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Automated Deployment of Machine Learning Applications on a Scalable Heterogeneous GPU-Accelerated Apache Spark Cluster

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Zusammenfassung

Die wachsende Rechenkomplexität beim trainieren von Machine Learning-Modellen mit Big Data erfordert eine Erhöhung der Skalierbarkeit von Rechenclustern. In verteilten Systemen kann ein Rechencluster dynamisch skaliert werden, sobald eine Leistungsschwelle erreicht wird. Ein beliebtes Framework für verteiltes Rechnen ist Apache Spark, das die parallele Datenverarbeitung auf einem Rechencluster ermöglicht. Mit der jüngsten Entwicklung der RAPIDS-Plugin-Suite kann die Rechenleistung weiter gesteigert werden, indem Apache Spark die Nutzung von GPUs ermöglicht wird. Außerdem ist durch die Popularität der DevOps-Kultur die Automatisierung von Entwicklungsprozessen zu einem trivialen Prozess geworden. Das Training von Machine Learning-Modellen ist ein komplexer Prozess, der mithilfe einer CI-Pipeline automatisiert werden kann. Ziel dieser Arbeit ist es, ein Entwurf und die Implementierung einer skalierbaren verteilten Rechenumgebung für das Training von Machine Learning-Modellen mit Apache Spark vorzustellen. Dazu wird die Leistung des Apache Spark-Clusters durch die Nutzung von GPUs unter Verwendung der RAPIDS-Plugin-Suite erhöht. Ein *Auto-Scaler*, der die Anzahl der Apache Spark-Worker skaliert, wird implementiert und der Rechenumgebung hinzugefügt, um die Skalierbarkeit weiter zu erhöhen. Darüber hinaus wird ein CI-Pipeline-Entwurf und eine Implementierung mittels GitLab CI/CD vorgestellt, die das Training einer Machine Learning-Anwendung auf Apache Spark automatisiert. Die Leistung der Rechenumgebung wird mit zwei unterschiedlichen Machine Learning-Algorithmen bewertet. Die Ergebnisse zeigen, dass die Leistung des Apache Spark-Clusters durch die Verwendung von GPUs signifikant verbessert wurde, während die *Auto-Scaler*-Implementierung die Leistung des Apache Spark-Clusters nicht erhöht hat.

Abstract

The growing computational complexity of training Machine Learning models on Big Data requires increasing the scalability of computing clusters. With distributed computing, a cluster can dynamically be scaled whenever a performance threshold is reached. A popular framework for distributed computing is Apache Spark, which enables parallel data processing on a large computing cluster. With the recent development of the RAPIDS plugin suite, the computational power can further be increased by enabling Apache Spark to leverage GPUs. Furthermore, due to DevOps culture popularity, automating development processes has become a trivial process. The training of machine learning models is a complex process that can be automated using a CI pipeline. This thesis aims to present a design and implementation of a scalable distributed computing environment for training Machine Learning models using Apache Spark. Therefore, the Apache Spark cluster's performance is increased by leveraging GPUs using the RAPIDS plugin suite. An *Auto-Scaler* that scales the number of Apache Spark workers is implemented and added to the computing environment to increase the scalability further. Additionally, a CI pipeline design and implementation using GitLab CI/CD is introduced, which automates the deployment of an application to the Apache Spark cluster. The performance of the computing environment is evaluated using two different Machine Learning algorithms. The results show that the performance of the Apache Spark cluster has significantly been improved using GPUs, whereas the *Auto-Scaler* implementation did not increase the performance of the Apache Spark cluster.

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API	Application Programming Interface
CD	Continuous Delivery/Deployment
CI	Continuous Integration
CLI	Command-Line Interface
CPU	Central Processing Unit
CUDA	Compute Unified Device Architecture
DCGM	Data Center GPU Manager
ETL	Extract-Transform-Load
GPU	Graphical Process Unit
HTTP	Hypertext Transfer Protocol
JAR	Java ARchive
JRE	Java Runtime Environment
JVM	Java Virtual Machine
KHPA	Kubernetes Horizontal Pod Auto-Scaling
ML	Machine Learning
MAPE	Monitor Analyse Plan Execute
OS	Operating System
RDD	Resilient Distributed Dataset
RMI	Java Remote Method Invocation
SLA	Service Level Agreement
SDK	Software Development Kit
SQL	Structured Query Language
TSDB	Timeseries Database
URI	Uniform Resource Identifier
URL	Uniform Resource Locator
YAML	YAML Ain't Markup Language
XGBoost	XGBoost

Chapter 1

Introduction

This chapter introduces the concepts of distributed computing, GPU acceleration, auto-scaling, and automated deployment pipeline. Next, the research objective and the research questions, and the problem statement of this thesis is described. Finally, the structure of this thesis is explained.

1.1 Distributed Computing

Machine Learning (ML) and Big Data projects consist of combining 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 is 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 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 allows solving 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 chaining multiple MapReduce jobs together. This causes a huge amount of writing and reading operation to the disk with a 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 improvement 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 Central Processing Unit (CPU) cores to enable parallelism. A CPU is build of multiple cores that are optimized for sequential serial processing. Performing computationally intensive applications on an Apache Spark cluster consumes many CPU cycles with a 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. Graphical Process Units (GPUs) have become first class citizens in modern data centers to perform computationally complex applications with better performance. A GPU architecture 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 positively impact 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 deep knowledge about the environment and regularly watches performance spikes. This is a resource-wasting process. Optimally, an automized process would watch the computing environment, analyse performance metrics and automatically add or remove

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

resources to optimize the performance and cost of running. This process is called auto-scaling.

Hiring experts to manually watching an application and scaling a 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 a 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, it can take more throughput and perform more specialized tasks [LT15]. Adjusting the nodes in a computing environment is referred to as horizontal scaling [Wil12]. Increasing the number of nodes in an environment increases the overall computing capacity. Additionally, the workload can be distributed across all nodes [Wil12, LT15]. It is important to note that both approaches are not exclusive to 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 unavailable [LT11]. Therefore, horizontal scaling is the preferred approach to enable auto-scaling.

1.4 Automated Deployment Pipeline

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 application's 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 is implemented at the Center for Cyber Cognitive Intelligence at the Fraunhofer IPA[2]. At the IPA, CPU and GPU resources have only been combined to a limited extent in order to optimize machine learning model training. Therefore, an APache Spark cluster prototype is created, which automatically allocates resources depending on the load and thus scales itself. This results in the following research questions:

- RQ1: Is it possible to scale the number of Apache Spark Workers according 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 Apache Spark applications?

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 that 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 CPU.

The last research question has a more applied nature. Automating the development cycle of an application is a well-investigated topic. The IPA uses a platform called GitLab (introduced in Section 4.7), which provides an Application Programming Interface (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.

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

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 of available GPUs to accelerate the model training process.

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 must 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

Chapter 2 provides the theoretical foundation about concepts that have been introduced in this chapter. Chapter 3 focuses on related work that provides solutions to solve this thesis's given problems introduced in Section 1.6. In Chapter 4, all used technologies to implement the objective of this thesis are being introduced. Afterward, 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. Finally, Chapter 8 concludes this thesis and introduces further work, which has been discovered during this thesis's work, as well as improvements for the implementation.

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 is 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 cannot 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 an 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 can 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 for 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 available hardware. Additionally, changing the physical hardware of a running system can require a downtime. For most systems, 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. Furthermore, 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 automated scripts validate each change on a primary codebase. 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 times [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 been made to the code base. Each run is processed the 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 for monitoring the code base for changes. If a change is committed, the build server automatically executes the CI scripts in order [Ros17, DMA07].

3. Build scripts: 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 sequence to integrate the software. Finally, the CI server sends feedback to inform the developer about the build script status [DMA07].

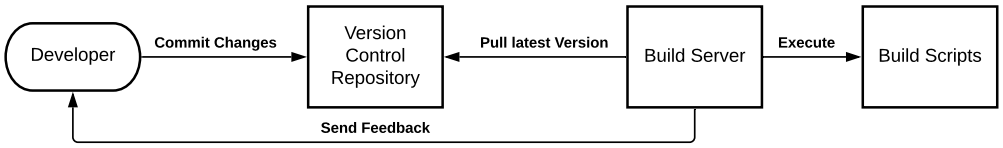

Figure 2.1: Continuous Integration Scenario - Source: Authors own model, based on [DMA07].

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.

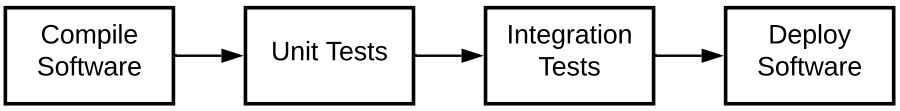

Figure 2.2: An example of a logical build script order for a CI process- Source: Authors own model, based on [DMA07].

2.3 Autonomic Computing

Autonomic computing is the ability of an IT infrastructure to automatically manage itself according 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 autonomous [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 can efficiently maximize resource allocation and utilization [JSAP04]. To accomplish this requirement, the environment must monitor all resources to determine if an action is needed [Mur04].
- Self-healing: Self-healing environments can detect problematic operations and then perform policy-based actions to ensure that the system's health is stable [Sin06, JSAP04]. The actions' policies 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 by 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 sensors and an adoption engine (autonomic manager) to manage resources

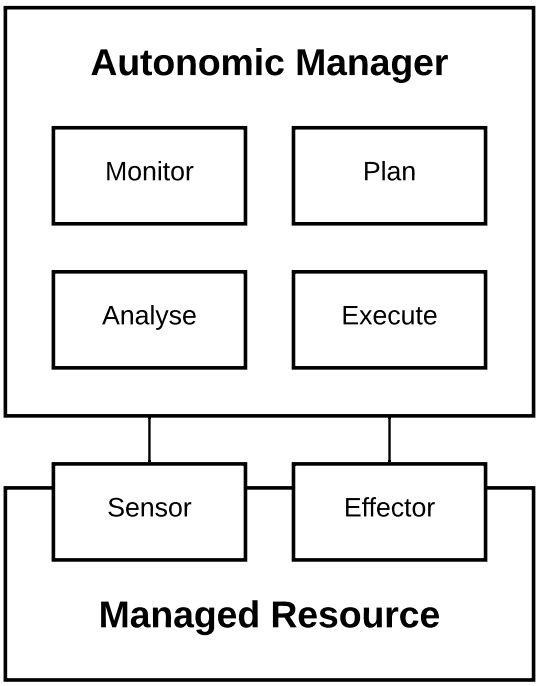

Figure 2.3: Autonomic computing concept - Source: Authors own model, based on [JSAP04].

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

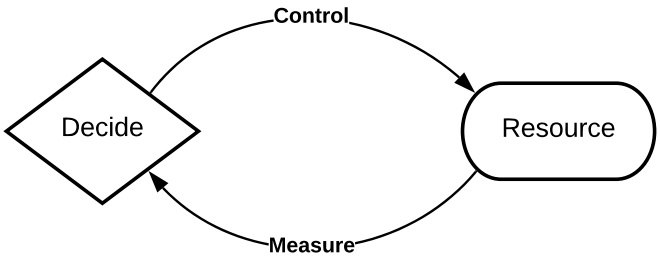

Figure 2.4: The control-loop concept - Source: Authors own model, based on [Mur04].

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].

