1. Version control repository: To manage changes to the code base, the source code and all other assets like the build script should be hosted on a single version control repository. Each change on the code base

triggers the CI process on the build server to run against the latest version available [DMA07].

2. Build server: The build server is responsible to monitor the code base for changes. If a change is committed, the build server automatically executes the CI scripts in order [Ros17, DMA07].

3. Build script: This includes all automation scripts to validate the source code [DMA07]. Typical examples are:
   - Building the software binaries (e.g. `.jar` binaries for Java source code).
   - Running unit and integration tests.
   - Deploying the binaries to a test or production environment.

2.2.3 Continuous Integration Process Implementation Example

Figure 2.1 demonstrates the CI scenario. First a developer commits changes to the version control repository. The CI server monitors the repository for changes. After the change has been committed, the CI server pulls the latest version of the source code and executes all build scripts in order to integrate the software. Finally, the CI server sends feedback to inform the developer about the build script status [DMA07].

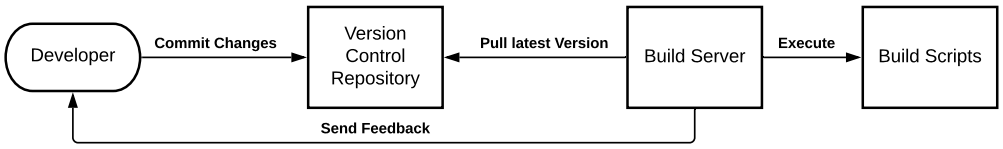

Figure 2.1: Continuous Integration Scenario - Source: Authors own model, based on [DMA07].

A CI run should be executed in a headless automated process. It is not feasible to rely on a manual process. All assets to perform the CI run should be accessed from the repository. Therefore a machine can start the build script process by executing a command script in an automated fashion [DMA07]. An example of a logical build script order is illustrated in Figure 2.2.

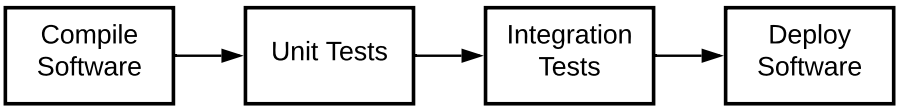

Figure 2.2: An example of a logical build script order for a CI process- Source: Authors own model, based on [DMA07].

2.3 Autonomic Computing

Autonomic computing is the ability of an IT infrastructure to automatically manage itself in accordance to high level objectives defined by administrators [KC03]. Autonomic computing gives an IT infrastructure the flexibility to adapt dynamic requirements quickly and effectively to meet the challenges of modern business needs [Mur04]. Therefore, autonomic computing environments can reduce operating costs, lower failure rates, make systems more secure and quickly respond to business needs [JSAP04].

Computing systems need to obtain a detailed knowledge of its environment and how to extend its resources to be truly autonomic [Mur04]. An autonomic computing system is defined by four elements:

- Self-configuring: Self-configuring refers to the ability of an IT environment to adapt dynamically to system changes and to be able to deploy new components automatically. Therefore, the system needs to understand and control the characteristics of a configurable item [Mur04, Sin06].
- Self-optimizing: To ensure given goals and objectives, a self-optimizing environment has the ability to efficiently maximize resource allocation and utilization [JSAP04]. To accomplish this requirement, the environment has to monitor all resources to determine if an action is needed [Mur04].
- Self-healing: Self-healing environments are able to detect problematic operations and then perform policy-based actions to ensure that the systems health is stable [Sin06, JSAP04]. The policies of the actions have to be defined and should be executed without disrupting the system [Sin06, JSAP04].
- Self-protecting: The environment must identify unauthorized access and threats to the system and automatically protect itself taking appropriate actions during its runtime [Sin06, JSAP04].

2.3.1 Autonomic Computing Concept

Figure 2.3 demonstrates the main concept of an autonomic computing environment. The autonomic computing architecture relies on monitoring

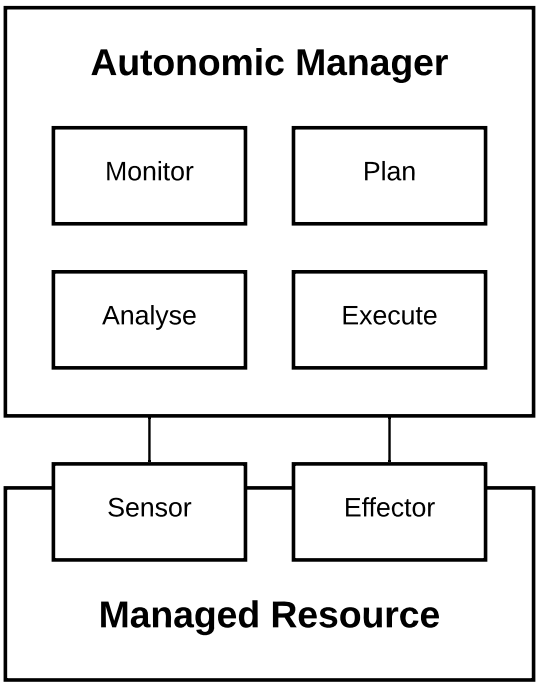

Figure 2.3: Autonomic computing concept - Source: Authors own model, based on [JSAP04].

sensors and an adoption engine (autonomic manager) to manage resources in the environment [GBR11]. In an autonomic computing environment, all components have to communicate to each other and can manage themselves. Appropriate decisions will be made by an autonomic manager that knows the given policies [JSAP04].

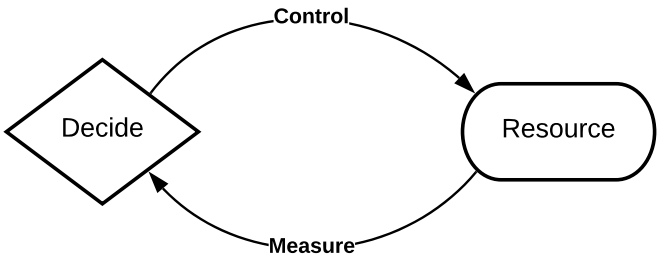

Figure 2.4: The control-loop concept - Source: Authors own model, based on [Mur04].

The core element of the autonomic architecture is the control-loop. Figure 2.4 illustrates the concept of a control-loop. The control-loop collects details about resources through monitoring and makes decisions based on analysis of the collected details to adjust the system if needed [Mur04].

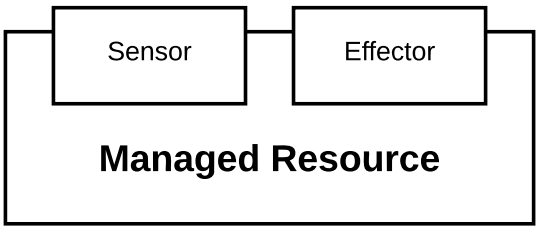

Figure 2.5: Managed resource - Source: Authors own model, based on [JSAP04].

2.3.2 Managed Resources

A managed resource is a single component or a combination of components in the autonomic computing environment [Mur04, JSAP04]. A component can be a hardware or software component, e.g. a database, a server, an application or a different entity [Sin06]. They are controlled by their sensors and effectors, as illustrated in Figure 2.5. Sensors are used to collect information about the state of the resource and effectors can be used to change the state of the resource [JSAP04]. The combination of sensors and effectors is called a touchpoint, which provides an interface for communication with the autonomic manager [Sin06]. The ability to manage and control managed resources makes them highly scalable [Mur04].

2.3.3 Autonomic Manager

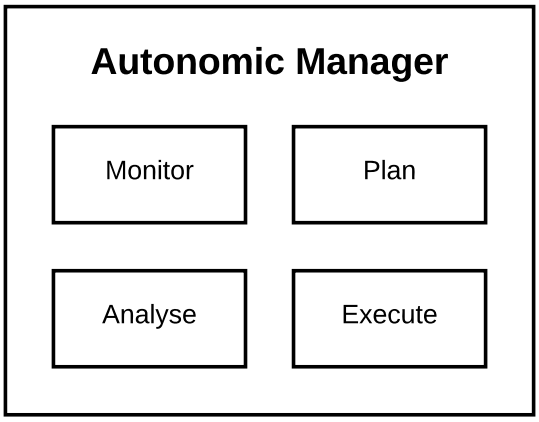

Figure 2.6: Autonomic manager - Source: Authors own model, based on [JSAP04].

The autonomic manager implements the control-loop to collect, aggregate, filter and report system metrics from the managed resources. It can only make adjustments within its own scope and uses predefined policies to make decisions of what actions have to be executed to accommodate the goals and objectives [Mur04, Sin06]. In addition, the autonomic manager

gains knowledge through analysing the managed resources [Mur04]. The autonomic computing concept digests the MAPE model to implement an autonomic manager, as illustrated in Figure 2.6 [GBR11].

- Monitor: The monitor phase is responsible to collect the needed metrics from all managed resources and applies aggregation and filter operations to the collected data [Sin06].
- Analyze: The autonomic manager has to gain knowledge to determine if changes have to made to the environment [Sin06]. To predict future situations, the autonomic manager can model complex situation given the collected knowledge [JSAP04].
- Plan: Plans have to be structured to achieve defined goals and objectives. A plan consists of policy-based actions [JSAP04, Sin06].
- Execute: The execute phase applies all necessary changes to the computing system [Sin06].

Multiple autonomic manager can exist in an autonomic computing environment to perform only certain phases. For example, an autonomic manager which is responsible to monitor and analyse the system and an autonomic manager to plan and execute. To create a complete and closed control-loop, multiple autonomic manager can be composed together [Sin06].

2.4 System Performance

2.4.1 Performance Metrics

Performance metrics are statistics that describe the system performance. These statistics are generated by the system, applications or other tools [Gre20]. Common types for performance metrics are:

- Throughput: Volume of data or operations per second [Gre20].
- Latency: Time of operation [Gre20].
- Utilization: Usage of a hardware resource [Gre20].

It is important to note that measuring performance metrics can cause an overhead. To gather and store performance metrics, additional CPU cycles must be spent. This can have a negative affect on the target performance [Gre20].

2.4.2 Time-Based Utilization

Utilization is a performance metric that describes the usage of a device, e.g. CPU device usage. A time-based utilization describes the usage of a component during a time period where the component was actively performing work [Gre20].

The performance of a hardware resource can degrade significantly if the utilization approaches 100%. Hardware which is able to perform work in parallel, might not have a performance degrade at 100%. Those hardware is able to accept additional work at a high utilization at a later time [Gre20].

2.5 Monitoring

Monitoring is a process, that aims to detect and take care of system faults. In a dynamic environment, becoming aware of the system is a trivial process [Lig12]. A monitoring system consists of a set of multiple which are responsible to perform measurements on components in the computing environment and collect, store and interpret the monitored data [Lig12].

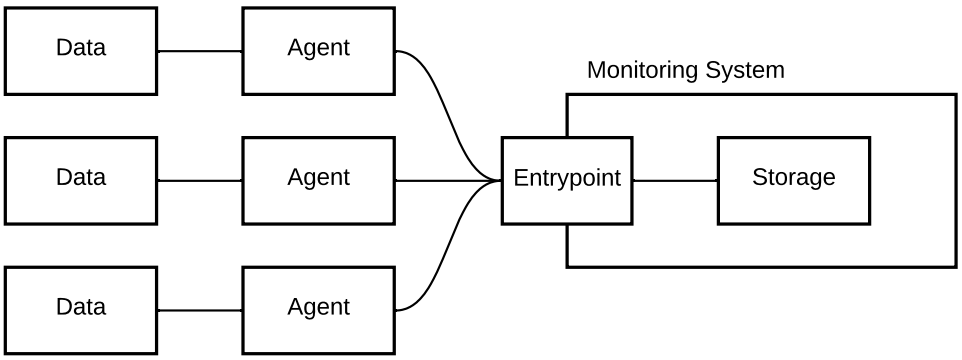

Figure 2.7: The monitoring process

In the monitoring process, illustrated in Figure 2.7, data is continuously collected by agents. An agent is a process that continuously gathers metrics. Data can be device statistics, logs or system measurements. Agents will group these data into metrics and submit them to the monitoring system. The monitoring system will store the metrics in its database [Lig12].

