HOCHSCHULE DER MEDIEN

Fraunhofer IPA

# Bachelor Thesis

## My Bachelor Thesis


vorgelegt von

**Marcel Pascal Stolin**

32168

geboren am 03.04.1993 in Kamen


Verfasst am

**Fraunhofer-Institut für Produktionstechnik und Automatisierung IPA**

und

**Hochschule der Medien Stuttgart**

| | |
|---|---|
| Erstprüfer: | Prof. Walter Kriha |
| Zweitprüfer: | Prof. Dr. Marco Huber |
| Betreuung: | M.Sc. Christoph Hennebold |

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# Eidesstattliche Erklärung

Ich versichere hiermit, dass ich, Marcel Pascal Stolin, die vorliegende Bachelor Thesis selbstständig angefertigt, keine anderen als die angegebenen Hilfsmittel benutzt und sowohl wörtliche als auch sinngemäß entlehnte Stellen als solche kenntlich gemacht habe. Die Arbeit hat in gleicher oder ähnlicher Form noch keiner anderen Prüfungsbehörde vorgelegen.

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# Zusammenfassung

Hier kommt eine deutschsprachige Zusammenfassung hin.

# Abstract

Abstract in English.

# Contents

# 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

## 1.1 Distributed Computing

Performing ETL applications on a single machine, limits the scale and performance of the application. Given this limitation, the idea of distributed computing evolved, where multiple machines with commodity hardware form a cluster to utilize their resources to solve high complex problems [GOKB16].

Several companies utilized the idea of distributed computing to solve some of their business problems. Google developed the MapReduce [DG04] framework. MapReduce gave the opportunity to solve massive complex problems in parallel on a cluster of single machines. Yahoo published an ecosystem platform for distributed computing called Hadoop QUELLE. Hadoop contributed to create a cluster to process massive amounts of data in parallel. Implementing data pipelines 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 application 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 Data Processing Acceleration with GPUs

Apache Spark only knows about CPUs. It performs its application on several CPU cores to enable parallization. A CPU is build of multiple cores which are optimized for sequential serial processing QUELLE. On the other hand, the architecture of a Graphical Process Unit (GPU) consists of a huge amount of smaller and more efficient cores which are optimized for darallel data processing (handling multiple tasks simoultaneously). In general, GPUs process data at a much faster rate than CPUs are capable.

## 1.3 Auto-Scaling

Adjusting the resources in a computing environment is not an easy task. To do it manually, a system administrator needs deep knowledge about hte environment and has to watch performance spikes regualarly. This is a resource wasting process. In an optimal way, an automized process would watch the computing enviroment, analyze perofmrance metrcis and automatically add or remove resource to optimize the performance and cost. This process is called an Auto-Scaler.

Hiring experts to manually watching an application and scaling an computing environment is a waste of reources and cost. AN Auto-Scaler takes care of watching the environment and adding and removing resources to the computing needs. An Auto-Scaler can be configured to take care of optimal resource allocation and keeping the cost of running low.

Auto-scaling a computing environment can be achieved with two different scaling approaches: 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 to horizontal scaling [Wil12]. Increasing the number of nodes in an environment, increases the overall computing capacity and in addition, the workload can be distributed across all nodes [Wil12, LT15]. Both scaling approaches are not exclusive. A computing environment can be designed to scale vertically, horizontally or both [Wil12]. Vertical scaling is limited by the maximum hardware capacity. In addition, 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 DevOps

## 1.5 Problem Statement

## 1.6 Research Questions

The goal of this thesis is to implement a computing environment to perform machine learning applications distributed. The environment should be able to scale itself automatically in accordance to the workload caused by performing the Machine Learning applications. In addition, the Machine Learning application should be performed automatically in a DevOps process. To address the goal of this research work, the following two research question will be investigated:

*Is it possible to extend the number of Spark Worker in accordance to performance?*

This thesis investigates approaches to implement an Auto-Scaler that is able to add and remove Spark worker instances automatically in accordance to the workload. The Auto-Scaler needs to monitor the performance of the environment periodically and should make decisions according on that.

**Can we accelerate Machine Learning algorithms execution with GPU support?** Apache Spark runs on CPU only. In this thesis, a way will be investigated to enable GPU acceleration for Apache Spark applications.

## 1.7 Thesis Structure

## 1.8 Research Methodologies

Chapter 2

# Technical Background

In this chapter bla bla

**TODO: Describe Chapter**

## 2.1 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 it‘s environment and how to extend it‘s 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].