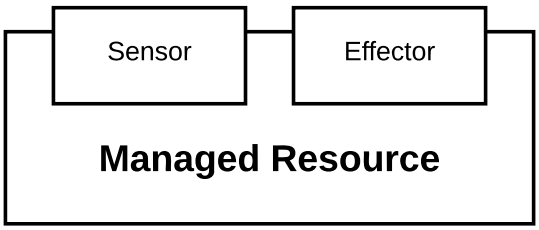

Figure 2.5: Managed resource - Source: Authors own model, based on [JSAP04].

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

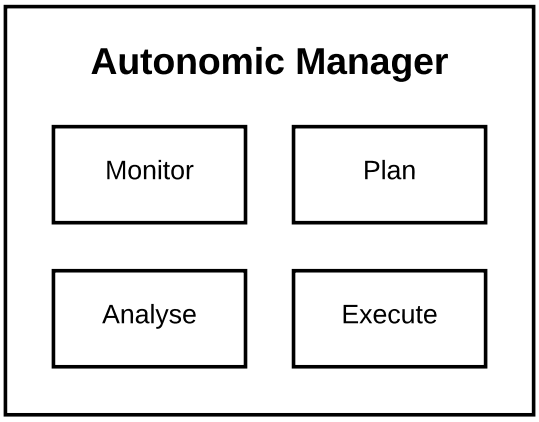

Figure 2.6: Autonomic manager - Source: Authors own model, based on [JSAP04].

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 scope and uses predefined policies to decide 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 for collecting 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 be made to the environment [Sin06]. To predict future situations, the autonomic manager can model complex situations 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 managers 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 managers can be composed together [Sin06].

2.4 Performance Metrics

Performance metrics are statistics that describe the system's 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 effect on the target performance [Gre20].

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

The performance of a hardware resource can degrade significantly if the utilization approaches 100%. Hardware that can perform work in parallel might not have a performance degrade at 100%. That hardware can 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 multiple components responsible for performing measurements on components in the computing environment and collecting, storing, and interpreting the monitored data [Lig12].

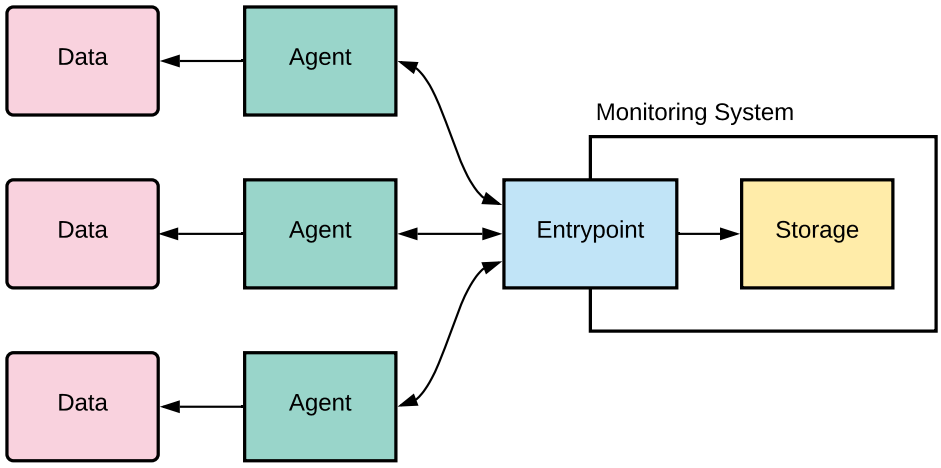

Figure 2.7: The monitoring process

In the monitoring process, illustrated in Figure 2.7, data is continuously collected by agents. An agent is a process that continuously gathers data from a target. The data can be device statistics, logs, or system measurements. A pull-based monitoring system pulls the data from all specified agents. In contrast, push-based monitoring expects data to be pushed from agents. These two approaches are described in Section 2.5.2. After the monitoring system has received the data, it groups the data into metrics and stores the metrics in its database [Lig12].

The requirements for a monitoring system that can 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]
- A multi-dimensional data-model [Far17]
- A powerful query language [Far17]

2.5.1 Database

Continuous data needs to be stored in the most efficient way. Time-series databases (TSDBs) are optimized to store and retrieve time-series data. In a TSDB, metrics are 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 gather 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 monitoring system's existence 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].

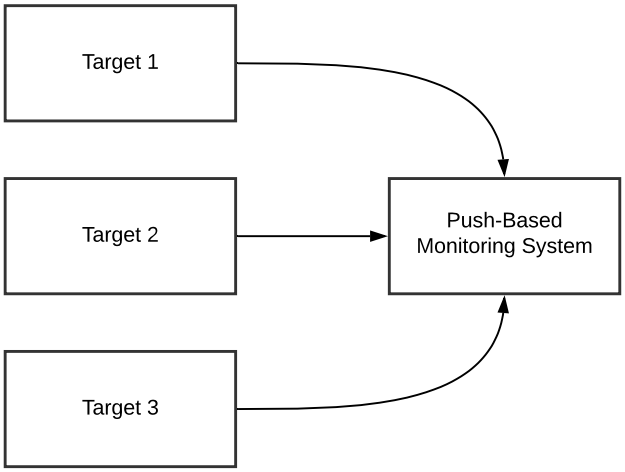

Figure 2.8: Push-based monitoring approach

In a push-based environment, services only need to know the monitoring service's address 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 Data Model

Metrics are store as time-series data, where a time-series is a combination of a name and a set of optional key-value pairs called labels. The name of a time-series identifies the metric which is measured. Labels provide a multi-dimensional data-model to the stored data. Each combination of labels represents a specific dimensional instantiation of a metric [Thed]. In a dynamic environment, services are dynamically added and removed. Therefore, a dynamic environment needs a multi-dimensional data model to represent all dimensions in the environment [Far18]. A powerful query

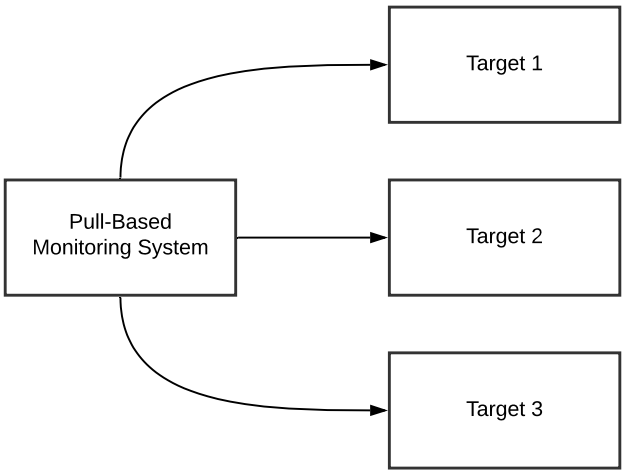

Figure 2.9: Pull-based monitoring approach

language that provides capabilities to perform aggregations and filtering on dimensions is needed in addition to a multi-dimensional data model.

```
container_cpu_user_seconds_total
```

Listing 2.1: Example of a dimensionless-metric

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

Listing 2.2: Example of a metric with dimensions

Listing 2.1 provides an example of a metric without labels, and Listing 2.2 shows an example of a metric with a label. As the examples show, The metric with a label provides more efficient querying to gather specific information about a metric.

Chapter 3

Related Work

This chapter provides an overview of related literature for this thesis. Furthermore, the surveyed literature is built on the theoretical foundation introduced in Chapter 2. This chapter 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 literature about auto-scaling and explain auto-scaling process proposals in a cloud environment. It is mentioned that an *Auto-Scaler* is responsible to find a trade-off between meeting the Service Level Agreement (SLA) and keeping the cost of renting resources low. Two types of SLA exists while maintaining an acceptable trade-off: The application SLA and the resource SLA. The former is a contract between the application owner and the end-users (e.g., a certain response time). The resource SLA is agreed upon by the infrastructure provider and the application owner (e.g., 99.9% availability). They introduced three problems *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: Applications with more resources available than needed will lead to unnecessary costs for the client.

3. Oscillation: If scaling-actions are 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 allows preventing oscillation.

To prevent the mentioned problems from occurring, the authors introduced and explained the MAPE architecture (cf. Section 2.3). MAPE consists of four different phases: Monitor, Analyse, Plan, and Execute. There exist *Auto-Scaler* proposals which only focus on the Analyse, and Planning phase architecture of the MAPE architecture. 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. There exist *Auto-Scaler* which uses techniques to predict the future state of the environment (e.g., reinforcement learning). These are called proactive *Auto-Scalers*. Reactive *Auto-Scalers* use techniques to respond to the environment's current status (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 is to balance the overall resource utilization across microservices in the environment. The proposed auto-scaling strategy performed better than state-of-the-art algorithms in processing time, processing cost, and resource utilization. The processing cost of microservices was reduced by 12-20%. The CPU and memory utilization of cloud-servers were maximized by 9-15% and 10-18%, respectively.

Lorido-Botrán et al. [LBMAL13] compared different representative auto-scaling techniques in a simulation in terms of cost and SLA 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 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 can 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 and is explained in detail in Section 4.8.2.

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 could 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, storing time-series data, and Grafana for visualizing metrics. Absolute metrics are more appropriate when it comes to efficient resource allocation. Therefore, the KHPA-A algorithm is more efficient in vertical scaling of resources. 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 4.9.

3.2 GPU accelerated Apache Spark Cluster

This thesis aims to enable GPU acceleration for Apache Spark. In research, many solutions have been proposed which try to solve the problem in similar ways. In the following, three different approaches are 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 Remote Method Invocation (RMI) API. To execute operations on the GPU, the CPU Java Virtual Machine (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 an 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 accelerated 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 built 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 of Apache Spark 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 Compute Unified Device Architecture (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 the 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.

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

To extend the programming API, SparkGPU provides a new Resilient Distributed Dataset (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.

SparkGPU can execute Structured Query Language (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. When memory contention happens, the library will ensure 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 literatures. In this sections the primary literature used throughout the implementation of this thesis work is being introduced.

The conceptual design and implementation of an automated deployment pipeline in this thesis were 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]. 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 code 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 provides information about the technologies and algorithms used for this thesis. It explains the fundamental concepts of Docker, Apache Spark, RAPIDS accelerator plugin, Prometheus, cAdvisor, and GitLab CI/CD. Additionally, the Scaling Heat, and Kubernetes Horizontal Pod Autoscaler algorithms are introduced.

4.1 Docker

Docker is an open-source platform that enables the 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 daemon [Doc].
- Docker Deamon: The Docker daemon manages all containers running on the host system and handles container resources, networks and, volumes [BMDM20].
- Docker Registry: A Docker registry stores images. Images can be pushed to or pulled from public or private registries to build a container [Doc].