The requirements for a monitoring system, that is able to monitor a dynamic changing environment, are the following:

- An efficient database to store metrics [Far17]
- A push or pull based way of gathering metrics [Far17]
- Multi-dimensional metrics [Far17]
- A powerful query language [Far17]

2.5.1 Database

Continuous data needs to be stored in the most efficient way. Time-series databases (TSDB) are optimized to store and retrieve time-series data. In a time-series database, metrics will be stored in a compact and optimized format. This allows the database to store a massive amount of time-series data on a single machine.

2.5.2 Push and Pull Based Monitoring Systems

The approach how the monitoring systems gathers metrics to store in the database plays a significant role. Push- and pull-based systems are the two primary approaches to gather metrics from services. Push-based monitoring systems expect services to push metrics to their storage. Pull-based monitoring systems scrape metrics from all defined targets. Targets do not know about the existence of the monitoring system and only need to collect and expose metrics [Far17].

Service discovery is an important aspect to decide whenever to use a pull- or push-based monitoring system [Far17].

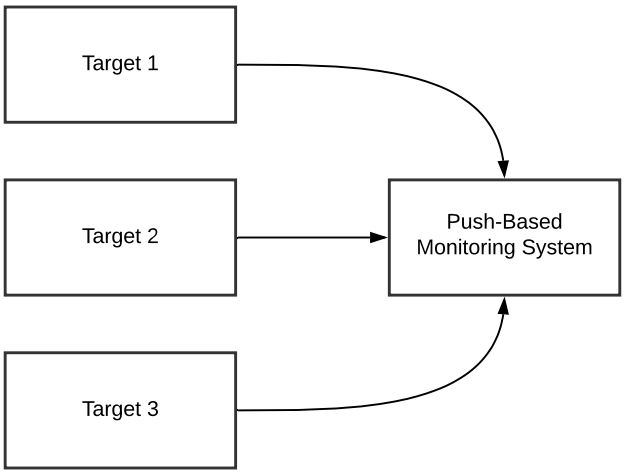

Figure 2.8: Push-based monitoring approach - Source: Authors own model.

In a push-based environment, services only need to know the address of the monitoring service to push their data to the storage [Far17].

A pull-based monitoring tool needs to know the address of each target in the environment. The advantage of a pull-based monitoring system is the simplicity to detect whenever a target has failed or is not available [Far17].

2.5.3 Multi-Dimensional Metrics

For query languages to be effective, metrics need to be dimensional. Metrics without dimensions, are limited in their capabilities. In a dynamic environment, services are dynamically added and removed. Therefore, a dynamic

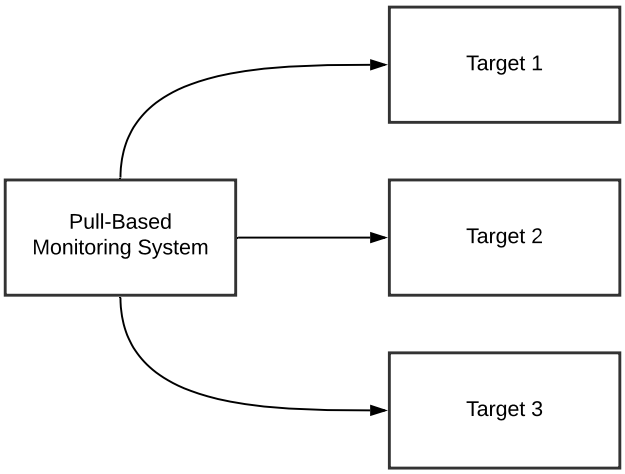

Figure 2.9: Pull-based monitoring approach - Source: Authors own model.

environment needs dynamic analytics where metrics represent all dimension in the environment [Far18].

```
1 container_cpu_user_seconds_total
```

Listing 2.1: Example of a dimensionless-metric

```
1 container_cpu_user_seconds_total{image="spark-worker:3.0.1-
    hadoop2.7"}
```

Listing 2.2: Example of a metric with dimensions

As the example Listing 2.1 and Listing 2.2 show, the metric with dimension provides more efficient querying to gather informations about the environment.

2.5.4 Query Language

Another requirement is a powerful and flexible query language. It should have the ability to query a multi-dimensional data model. Furthermore, the query language must allow aggregations on time-series data.

Chapter 3

Related Work

This chapter provides an overview of related literature for this thesis. It introduces work about auto-scaling computing environments, GPU accelerated Apache Spark cluster and the implementation of an automated deployment pipeline. These topics are related to the choice of technologies (Chapter 4), the proposed conceptual design of this thesis (Chapter 5), and the resulting implementation (Chapter 6).

3.1 Auto-Scaling Computing Environments

In recent years, container technologies have been used efficiently in complex computing environments. Dynamic scaling of containerized applications is an active area of research. To accommodate this thesis research objective, the literature research according to auto-scaling environments was focused on two topics: Concepts of Auto-Scalers and auto-scaling algorithms.

3.1.1 Auto-Scaler Concepts

Lorido-Botrán et al. [LBMAL14] reviewed state-of-the-art literatures about auto-scaling and explain proposals of an auto-scaling process in a cloud environment. It is mentioned that an Auto-Scaler is responsible to find a trade-off between meeting the SLA and keeping the cost of renting resources low.

They introduced three problems an Auto-Scaler faces while scaling an environment and meeting the SLA:

1. Under-provisioning: An application is under-provisioned if it needs more resources to process the incoming workload. To make resources available and return the application to its normal state may take some time which causes SLA violations.

2. Over-provisioning: If an application has more resources available than needed will lead to unnecessary costs for the client.

3. Oscillation: If scaling-actions are being executed too quickly before the impact is available, a combination of over-provisioned and under-provisioned applications can occur. A cooldown period after a scaling-action can be activated to prevent oscillation.

To prevent the mentioned problems from occurring, the authors mentioned and explained the MAPE architecture (described in detail in Section 2.3). MAPE consists of four different phases: Monitor, analyse, plan, and execute. The authors mention that some Auto-Scaler proposals only focus on the analyse and planning phase. Several techniques for the analyse phase are being introduced: Queuing theory and time-series analysis. As well as for the planning phase: Threshold-based rules, reinforcement learning, and control theory. Some Auto-Scaler uses techniques to predict the future state of the environment (e.g. reinforcement learning). These are called reactive Auto-Scalers. Proactive Auto-Scalers use techniques to respond to the current status of the environment (e.g. threshold-based rules).

Srirama et al. [SAP20] designed a heuristic-based auto-scaling strategy for container-based microservices in a cloud environment. The purpose of the auto-scaling strategy was to balance the overall resource utilization across microservices in the environment. The proposed auto-scaling strategy performed better results than state-of-the-art algorithms in processing time, processing cost and resource utilization. The processing cost of microservices could be reduced by 12-20% and the CPU and memory utilization of cloud-servers have been maximized by 9-15% and 10-18%.

Lorido-Botrán et al. [LBMAL13] compared different representative auto-scaling techniques in a simulation in terms of cost and SLO violations. They compared load balancing with static threshold-based rules, reactive and proactive techniques based on CPU load. Load balancing is based on static rules defining the upper and lower thresholds of a specific load (e.g. *if CPU > 80% then scale-out; if CPU < 20% then scale-in*). The difficulty of this technique is to set the ideal rules. False rules can lead to bad performance. Proactive techniques try to predict the future values of performance metrics based on historical data. Reactive techniques are based on control theory to automate the system management. To overcome the difficulties of static thresholds, the authors proposed a new auto-scaling technique using rules with dynamic thresholds. The results showed, that for auto-scaling techniques to scale well, it highly depends on parameter tuning. The best result was achieved with proactive results with a minimum threshold of 20% and a maximum threshold of 60%.

3.1.2 Auto-Scaling Algorithms

Barna et al. [BKFL17] proposed an autonomic scaling architecture approach for containerized microservices. Their approach focused on creating

an autonomic management system, following the autonomic computing concept [KC03], using a self-tuning performance model. The demonstrated architecture frequently monitors the environment and gathers performance metrics from components. It has the ability to analyze the data and dynamically scale components. In addition, to determine if a scaling action is needed, they proposed the *Scaling Heat Algorithm*. The Scaling Heat algorithm is used to prevent unnecessary scaling actions, which can throw the environment temporarily off. The Scaling Heat algorithm will be used for decision making in this thesis work, it is explained in detail in Section 4.7.2.

Casalicchio et al. [CP17] focused on the difference of absolute and relative metrics for container-based auto-scaling algorithms. They analysed the mechanism of the *Kubernetes Horizontal Pod Auto-Scaling* (KHPA) algorithm and proposed a new auto-scaling algorithm based on KHPA using absolute metrics called *KHPA-A*. The results showed, that KHPA-A can reduce response time between 0.5x and 0.66x compared to KHPA. In addition, their work proposed an architecture using cAdvisor for collecting container performance metrics, Prometheus for monitoring, alerting and storing time-series data and Grafana for visualizing metrics. KHPA-A is more efficient with the vertical scaling approach. In this thesis, the focus for scaling strategies is based on the horizontal scaling approach. Therefore, the KHPA algorithm will be used throughout this thesis and is explained in detail in Section 4.8.

3.2 GPU accelerated Apache Spark Cluster

This thesis is targeting at enabling GPU acceleration for Apache Spark. Several solutions exist which are trying to solve the problem in similar ways. In research, many solutions have been proposed. In the following, three different approaches will be introduced.

Li et al. [PYNY15] developed a middleware framework called *HeteroSpark* to enable GPU acceleration on Apache Spark worker nodes. HeteroSpark listens for function calls in Apache Spark applications and invokes the GPU kernel for acceleration. For communication between CPU and GPU, HeteroSpark implements a CPU-GPU communication layer for each worker node using the Java RMI API. To execute operations on the GPU, the CPU JVM will send serialized data to the GPU JVM using the RMI communication interface. The GPU JVM will deserialize the received data for execution. The design provides a plug-n-play approach and an API for the user to call functions with GPU support. Overall, HeteroSpark is able to achieve a 18x speed-up for various Machine Learning applications running on Apache Spark.

Klodjan et al. [HBK18] introduced *HetSpark*, a modification of Apache Spark. HetSpark extends Apache Spark with two executors, a GPU ac-

celerated executor and a commodity class. The accelerated executor uses VineTalk[MPK+17] for GPU acceleration. VineTalk contributes as a transport layer between the application and accelerator devices (CPU or GPU). To detect suitable tasks for GPU acceleration, HetSpark uses the ASM[1] framework to analyse the byte code of Java binaries. The authors observed, that for compute intensive tasks, GPU accelerated executers are preferable while for linear tasks CPU-only accelerators should be used.

Yuan et al. [YSH+16] proposed *SparkGPU* a CPU-GPU hybrid system build on top of Apache Spark. The goal of SparkGPU is to utilize GPUs to achieve high performance and throughput. SparkGPU tries to solve the following problems statements:

1. The iterator model Apache Spark uses, executes one element at a time. This approach does not match the GPU architecture and underutilizes GPU resources.