### 2.1.1 Autonomic computing concept

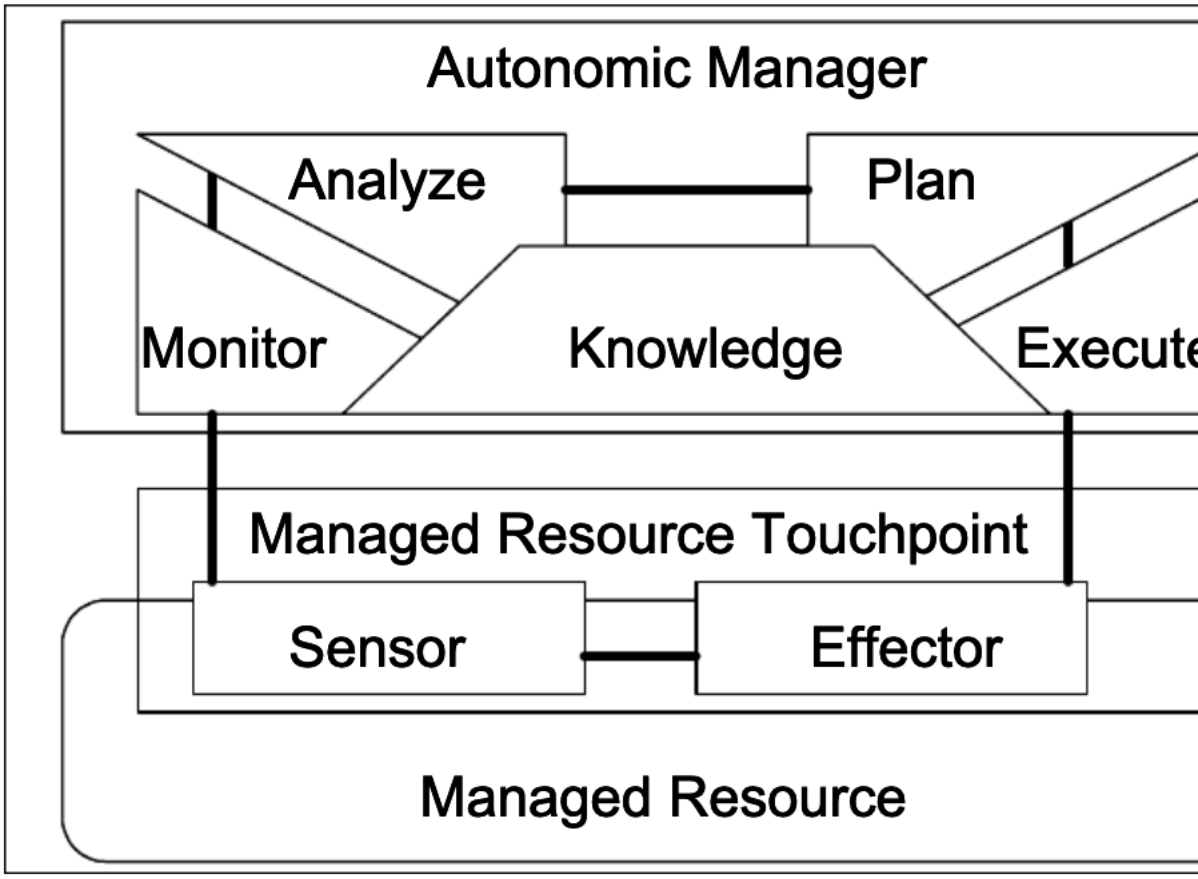


**Figure 2.1:** Autonomic computing concept - Source: Authors own model, based on [JSAP04].

Figure 2.1 demonstrates the main concept of an autonomic computing environment. The autonomic computing architecture relies on monitoring 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].

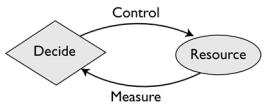


**Figure 2.2:** The control-loop concept - Source: Authors own model, based on [Mur04].

The core element of the autonomic architecture is the control-loop. Figure 2.2 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].

### 2.1.2 Managed resources

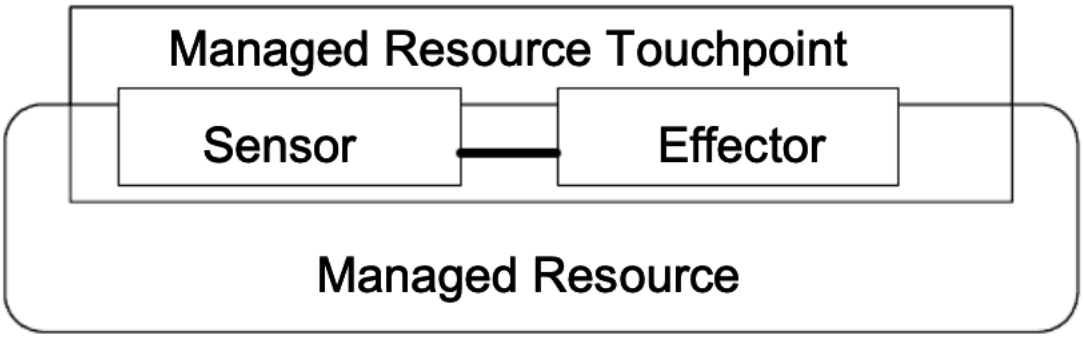


**Figure 2.3:** Managed resource - Source: Authors own model, based on [JSAP04].

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 2.3. 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 make them highly scalable [Mur04].