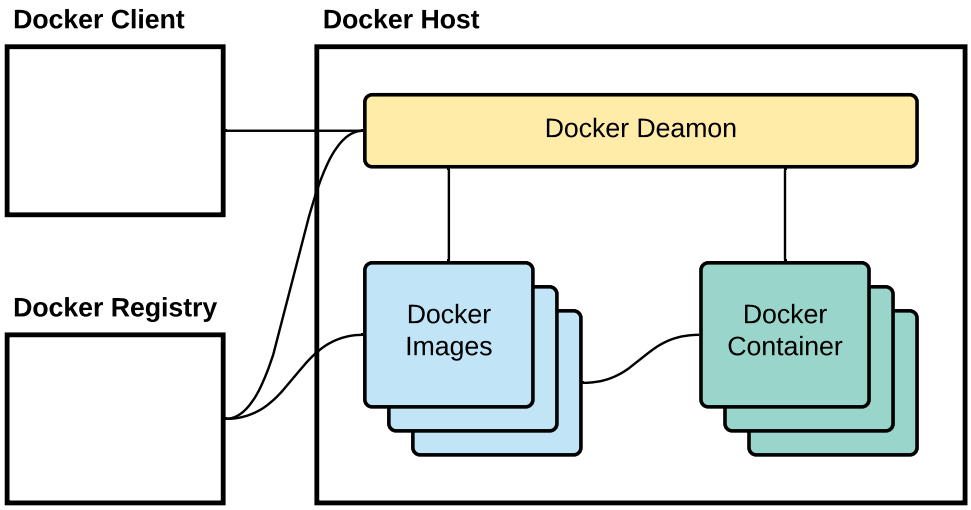

Figure 4.1: Docker architecture - Source: Authors own model, based on [Doc].

4.1.2 Docker Image

An Image is a snapshot of the environment 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 correctly [Doc, NK19]. Images can be created from existing containers or from executing a build script called *Dockerfile* [NK19].

Images can be built automatically by executing a build script called Dockerfile, a text document that contains specific build instructions. Instructions are commands which are executed in order to assemble an image. A Dockerfile must begin with a `FROM` instruction which defines the parent image from which the image is built [Doc].

Listing 4.1 provides a basic example of a Dockerfile. In the example, *ubuntu* is defined as the parent image at line 1. Next, from 3 to 4, the Ubuntu package list is updated, and the *nginx* package is installed using the `apt-get` command. Finally, at line 6, the Docker image is instructed to listen to port 80 at runtime with the `EXPOSE` instruction.

```
1 FROM ubuntu
2
3 RUN apt-get update -qy && \
4     apt-get install -y nginx
5
6 EXPOSE 80
```

Listing 4.1: Basic example of a Dockerfile

4.1.3 Docker Container

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

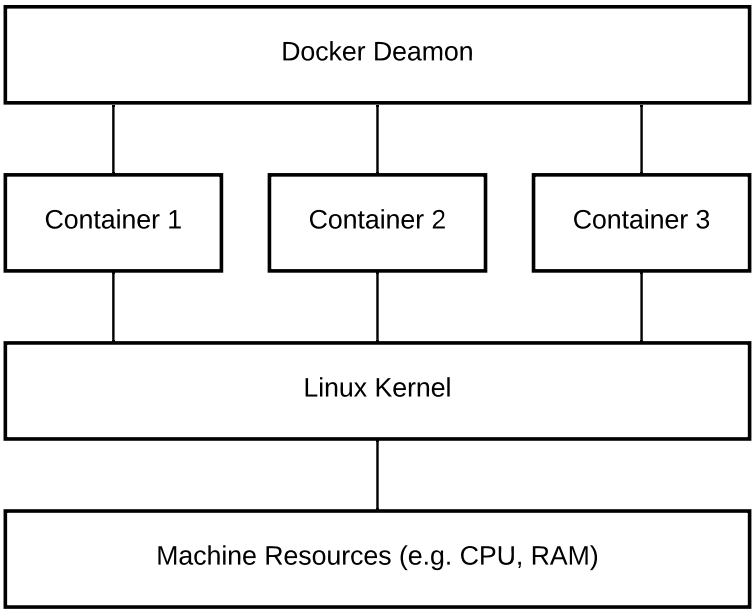

Figure 4.2: Docker basic container structure - Source: Authors own model, based on [BMDM20].

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 for 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 used to distribute and test applications. A container can be configured to expose specific 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 for maintaining the desired state of a service [Doc].

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

- Desired state: The manager node monitors each service's state 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 command-line interface (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 is defined for each service. The manager node automatically adapts 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, and new services will automatically be added to it [Doc].

Services and Tasks

A service 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 is managed by the manager node. A task can be executed on worker and manager nodes [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 and 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 are submitted to the manager node [Doc].

Worker nodes are responsible for executing the tasks received by the manager node. While performing tasks, the worker node notifies the manager node about each task state [Doc].

Stack

A stack is a named collection of first-class Docker resources (e.g., services, volumes, networks) that can be deployed to a swarm. The docker-compose file format allows describing a stack in a single YAML[1] file. With the `docker stack` command, a docker-compose file can be used to create a stack and deploy it to a swarm. Listing 4.2 provides an example of a stack described in the docker-compose file format. It defines two services called *prometheus* and *cadvisor*. Both services are attached to the *computing-net* network.

1 YAML Ain't Markup Language - `https://yaml.org/` (Accessed: 2021-02-18)

```
version: "3.7"

networks:
    computing-net:
        name: computing_net

services:
    prometheus:
        image: prom/prometheus:latest
        networks:
            - computing-net

    cadvisor:
        image: google/cadvisor:latest
        networks:
            - computing-net
```

Listing 4.2: Basic example of stack describes in the docker-compose file format

Listing 4.3 shows the usage of the `docker stack` command. It deploys a stack with the name *computing-stack* using a docker-compose file.

```
$ docker stack deploy -c computing-stack.yml computing-stack
```

Listing 4.3: Usage of the docker stack command to deploy a stack

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 a 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]. However, Spark accomplished to outperform Hadoop by 10x for iterative Machine Learning [ZCF+10] and is now one of the most popular frameworks for distributed computing. It is implemented in Scala[2], a JVM-based programming language. It provides a programming interface for Scala, Java[3], Python[4], and R[5]. Additionally, Apache Spark includes an interactive SQL shell and libraries to implement ML and streaming applications [CZ18].

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

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 are automatically optimized by the Catalyst optimizer to run operations quickly and efficient [CZ18, Luu18].

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].

Resilient Distributed Datasets

Resilient Distributed Datasets are fault-tolerant, parallel data structures to enable data sharing across cluster applications [ZCD+12]. They express different cluster programming models like MapReduce, SQL, and batched stream processing [ZCD+12]. RDDs have been implemented in Apache Spark and serve as the Spark structured API's underlying data structure [ZCD+12]. RDDs are an immutable, partitioned collection of records. They 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 Catalyst

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

Logical plans are created from a DataFrame or a SQL query and represent 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].

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

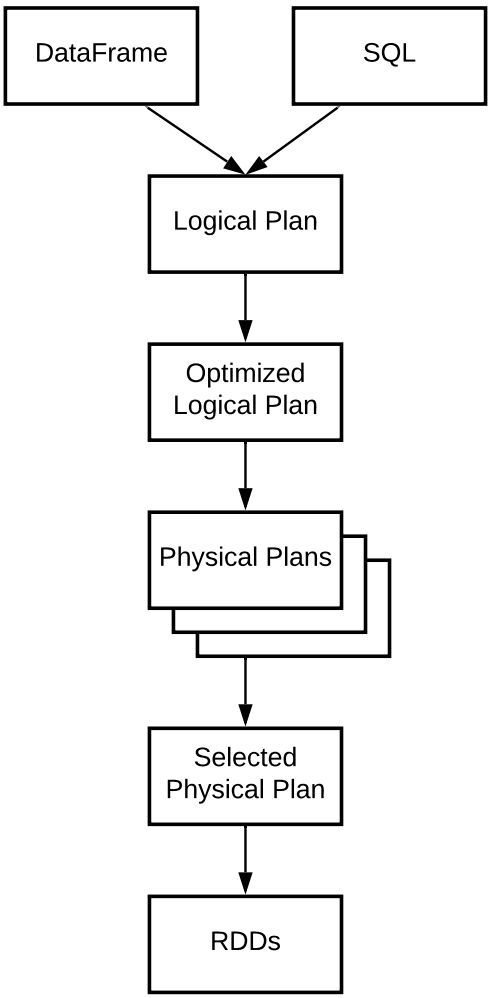

Figure 4.3: Optimization process of the Spark Catalyst - Source: Authors own model, based on [Luu18].

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. 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].

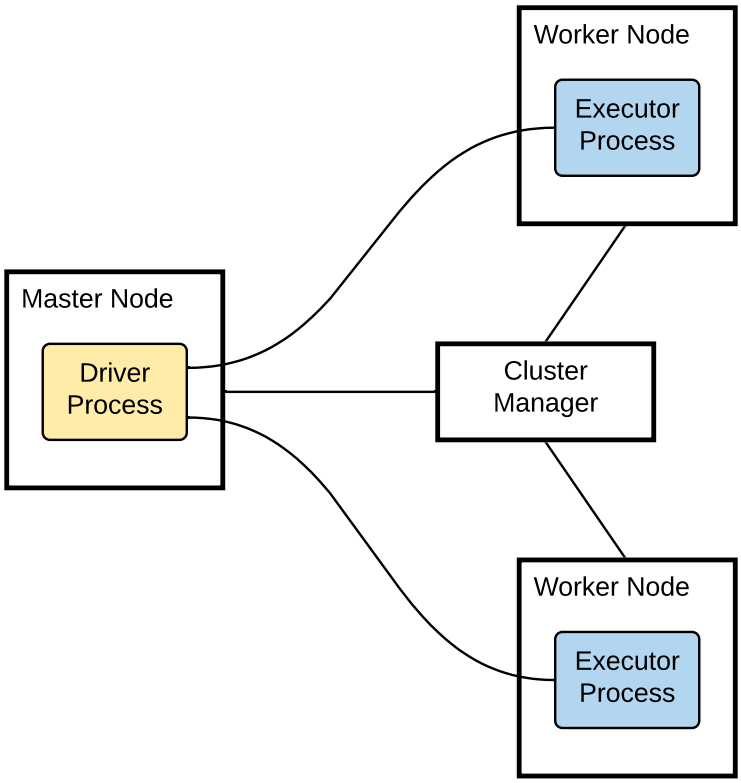

Figure 4.4: Overview of a Spark cluster architecture - Source: Authors own model, based on [Theb].

Driver Process

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

Executor Process

The executor process is a JVM process that runs through the whole duration of an application [Luu18, Theb]. It is responsible for performing all tasks (units of work) assigned by the driver process [CZ18]. After the executor process finishes, it reports back to the driver process [CZ18]. Each task is 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 the driver- and executor processes are launched in the cluster. Additionally, the cluster manager maintains each node's resources in the cluster [Luu18, CZ18].

Apache Spark supports different services that can run as cluster manager, such as Standalone mode (introduced in Section 4.2.3), Apache Mesos[6], Hadoop YARN[VMD+13], and Kubernetes[7] [Theb]. The cluster manager provides three different deploy modes for acquiring resources in the cluster.

- Cluster mode: To run an application in cluster mode, the user must submit a precompiled Java ARchive (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 only to run Apache Spark but supports workloads at a large scale [CZ18].

Starting Master and Worker Nodes

Apache Spark provides executable launch scripts to start master and worker nodes in standalone mode. Inside the Apache Spark installation directory, 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 Uniform Resource Identifier (URI) as a parameter [Theb].

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

Listing 4.4: Usage of master launch script

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

Listing 4.5: Usage of worker launch script

Listing 4.4 and Listing 4.5 provide an example of using both executables to start a master and a worker node. The URI `spark://spark-master:7077` in Listing 4.5 is an example of a master node URI. The master node launch script will print out the master URI after being executed successfully [Theb].