2. Apache Spark runs on the JVM and therefore stores its data on the heap memory. GPU programs are usually implemented with GPU programming models like CUDA which cannot access data on the heap. Therefore, data must be copied between the heap and native memory frequently. These copy operations are expensive.

3. Existing cluster manager of Apache Spark manage GPUs in a coarse grained fashion. This can lead to crashes because of insufficient memory when multiple programs run on the GPU concurrently.

To solve the mentioned problem statements, SparkGPU extends Apache Spark in the following ways:

- Enable block processing on GPUs by extending Apache Sparks iterator model. Therefore Apache Spark can better utilize GPUs to accelerate application performance.

- To offload queries to the GPU, SparkGPU extends the query optimizer. The query optimizer will create query plans with both CPU and GPU operators.

- To manage GPUs efficiently, SparkGPU extends the cluster manager and the task scheduler.

To extend the programming API, SparkGPU provides a new RDD type called GPU-RDD. A GPU-RDD is optimized to utilize the GPU. SparkGPU utilizes native memory on the GPU instead of the Java heap to buffer data in GPU-RDDs. Operations performed on a GPU-RDD can be performed on the GPU. Several built-in operators on the GPU-RDD are provided which support data-parallelism.

1 ASM - `https://asm.ow2.io/` (Accessed: 2021-01-11)

SparkGPU is able to execute SQL queries on both CPU and GPU. By adding a set of GPU rules and strategies, SparkGPU extends the query optimizer to find the best execution plan for GPU scheduling.

To manage GPU memory on shared GPUs, SparkGPU provides a user-level GPU-management library. The library will ensure, when memory contention happens, that SparkGPU will stop scheduling new tasks to the Apache Spark cluster.

SparkGPU accomplished to improve the performance of machine learning algorithms up to 16.13x and SQL query execution performance up to 4.83x.

3.3 Implementation of an Automated Deployment Pipeline

Implementing an automated deployment pipeline is a more applied topic and well described in many literature. In this section the main literature which has been used throughout the implementation of this thesis work is being introduced.

The conceptual design and implementation of an automated deployment pipeline in this thesis was mostly inspired by the proposed solution of the book *Continuous Delivery: Reliable Software Releases through Build, Test, and Deployment Automation* by Humble et al. [FH10]. Throughout this book, the authors explain the theoretical idea behind an automated deployment pipeline and explaining an example implementation. The proposed implementation covers the software lifecycle from compiling source to delivering the software to a production environment. The commit stage which covers the build and test part of the software can be applied in parts for this thesis work.

Chapter 4

Technical Background

This chapter introduces the technologies and algorithms used for this thesis work. It explains the fundamental concepts as well as installation requirements if needed.

4.1 Docker

Docker is an open-source platform that enables containerization of applications. Containerization is a technology to package, ship and run applications and their environment in individual containers. Docker is not a container technology itself. It hides the complexity of working with container technologies directly and instead provides an abstraction and the tools to work with containers [NK19, BMDM20, PNKM20].

4.1.1 Docker Architecture

Figure 4.1 illustrates the client server architecture of Docker. It consists of a Docker Client, the Docker Deamon, and a Docker Registry.

Docker Client: The Docker client is an interface for the user to send commands to the Docker deamon [Doc].

Docker Deamon: The Docker deamon manages all containers running on the host system and handles the containers resources, networks and volumes [BMDM20].

Docker Registry: A Docker registry stores images. Images can be pushed to a public or private registry and pulled from it to build a container [Doc].

4.1.2 Docker Image

An Image is a snapshot of the environment that is needed to run an application in a Docker container. The environment consists of all files, libraries

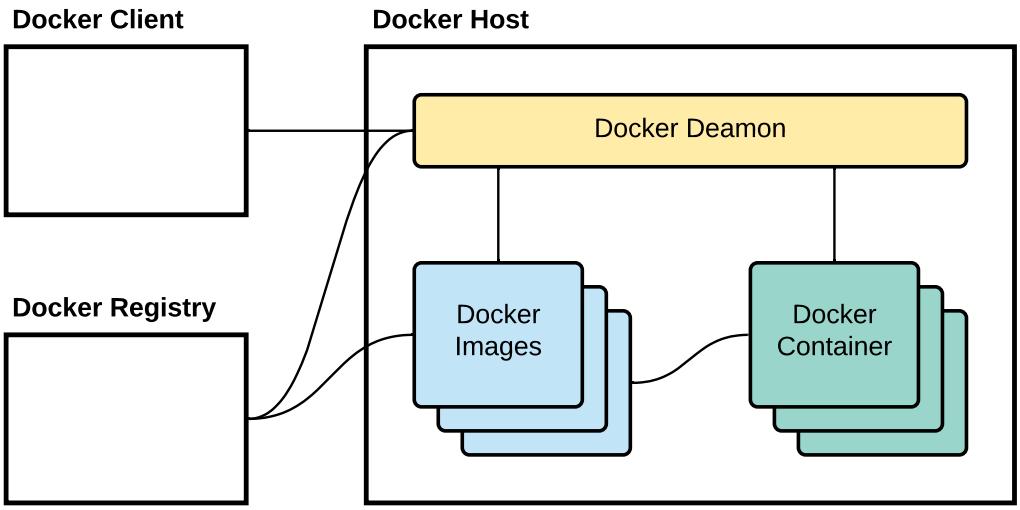

Figure 4.1: Docker architecture - Source: Authors own model, based on [Doc].

and configurations that are needed for the application to run properly [Doc, NK19]. Images can be created from existing containers or from executing a build script called Dockerfile. A Dockerfile is a text file consisting of instructions for building an image. The Docker image builder executes the instructions of a Dockerfile from top to bottom [NK19].

4.1.3 Docker Container

A container is an execution environment running on the host-system kernel.

The advantage of a container is its lightweight nature. As illustrated in Figure 4.2, containers take advantage of OS-level virtualization instead of hardware-virtualization without the need of a hypervisor [Doc, NK19]. Containers share the resources of the host-system instead of using reserved resources [BMDM20]. Multiple containers can run on the host-system kernel and are by default isolated from each other [Doc]. In Docker, a container is a runnable unit of an image and is used for distributing and testing applications. A container can be configured to expose certain resources to the host system, e.g. network ports [BMDM20].

4.1.4 Docker Swarm Mode

Docker Swarm mode is the native cluster orchestration and management tool embedded in the Docker engine. In Docker Swarm mode, a cluster of multiple nodes is called a swarm. All nodes run in Swarm mode and act as managers or workers. In a swarm, multiple services can be deployed. The manager node is responsible to maintain the desired state of a service [Doc].

Many properties of Docker Swarm mode contribute the fact that it is an ideal tool to create self-healing and self-adapting environment:

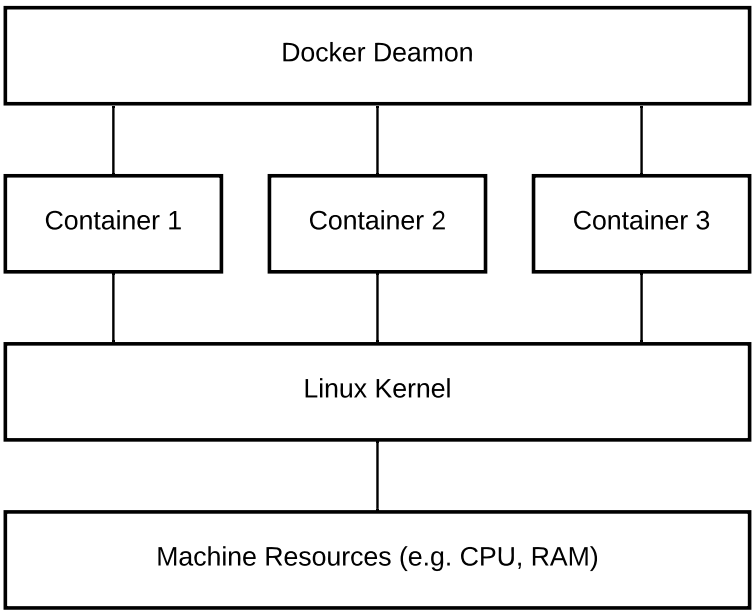

Figure 4.2: Docker basic container structure - Source: Authors own model, based on [BMDM20].

- Desired state: The manager node monitors the state of each service in the swarm and adapts the environment to maintain the desired state [Doc].
- Cluster management and orchestration: Docker Swarm mode is integrated within the Docker engine. A swarm can be created and managed using the Docker CLI [Doc].
- Service model: The Docker engine allows to define the desired state of a service. The manager node maintains the desired state of all services in the swarm [Doc].
- Scaling: The number of replicas can be defined for each service. The manager node will automatically adapt the number of replicas for a service to keep the desired state [Doc].
- Multi-host networking: A swarm runs all services in an overlay network. New services will automatically be added to the overlay network [Doc].

Nodes

A Docker engine participating in the swarm is called a node. Nodes can act as manager nodes, worker nodes or both [Doc].

The manager node is responsible for cluster orchestration an management. It maintains the desired state of all services and tasks in the swarm. In addition, the manager node dispatches tasks to worker nodes when service definitions will be submitted to the manager node [Doc].

Worker nodes are responsible to execute the tasks receives by the manager node. While performing the tasks, the worker node notifies the manager node about the tasks state [Doc].

Services and Tasks

A services defines the desired state of a task. The state is defined by the number of replicas of a service and the configuration for the Docker container, e.g. Docker Image, resources, network, and more [Doc].

A task is a running Docker container. The task is defined by the corresponding service and will be managed by the manager node. A task can be performed on worker and manager nodes [Doc].

4.2 Apache Spark

Apache Spark is an open-source computing framework for parallel data processing on a large computer cluster. Apache Spark manages the available resources and distributes computation tasks across a cluster to perform big-data processing operations at large scale [CZ18]. Before Apache Spark was developed, Hadoop MapReduce [DG10] was the framework of choice for parallel operations on a computer cluster [ZCF+10]. Spark accomplished to outperform Hadoop by 10x for iterative Machine Learning [ZCF+10]. It is implemented in Scala[1], a JVM-based language and provides a programming interface for Scala, Java[2], Python[3], and R[4]. Additionally, Apache Spark includes an interactive SQL shell and libraries to implement Machine Learning and streaming applications [CZ18].

4.2.1 Spark Programming Model

Apache Spark provides resilient distributed datasets (RDDs) as the main abstraction for parallel operations [ZCF+10]. Core types of the higher-level structured API are built on top of RDDs and will automatically be optimized by the Catalyst optimizer to run operations quick and efficient [CZ18, Luu18].

Resilient distributed datasets

Resilient distributed datasets are fault-tolerant, parallel data structures to enable data sharing across cluster applications [ZCD+12]. They allow to express different cluster programming models like MapReduce, SQL and

1 The Scala programming language - `https://www.scala-lang.org/` (Accessed: 2020-12-18)
2 Java Software - `https://www.oracle.com/java/` (Accessed: 2020-12-18)
3 Python programming language - `https://www.python.org/` (Accessed: 2020-12-18)
4 The R Project for Statistical Computing - `https://www.r-project.org/` (Accessed: 2020-12-18)

batched stream processing [ZCD+12]. RDDs have been implemented in Apache Spark and serve as the underlying data structure for higher level APIs (Spark structured API) [ZCD+12]. RDDs are a immutable, partitioned collection of records and can only be initiated through transformations (e.g. map, filter) on data or other RDDs. An advantage of RDDs is, that they can be recovered through lineage. Lost partitions of an RDD can be recomputed from other RDDs in parallel on different nodes [ZCD+12]. RDDs are lower level APIs and should only be used in applications if custom data partitioning is needed [CZ18]. It is recommended to use Sparks structured API objects instead. Optimizations for RDDs have to be implemented manually while Apache Spark automatically optimizes the execution for structured API operations [CZ18].