### 2.1.3 Autonomic manager

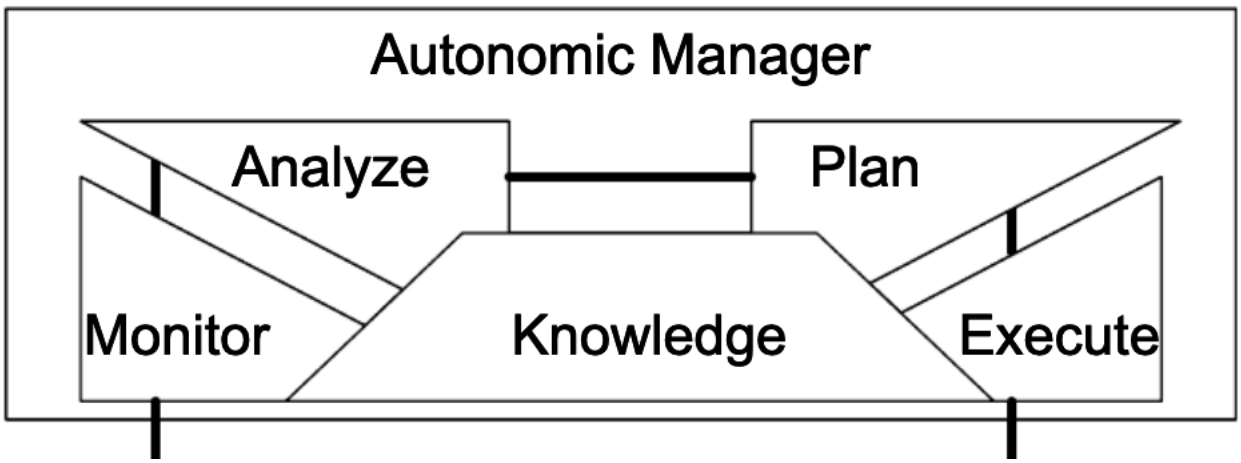


**Figure 2.4:** Autonomic manager - Source: Authors own model, based on [JSAP04].

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 it‘s 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 analyzing the managed resources [Mur04]. The autonomic computing concept digests the MAPE-K model to implement an autonomic manager, as illustrated in Figure 2.4 [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].
- **Knowledge:** HIER KNOWLEDGE!!.

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

## 2.2 Docker

**TODO: Mehr zum Thema DevOps**

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].

### 2.2.1 Docker architecture

Figure 2.5 illustrates the client server architecture of Docker which consists of of a Docker client, the Docker deamon and a registry.

**Docker client:** The Docker client is an interface for the user to send commands to the Docker deamon [Inc20].

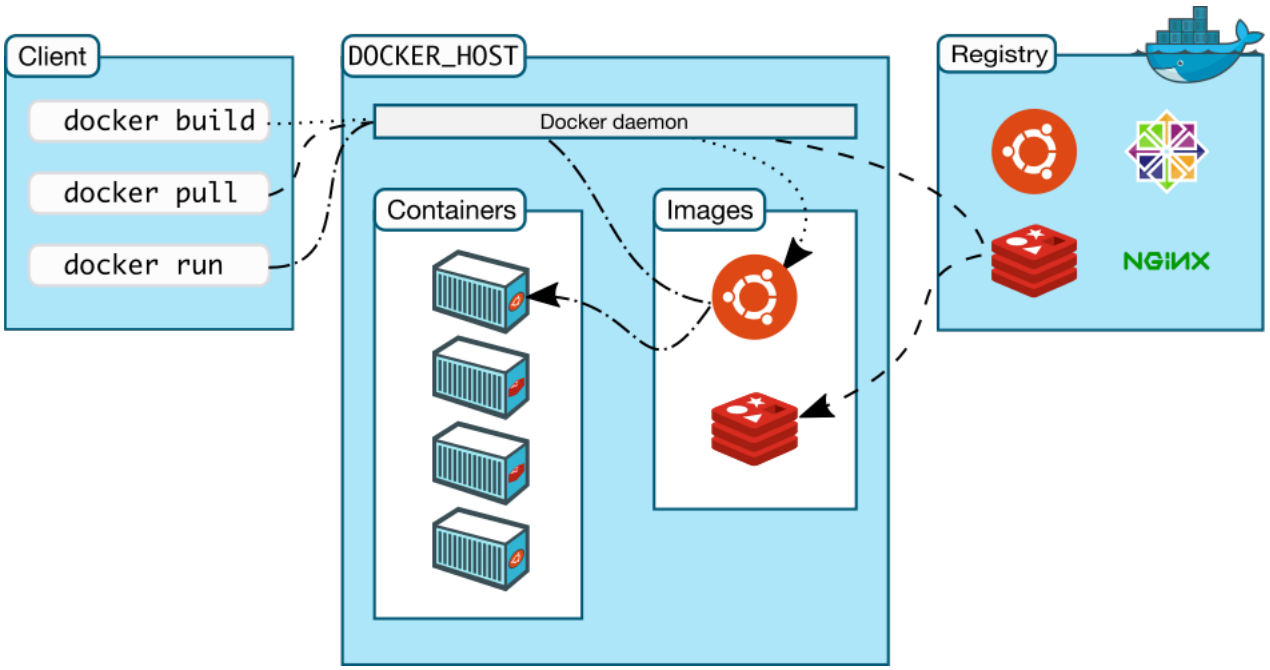


**Figure 2.5:** Docker architecture - Source: Authors own model, based on [Inc20].

**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 [Inc20].

### 2.2.2 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 and configurations that are needed for the application to run properly [Inc20, 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].

```
FROM ubuntu:latest

RUN apt-get update && apt-get install -y git

ENTRYPOINT ["git"]
```

**Listing 2.1:** Example of a Dockerfile

Listing 2.1 provides an example of a Dockerfile with three instructions.

1. `FROM ubuntu:latest` - This image is build on top of the latest Ubuntu image. Dockerfiles have to start with a `FROM` instruction [NK19].

2. `RUN apt-get update && apt-get install -y git` - Update the package manager and install Git.
3. `ENTRYPOINT ["git"]` - Set the git command as the entrypoint of this image.