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

Resource Allocation

In standalone mode, workers 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) is 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].

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

Listing 4.6: Example usage of the spark-submit executable

Listing 4.6 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 by executing pipelines entirely on GPUs. It is available for Apache Spark 3 [NVI]. The plugin uses the RAPIDS AI cuDF[8] library to extend the Apache Spark programming model, introduced in Section 4.2.1 [NVI, McD20, APW19].

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[9] data structures. The new DataFrame API aims to accelerate loading, filtering, and manipulation operations on large datasets. In addition, the Catalyst optimizer (described in Section 4.2.1) is extended to generate GPU-aware query plans [McD20, APW19]. Apache arrow is a data platform to build high-performance applications that work

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

with large datasets and 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].

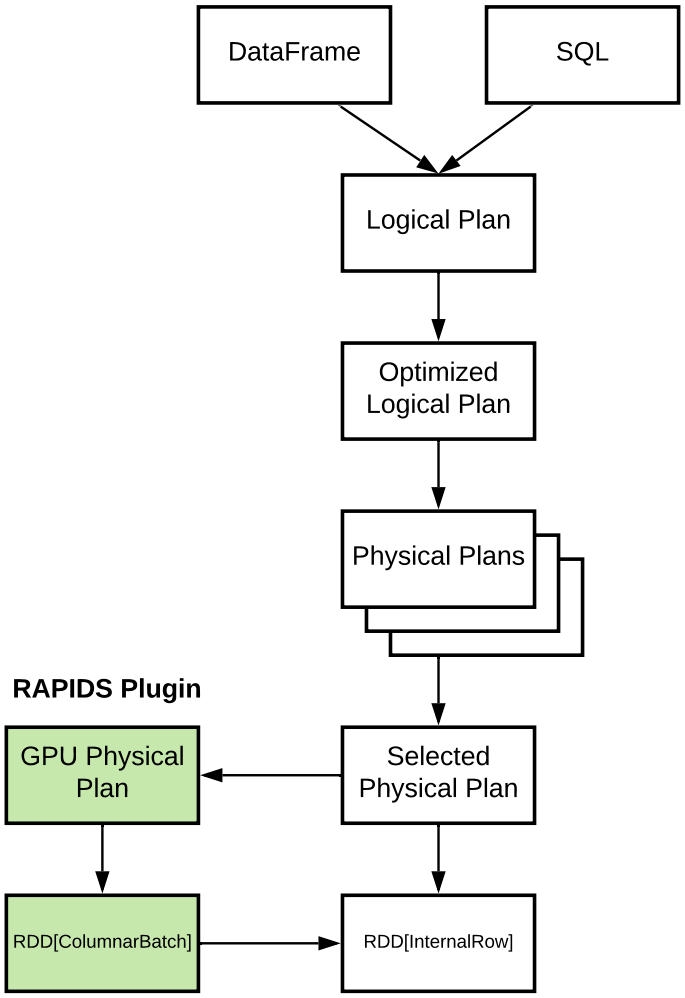

Figure 4.5: Catalyst optimization with RAPIDS accelerator for Apache Spark - Source: Authors own model, based on [McD20].

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

4.3.2 GPU Accelerated Machine Learning with XGBoost

RAPIDS accelerates SparkSQL operations and operations on a DataFrame. Additionally, RAPIDS aims to accelerate the training process of machine learning models. Currently, RAPIDS only supports GPU-acceleration for Extreme Gradient Boosting (XGBoost) in SparkML [McD20].

XGBoost is a scalable, distributed gradient-boosted machine learning library. It tries to solve many data science problems, by implementing ML algorithms using the gradient boosting technique. With the XGBoost4j-Spark[10] library, XGBoost integrates into the Apache SparkML library [xgb].

4.3.3 Installation Requirements for Apache Spark Standalone Mode

The RAPIDS accelerator for Apache Spark is available for a standalone mode Apache Spark cluster. To operate efficiently, 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[11]
- RAPIDS accelerator for Apache Spark Java library
- cuDF Java library that is supported by the RAPIDS accelerator Java library, and the installed CUDA toolkit
- XGBoost4j Java library
- XGBoost4j-Spark Java library
- 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 by using the PromQL query language [SP20]. PromQL is a functional query language for selecting and aggregating time-series data in real-time [Thed]. Prometheus follows the pull-based approach described in Section 2.5.2 to scrape metrics from hosts and services [BP19].

10 XGBoost Documentation - `https://xgboost.readthedocs.io/en/latest/jvm/xgboost4j_spark_tutorial.html` (Accessed: 2021-01-28)

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

4.4.1 Prometheus Architecture

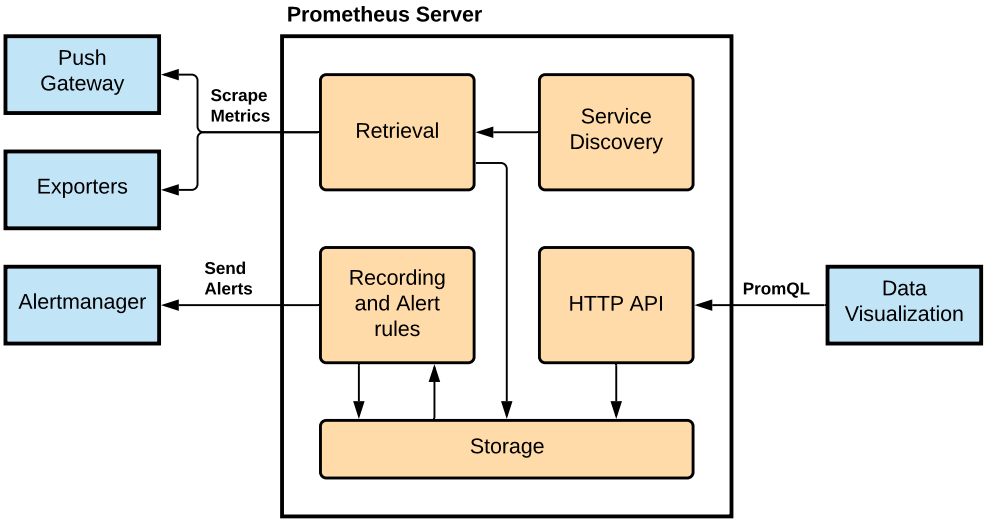

Figure 4.6: Prometheus high-level architecture - Source: Authors own model, based on [Thed, Bra18].

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

Prometheus Server

The Prometheus server is the main component of a Prometheus system. It is responsible for collecting 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]. The core components of the Prometheus server, as illustrated in Figure 4.6, are the following:

- Service Discovery: As being 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 a changing infrastructure [BP19]. Therefore, Prometheus is able to notice targets that are not responding [Bra18].
- Retrieval: Prometheus sends an Hypertext Transfer Protocol (HTTP) request to each target to scrape metrics. The request is sent each interval, which can be set in the configuration [Bra18].

- HTTP API: Prometheus provides an HTTP API. This API can be used to request raw data and evaluate PromQL queries. A data visualization tool can use this API to create visualizations of the requested metrics [Bra18].
- Recording and alert rules: Recording rules enable to precompute frequently needed or compute-intensive PromQL expressions. The result will be saved as a set of time-series in the local storage. This enables to query a recording rule at a much faster speed than the original PromQL expression [Bra18, Thed].

  Alert rules define conditions based on PromQL expressions. If a condition becomes true, an alert will be sent to an external service [Thed].
- Storage: Received data is stored in a custom highly efficient format on a local on-disk time-series database [Thed]. Prometheus does not offer a solution for distributed storage across a cluster of machines [Bra18].

Optional Components

The Prometheus ecosystem offers a set of optional components and can be activated depending on the monitoring needs. The optional components illustrated in Figure 4.6 are the following:

- 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].
- 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].
- Data Visualisation: Prometheus supports various visualization tools, such as its built-in visualization or third-party tools. One of the widely used tools for this occasion is Grafana[12].

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

4.4.2 Prometheus Configuration

Prometheus scraping jobs and rules can be configured using external YAML files [Thed]. Listing 4.7 shows a valid configuration file example. In the `global` configuration section, default values can be set. Targets are defined in the `scrape_configs` section. Each target is defined as a scrape job with a unique name. A target can be defined statically using the `static_configs` parameter or dynamically using the available service discovery mechanisms [Thed]. Rules have to be configured in a separate YAML file. To load rules into Prometheus, the file path has to be set in the `rule_files` parameter.

```
global:
  scrape_interval: 5s

scrape_configs:
  - job_name: cadvisor
    static_configs:
      - targets: ["cadvisor:8080"]
        labels:
          group: "cadvisor"

rule_files:
  - "/etc/prometheus/recording_rules.yml"
```

Listing 4.7: Prometheus configuration file example

Listing 4.8 shows a configuration example of a recording rule which are defined in groups. Each rule is defined by a name and a valid PromQL expression [Thed].

```
groups:
  - name: http_requests
     - record: job:http_inprogress_requests:sum
       expr: sum by (job) (http_inprogress_requests)
```

Listing 4.8: Prometheus rules configuration file example

4.5 cAdvisor

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

4.6 DCGM-Exporter

DCGM-Exporter is a monitoring agent for collecting health and performance metrics from NVIDIA GPUs. It exports collected metrics in the Prometheus

format and makes them available using an HTTP endpoint [13]. The DCGM-Exporter is built on top of the NVIDIA Data Center GPU Manager (DCGM), a tool-suite for managing and monitoring NVIDIA GPUs in a cluster [14]. It can be deployed to a cluster using a Docker container. Listing 4.9 provides an example of deploying the DCGM-Exporter using a Docker container. As a requirement, the NVIDIA Container Toolkit[15] has to be installed on the host.

```
$ docker run -d --rm \
    -p 9400:9400 \
    --runtime nvidia \
    nvidia/dcgm-exporter:2.0.13-2.1.1-ubuntu18.04
```

Listing 4.9: DCGM-Exporter deployment using a Docker container

4.7 GitLab CI/CD

GitLab CI/CD is a tool integrated into the GitLab platform that enables Continuous Integration (CI) and Continuous Delivery/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 of scripts to automate the software development cycle's CI and CD processes. A CI pipeline consists of scripts that build, test, and validate the updated codebase. A CD pipeline is responsible for deploying the application for production after the CI pipeline was executed successfully. Adding CI/CD pipelines to the software development cycle of an application allows to catch bugs and errors early. This ensures that an application deployed to production will conform to established standards [Git].

4.7.1 CI/CD Pipeline

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

13 DCGM-Exporter - `https://ngc.nvidia.com/catalog/containers/nvidia:k8s:dcgm-exporter` (Accessed: 2021-02-12)
14 NVIDIA DCGM - `https://developer.nvidia.com/dcgm` (Accessed: 2021-02-12)
15 NVIDIA Cloud Native technologies documentation - `https://docs.nvidia.com/datacenter/cloud-native/container-toolkit/overview.html` (Accessed: 2021-01-28)

- Jobs: Jobs are responsible for performing the scripts defined by administrators. The scripts define necessary actions. For example compiling the source code or performing tests [Git].

GitLab CI/CD is configured by a `.gitlab-ci.yml` file. The file must be located in the repository root directory. The configuration file will create a pipeline that performs after a push to the repository [Git].