Apache Spark Structured API

Apache Spark provides high level structured APIs for manipulating all kinds of data. The three distributed core types are Datasets, DataFrames and SQL Tables and Views [CZ18]. Datasets and DataFrames are immutable, lazy evaluated collections that provide execution plans for operations [CZ18]. SQL Tables and Views work the same way as DataFrames, except that SQL is used as the interface instead of using the DataFrame programming interface [CZ18]. Datasets use JVM types and are therefore only available for JVM based languages. DataFrames are Datasets of type `Row`, which is the optimized format for computations [CZ18].

Apache Spark Catalyst

Apache Spark also provides a query optimizer engine called Apache Spark Catalyst. Figure 4.3 illustrates how the Spark Catalyst optimizer automatically optimizes Apache Spark applications to run quickly and efficient. Before executing the users code, the Catalyst optimizer translates the data-processing logic into a logical plan and optimizes the plan using heuristics [Luu18]. After that, the Catalyst optimizer converts the logical plan into a physical plan to create code that can be executed [Luu18].

Logical plans get created from a DataFrame or a SQL query. A logical plan represents the data-processing logic as a tree of operators and expressions where the Catalyst optimizer can apply sets of rule-based and cost-based optimizations [Luu18]. For example, the Catalyst can position a filter transformation in front of a join operation [Luu18].

From the logical plan, the Catalyst optimizer creates one ore more physical plans which consist of RDD operations [CZ18]. The cheapest physical plan will be generated into Java bytecode for execution across the cluster [Luu18].

4.2.2 Application Architecture

Figure 4.4 illustrates the main architecture of an Apache Spark cluster running an application. The architecture follows the master-worker model.

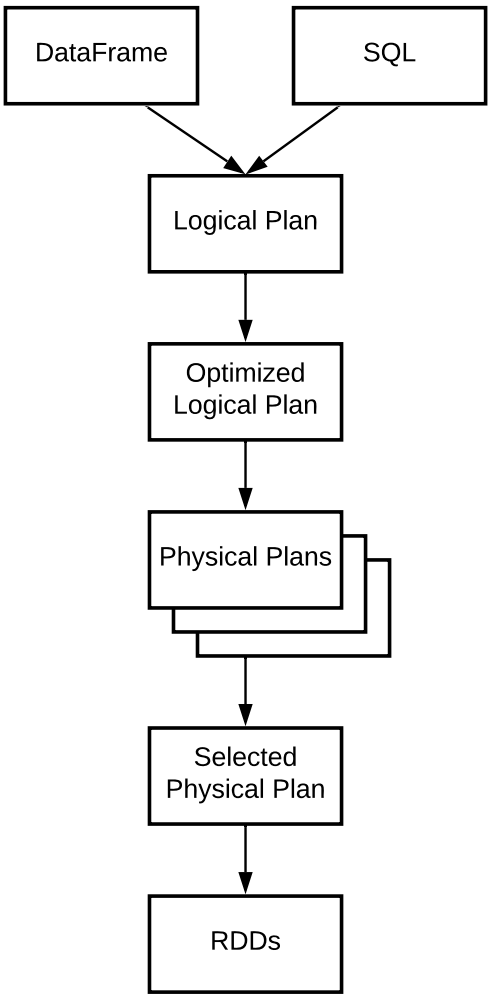

Figure 4.3: Optimization process of the Spark Catalyst - Source: Authors own model, based on [Luu18].

Each running application has one driver process (master) and multiple executor processes (worker) exclusively assigned by the cluster manager. Furthermore, the cluster manager decides on which nodes the processes will be executed [Luu18].

Driver Process

The driver process is a JVM process running on a physical machine and responsible to maintain the execution of an Apache Spark application [CZ18]. It coordinates the application tasks onto each available executor [Luu18]. The driver interacts with the cluster manager to launch executors and allocate hardware resources [CZ18, Luu18].

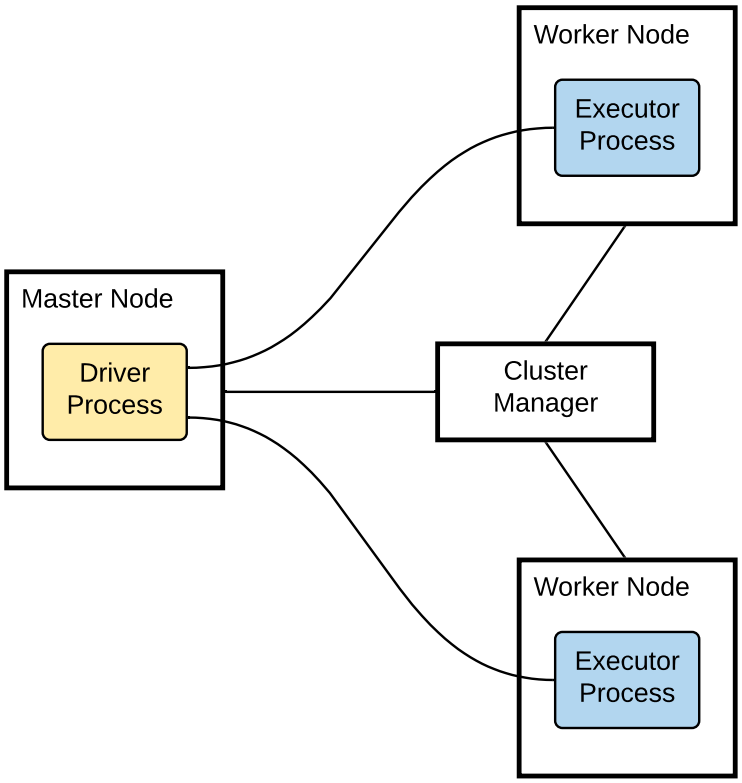

Figure 4.4: Overview of a Spark cluster architecture - Source: Authors own model, based on [Theb].

Executor Process

The executor process is a JVM process, that runs through the whole duration of an application [Luu18, Theb]. It is responsible to perform all tasks (units of work) assigned by the driver process [CZ18]. After the executor process finish, it reports back to the driver process [CZ18]. Each task will be performed on a separate CPU core to enable parallel processing [Luu18].

Cluster Manager

The cluster manager is an external service that orchestrates the work between available machines in the cluster [Luu18, Theb]. It decides on which nodes in the cluster the driver process and the executor processes will be launched. Additionally, the cluster manager manages the resources of each node in the cluster [Luu18, CZ18]. Apache Spark supports different services that can run as cluster manager: Standalone mode (introduced in Section 4.2.3), Apache Mesos[5], Hadoop YARN[VMD+13], and Kubernetes[6] [Theb]. The cluster manager provides three different deploy modes for acquiring resources

5 Apache Mesos - `https://mesos.apache.org/` (Accessed: 2021-01-02)
6 Kubernetes - `https://kubernetes.io/` (Accessed: 2021-01-02)

in the cluster.

- Cluster mode: To run an application in cluster mode, the user has to submit a precompiled JAR, python script or R script to the cluster manager [CZ18]. After that, the cluster manager starts the driver process and executor processes exclusively for the Apache Spark application on machines inside the cluster [CZ18, Luu18].
- Client mode: The difference between the client mode and the cluster mode is that, the driver process runs on the client machine outside of the Spark cluster [CZ18].
- Local mode: The local mode starts an Apache Spark application on a single computer [CZ18]. It is important to mention, that the local mode is not recommended to use in production. Instead it should be used for testing Apache Spark applications [CZ18].

4.2.3 Standalone Cluster Deployment

The standalone mode is a basic cluster-manager build specifically for Apache Spark. It is developed to only run Apache Spark but supports workloads at large scale [CZ18].

Starting Master and Worker Nodes

Apache Spark provides executable launch scripts to start master and worker nodes in standalone mode. The executables can be found at `sbin/start-master.sh` to start a master node and at `/start-slave.sh` to start a worker node. The worker launch executable requires the master node URI as parameter [Theb].

```
1 $ ./sbin/start-master.sh
```

Listing 4.1: Usage of master launch script

```
1 $ ./sbin/start-slave.sh spark://spark-master:7077
```

Listing 4.2: Usage of worker launch script

Listing 4.1 and Listing 4.2 provide an example of how to use both executables to start a master and a worker node. The URI `spark://spark-master:7077` in Listing 4.2 is an example of a master node URI. The master node launch script will print out the master URI after being executed successfully [Theb].

Resource Allocation

In standalone mode, worker need a set of resources configured. Therefore, a worker can assign resources to executors. To specify how a worker discovers resources, a discovery script has to be available [Theb].

Submitting Applications with spark-submit

To submit an application to a standalone cluster, Apache Spark provides the `spark-submit` executable. The executable file is available at `bin/spark-submit` in the installation folder of Apache Spark. In cluster mode the driver of an Apache Spark application (see Section 4.2.2) will be launched from one of the worker processes inside the cluster. The submit process will finish after it has submitted the application. It does not wait for the submitted application to finish [Theb].

```
1 $ bin/spark-submit --master spark://spark-master:7077
    application.py
```

Listing 4.3: Example usage of the spark-submit executable

Listing 4.3 shows how the spark-submit executable can be used to submit a Python application to a standalone Apache Spark cluster. Spark-submit requires the master node URI and the path to the desired Spark application file. With the spark-submit executable it is possible to submit Python, Java and R applications [Theb].

4.3 RAPIDS accelerator for Apache Spark

RAPIDS accelerator for Apache Spark is a plugin suite that aims to accelerate computing operations for Apache Spark using GPUs. It is available for Apache Spark 3 [NVI]. The plugin uses the RAPIDS[7] libraries to extend the Apache Spark programming model, introduced in Section 4.2.1 [NVI, McD20].

4.3.1 Extension of the Spark programming model

The plugin suite extends the Apache Spark programming model with a new DataFrame based on Apache Arrow[8] data structures. In addition, the Catalyst optimizer (described in Section 4.2.1) is extended to generate GPU-aware query plans [McD20]. Apache arrow is a data platform to build high performance applications that work with large datasets and to improve analytic algorithms. A component of Apache Arrow is the Arrow Columnar Format, an in-memory data structure specification for efficient analytic operations on GPUs and CPUs [Thea].