**TODO: Vielleicht noch erklären wie Images mit Docker build erstellt werden.**

### 2.2.3 Docker Container

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

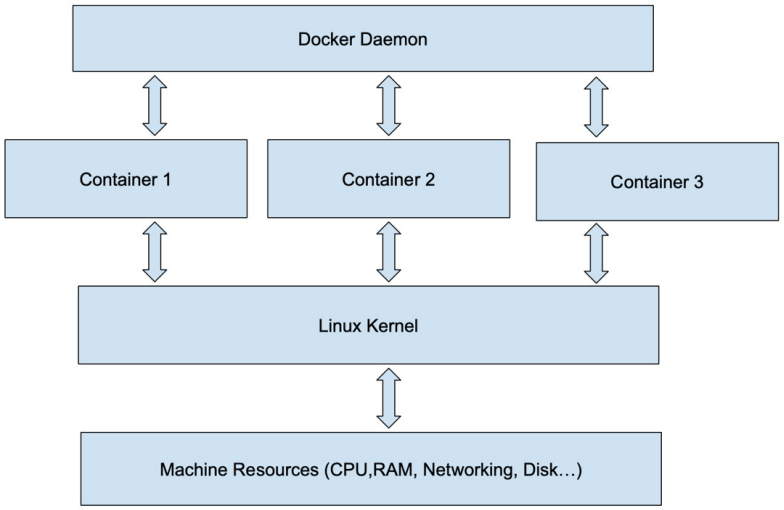


**Figure 2.6:** Docker basic container structure - Source: Authors own model, based on [BMDM20].

The advantage of a container is its lightweight nature. As illustrated in Figure 2.6, containers take advantage of OS-level virtualization instead of hardware-virtualization without the need of a hypervisor [Inc20, 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 [Inc20]. 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].

### 2.2.4 Docker Compose

Docker Compose is a tool to run multi-container applications on a single host. A multi-container application consists of a stack of services, where each service is deployed as a container [BMDM20, Inc20]. Services can be configured in a YAML[1] file called *docker-compose.yml*. This file defines the requirements of each service and determines how a service communicates to other services [KK18].

**TODO: Beispiel docker-compose**

1 YAML Ain't Markup Language - https://yaml.org/

## 2.3 Apache Spark

Apache Spark is an open-source computing framework for parallel data processing on a large computer cluster. Spark manages the available resources and distributes computation tasks across a cluster to perform big-data processing operations at large scale [CZ18]. Before 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[2], a JVM-based language and provides a programming interface for Scala, Java[3], Python[4] and R[5]. In addition, Spark includes an interactive SQL shell and libraries to implement Machine Learning and streaming applications [CZ18]. It was developed in 2009 as the Spark research project at UC Berkeley and became an Apache Software Foundation project in 2013 [CZ18].

### 2.3.1 Spark programming model

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

**TODO: Master-Slave Architektur + Bild**

**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 batched stream processing [ZCD+12]. RDDs have been implemented in Spark and serve as the underlying data structure for higher level APIs (Spark structured API) [ZCD+12]. RDD's are a immutable, partitioned collection of records and can only be initiated through transformations (e.g. map, filter) on data or other RDD's. 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 Spark automatically optimize the execution for structured API operations [CZ18].

**Spark structured API:** Spark provides high level structured APIs for manipulating all kinds of data. The three distributed core types are Datasets,

2 Scala programming language. https://www.scala-lang.org/
3 Java programming language. https://www.oracle.com/java/
4 Python programming language. https://www.python.org/
5 R programming language. https://www.r-project.org/

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 Spark internal optimized format for computations. This has advantages over JVM types which comes with garbage collection and object instantiation [CZ18].

**Spark Catalyst:** Spark also provides a query optimizer engine called Spark Catalyst. Figure 2.7 illustrates how the Spark Catalyst optimizer automatically optimizes Spark applications to run quickly and efficient. Before executing the user‘s 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 will be generated into Java bytecode for execution across the cluster [Luu18].

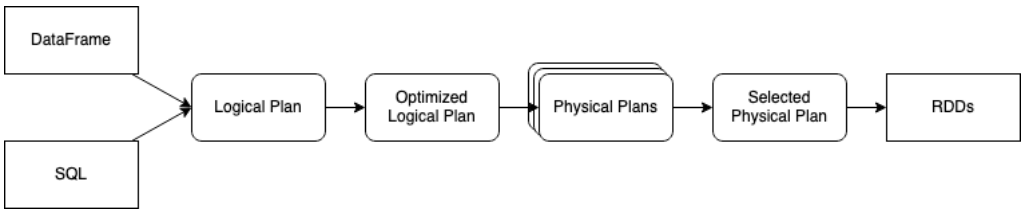


**Figure 2.7:** Optimization process of the Spark Catalyst - Source: Authors own model, based on [Luu18].

**TODO: Bild nochmal machen mit abstand + QUELLE anpassen**

## 2.3.2 Spark application architecture

**TODO: Lieber Doch Master/Slave ???. Was ist mit dem CLuster-Manager**

**TODO: Nicht ganz richtig, Master und Worker sind machines und driver und executor sind prozesse**

Figure 2.8 illustrates the main architecture of a Spark cluster. The architecture follows the master-worker model where the Spark driver is the master and the Spark executors are the worker [Luu18].