4.7.2 Example of a Basic CI/CD Pipeline Architecture

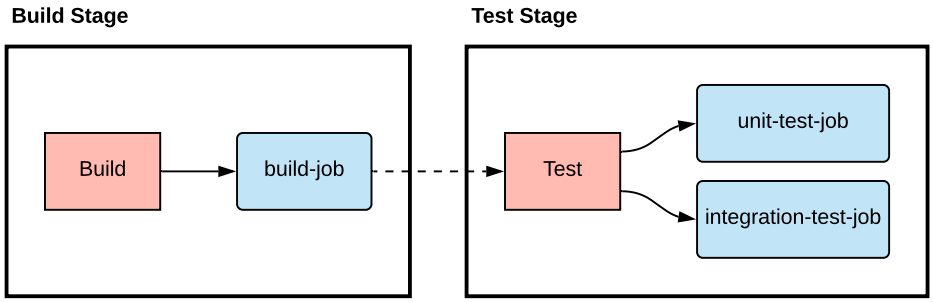

Figure 4.7: Basic architecture of a GitLab CI/CD pipeline - Source: Authors own model, based on [Git].

Figure 4.7 illustrates an architecture of a basic CI/CD pipeline. The pipeline consists of a build and a test stage, which are performed in order. The test stage will only be performed after the build stage was successful. The build stage consists of a single job named *build-job*, which is executed first after a change is pushed to the repository. The test stage consists of two jobs called *unit-test-job* and *integration-test-job*. If a stage consists of more than one job, then all jobs are executed in parallel when the stage is triggered.

Listing 4.10 provides the configuration for the basic pipeline example. Each job executes a shell script to perform the desired actions. The shell scripts have to be located in the source code repository.

```
stages:
  - build
  - test

build-job:
  stage: build
  script:
    - build_software.sh

unit-test-job:
  stage: test
  script:
    - run_unit_tests.sh

integration-test-job:
  stage: test
  script:
    - run_integration_tests.sh
```

Listing 4.10: Example of a `.gitlab-ci.yml` configuration file

4.7.3 Job Execution

GitLab runners will perform jobs that are defined in the configuration file. A GitLab runner is a lightweight and highly scalable application that runs on a server and performs one or multiple executors. Furthermore, it performs given jobs in its environment and responds the result back to the GitLab instance. An executor provides the environment where jobs are executed in. GitLab runner provides multiple executors, such as 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 for specific projects or be available to all projects on the GitLab platform [Git].

4.8 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].

4.8.1 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 the decision algorithm performs 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 is only performed until a performance threshold is violated n times [BKFL17].

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

4.8.2 Scaling Heat Algorithm Concept

Algorithm 1 introduces the Scaling Heat algorithm. The algorithm is based on a concept called *heat*. The value of heat indicates if a scaling action of adding or removing 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 is executed. After executing a scaling action, the heat value is reset to 0 [BKFL17].