Figure 4.5 illustrates how the RAPIDS plugin suite extends the Catalyst optimization process illustrated previously in Figure 4.3. The Spark Catalyst optimizer identifies operators in a query plan that are supported by the

7 Open GPU Data Science - `https://rapids.ai/` (Accessed: 2021-01-01)
8 Arrow. A cross-language development platform for in-memory data - `https://arrow.apache.org/` (Accessed: 2020-12-03)

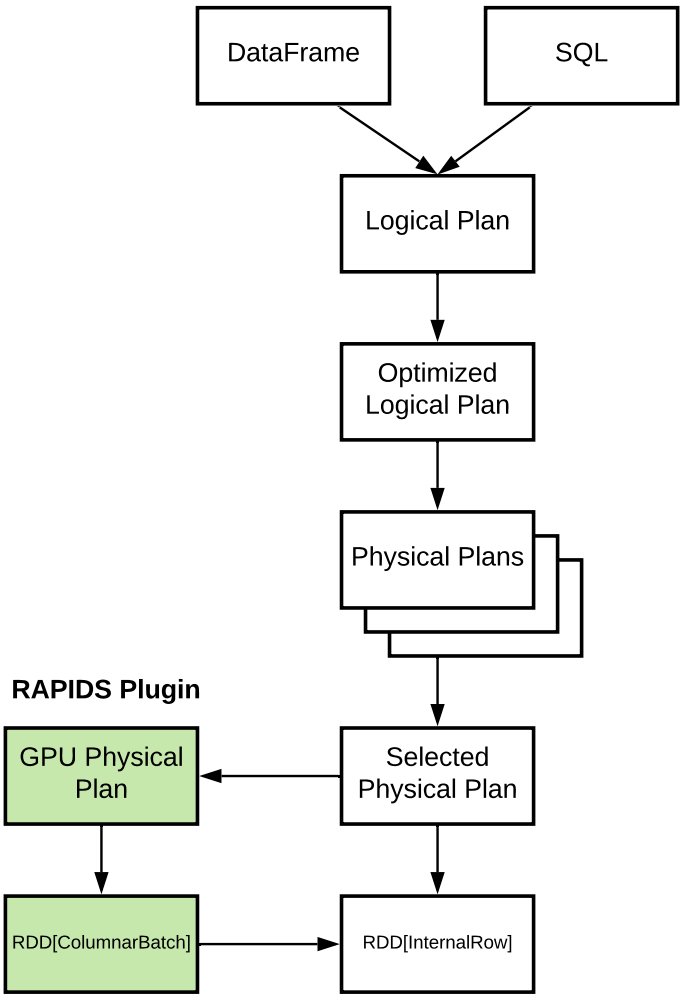

Figure 4.5: Catalyst optimization with RAPIDS accelerator for Apache Spark - Source: Authors own model, based on [McD20].

RAPIDS API. To execute the query plan, these operators can be scheduled on a GPU within the Spark cluster [McD20]. If operators are not supported by the RAPIDS APIs, a physical plan for CPUs will be generated by the Catalyst optimizer to execute RDD operations [McD20].

4.3.2 Installation Requirements for Apache Spark Standalone Mode

The RAPIDS accelerator for Apache Spark is available for a standalone mode Apache Spark cluster. To operate effectively, the following requirements need to be installed on all Apache Spark nodes in the cluster [NVI]:

- Java Runtime Environment (JRE)
- NVIDIA GPU driver

- CUDA Toolkit[9]
- RAPIDS accelerator for Apache Spark Java library
- cudf Java library which is supported by the RAPIDS accelerator Java library and the installed CUDA toolkit
- GPU resource discovery script

4.4 Prometheus

Prometheus is an open-source monitoring and alerting system [Thed]. To collect and store data, Prometheus supports a multi-dimensional key-value pair based data model, according to Section 2.5.3, which can be analyzed in real-time using the PromQL query language [SP20]. Prometheus follows the pull-based approach, as described in detail in Section 2.5.2, to scrape metrics from hosts and services [BP19].

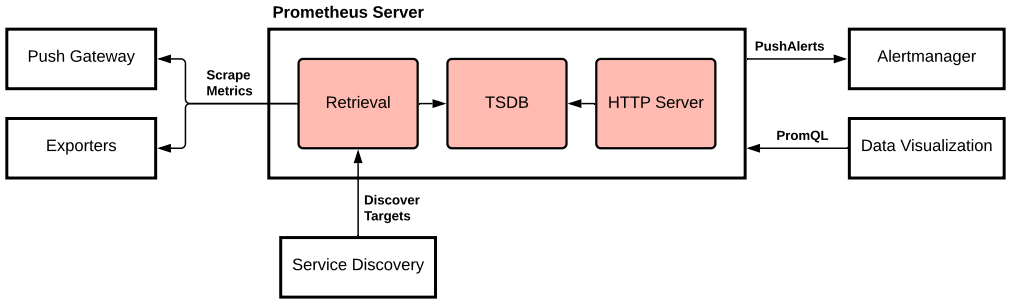

Figure 4.6: Prometheus high-level architecture - Source: Authors own model, based on [Thed, BP19].

Figure 4.6 illustrates the high-level architecture of Prometheus. The Prometheus ecosystem provides multiple components. Components can be optional, depending on the monitoring needs of the environment [BP19]. The main components of a Prometheus system are Prometheus server, Alertmanager, service discovery, exporters, Push Gateway, and data visualization tools [Thed].

Prometheus server: The Prometheus server is the main component of a Prometheus system. It is responsible to collect metrics as time-series data from targets and stores the collected data in the built-in TSDB [BP19]. Prometheus uses the concept of scraping to collect metrics from a target. A target host has to expose an endpoint to make metrics available in the Prometheus data format [SP20]. Additionally, the Prometheus server triggers alerts to the Alertmanager if a configured condition becomes true [Thed].

9 CUDA Toolkit - `https://developer.nvidia.com/cuda-toolkit` (Accessed: 2021-01-01)

Alertmanager: If an alerting rule becomes true, the Prometheus server generates an alert and pushes it to the Alertmanager. The Alertmanager generates notifications from the received alerts. A notification can take multiple forms like emails or chat messages. Webhooks can be implemented to trigger custom notifications [BP19].

Service discovery: As mentioned before, Prometheus follows a pull-based approach to fetch metrics from a target. To know about all targets, Prometheus needs a list of the corresponding hosts. The service discovery manages the complexity of maintaining a list of hosts manually in an changing infrastructure [BP19].

Exporters: If an application does not support an endpoint for Prometheus, an exporter can be used to fetch metrics and make them available to the Prometheus server. An exporter is a monitoring agent running on a target host that fetches metrics from the host and exports them to the Prometheus server [SP20].

Push Gateway: If a target is not designed to be scraped, metrics can be pushed against the Push Gateway [Thed]. The Push Gateway converts the data into the Prometheus data format and passes them to the Prometheus server [SP20].

Visualization: Prometheus supports various tools for virtualization of the scraped data. Grafana[10] is one of the widely used tools for this occasion.

4.5 cAdvisor

Container Advisor (cAdvisor) is a running deamon that collects, aggregates, analyses and exposes performance metrics from running containers. It has native support for Docker container and is deployed as a Docker container. cAdvisor collects metrics from the container deamon and Linux cgroups. Collected metrics will be exposed in the Prometheus file format [BP19, Goo].

4.6 GitLab CI/CD

GitLab CI/CD is a tool integrated into the GitLab platform that enables Continuous Integration (CI), Continuous Delivery (CD) and Continuous Deployment (CD) for software development. The GitLab platform integrates many development features like Git repository management and CI/CD. By pushing code changes to the codebase, GitLab CI/CD executes a pipeline

10 Grafana: The open observability platform - `https://grafana.com/` (Accessed: 2021-01-19)

of scripts to automate CI and CD processes of the software development cycle. A CI pipeline will consist of scripts that builds, tests and validate the updated codebase. A CD pipeline is responsible to deploy the application for production after the CI pipeline has executed successfully. Adding CI/CD pipelines to the software development cycle of an application, allows to catch bugs an errors early. This ensures that an application deployed to production will conform to established standards [Git].

4.6.1 CI/CD Pipeline

The fundamental component of GitLab CI/CD is called a pipeline. Pipelines will perform based on conditions. A conditions might be a push to the main branch of the repository [Git]. A pipeline comprises two components:

- **Stages:** A stage consists of one or multiple jobs that run in parallel. Furthermore, a stage defines how jobs will be executed. For example, a build stage only performs after a test stage has performed successfully [Git].
- **Jobs:** Jobs are responsible to perform the scripts defined by administrators. The scripts define necessary actions. For example compiling the source code or performing tests [Git].

Configuration

GitLab CI/CD is configured by a *.gitlab-ci.yml* file. It is necessary that this file is located in the repositories root directory. The configuration file will create a pipeline that performs after a push to the codebase [Git].

Basic Architecture

4.6.2 Job Execution

Jobs which are defined in the configuration file will be performed by GitLab runners. A GitLab runner is an agent that performs the jobs in its own environment and responds the result back to the GitLab instance. A runner is a lightweight and highly scalable application that runs on a server and performs one or multiple executors. An executor provides the environment where jobs will be executed in. GitLab runner provides multiple variants of executors. For example the Docker executor that connects to the underlying Docker engine. In addition, the Docker executor performs a job in a separate and isolated Docker container. GitLab runner can be set up only for specific projects or be available to all project on the GitLab platform [Git].

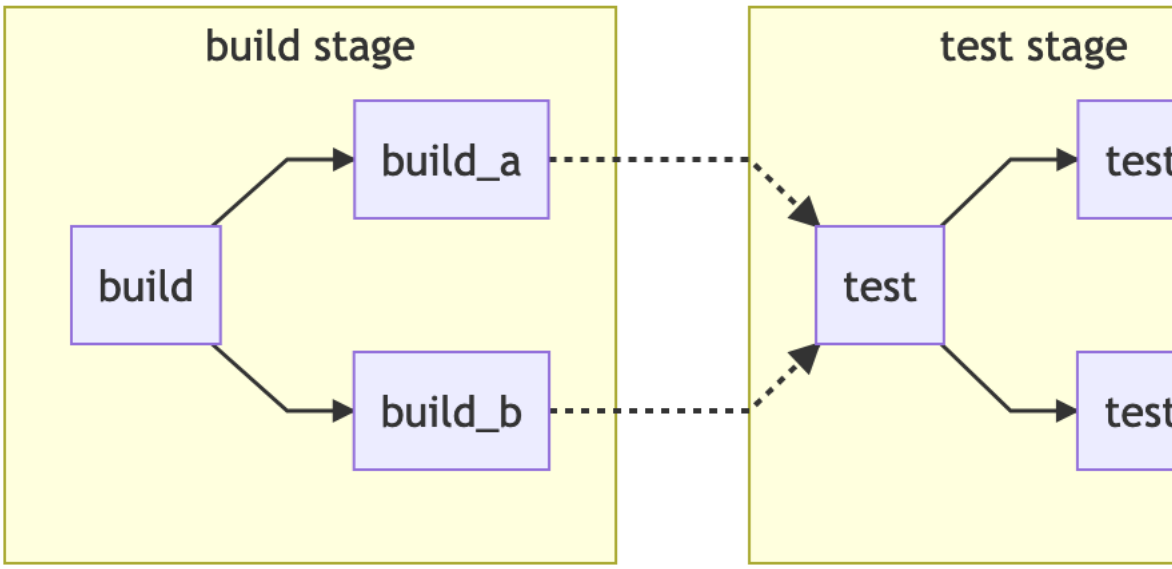

Figure 4.7: Basic architecture of a GitLab CI/CD pipeline - Source: Authors own model, based on [Git].

4.7 Scaling Heat

The Scaling Heat algorithm is a decision making algorithm to determine if a scaling action is necessary. It was introduced by Barna et al. [BKFL17] to overcome issues of traditional recurrence factor algorithms [BKFL17].

4.7.1 Recurrence Factor

In an Autonomic Computing environment, a scaling decision is made in each interval after data has been retrieved from the monitoring system (see Section 2.3 for the Autonomic Computing architecture). Sudden performance spikes can occur and can cause the decision algorithm to perform unnecessary scaling actions. These unnecessary scaling actions can have a negative impact on the overall computing performance. To overcome this issue, a recurrence factor needs to be introduced to the decision making algorithm. With a recurrence factor (n), a scaling action will only be performed until a performance threshold has been violated n times [BKFL17].

Traditional recurrence factor algorithm require violations to occur regularly. If a performance violation of the opposite direction occurs, the algorithm can get stuck in the violation process. Therefore, no scaling actions will be performed [BKFL17].