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

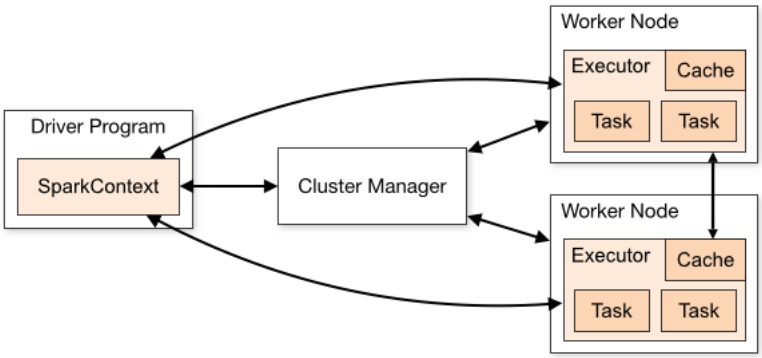


**Figure 2.8:** Overview of a Spark cluster architecture - Source: Authors own model, based on [Apa20].

**Spark Executor:** A Spark executor performs the tasks given by the Spark driver [CZ18]. It runs as a JVM process and runs until the Spark application finishes [Luu18]. After the executor finishes, it reports back to the Spark driver [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 the machines in the cluster [Luu18, Apa20]. The cluster manager knows about the resources of each worker and decides on which machine the Spark driver process and the executor processes run [Luu18, CZ18]. Spark supports different services that can run as the cluster manager: Standalone, Apache Mesos[6], Hadoop YARN[VMD+13] and Kubernetes[7] [Apa20]. The cluster manager provides three different deploy modes for acquiring resources in the cluster.

**TODO: Explain standalone**

- Cluster mode
- Client mode
- Local 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 Spark application on machines inside the cluster [CZ18, Luu18].

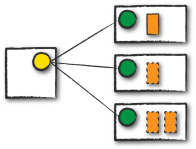

**Figure 2.9:** Spark's cluster mode - Source: Authors own model, based on [CZ18].

6 Apache Mesos. https://mesos.apache.org/
7 Kubernetes. https://kubernetes.io/

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].

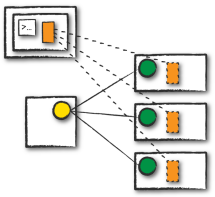

**Figure 2.10:** Spark's client mode - Source: Authors own model, based on [CZ18].

The local mode starts a Spark application on a single computer [CZ18]. It is not recommended to use the local mode in production, instead it should be used for testing Spark applications or learning the Spark framework [CZ18].

### 2.3.3 Spark application implementation

The concept of a Spark application consists of calling transformations and actions. A transformation creates a DataFrame or a Dataset, the logical data structures of a Spark application. The computation of a Spark application gets processed when an action gets called in the application. The transformations of a Spark application build up a directed acyclic graph (DAG) of instructions. By calling an action, the DAG will break down into stages and tasks to create a single job for execution [CZ18].

```
# Initialize a SparkSession
sparkSession = SparkSession\
    .builder\
    .getOrCreate()

# Create a dataframe with a transformation
dataframe = sparkSession.range(1, 1000)
# Apply another transformation
dataframe = dataframe.filter(dataframe.id % 2 == 0)
# Call an action
count = dataframe.count()
```

**Listing 2.2:** Example of a Python3 Spark application

Listing 2.2 demonstrates an example implementation of a Spark application. At first a SparkSession gets initialized. Each Spark application must include a SparkSession to initialize the application driver and executors [CZ18]. In Addition, the SparkSession provides an API for data-processing logic and configuration of the Spark application [Luu18]. After that, a DataFrame gets created with the range transformation to include each number from 1 to 1000 in the DataFrame. Next, a filter transformation is applied on the DataFrame to sort out any odd number. At the end, the number of rows gets saved in a variable with the count action.

**TODO: Create listing macro**

**TODO: Tabelle von Luu18 vll als Anhang(Table 2-1 Subdirectories Inside the spark-2.1.1-bin-**

The Spark framework provides a spark-submit executable to launch a Spark application inside a cluster.

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

**Listing 2.3:** Execution of a Spark Python application using the spark-submit executable

Listing 2.3 provides an example how the spark-submit executable can be used to launch a Spark Python application.

### 2.3.4 Spark standalone cluster deployment

**TODO: Why only standalone**

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

Spark provides build-in scripts to start a master node and worker nodes in standalone mode. ABC demonstrates how a master node and worker node gets launched using the build-in scripts.

## 2.4 RAPIDS accelerator for Apache Spark

The RAPIDS accelerator for Apache Spark is a plugin suite to enable GPU acceleration for computing operations on Apache Spark 3.x [Spa20]. To accelerate computing operations, it uses the RAPIDS[8] libraries and extends the Spark programming model (see Subsection 2.3.1) [Spa20, McD20].

### 2.4.1 Extension of the Spark programming model

The plugin suite extends the Spark programming model with a new DataFrame based on Apache Arrow[Fou20] data structures and the Catalyst optimizer to generate GPU-aware query plans [McD20].

Apache arrow is a data platform to build high performance applications that work with large dataset‘s 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 [Fou20].

Spark‘s DataFrame and SQL use the RAPIDS APIs to run tranformations and actions on a GPU. The Spark Catalyst optimizer identifies operator in a query plan that are supported by the RAPIDS APIs. 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

8 Open GPU Data Science - https://rapids.ai/

operations [McD20]. Figure 2.11 illustrates, how a query plan gets optimized with the RAPIDS accelerator for Spark enabled.