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
```

4.9 Kubernetes Horizontal Pod Autoscaler

Kubernetes Horizontal Pod Autoscaler (KHPA) is an auto-scaling algorithm used in Kubernetes, which 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. KHPA scales the number of replicas per Pod based on the utilization of performance metrics. 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 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 replicas for a pod ($active\_replicas$), the utilization of the performance metric of each replica ($pod\_utilization$), and the target utilization of the performance metric ($target\_utilization$). 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

In this chapter, the conceptual design of the implementation is introduced. This chapter's concept is based on the theory of Chapter 2 and uses the technologies introduced in Chapter 4.

5.1 Choice of Technologies

The following technologies are used to create the conceptual design of the implementation:

- Python programming language: Python is used as the main programming language for Apache Spark applications.
- Docker: Docker is used to deploying components in the computing environment as a container. This enables to create homogeneous nodes in the environment. Furthermore, Docker Swarm is used as an orchestration tool and takes care of each component's health status.
- GitLab: The source code repository is hosted on the GitLab platform. Furthermore, the automated deployment pipeline is designed using the CI/CD feature of GitLab. Therefore, using GitLab fulfils the version control and build server requirements mentioned in Section 2.2.2.
- Apache Spark: Apache Spark is used to distribute the workload of training machine learning applications across multiple workers. The goal is to scale the replicas of Apache Spark workers to increase the performance of the cluster.
- NVIDIA RAPIDS: In addition to scaling Apache Spark worker node replicas, the NVIDIA RAPIDS plugin suite is used to enable GPU acceleration on the Apache Spark cluster. Enabling Apache Spark to leverage GPUs increases the computational power as well.
- Prometheus: Prometheus fulfils all requirements of a monitoring system introduced in Section 2.5. It provides a powerful multi-dimensional

data-model and a query language for aggregations and filtering of multi-dimensional time-series data. Additionally, Prometheus is a pull-based monitoring system and includes a time-series database.

- cAdvisor: cAdvisor serves as a monitoring agent. It scrapes performance metrics from Docker containers. Prometheus pulls the data from cAdvisor to save it in its time-series database.
- DCGM-Exporter: The DCGM-Exporter is used as a monitoring agent as well. It is used to monitor the utilization of the available GPUs.

5.2 Computing Environment Architecture

The computing environment is deployed on a single machine. The goal is to create a self-optimizing autonomic computing environment (described in Section 2.3). Furthermore, to manage the environment's components and resources, an autonomic manager is designed according to the MAPE architecture (introduced in Section 2.3.3). For simplicity, each node in the computing environment is deployed as a Docker service in a Docker swarm (introduced in Section 4.1.4). This allows to define the state of each service, which includes the number of replicas. The number of replicas can be updated during runtime.

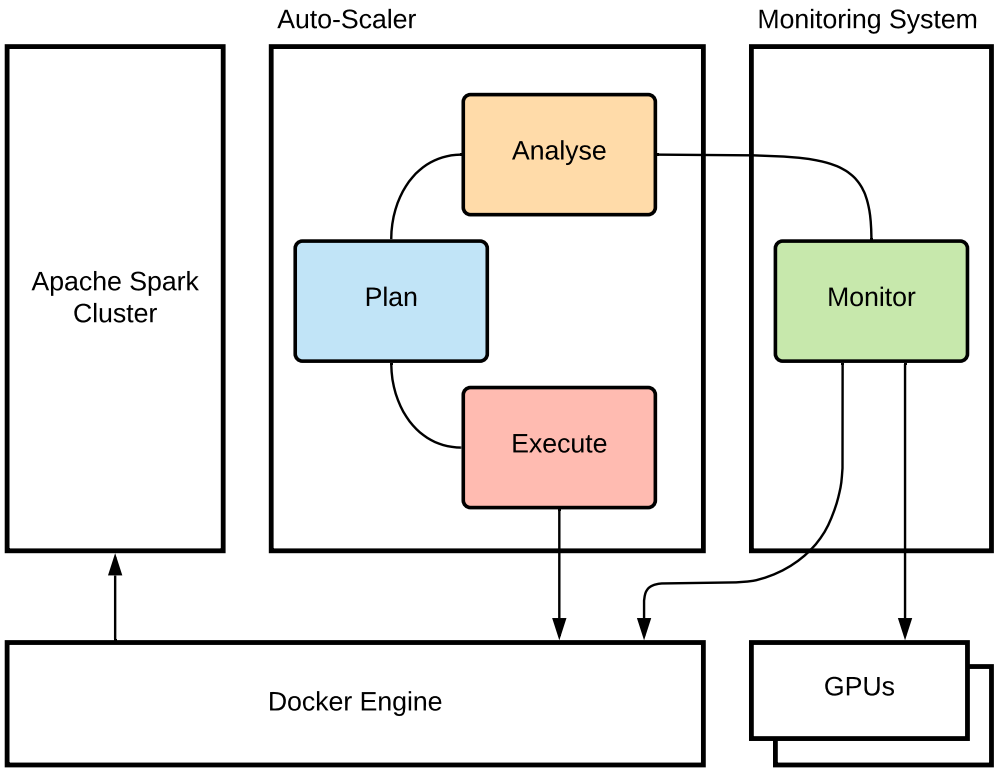

Figure 5.1: Full MAPE control loop architecture

Figure 5.1 provides an overview of the computing environment concept. The managed resources (introduced in Section 2.3.2) in this environment are the Apache Spark cluster and the GPUs. These resources are managed by the autonomic manager, which consists of the *Auto-Scaler*, and the monitoring system. Furthermore, the autonomic manager implements all four phases of the MAPE architecture and executes the control-loop. As mentioned previously, all components are deployed using Docker. Therefore, to manage components in the computing environment, the autonomic manager needs to interact with the overlaying Docker engine.

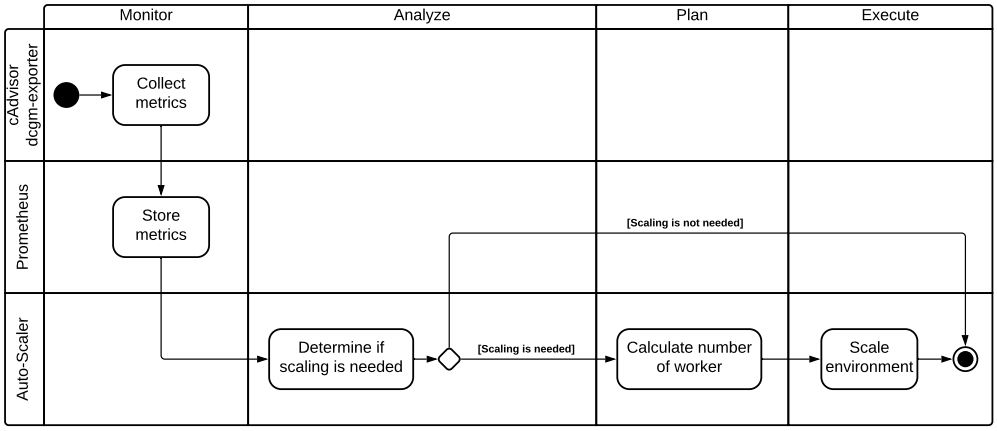

Figure 5.2: UML activity model of the autonomic manager process

Control-loop workflow: The control-loop workflow is illustrated in Figure 5.2. It starts in the Monitor phase. All monitoring agents (cAdvisor and DCGM-Exporter) collect performance metrics from their targets. Next, Prometheus pulls the metrics from all monitoring agents and saves the data in its time-series database. In the analyse phase, the *Auto-Scaler* determines if a scaling action is necessary. If a scaling action is not needed, the iteration ends. Otherwise, the *Auto-Scaler* determines the number of Apache Spark worker replicas in the Plan phase. Lastly, in the Execute phase, the *Auto-Scaler* scales the Apache Spark worker Docker service's replicas.

5.3 Apache Spark Cluster

The Apache Spark cluster is the computing unit of the environment. It is responsible for distributing the workload of training machine learning models. Figure 5.3 illustrates the architecture of the Apache Spark cluster. It consists of a master node, multiple worker nodes, and spark-submit nodes.

- Master: The master is responsible for distributing the workload of an application, submitted by a *spark-submit* node, across all available worker nodes. The Apache Spark application architecture is explained in Section 4.2.2.

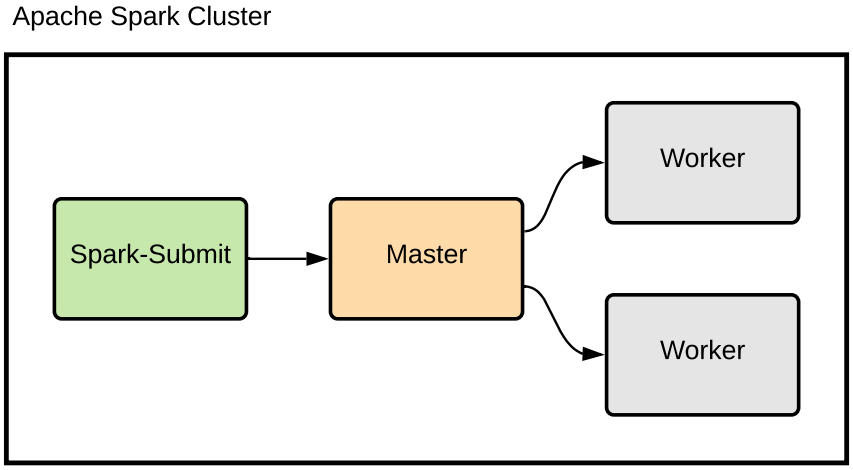

Figure 5.3: Apache Spark cluster architecture

- Worker: A worker node is responsible for performing the workload given by the master node. Furthermore, the replicas of active worker nodes in the cluster are dynamically adapted by the *Auto-Scaler* at runtime.
- Spark-Submit: A *spark-submit* node is deployed whenever an application is submitted to the cluster.

The cluster is deployed in standalone mode (Section 4.2.3). Because Docker Swarm is used as the orchestration tool that controls nodes' state, there is no need to use another orchestration tool like Apache Mesos or Kubernetes as the cluster manager. Additionally, this simple approach allows running each node of the cluster in a Docker container without additional configuration.

5.3.1 Homogeneous Apache Spark Worker Nodes

The *Auto-Scaler* scales the replicas of Apache Spark worker nodes. Therefore, the cluster is scaled horizontally. As explained in Section 2.1.1, the horizontal scaling approach is more efficient when scaling homogeneous nodes Each node adds the same amount of computational power to the cluster. To ensure that the worker nodes are homogeneous, the worker service uses the same Docker image for each worker node. The Docker image is created from a custom Dockerfile. This guarantees that each worker uses the same software and has the same amount of computational resources available. Additionally, all requirements mentioned in Section 4.3.3 to enable GPU acceleration with RAPIDS are installed in a worker image.

5.3.2 Deploying an Application with spark-submit

Whenever the CI pipeline submits an application to the Apache Spark cluster, it deploys a *spark-submit* Docker container. The *spark-submit* container's purpose is to submit an application with the spark-submit executable (described in Section 4.2.3) to the cluster. Additionally, the *spark-submit* container sets the number of resources for the executors running on the worker nodes. Apache Spark cluster's standalone mode does not support submitting Python applications with the spark-submit executable from outside of the cluster. Therefore, the spark-submit executable must be executed on the host machine with access to the master node [Theb]. To submit an application to the master node, the *spark-submit* container needs to be in the same Docker swarm network. The node is deployed as a Docker container instead of a Docker service. Each spark-submit container is deployed with a different setting depending on the configuration and application of the CI pipeline. After the application has been submitted, the spark-submit node automatically exits.

5.4 Autonomic Manager

The autonomic manager is one of the main modules of the computing environment. It is responsible for monitoring all Apache Spark worker node performance metrics and automatically scales the number of worker nodes to adapt to a specified performance goal. The autonomic manager is implemented according to the MAPE architecture, as described in Section 2.3.3. To create a complete control-loop, the autonomic manager comprises multiple components, as illustrated in Figure 5.4. It consists of a monitoring system (see Section 2.5) and an *Auto-Scaler* module. Each component in the computing environment is deployed as a Docker service. Therefore, Docker swarm takes care of the health status of each component. To monitor overall Docker container performance in the computing environment, the autonomic manager needs access to the overlaying Docker engine. Additionally, to monitor GPU performance, a monitoring agent is needed to scrape metrics from the GPUs. Furthermore, the autonomic manager is responsible for scaling the replicas of Apache Spark worker nodes. As introduced in Section 5.3, a worker service takes care of all worker nodes. Therefore, the autonomic manager needs access to the host machine's Docker Engine in order to send scaling instructions.

5.4.1 Monitoring System

The monitoring system is responsible for performing the Monitor phase. Therefore it monitors the performance of components in the computing environment and makes them available to the *Auto-Scaler*. In this environment, the monitoring system collects worker container performance metrics, and the GPU performance. It is essential to mention that the number of worker

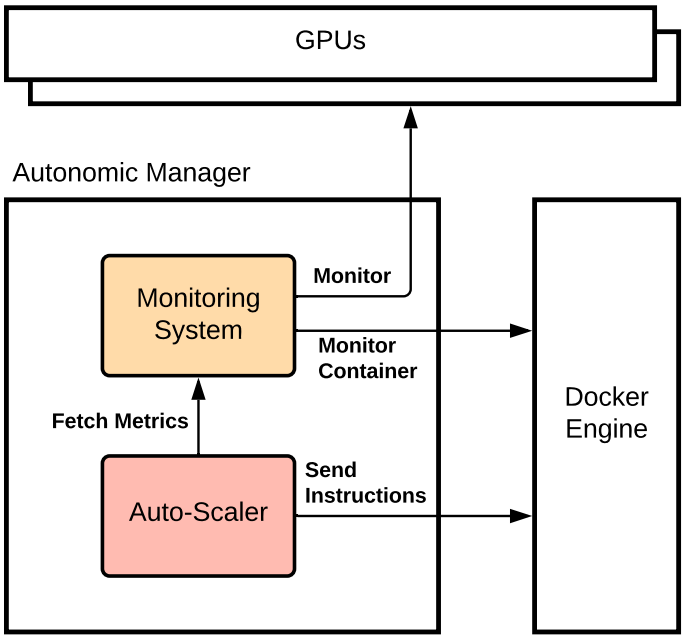

Figure 5.4: Autonomic manager component design

nodes varies over time because the *Auto-Scaler* scales the worker nodes' replicas according to the system performance. Figure 5.5 illustrates the

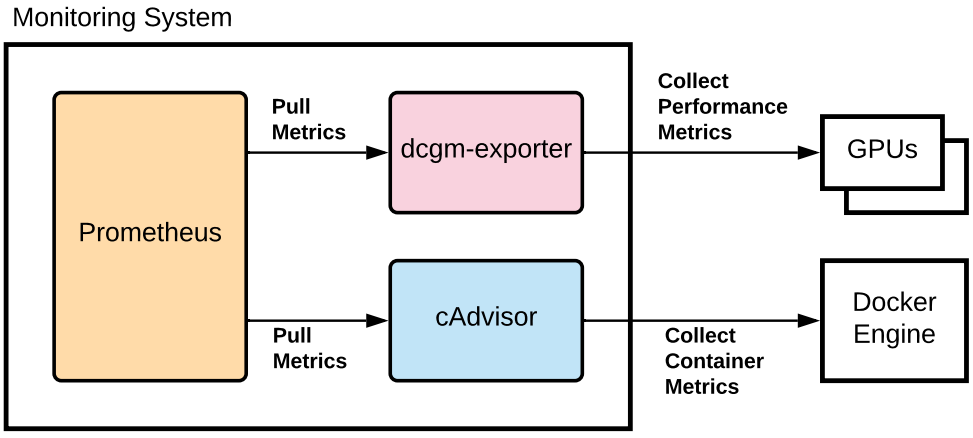

Figure 5.5: Monitoring system conceptual design

architecture of the monitoring system, which consists of three components:

- DCGM-Exporter: A monitoring agent that is responsible for collecting GPU performance metrics.
- cAdvisor: A monitoring agent that collects performance metrics of Docker containers in the environment.

- Prometheus: It collects the performance metrics from all monitoring agents and saves them as time-series data in a time-series database.

5.4.2 Auto-Scaler

The *Auto-Scaler* is the second module of the autonomic manager and responsible to dynamically adjust the replicas of Apache Spark worker nodes in the computing environment to accommodate specified performance goals. It implements the Analyse, Plan, and Execute phases of the MAPE architecture. Together with the monitoring system, it creates a complete autonomic manager implementing all phases of the MAPE architecture. The *Auto-Scaler* is designed as a reactive auto-scaler and uses a threshold-based algorithm to scale worker nodes. To define the thresholds, it can be configured using a configuration file.

As illustrated in Figure 5.4, the *Auto-Scaler* fetches performance metrics from the Prometheus HTTP API. After it received the performance metrics, the *Auto-Scaler* analyses the metrics, plans scaling-actions to adjust the number of worker replicas, and sends instructions to the Docker engine.

MAPE Phases

Mentioned above, the *Auto-Scaler* implements the Analyse, Plan, and Execute phases of the MAPE architecture. Each phase has a different workflow to accommodate its goal.

Analyse: During each period, the *Auto-Scaler* fetches the performance metrics defined in the configuration file from the Prometheus HTTP API. After the metrics are received, the *Auto-Scaler* determines if a scaling action is needed using the Scaling Heat algorithm (introduced in Section 4.8.2). If scaling is not necessary, the *Auto-Scaler* continues to collect and analyse performance metrics.

Plan: If a scaling action is necessary, the *Auto-Scaler* is responsible for determining the number of Apache Spark worker replicas needed to reach the defined utilization goal. To calculate the number of worker nodes, the *Auto-Scaler* uses the Kubernetes Horizontal Pod Auto-Scaling algorithm (introduced in Section 4.9). If number of needed replicas violates the upper or lower thresholds of active Apache Spark worker nodes, the *Auto-Scaler* uses the maximum or the minimum number of worker nodes as the desired replicas.

Execute: After the number of needed replicas have been calculated, the *Auto-Scaler* sends the instruction to scale the Apache Spark worker service to the desired number of replicas. Afterward, a cooldown period is activated, which has the effect that the Apache Spark cluster needs time to distribute the workload across all new worker nodes efficiently. During the cooldown period, no scaling actions are executed.

Configuration

The *Auto-Scaler* needs specific configuration properties to collect the correct metrics from Prometheus and scale the Apache Spark worker service replicas. The following are properties that have to be defined to ensure that the *Auto-Scaler* can collect meaningful metrics and scale Apache Spark workers as expected.

- General properties:
  - Interval seconds: The number of seconds after the *Auto-Scaler* starts a new process.
  - Cooldown period: The duration in seconds the *Auto-Scaler* has to wait after a scaling action is performed.
  - Recurrence factor: To prevent too many scaling actions, the autonomic manager should only execute a scaling action, if the utilization thresholds are violated n times.
  - Prometheus URL: The Uniform Resource Locator (URL) of the Prometheus HTTP API.
- Metrics: It is possible to define a list of metrics, where each metric needs to have a variety of properties configured.
  - Target utilization: The desired utilization of the performance metric.
  - Utilization thresholds: To determine if a scaling action is needed, the scaling heat algorithm needs the minimum and maximum utilization of the performance metric.
  - Query: A PromQL query defines a performance metric.
- Apache Spark worker properties:
  - Worker service name: The Docker worker's service name is needed to update the number of replicas.
  - Worker thresholds: The maximum and the minimum number of concurrent Spark workers should be defined. To avoid the cold start effect, the minimum amount of workers should be at least 1.
  - Apache Spark master URI: To distribute the Spark Worker workload, all Spark Worker need to communicate with the Spark master.

5.5 Identification of Suitable Metrics for Scaling

Suitable metrics are needed to measure the system performance while the Apache Spark cluster is actively performing work. With the RAPIDS accelerator for Apache Spark, the cluster utilizes CPU and GPU computing power to enable parallelization. Therefore, suitable metrics to measure the

system performance are the CPU and GPU utilization when the cluster is actively performing computations.

5.5.1 CPU Utilization

All Apache Spark workers run on the same machine. Therefore, all available CPU cores on the machine are shared across each Apache Spark worker. To get a value that indicates the CPU utilization between 0% and 100%, a metric is needed that represents the percentage of time all performing applications occupy CPU cycles. cAdvisor provides a performance metric called `container_cpu_usage_seconds_total`[1]. This metric provides the total amount of CPU seconds consumed by core of a container. To calculate the overall CPU utilization for all Apache Spark worker, the value of the performance metric for each worker container over a specific rate is summed up. In this case, the CPU utilization (U_{CPU}) is defined by (5.1) with $n \in \mathbb{N}$ the number of active workers.

$$U_{CPU} = \sum_{n=1}^{\mathbb{N}} container\_cpu\_usage\_seconds\_total_n \tag{5.1}$$

5.5.2 GPU Utilization

In addition to the CPU utilization, Apache Spark workers can utilize GPUs to accelerate the computation work. The dcgm_exporter agent provides the `dcgm_fi_dev_gpu_util` performance metric. This metric returns the percentual utilization per GPU. Therefore, the GPU utilization (U_{GPU}) is defined by (5.2) with $n \in \mathbb{N}$ the number of available GPUs.

$$U_{GPU} = \frac{\sum_{n=1}^{\mathbb{N}} dcgm\_fi\_dev\_gpu\_util_n}{\mathbb{N}} \tag{5.2}$$

5.6 Automated Deployment Pipeline

This thesis aims to train Machine Learning models by automatically submitting Apache Spark applications to an Apache Spark cluster. Therefore, the training process of a model has to be integrated into the application development lifecycle. The application development lifecycle is automated using a deployment pipeline (introduced in Section 2.2). In this conceptual design, a CI pipeline is used to automate the training phase of an application and submit the application to an Apache Spark cluster after the test stage was successful.

Figure 5.6 illustrates the conceptual design of the CI pipeline, which consists of two stages:

1 Monitoring cAdvisor with Prometheus - `https://github.com/google/cadvisor/blob/master/docs/storage/prometheus.md` (Accessed: 2021-01-21)

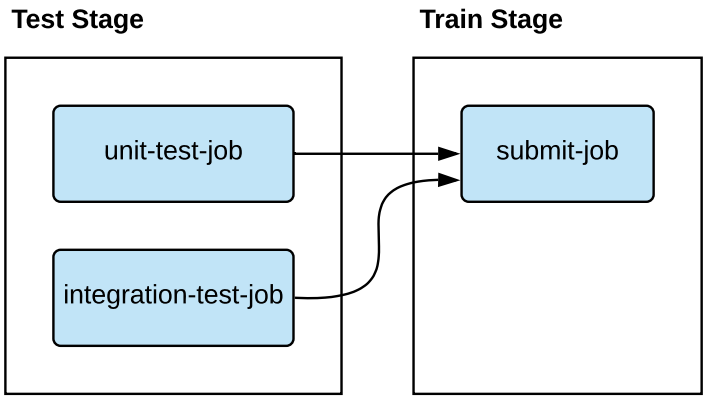

Figure 5.6: Automated Deployment Pipeline concept

1. Test stage: Responsible for performing all tests to validate the application source code.
2. Train stage: If the test stage is successful, the application is submitted to the Apache Spark cluster, in order to train the model.

It is important to mention that a build stage is missing in this conceptual design. The build stage includes compiling source code into a format that can be executed directly. Python is an interpreted language and does not need to be compiled for execution.

5.6.1 Test Stage

Before training the machine learning model, the application source must be validated by a series of tests, which can include:

- Unit tests
- Integration tests
- End-to-end tests

Each test is performed as a separate job. All jobs perform in parallel after the test stage has been triggered. If a job fails, the whole test stage is marked as a failure, which notifies participating developers.

5.6.2 Train Stage

The train stage is responsible for submitting the Apache Spark application to the Apache cluster after the test stage was successful. A *spark-submit* Docker container has to be deployed to the same Docker network to submit an application to the Apache Spark cluster. How a *spark-submit* container performs an application, is explained in Section 5.3.2.

Deploying *spark-submit* Docker containers in the Apache Spark cluster network requires access to the overlying Docker engine. To access the Docker engine within a job of the train stage, the job has to be executed by a GitLab runner on the same host machine. Figure 5.7 illustrates the steps to deploy

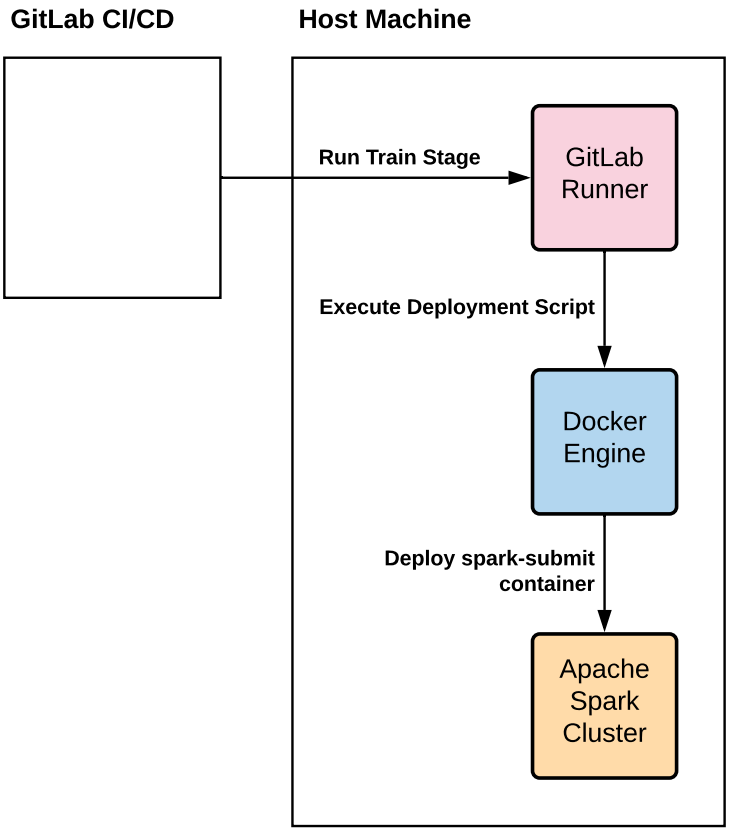

Figure 5.7: Deployment of a spark-submit container

a *spark-submit* container in the Apache Spark cluster swarm network. The GitLab CI/CD server connects to a GitLab instance on the host machine and instructs it to execute the train stage. The runner then performs the scripts that instruct the Docker engine to deploy a spark-submit container in the Apache Spark cluster.

Chapter 6

Implementation

This chapter explains the implementation process of the conceptual detail introduced in Chapter 5.

6.1 Implementation Environment

To implement this thesis concept, an NVIDIA DGX1[1] machine is available. This machine is a shared live-system. Therefore, multiple applications are performing simultaneously on this machine and share the same resources.

6.1.1 Technical Details

The hardware specification of the machine is the following:

- Memory: 512GB
- Disk space: 4x 1.92TB (7.68TB total)
- GPUs: 8x NVIDIA Tesla v100, each having 32GB of memory (256GB total)
- CPU: Dual 20-Core Intel Xeon E5-2698 v4 2.2 GHz

The following software, which is required for the implementation, is installed on the machine:

- Ubuntu 18.04.5 LTS
- Docker version 18.09.4

1 The Universal System for AI Infrastructure - `https://www.nvidia.com/en-us/data-center/dgx-1/` (Accessed: 2021-01-30)

6.1.2 NVIDIA Docker Runtime

The NVIDIA Container Toolkit has to be installed on the host machine to enable GPU support for Docker containers. This toolkit provides a runtime library that automatically enables Docker containers to leverage NVIDIA GPUs. It is possible to define the runtime of a Docker container with the docker `run` command. However, this is not supported by Docker services. The NVIDIA runtime has to be set as the default runtime for Docker to deploy Docker services with the NVIDIA runtime enabled. How the NVIDIA Container toolkit is installed, and the runtime is set as default runtime is thoroughly explained in the NVIDIA Container Toolkit documentation[2].

The NVIDIA Container Toolkit is installed on the host machine, but the NVIDIA runtime is not set as default runtime. Changing the default runtime requires a restart of the Docker service. Restarting the Docker service is impossible because it requires quitting all running Docker containers on the machine. Therefore, components that require access to GPU resources cannot be deployed as Docker services. The solution to this problem is to deploy these components as Docker container instead of Docker services. Given this problem, the DCGM-Exporter monitoring agent must be deployed as a Docker container with the NVIDIA runtime enabled. Listing 6.1 shows an example of the docker run command to deploy a Docker container using the NVIDIA runtime.