4.7.2 Scaling Heat Algorithm Concept

Algorithm 1: Scaling Heat decision making algorithm[BKFL17]

Input: *utilization* - The retrieved utilization for a performance metric
Input: *lower_threshold* and *upper_threshold* - Range limit of the performance metric
Input: *heat* - Current heat value of a performance metric. Indicating if a scaling action is necessary
Output: *heat* - New heat value for the next iteration

```
1  if utilization ≥ upper_threshold then
       // cluster overload
2      if heat < 0 then
           // reset heat for removal
3          heat ← 0;
4      heat ← heat + 1;
5  else if utilization ≤ lower_threshold then
       // cluster overload
6      if heat > 0 then
           // reset heat for adding
7          heat ← 0;
8      heat ← heat − 1;
9  else
       // utilization is within threshold range
       // move heat towards 0
10     if heat > 0 then
11         heat ← heat − 1;
12     else if heat < 0 then
13         heat ← heat + 1;
14 end
15 if heat = n then
16     Perform a scale-out action;
17     heat ← 0;
18 else if heat = −n then
19     Perform a scale-in action;
20     heat ← 0;
21 return heat
```

Algorithm 1 introduces the Scaling Heat algorithm. The algorithm is based in a concept called *heat*. The value of heat indicates if a scaling action of removing or adding components is necessary. If the given utilization of a performance metric violates the upper threshold, the heat value will increase. Violations of the lower threshold will cause a decrease respectively. When the heat reaches the recurrence factor n, positive for adding and negative for removing nodes, a scaling action will be executed. After executing a scaling

action, the heat value will be set to 0 [BKFL17].

4.8 Kubernetes Horizontal Pod Autoscaler

Kubernetes Horizontal Pod Autoscaler (KHPA) is an auto-scaling algorithm used in Kubernetes. KHPA scales the number of replicas per Pod based on the utilization of performance metrics. Kubernetes is an orchestration tool that allows to create and deploy units called Pods. A Pod is a running process on a cluster that encapsulates an application. The algorithm is based on a control loop. Each n seconds, the algorithm gathers performance metrics and computes the target number of replicas to achieve the desired utilization of a performance metric [CP17].

The algorithm computes the number of desired replicas for a single performance metric. If a scaling action depends on multiple performance metrics, the number of replicas has to be computed for each performance metric. The largest number of replicas is used as the target number of replicas [Thec].

KHPA takes as input the number of active pods running in the cluster, the utilization of the desired performance metric of each pod, and the target utilization of the performance metric. The formula to compute the target number of pods P is defined by [Thec]:

$$P = \left\lceil active\_replicas \times \left(\frac{\sum pod\_utilization}{target\_utilization} \right) \right\rceil \tag{4.1}$$

Chapter 5

Conceptual Design

TODO: Describe Chapter

5.1 Design Restrictions

The design of the computing environment will be restricted by several points. These factors are given because of technological choices and requirements from up there.

- **Running on a NVIDIA DGX A100[1]:** The environment will run on a NVIDIA DGX A100 workstation. The workstation has 80 CPUs and 8 GPUs installed. For this computing environment, 2 GPUs will be available.
- **Apache Spark for distributed computing:** Apache Spark will be used as a distributed computing framework.
- **Python as the main programming language:** Python will be used as the main programming language for Apache Spark applications. Therefore, examples will use Python code. Configurations for the system are optimized for using Python in production.

5.2 CI/CD

5.3 Identification of suitable Metrics for Scaling

To analyze the Apache Spark cluster computing performance suitable metrics have to be defined. As mention in SECTION XY, Apache Spark distributes its workload across multiple CPU cores. In addition, one objective of this thesis is to accelerate the computing performance of the Apache Spark cluster with GPUs. Therefore suitable performance metrics are CPU utilization of all Apache Spark worker and the utilization of all available GPUs. These

1 The Universal System for AI Infrastructure - `https://www.nvidia.com/en-us/data-center/dgx-a100/`

utilization metrics will be based on the time, when the Apche Spark cluster is actively performing computations.

5.3.1 CPU Performance

TODO: Hier auf Tabelle verweisen (Anhang) Metriken die von Prometheus + cAdvisor bereitgestellt werden

To adapt to business needs, the CPU percentage of each Spark Worker will be calculated. Prometheus provides several metrics to calculate the CPU percentage. The CPU percentage of all Worker can be calculated as follows:

Each Apache Spark worker has a number of CPU cores to perform work. To calculate the CPU utilization of an Apache Spark worker,

$$SparkWorkerCPUUtilization = \frac{\sum CPUCoreUtilization}{NumberOfCPUCores} \tag{5.1}$$

$$OverallCPUUtilization = \frac{\sum SparkWorkerCPUUtilization}{NumberOfSparkWorker} \tag{5.2}$$

5.3.2 GPU Performance

The system has a fixed number of GPUs to use.

$$GPUUtilization = \frac{\sum SparkWorkerGPUUtilization}{NumberOfSparkWorker} \tag{5.3}$$

5.4 Computing environment Architecture

TODO: Only self-adapting -> wegen autonomic computing

5.4.1 Overall

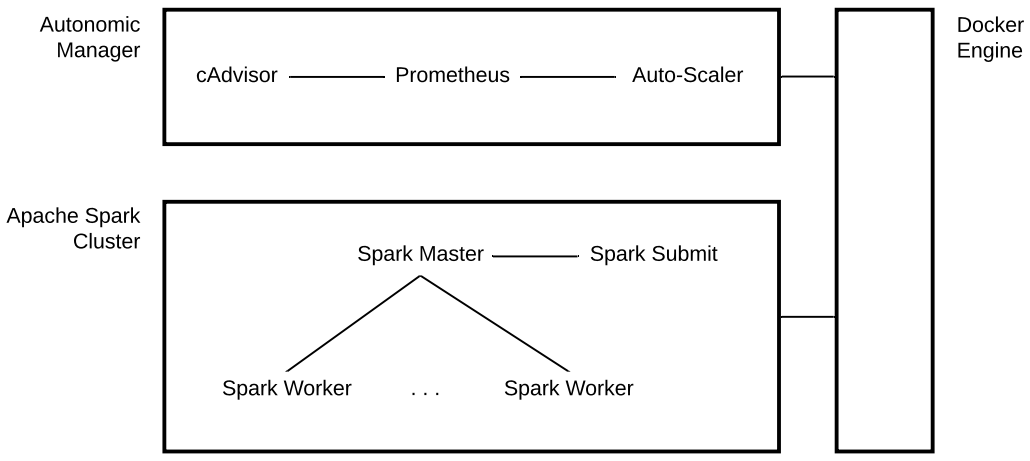

Figure 5.1: Overall cluster architecture - Source: Authors own model.

Figure 5.1 illustrates the overall architecture with all components of the computing environment. The two main components in the environment are an Apache Spark cluster and an autonomic manager. The autonomic manager will be implemented according to the MAPE architecture (introduced in Section 2.3.3). It is responsible for monitoring and auto-scaling the Apache Spark cluster. To enable distributed computing, an Apache Spark cluster will be set up to execute machine learning applications. The autonomic manager and the Apache Spark cluster consist each of multiple nodes. Each node of a component will run as a Docker container. All containers will run as services in Docker Swarm mode. As described in Section 4.1.4, Docker Swarm mode will maintain a healthy state of all running containers. Therefore, the environment will enable self-healing according to the requirements of Autonomic Computing described in Section 2.3.

5.4.2 Apache Spark Cluster

Master and Worker

TODO: Why standalone -> Because most simple way; Master und worker -> Managed Resources

The Apache Spark cluster will consist of a Spark master node and a dynamic number of Spark worker nodes. The Spark master node is responsible to distribute the application workload across available Spark worker nodes. A Spark worker node will execute the workload given by the master node. Each Spark worker is homogeneous. Homegenneosity is important to scale the number of worker nodes. To enable homogeneous nodes, each SPark worker node is a Docker container running the same Docker image. In addition, each worker is given the same computing resources. With homogeneous Spark worker nodes, each worker will respond as all other nodes. To enable GPU acceleration, each WORKER/MASTER will have the RAPIDS plugin installed. The cluster will be deployed in standalone mode. To be able to run Python applications

Spark Submit

Because the Apache Spark cluster ill be executed in standalone mode, a node inside the cluster is required to run Spark applications. When a Spark application will be executed, a Spark Submit container will be deployed in the cluster. When the appliccation has finished, the container will be automatically removed. Each app will be executed by a unique Spark Submit node. The Spark Submit node will be deployed via the CI pipeline (SECTION XY). The prupose of this

5.4.3 Autonomic Manager

The design of the autonomic manager needs to fullfill all requirements given by the MAPE architecture (described in Section 2.3.3). It will be responsible to monitor the performance of Apache Spark worker nodes in the environment, analyze the metrics and plan and execute scaling actions in

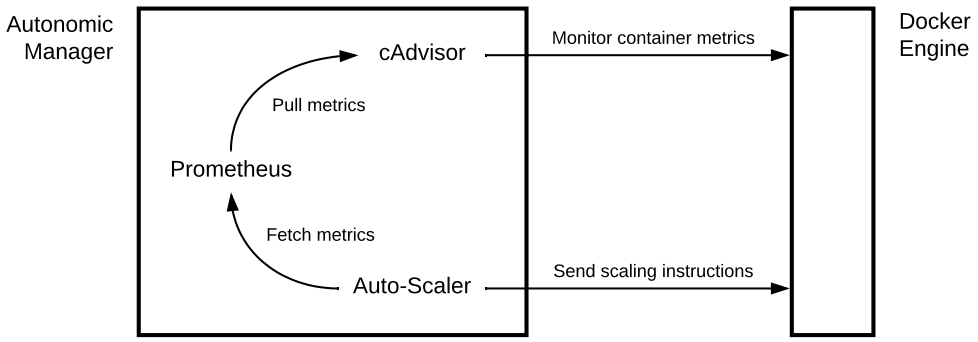

Figure 5.2: Autonomic manager component design - Source: Authors own model.

accordance to fullfill the performance goals. As illustrated in Figure 5.2, the autonomic manager consists of a cAdvisor, Prometheus and Auto-Scaler node. Together, all three nodes build a complete autonomic manager in accordance to the MAPE architecture. Each node will run as a Docker container. For monitoring, cAdvisor collects metrics from all available Docker container in the computing environment. Prometheus pulls metrics from cAdvsior. The Auto-Scaler will fetch metrics from Prometheus and send scaling instructions to the Docker engine.

Monitoring System

The design introduced in Section 5.4.1 is a dynamic changing computing environment. To monitor this dynamic environment, a monitoring-system is needed that fullfills the requirements described in Section 2.5.

cAdvisors will be used as an agent to collect performance metrics from all running Docker containers in the environment. Prometheus pulls the collected performance metrics from cAdvisor and stores the data as time-series data in its database. In addition, Prometheus provides a powerful multi-dimensional query language to aggregate and analyze the stored data.

Workflow

The workflow of the autonomic manager is implemented as a loop.

Figure 5.3 illustrates all steps of each component of the autonomic manager process according to the MAPE architecture.