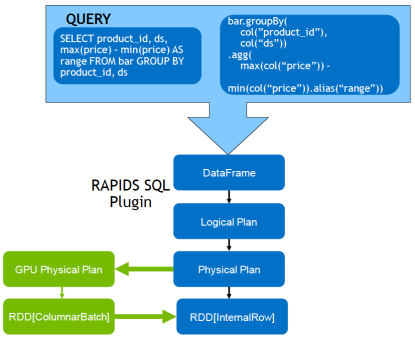


**Figure 2.11:** Catalyst optimization with RAPIDS accelerator for Apache Spark - Source: Authors own model, based on [McD20].

## 2.5 Prometheus

Prometheus is an open-source monitoring and alerting system [Pro20]. To collect and store data, Prometheus supports a multi-dimensional key-value pair based data model which can be analyzed in real-time using the PromQL query language [SP20]. It follows the pull-based approach to scrape metrics from hosts and services [BP19].

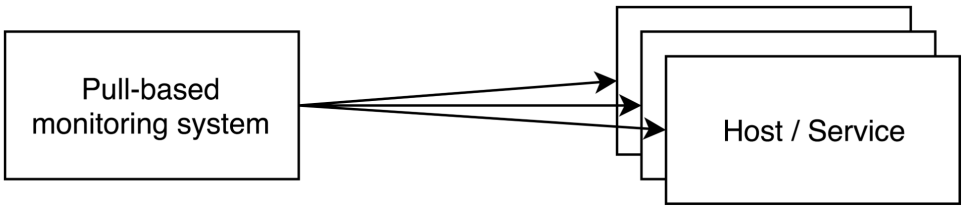


**Figure 2.12:** Pull-based approach to scrape metrics - Source: [BP19].

As Figure 2.12 demonstrates, a pull-based monitoring system scrapes metrics from services which makes them available for the monitoring system. In this case, the monitoring system needs a list of all hosts and services to monitor [BP19].

A monitoring system keeps track of the health status of components in a computing cluster. Because of the complexity of modern computing clusters, the effort is to high to observe components manually [BP19].

A metric is an observed property of software or hardware, e.g. the usage of a CPU core. To measure metrics, data-point‘s will be recorded at a fixed time interval. A data-point is a pair of a value and a timestamp. The combination of multiple data-point‘s is called a time-series [Tur16].

### 2.5.1 Prometheus architecture

**TODO: Bilder für components**

Figure 2.13 illustrates the high-level architecture of Prometheus. The Prometheus ecosystem provides multiple components. Components can

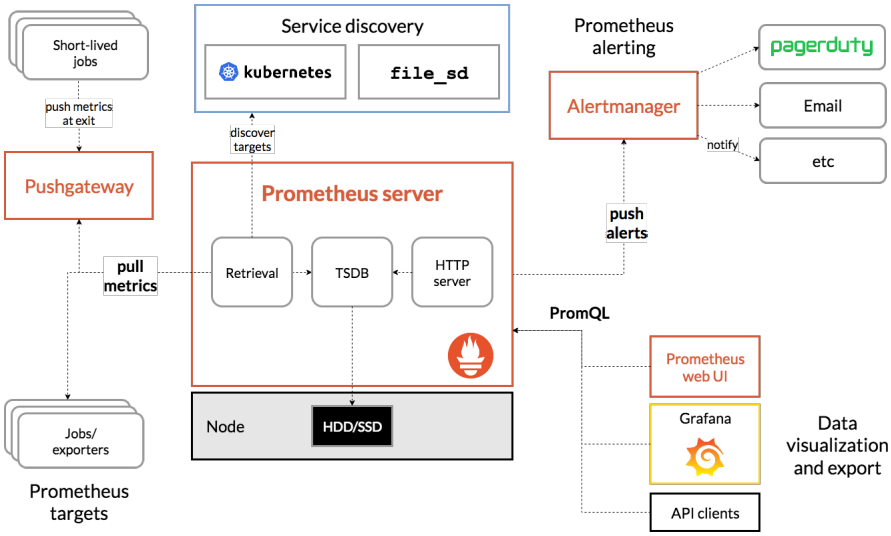


**Figure 2.13:** Prometheus high-level architecture - Source: Authors own model, based on [Pro20, BP19].

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, Pushgateway and visualization tools [Pro20].

**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 [Pro20].

**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 metric from the host and exports them to the Prometheus server [SP20].

**Pushgateway:** If a target is not designed to be scraped, metrics can be pushed against the Pushgateway[Pro20]. The Pushgateway 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[9] is one of the widely used tools for this occasion.

### 2.5.2 Monitoring Docker container

**TODO: Wahrscheinlich erst nach der implementation**

## 2.6 Gitlab

## 2.7 K-MEANS

## 2.8 Naive Bayes Classifier

## 2.9 Scaling heat

## 2.10 KHP

9 Grafana: The open observability platform - https://grafana.com/

Chapter 3

# Related Work

This chapter provides background information about ...

**TODO: Describe Chapter**

## 3.1 Elastic Environments

In recent years, container technologies have been used efficiently in complex IT environments. Dynamic scaling of containerized applications is an active area of research. The studied research can be divided in two parts.