```
$ docker run -d --rm --runtime=nvidia --name dcgm-exporter
    nvidia/dcgm-exporter:latest
```

Listing 6.1: Docker run command to deploy a container using the NVIDIA runtime

6.2 Computing Environment

The computing environment is deployed as a Docker swarm (described in Section 4.1.4). It consists of several components that are all deployed as Docker services. The conceptual design is explained in Section 5.2. As mentioned previously, components that require GPUs are not created as Docker services. These components are deployed as Docker containers in the same swarm network. Overall, the computing environment consists of the following components:

- Autonomic Manager
  - Auto-Scaler
  - Prometheus

2 NVIDIA Cloud Native technologies documentation - `https://docs.nvidia.com/datacenter/cloud-native/container-toolkit/overview.html` (Accessed: 2021-01-28)

  - cAdvisor
  - DCGM-Exporter
- Apache Spark Cluster
  - Apache Spark master node
  - Apache Spark worker nodes
  - *spark-submit* nodes

6.2.1 Deployment of the Computing Environment

To simplify the deployment of a stack of services, Docker provides to define all services in a *docker-compose*[3] file. The computing environment *docker-compose* file is defined in Listing B.1. Table 6.1 shows all Docker Services defined in the `docker-compose.yml` with the used Docker image. It defines all services, except the DCGM-Exporter because it requires the NVIDIA Docker runtime. The whole stack can be deployed using the `docker stack` command. Then, the DCGM-Exporter container has to be deployed and added to the same network. Listing 6.2 shows the process of how to deploy the stack and the DCGM-Exporter container. First, all services are deployed using the `docker stack` command. Afterward, the DCGM-Exporter is deployed in a Docker container using the NVIDIA runtime and attached to the same network.