The workflow starts with collecting metrics in the monitor phase. cAdvisor is responsible to collect metrics from the Docker engine. After that, Prometheus stores the collected metrics as time-series data in its database. Next, in the analyze phase, the Auto-Scaler needs to determine if a scaling action is needed. If scaling the Apache Spark worker nodes is not needed, the process has finished and will repeat from the beginning in the next period. If the performance is over- or under-utilized, a scaling action is needed. Then, the Auto-Scaler needs to determine how many Apache Spark worker

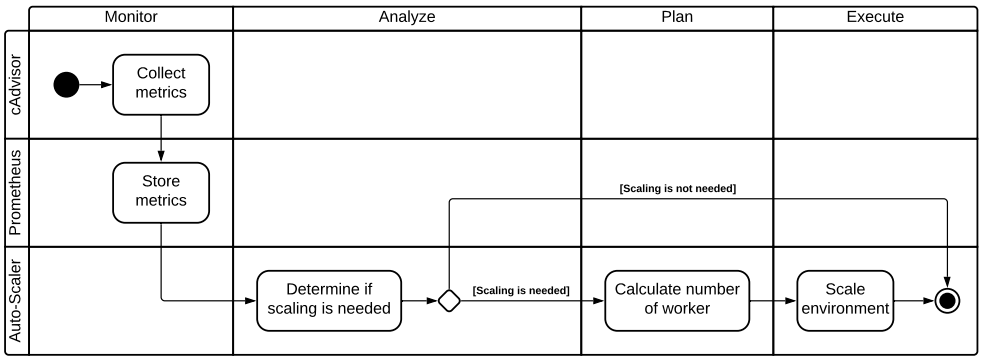

Figure 5.3: UML activity model of the autonomic manager process - Source: Authors own model.

nodes are needed to reach the performance goal. Lastly, the Auto-Scaler is responsible to send the scaling instructions to the Docker engine.

5.5 Auto-Scaler

The Auto-Scaler is a component of the the Autonomic Manager and is responsible for the analyze, plan and execution phase. Together with cAdvisor and Prometheus, the Auto-Scaler builds a complete Autonomic Manager according to Section 2.3.3. In addition, the Auto-Scaler implements the control-loop which is responsible to make adjustments in the environment according to the performance. To adjust the number of Apache Spark worker in the environment, the Auto-Scaler needs to perform queries on the performance metrics stored in Prometheus. After analyzing the performance metrics, the Auto-Scaler will send instructions to adjust the number of Apache Spark worker to the Docker engine. The Docker engine tells the Swarm manager to scale the replicas of the Apache Spark service in accordance to the Auto-Scaler instructions.

TODO: HIER NOCH BILD VON SCALER WIE MIT DER MAPE ARCH; Reactive Auto-Scaler, threshold-based rules

5.5.1 Configuration

The Auto-Scaler needs specific configuration properties to be able to collect the correct metrics from Prometheus and deploy new Apache Spark worker container in the environment. The following are properties that have to be defined to ensure that the Auto-Scaler is able to collect meaningful metrics and scale Apache Spark worker as expected.

General properties

- **Interval seconds:** The number of seconds when the loop has to repeat needs to be defined.

- **Cooldown period:** The duration in seconds, the Auto-Scaler has to wait after a scaling action was performed.
- **Recurrence factor:** To prevent to many scaling actions, the autonomic manager should only execute a scaling action, if the utilization thresholds is violated n times.
- **Prometheus URL:** The Auto-Scaler will fetch the configured metrics from the Prometheus REST API.

Metrics

To support to analyze multiple metrics, the user should be able to create a dynamic list if metrics. Each metric needs to have a variety of properties configured.

- **Target utilization:** The relative target utilization of a metrics needs to be defined to calculate the number of Spark worker to add or to remove to reach the defined goal.
- **Utilization thresholds:** To determine if a scaling action is needed, the scaling heat algorithm needs the minimum and maximum utilization defined by an administrator.
- **Query:** A PromQL query needs to be defined to collect the metric for all Spark Worker.

Apache Spark worker properties

- **Worker image:** To guarantee that each Spark worker is homogeneous, all worker container should be created with the same image.
- **Worker network:** To establish communication between all Spark worker and the Spark master, all new Spark worker container should be in the same network.
- **Worker thresholds:** The minimum and maximum number of concurrent Spark worker should be defined. To avoid the cold start effect, the minimum amount of worker should be 1.
- **Apache Spark master URI:** To distribute the workload across all Spark Worker, all Spark Worker need to communicate with the Spark master.

5.5.2 Analyze

In order to determine if a scaling-action is necessary, the Auto-Scaler has to process the collected metrics. During each period, the Auto-scaler queries the Prometheus time-series database with the configured queries to get all needed metrics. After the metrics are received, the Auto-Scaler determines

if a scaling action is needed using the Scaling Heat algorithm (introduced in Section AB). If scaling is not necessary, the Auto-Scaler continues to collect metrics from Prometheus.

5.5.3 Plan

If a scaling-action is necessary, the Auto-Scaler is responsible to plan how to scale the number of Spark worker to satisfy the defined utilization goals. A scaling plan consists of instructions to add or remove Spark worker which will be send to the Docker engine. To calculate the number of Spark worker, needed to accomplish the defined target utilization, the Auto-Scaler uses the *Kubernetes Horizontal Pod Auto-Scaling* algorithm. In addition, the Auto-Scaler needs to check if the estimated number of Spark worker fall bellow the minimum threshold or exceed the maximum threshold of concurrent Spark worker.

5.5.4 Execute

After a scaling plan has been created, the Auto-Scaler needs to send the instructions to the Docker engine. After scaling the environment, it needs time for changes to take effect. Therefore a cooldown period will be activated after each scaling action. During the cooldown period, no scaling actions will be forwarded to the Docker engine.

Chapter 6

Implementation

6.1 Background

TODO: Describe Chapter

Mentioned before, the goal is to create a self-healing and self-adapting computing environment. In addition, Apache Spark applications should be able to deploy automatically via a CI pipeline to the cluster. Therefore, to implement the conceptual design described in SECTION XY, the following requirements need to be implemented:

TODO: NVIDIA RUNTIME MUSS INSTALLIERT SEIN UND ALS DEFAULT

1. Implementing the Auto-Scaler Python module
2. Dockerizing the Auto-Scaler
3. Creating the computing environment in a Docker swarm
   - Create an Apache Spark cluster with GPU acceleration
   - Create an autonomic manager with a monitoring system and an Auto-Scaler
4. Implement a GitLab CI pipeline to deploy Apache Spark applications to the cluster

6.2 Auto-Scaler

The conceptual design of the Auto-Scaler is described in detail in Section 5.5. The Auto-Scaler will be implemented as a module in Python 3.8. To deploy the Auto-Scaler in a Docker swarm, the Auto-Scaler needs to be dockerized in a Docker Image.

TODO: AUto-Scaler control loop: Periodically checks if the number of desired worker replicas is running, vll auch eher in design

6.2.1 Configuration

The configuration parameter for the Auto-Scaler have been introduced in Section 5.5.1. The configuration for the Auto-Scaler will be specified in a YAML file. Listing 6.1 describes an example of an Auto-Scaler configuration.

Overall, a configuration file is structured in three sections: General, metrics and worker. Table 6.1 lists all available configuration parameters. It describes the value type and the default value of each parameter. Some parameters are required to be defined by the administrator and have no default value.

General: The general section defines details about the scaling and heat algorithm and the Prometheus URL.

TODO: Multi-dimensional metrics/queries

Metrics: Metrics is a list of performance metrics configuration parameters. The name of a metric (*cpu* and *gpu* in the example Listing 6.1) can be set by the administrator. A performance metric requires a query in the PromQL syntax. Additionally a target utilization is needed and the minimum and maximum utilization of the performance metric.

Worker: To scale the replicas of the Apache Spark worker service, the name of the Docker service needs to be set. In addition, the minimum and maximum number of concurrent worker nodes needs to be defined to prevent an overhead of running worker nodes.

```
1  general:
2    interval_seconds: 5
3    cooldown_period_seconds: 180
4    recurrence_factor: 3
5    prometheus_url: "http://localhost:9090"
6
7  metrics:
8    cpu:
9      query: 'sum(rate(container_cpu_user_seconds_total{image
       ="spark-worker:3.0.1-hadoop2.7"}[30s]))'
10     target_utilization: 0.5
11     thresholds:
12       min: 0.2
13       max: 0.6
14
15   gpu:
16     query: 'sum(rate(container_cpu_user_seconds_total{image
       ="spark-worker:3.0.1-hadoop2.7"}[30s]))'
17     target_utilization: 0.3
18     thresholds:
19       min: 0.2
20       max: 0.6
21
22 worker:
23   service_name: "computing_spark-worker"
24   thresholds:
25     min: 1
26     max: 30
```

Listing 6.1: Auto-Scaler configuration YAML file

Name	Type	Default
general		
interval_seconds	Integer	1
cooldown_period_seconds	Integer	180
recurrence_factor	Integer	1
prometheus_url	String	*Required*
metrics		
query	String	*Required*
target_utilization	Float	0.5
thresholds		
min	Float	0.5
max	Float	0.5
worker		
service_name	String	*Required*
thresholds		
min	Float	0.5
max	Float	0.5

Table 6.1: Auto-Scaler configuration parameter

6.2.2 Scaling the Apache Worker Service

docker service apache-worker scale replicas=4 Not possible to use nvidia-runtime because of restart -> scale docker container

Estimation of Necessary Scaling Actions

The Scaling Heat algorithm, introduced in Section 4.7, is being used to estimate if a scaling action is necessary. The algorithm is being used because it will prevent the Auto-Scaler to perform unnecessary scaling actions. During each interval, after performance metrics have been received from the monitoring system, a heat value will be calculated for each performance metric specified in the configuration under *metrics*. The algorithm uses a recurrence factor which has to be defined in design time. The Auto-Scaler configuration provides a parameter called *recurrence_factor* (see Table 6.1 for details).

To store and calculate the heat for each performance metric, a class called `HeatStore` was created. FIGURE XY describes the UML class diagram for the `HeatStore` Python class. The class can be used to retrieve, update and reset the heat for a list of performance metrics.

Calculating the Number of Needed Worker Nodes

The KHPA algorithm will be used to calculate how many worker are needed to reach the target utilization (see SECTION XY for algorithm details). In

this project, the calculation is done for the CPU and GPU utilization. The highest number of the desired worker node replicas is chosen.

Performing a Scaling Action

Docker provides a Python library for the Docker Engine[1]. This library will be used to perform the swarm scaling action.

If worker need to be removed, it is necessary to check if the worker are running any applications. Removing a worker while an application is performing will cause the cancellation of the application. To check if applications

After a scaling action has been performed, a cooldown period will be applied. The cooldown period is needed because the number of desired worker nodes can keep fluctuating due to the dynamic nature of performance metrics.

6.2.3 Docker Image

- Dockerfile hier erklären - Wie den Auto-Scaler per konsole starten (mit config parameter)

6.3 Deployment of a Docker Swarm

6.3.1 Hardware

6.3.2 Software info

Hier tabelle mit versionen von eingesetzter software

6.3.3 Swarm

Vielleicht euch einfach das ganze kapitel Swarm nennen? - Dockerfile erläutern - GPUs (nur die 2 bestimmten)

6.3.4 Build Script

6.3.5 Apache Spark Cluster with GPU Acceleration

The Apache Spark cluster is created in standalone mode, see Section 4.2.3 for deployment details. The cluster consists of a single Apache Spark master node and a dynamic number of Apache Spark worker nodes. The master and worker container will run as a service in a swarm (see Section 4.1.4).

1 Docker SDK for Python 4.4.1 Documentation - `https://docker-py.readthedocs.io/en/4.4.1/` (Accessed: 2021-01-05)

For submitting an application to the cluster, an individual container performing the spark-submit executable will be deployed. Each node runs in an independent Docker container.

Overall four Docker images are needed to create the Apache Spark cluster introduced in Section 5.4.2:

- Base image
- Master image
- Worker image
- Submit image

The master, worker and submit image require common packages to be installed and a set of common configuration. Therefore, an additional base image will serve as a base image.