### 3.1.1 Architecture

In the work by Lorido-Botrán et al. they reviewed state-of-the-art literatures about auto-scaling and proposed a process for auto-scaling homogeneous elastic applications. They mentioned three different problems, auto-scaler face while remaining the Quality of Service (QoS): Under-provisioning, over-provisioning and oscillation. Under-provisioning refers to, if not enough resources are available, over-provisioning means that more resources are available than needed and oscillation occurs when the environment gets scaled too quickly before the impact is clear. They mentioned the MAPE-Loop which consists of four different parts: Monitor, Analyze, Plan and Execute. The Auto-Scaler is part

### 3.1.2 Auto-Scaler

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. For example *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 systems management. In Addition, the authors proposed a new auto-scaling technique. 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%.

### 3.1.3 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.

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.

## 3.2 Heterogenous GPU aware Spark systems

Apache Spark is a computing framework that distributes tasks between CPU cores. Data and compute intensive applications profit from GPU acceleration. Therefore, various research projects took effort to bring GPU acceleration to Apache Spark.

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 Spark applications and invokes the GPU kernel for acceleration. For communication between CPU and GPU, HeteroSpark uses the Java RMI[1] API to send data from the CPU JVM to the GPU JVM 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 heterogeneous modification of Apache Spark. HetSpark extends Apache Spark with two executors, a GPU accelerated executor and a commodity class. The GPU accelerated executor is based on VineTalk[MPK+17] for GPU acceleration. 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 to enable parallel processing with GPUs in Apache Spark and contributes to achieve high performance and high throughput in Apache Spark applications. SparkGPU extends Apache Sparks to determine the suitability of parallel-processing for a task to enable task scheduling between CPU and GPU. SparkGPU accomplished to improve the performance of machine learning algorithms up to 16.13x and SQL query execution performance up to 4.83x.

1 Java Remote Method Invocation

Chapter 4

# Conceptual Design

## 4.1 Cluster Architecture

**TODO: Describe Chapter**

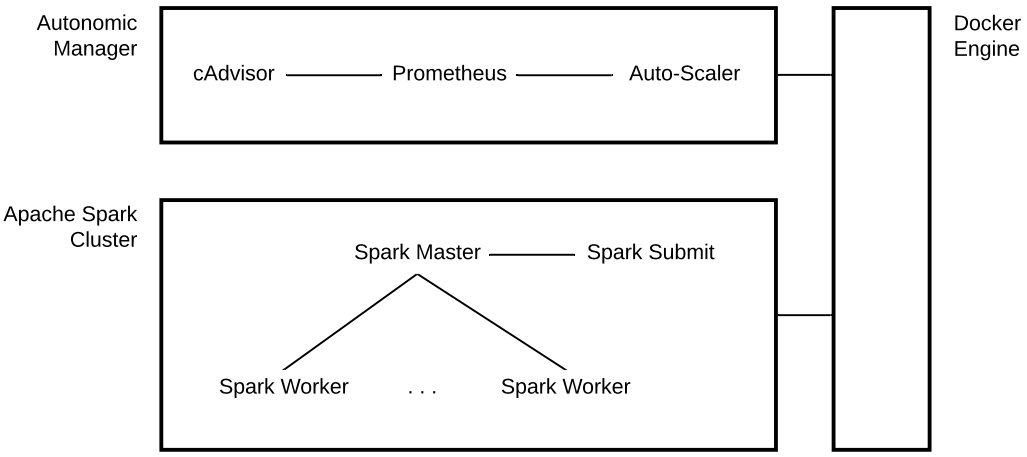


**Figure 4.1:** Scaling process UML activity model - Source: Authors own model.

The cluster consists of two main parts, the Autonomic Manager and the Apache Spark cluster. The autonomic manager consists of three components, cAdvisor for collecting metrics from all running Docker container, Prometheus to store metrics and the auto-scaler to scale the number of Spark worker according to the workload. The Apache Spark cluster is the computing environment, consisting of one Apache Spark master and a dynamic number of Apache Spark worker. A Spark-Submit component which will deployed if a Spark application gets executed in the cluster. Each component is supposed to be a Docker container running on the same host. The autonomic manager and the Apache Spark cluster have its own Docker network. The autonomic manager and the Apache Spark cluster don't communicate between each other.The autonomic manager gets its metrics directly from the Docker engine and sends instructions to the Docker engine to scale the number of Spark worker.

## 4.2 Apache Spark Cluster

The Apache Spark cluster is responsible to execute the computing application. It consists of one Apache Spark Master and a dynamic number of Apache Spark Worker. To create a Apache Saprk cluster, the master and all worker are deployed in standalone mode (described in section XY). All Spark components run in a single isolated Docker network.

### 4.2.1 Computing Environment

Computing environment consists only of Apache Spark Master and Spark worker. All Spark components are deplyed in standalone mode and each is a single container in the same Docker network. The Apache Spark master distributed the workload of an application across all available spark worker.

### 4.2.2 Spark Submit

Spark submit is a single component in the Apache Spark cluster. It is a Apache Spark submit runtime running in a single Docker container. Whenever a Saprk application needs to be executed, a Spark submit container gets deployed in the Apache Saprk and submits the application to the Spark master. After completion, the Spark submit container gets removed automatically.

## 4.3 Autonomic Manager

The autonomic manager is implemented according to the MAPE architecture (introduced in SECTION AB). It is responsible to monitor the CPU and GPU utilization of all running Spark Worker and dynamically scales the number of Spark worker based on the observed metrics. As illustrated in Figure 4.1, the autonomic manager consists of three components to compose an autonomic manager.