Apache Spark Base Image Installation Details

The base image Dockerfile is available at Listing A.1. As parent, the base image uses the `nvidia/cuda:11.0-devel-ubuntu16.04` Docker image. The parent image runs Ubuntu[2] in version 16.04. Additionally the CUDA Toolkit and the NVIDIA GPU driver are already installed. Docker provides the ability to set build arguments. To be able to install a specific Apache Spark version, two arguments, can be set when building the Docker image. Apache Spark will be installed at `/opts/Spark`. This directory will be set as the working directory for the Docker image as well. Furthermore, required Ubuntu packages will be installed. This includes the Java Runtime Environment Version 8, which is a requirement for Apache Spark. To enable GPU acceleration on all Apache Spark nodes, the base image will install the compiled Java files for the RAPIDS plugin at `/opt/sparkRapidsPlugin` (for RAPIDS installation requirements, see Section 4.3.2). The .jar files can be downloaded in the maven repository. To enable Apache Spark to discover available GPUs, a GPU discovery script is needed (see Section 4.2.3 for details about resource allocation). This discovery script will be placed at `/opt/sparkRapidsPlugin` as well. The discovery script is introduced at Listing A.4.

Standalone Master and Worker Image

The master and worker image are build on top of the Apache Spark base image. Therefore, no additional installation steps are required. The master and worker nodes will be launched in standalone mode (see Section 4.2.3 for standalone mode details).

2 Enterprise Open Source and Linux - `https://www.ubuntu.com/` (Accessed: 2021-01-03)

Master image: Implementation of the master node Dockerfile is available at Listing A.2. The master node image needs two ports configured: The Apache Spark service port and the port for the web user interface. The Apache Spark service port ist set to 7077 and the web user interface port to 4040. To start the master node in standalone mode, the start-master.sh launchable will be set as image entrypoint which requires no additional arguments.

Worker image: Listing A.3 describes the implementation of the worker node Dockerfile. The port for the worker web interface will be exposed at 4041. To start the worker in standalone mode, the start-slave.sh executable will be set as entrypoint for the image. The launch script requires the master node URI as a parameter. To keep the configuration simple, the environment variable HIER DIE VAR will be set in the compose file. Listing 6.2 describes the configuration environment for the worker. As mentioned previously (in Section 5.1), for this project two GPUs are available on the DGX workstation. Furthermore, the worker needs to know where to find the GPU resource discovery script.

```
1 SPARK_WORKER_OPTS="-Dspark.worker.resource.gpu.amount=2 -
    Dspark.worker.resource.gpu.discoveryScript=/opt/
    sparkRapidsPlugin/getGpusResources.sh"
```

Listing 6.2: Environment configuration for all worker nodes

Submit Image

As mentioned in Section 5.1, a requirements is, that Apache Spark application will be implemented in Python. Accordingly, the pyspark Python module needs to installed on all submit nodes. Apache Spark application will be placed at */opt/spark-apps*. SECTION CI describes how an Apache Spark application will be copied to a submit node. As entrypoint, the image will perform a custom submit script (available at LISTING AB). This script performs the spark-submit executable (usage described in detail in Section 4.2.3).

6.3.6 Autonomic Manager

As mentioned in Section 5.4.3, the autonomic manager will consist of a monitoring system and the Auto-Scaler to create a complete control loop.

The monitoring system conceptual design was introduced in SECTION XY. It consists of a cAdvisor (SECTION XY) service and a Prometheus (SECTION XY) service. All modules will run as individual Docker services in the overall swarm. The following DOcker images will be used for the monitoring system:

- **cAdvisor:** google/cadvisor

- **Prometheus:** prom/prometheus

Prometheus Target Configuration

As mentioned in Section 4.4, Prometheus is a pull-based monitoring tool. It requires a list of targets to pull performance metrics from.

Listing 6.3 specifies the scrape configuration of the Prometheus system. The cAdvisor service is specified as a target. Prometheus will scrape every 5 seconds performance metrics from cAdvisor. All performance metrics will be labeled with the cAdvisor lable. The cAdvisor service is available at cadvisor:8080.

```
scrape_configs:
    - job_name: prometheus
      scrape_interval: 5s
      static_configs:
          - targets: ["localhost:9090"]

    - job_name: cadvisor
      scrape_interval: 5s
      static_configs:
          - targets: ["cadvisor:8080"]
            labels:
                group: "cadvisor"
```

Listing 6.3: Prometheus target configuration in YAML syntax

6.4 Automatic Deployment of Apache Spark Applications

Vielleicht eher das Kapitel so nennen - gitlab-ci.yml erklären - Screenshot von webui output

Chapter 7

Evaluation

TODO: Describe Chapter

7.1 Experimental Environment

The experiments have been conducted on a NVIDIA DGX. Table AB describes the hardware available on the DGX. Two of the eight GPUs have been available to conduct the experiments.

The DGX is a live-system as being mentioned in Section XY. Therefore not all available hardware resource have been exclusively available to conduct these experiments.

7.2 Workload

The performance evaluation of the implementation was conducted using two ML algorithms: K-Means and Naive Bayes. To implement the algorithms, Apache Sparks ML library has been used. The K-Means implementation is available at ANHANG A and the Naive Bayes implementation at ANHANG B.

The *infinite MNIST dataset*[LCB07] has been used to to perform the algorithms. It consists of 8 million datapoints.

7.2.1 K-Means

K-Means is a unsupervised machine learning algorithm for clustering. The algorithm aims to place unlabelled data, that appear to be related, into cluster.

In this section, we introduce perhaps the simplest unsupervised machine learning algorithms—k-means clustering. This algorithm analyzes unlabeled samples and attempts to place them in clusters that appear to be related. The k in “k-means” represents the number of clusters you’d like to see imposed on your data.The algorithm organizes samples into the number of clusters you specify in advance, using distance calculations similar to the k-nearest neighbors clustering algorithm. Each cluster of samples is grouped around a centroid—the cluster’s center point. Initially, the algorithm chooses k

centroids at random from the dataset's samples. Then the remaining samples are placed in the cluster whose centroid is the closest. The centroids are iteratively recalculated and the samples re-assigned to clusters until, for all clusters, the distances from a given centroid to the samples in its cluster are minimized. The algorithm's results are:

7.3 Efficiency of GPU Acceleration

7.4 Auto-Scaling using CPU Metrics

7.5 Results

Ab wie viele worker ist CPU besser wie GPU

Chapter 8

Outlook

TODO: Describe Chapter

8.1 Optimizing Scaling

Current approach: Wait until all applications have finished. Better approach: Blacklist worker for removing so no executor will be launchend on the worker. Create an external shuffle service, so worker can be remove on runtime.

8.2 Reinforcement Learning for Auto-Scaling

bla bla

Chapter 9

Conclusion

9.1 Cluster architecture

TODO: Describe Chapter

Appendix A

Apache Spark Cluster Implementation

```
FROM nvidia/cuda:11.0-devel-ubuntu16.04

LABEL maintainer="marcel.pascal.stolin@ipa.fraunhofer.de"

ARG SPARK_VERSION
ARG HADOOP_VERSION

# Install all important packages
RUN apt-get update -qy && \
    apt-get install -y openjdk-8-jre-headless procps python3
    python3-pip curl

# Install Apache Spark
RUN mkdir /usr/bin/spark/ && \
    curl https://ftp-stud.hs-esslingen.de/pub/Mirrors/ftp.
   apache.org/dist/spark/spark-${SPARK_VERSION}/spark-${
   SPARK_VERSION}-bin-hadoop${HADOOP_VERSION}.tgz -o spark.
   tgz && \
    tar -xf spark.tgz && \
    mv spark-${SPARK_VERSION}-bin-hadoop${HADOOP_VERSION}/*
   /usr/bin/spark/ && \
    rm -rf spark.tgz && \
    rm -rf spark-${SPARK_VERSION}-bin-hadoop${HADOOP_VERSION
   }/

# Add GPU discovery script
RUN mkdir /opt/sparkRapidsPlugin/
COPY getGpusResources.sh /opt/sparkRapidsPlugin/
   getGpusResources.sh
ENV SPARK_RAPIDS_DIR=/opt/sparkRapidsPlugin

# Install cuDF and RAPIDS
RUN curl -o ${SPARK_RAPIDS_DIR}/cudf-0.15-cuda11.jar https
   ://repo1.maven.org/maven2/ai/rapids/cudf/0.15/cudf-0.15-
   cuda11.jar
RUN curl -o ${SPARK_RAPIDS_DIR}/rapids-4-spark_2.12-0.2.0.
   jar https://repo1.maven.org/maven2/com/nvidia/rapids-4-
   spark_2.12/0.2.0/rapids-4-spark_2.12-0.2.0.jar
ENV SPARK_CUDF_JAR=${SPARK_RAPIDS_DIR}/cudf-0.15-cuda11.jar
```

```
ENV SPARK_RAPIDS_PLUGIN_JAR=${SPARK_RAPIDS_DIR}/rapids-4-
    spark_2.12-0.2.0.jar

# Set all environment variables
ENV JAVA_HOME=/usr/lib/jvm/java-8-openjdk-amd64
ENV SPARK_HOME /usr/bin/spark
ENV SPARK_NO_DAEMONIZE true
ENV PYSPARK_DRIVER_PYTHON python3
ENV PYSPARK_PYTHON python3
ENV PATH /usr/bin/spark/bin:/usr/bin/spark/sbin:$PATH

WORKDIR ${SPARK_HOME}
```

Listing A.1: Apache Spark base image Dockerfile

```
ARG SPARK_VERSION
ARG HADOOP_VERSION

FROM spark-base:$SPARK_VERSION-hadoop$HADOOP_VERSION

LABEL maintainer="marcel.pascal.stolin@ipa.fraunhofer.de"

# Set ports
ENV SPARK_MASTER_PORT 7077
ENV SPARK_MASTER_WEBUI_PORT 4040

EXPOSE 4040 7077

# Start master-node in standalone mode
ENTRYPOINT [ "sbin/start-master.sh" ]
```

Listing A.2: Apache Spark master image Dockerfile

```
ARG SPARK_VERSION
ARG HADOOP_VERSION

FROM spark-base:$SPARK_VERSION-hadoop$HADOOP_VERSION

LABEL maintainer="marcel.pascal.stolin@ipa.fraunhofer.de"

# Add spark-env
COPY spark-env.sh ${SPARK_HOME}/conf/spark-env.sh

# Set port
ENV SPARK_WORKER_WEBUI_PORT 4041

EXPOSE 4041

# Start worker-node
ENTRYPOINT ./sbin/start-slave.sh ${SPARK_MASTER_URI}
```

Listing A.3: Apache Spark worker image Dockerfile

```
#!/usr/bin/env bash

#
```

```
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# distributed under the License is distributed on an "AS IS" BASIS,
# WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied.
# See the License for the specific language governing permissions and
# limitations under the License.
#

# This script is a basic example script to get resource information about NVIDIA GPUs.
# It assumes the drivers are properly installed and the nvidia-smi command is available.
# It is not guaranteed to work on all setups so please test and customize as needed
# for your environment. It can be passed into SPARK via the config
# spark.{driver/executor}.resource.gpu.discoveryScript to allow the driver or executor to discover
# the GPUs it was allocated. It assumes you are running within an isolated container where the
# GPUs are allocated exclusively to that driver or executor.
# It outputs a JSON formatted string that is expected by the
# spark.{driver/executor}.resource.gpu.discoveryScript config.
#
# Example output: {"name": "gpu", "addresses":["0","1","2","3","4","5","6","7"]}

ADDRS=`nvidia-smi --query-gpu=index --format=csv,noheader | sed -e ':a' -e 'N' -e'$!ba' -e 's/\n/","/g'`
echo {\"name\": \"gpu\", \"addresses\":[\"$ADDRS\"]}
```

Listing A.4: GPU discovery script - Source: `https://github.com/apache/spark/blob/v3.0.1/examples/src/main/scripts/getGpusResources.sh` (Accessed: 2021-01-03)

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