### 4.3.1 Workflow

As illustrated in Figure 4.2, the workflow of the autonomic manager is implemented as a loop. In each iteration, the autonomic manager collects and analyzes related metrics. If needed, the autonomic manager will create a scaling plan and execute it in the end of an iteration.

Following, each step is described in detail:

1. **Collect metrics:** CPU and GPU metrics need to be collected from the Docker engine. The collected data needs to be filtered aggregated.

2. **Analyze metrics:** Collected metrics need to be analyzed to determine if a scaling action is need. If the computing environment runs smoothly

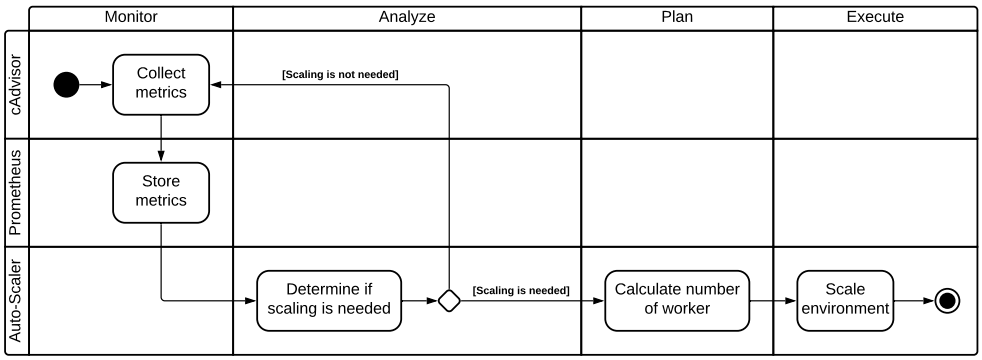


**Figure 4.2:** Scaling process UML activity model - Source: Authors own model.

and no scaling action is needed, the first two steps will be repeated until a scaling action is necessary.

3. **Create scaling plan:** If the computing environment has to be scaled, a scaling plan will be generated. The scaling plan consists of instructions how many Spark worker have to added or removed.

4. **Execute scaling plan:** The created scaling plan will be executed to accommodate the performance goals of the environment.

### 4.3.2 Design

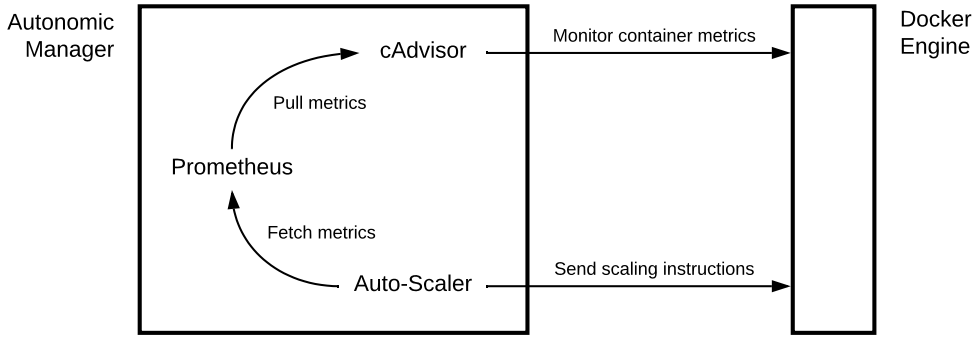


**Figure 4.3:** Scaling process UML activity model - Source: Authors own model.

The autonomic manager consists of three different components: cAdvisor, Prometheus, Auto-Scaler. Each components has a different responsibility.

cAdvisor constantly monitors all Docker containers in the environment and makes perormance and system metrics available via its API. Prometheus pulls the metrics from cAdvisor. The metrics can be filtered and aggregated via Prometheus PromQL language. In addition, Prometheus stores metrics as time-series data in its database. cAdvisor and Prometheus perform the monitor phase of the MAPE architecture.

The Auto-Scaler is responsible for the analyze, plan and execute phase. Each interval, the Auto-Scaler obtains the CPU and GPU metrics from the Prometheus API. It analyzes the metrics to determine if a scaling action is needed and creates and executes a scaling plan.

Each component of the autonomic manager is supposed to execute in an individual Docker container. To establish an isolated communication across all three components, all Docker container run in a single Docker network which is exclusively for the autonomic manager.

## 4.4 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 the architecture demonstrated in Subsection 2.1.3. In addition, the Auto-Scaler implements the control-loop which is responsible to make adjustments in the environment. Since Prometheus collects and stores available metrics from cAdvisor, the Auto-Scaler has not to communicate with cAdvisor.

### 4.4.1 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.

### 4.4.2 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.

### 4.4.3 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.

### 4.4.4 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.

## 4.5 Metrics

### 4.5.1 CPU Utilization

**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:

$$CPUUtilization = \frac{\sum SparkWorkerCPUUtilization}{NumberOfSparkWorker} \tag{4.1}$$

### 4.5.2 GPU Utilization

$$GPUUtilization = \frac{\sum SparkWorkerGPUUtilization}{NumberOfSparkWorker} \tag{4.2}$$

Chapter 5

# Implementation

## 5.1 Cluster architecture

**TODO: Describe Chapter**

Chapter 6

# Evaluation

## 6.1 Cluster architecture

**TODO: Describe Chapter**

Chapter 7

# Outlook

## 7.1 Cluster architecture

**TODO: Describe Chapter**

Chapter 8

# Conclusion

## 8.1 Cluster architecture

**TODO: Describe Chapter**

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