```
$ docker stack deploy -c docker-compose.yml computing

$ docker run -d --rm -p "9400:9400" \
    --runtime=nvidia \
    --name dcgm-exporter \
    --network computing_net \
    nvidia/dcgm-exporter:2.0.13-2.1.1-ubuntu18.04
```

Listing 6.2: Commands to deploy the computing environment

Service Name	Docker Image
auto-scaler	`auto-scaler:latest`
prometheus	`prom/prometheus:v2.24.1`
cadvisor	`google/cadvisor:v0.33.3`
DCGM-Exporter	`nvidia/dcgm-exporter:2.0.13-2.1.1-ubuntu18.04`
spark-master	`spark-master:3.0.1-hadoop2.7`
spark-worker	`spark-worker:3.0.1-hadoop2.7`

Table 6.1: The name and Docker image of each Docker service in the computing environment

3 Overview of docker-compose - `https://docs.docker.com/compose/` (Accesses: 2021-02-10)

6.2.2 Autonomic Manager

The autonomic manager is responsible for monitoring the computing environment and scaling the number of Apache Spark worker replicas. It is composed of a monitoring system and the *Auto-Scaler*. Furthermore, the monitoring system consists of Prometheus, cadvisor, and DCGM-Exporter components. Together, all components build an autonomic manager according to the MAPE architecture. The monitoring system monitors the components in the computing environment while the *Auto-Scaler* analyses the performance metrics and adapts the number of Apache Spark workers.

Prometheus Target Configuration

As being introduced in Section 4.4, Prometheus is a pull-based monitoring tool. It requires a list of targets to pull performance metrics from. How Prometheus is configured is described in Section 4.4.2.

Listing 6.3 specifies the scrape configuration of the Prometheus system. The `scrape_interval` parameter is set to *5s* which means, that every 5 seconds, Prometheus scraped performance metrics from all defined targets. Each target is configured using a URL and a label. The label is used to identify the metric source. In this configuration, the following targets are defined:

- cadvisor: All container-related performance metrics are received from the cAdvisor target.
- DCGM-Exporter: The DCGM-Exporter provides GPU related performance metrics.
- spark-master: The spark-master target provides metrics about the Apache Spark master service. This target is essential for the *Auto-Scaler* to get information about running worker nodes and the number of running applications.

```yaml
global:
  scrape_interval: 5s

rule_files:
  - "/etc/prometheus/recording_rules.yml"

scrape_configs:
    - job_name: cadvisor
      static_configs:
          - targets: ["cadvisor:8080"]
            labels:
                group: "cadvisor"

    - job_name: dcgm-exporter
      static_configs:
          - targets: ["dcgm-exporter:9400"]
            labels:
                group: "dcgm-exporter"

    - job_name: spark-master
      metrics_path: /metrics/master/prometheus/
      static_configs:
          - targets: ["spark-master:4040"]
            labels:
              group: "spark"
```

Listing 6.3: Prometheus target configuration in YAML syntax

Prometheus Recording Rules Configuration

As introduced in Section 4.4.1, Prometheus provides the ability to define recording rules. Recording rules can be queried at a much faster speed than PromQL queries because the results of recording rules are saved in the local storage of Prometheus. Therefore, all suitable metrics to monitor the computing environment's performance introduced in Section 5.5 are defined as recording rules. Listing 6.4 shows the configuration of both performance metrics as recording rules.

```yaml
groups:
    - name: performance_usage_percent
      rules:
        - record: instance:worker_nodes:cpu_usage:percent
          expr: SUM(RATE(container_cpu_usage_seconds_total{image="spark-worker:3.0.1-hadoop2.7"}[30s])) BY (image)
        - record: instance:gpu:usage:percent
          expr: SUM(DCGM_FI_DEV_GPU_UTIL{device=~"(?:nvidia4|nvidia5)"}) / 2
```

Listing 6.4: Prometheus target configuration in YAML syntax

The CPU query uses the `RATE` function to calculate the CPU usage's per-second rate over the last 30 seconds of each available worker node. Then the results are summed up using the `SUM` function. To get the utilization for two different GPU devices, PromQL provides selectors for labels. In

the configuration, the =~ selector is used for the device label. This selector selects all values that match the given regular-expression. The given regular expression selects the GPUs with the name *nvidia4* and *nvidia5*. Then both utilizations values are summed up and divided by the number of GPUs.

6.3 Auto-Scaler

The *Auto-Scaler* is one of the two main modules of the autonomic manager. It is responsible for analyzing performance metrics, planning scaling actions according to the performance metrics, and executing scaling actions to adapt the number of Apache Spark workers in the computing environment. It is implemented as a custom module in Python 3.8 and deployed as a Docker image using a custom Dockerfile to deploy the *Auto-Scaler* running in a Docker container.

The *Auto-Scaler* integrates the Analyse, Plan, and Execute phase of the MAPE architecture. Furthermore, it scales the Apache Worker service horizontally by automatically scaling the number of replicas. The *Auto-Scaler* runs as a background service that periodically performs each phase in order. It can be configured with a configuration in the YAML file format. The path to the configuration file has to be set as an argument. The *Auto-Scaler* can be started with the following command:

```
$ python3 run.py --config=config.yml
```

Listing 6.5: Auto-Scaler start command

6.3.1 Configuration

The configuration parameters for the *Auto-Scaler* have been introduced in Section 5.4.2. The configuration is defined in the YAML file format and is structured in three sections: General, metrics, and worker.

- General: The general section defines the length of seconds after an interval is performed, the length in seconds of the cooldown period, the recurrence factor, and the Prometheus URL.
- Metrics: Metrics is a list of performance metric configuration parameters. 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 worker service replicas, the *Auto-Scaler* needs to know the service name. The minimum and the maximum number of concurrent worker nodes need to be defined to prevent an overhead of concurrently running worker nodes.

Listing 6.6 provides an example of a configuration for scaling a Docker service. To scale a service using the Docker Software Development Kit(SDK's)

service API, only the service name is needed. Docker related configuration settings (e.g., environment variables) are defined in the `docker-compose.yml` explained in Section 6.2.1.

```
general:
  interval_seconds: 5
  cooldown_period_seconds: 180
  recurrence_factor: 3
  prometheus_url: "http://localhost:9090"

metrics:
  cpu:
    query: 'sum(rate(container_cpu_user_seconds_total{image
   ="spark-worker:3.0.1-hadoop2.7"}[30s]))'
    target_utilization: 0.5
    thresholds:
      min: 0.2
      max: 0.6

worker:
  service_name: "computing_spark-worker"
  thresholds:
    min: 1
    max: 30
```

Listing 6.6: *Auto-Scaler* configuration for scaling Docker Services

6.3.2 Scaling Apache Worker Nodes

The *Auto-Scaler* performs periodically. Each period fetches performance metrics, analyses the metrics, plans scaling-actions, and executes them if necessary. It uses the *APScheduler*[4] Python library that provides an API to schedule jobs periodically.

Estimation of Necessary Scaling Actions

To estimate if a scaling-action is necessary, the *Auto-Scaler* uses the Scaling Heat algorithm (introduced in Section 1). The algorithm uses the utilization of a performance metric, the lower- and upper-threshold, and the calculated heat of the last iteration as input parameters. The utilization is received from the Prometheus HTTP API. Furthermore, the *Auto-Scaler* fetches the utilization of all given performance metrics in each iteration. It calculates the heat value for each single performance metric. If a performance metrics' heat value is equal to the recurrence factor n ($+n$ or $-n$), a scaling-action is executed. This phase is not performed if a cooldown period of a previous iteration is active.

4 `https://pypi.org/project/APScheduler/` (Accessed: 2021-01-26)

Calculating the Number of Needed Worker Nodes

To calculate the number of needed Apache Spark workers, the *Auto-Scaler* uses the KHPA algorithm (introduced in Section 4.9). As input parameters, the algorithm takes the current number of active worker nodes, the utilization of the performance metric, and the target utilization.

Listing 6.7 shows the implementation of the KHPA algorithm in Python. To receive the number of active worker nodes, the Apache Spark master node must be defined as a Prometheus target. This enables to fetch the `metrics_master_aliveWorkers_Value` metric from the Prometheus HTTP API which returns the number of alive Apache Spark worker nodes in the cluster.

The utilization of the performance metric used for the KHPA algorithm has already been received in the previous phase. Lastly, the target utilization for the performance metric is defined in the *Auto-Scaler* configuration.

```
1 def calculate_number_of_needed_worker(active_worker: int,
2     utilization: float,
3     target_utilization: float):
4   return math.ceil(
5     active_worker * (utilization / target_utilization))
```

Listing 6.7: KHPA implementation using Python 3.8

Performing a Scaling Action

After the number of needed Apache Spark, worker nodes are calculated, the *Auto-Scaler* is responsible for scaling the worker service's replicas to reach the desired performance goal. To scale a Docker service using Python, Docker provides a Python library for the Docker Engine[5]. The SDK provides a services API that can be used to scale a given Docker Service replicas. After a scaling action has been executed successfully, a cooldown period is activated. The duration of the cooldown period can be set in the configuration. During this cooldown, no scaling actions are executed in further iterations.

Removing Apache Spark worker

As introduced in Section 4.2.1, Apache Spark is built on top of a data structure called RDD. An RDD consists of different partitions that are distributed across multiple executors across the cluster. If an executor stores essential data, the executor's worker node cannot be removed during runtime. If the worker is removed during runtime, it will cause the loss of necessary RDD partitions. Therefore, worker nodes will not be removed if applications are actively performing on the Apache Spark cluster. Prometheus provides a metric called `metrics_master_apps_Value`, which returns the number of running applications on the cluster. To fetch this metric, the Apache Spark

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

master node has to be set as a Prometheus target. The *Auto-Scaler* only reduces the number of worker replicas if this metric returns 0.

6.3.3 Docker Image

A Docker image is needed to deploy the *Auto-Scaler* as a Docker service in the computing environment. Therefore a custom Dockerfile is created to build an *Auto-Scaler* Docker image. Listing 6.8 shows the *Auto-Scaler* Dockerfile implementation. The `python:3` Docker image is set as the parent image. Next, the *Auto-Scaler* source code is copied to the image. Then, a Python virtual environment is created with all dependencies installed. As entrypoint, the Docker image starts the *Auto-Scaler* process.

```
1  FROM python:3
2
3  WORKDIR /usr/src/auto_scaler
4
5  # Copy the python module
6  COPY setup.py .
7  COPY src src/
8
9  # Update and install packages
10 RUN pip3 install -e .
11
12 ENTRYPOINT [ "python3", "src/run.py" ]
```

Listing 6.8: Auto-Scaler Dockerfile

To build the *Auto-Scaler* Docker image, a build script was implemented. Listing 6.9 shows the build script implementation. The script takes the version of the *Auto-Scaler* module as an input attribute. It uses the version to tag the Docker image. It builds two versions of the *Auto-Scaler*, one tagged with the current *Auto-Scaler* version (e.g., *auto-scaler:1.0*) and one tagged as *latest* (e.g., *auto-scaler:latest*).

```
#!/bin/bash

if [ $# -ge 1 ]
  then
    VERSION=$1

    PWD=$(pwd)

    CI_REGISTRY=${CI_REGISTRY-local}
    IMAGE_TAG_PATH="${CI_REGISTRY}/cci/distributed-computing
   -framework"

    docker build \
      -t $IMAGE_TAG_PATH/auto-scaler:$VERSION \
      $PWD

    docker build \
      -t $IMAGE_TAG_PATH/auto-scaler:latest \
      $PWD
  else
    echo "No arguments supplied\n"
      echo "Use the script as follows:"
      echo "build-image.sh <VERSION>"
      exit 1
fi
```

Listing 6.9: Auto-Scaler build script

The script can be used from the command line as `sh build-image.sh "1.0"`.

6.4 Apache Spark Cluster with GPU Acceleration

The conceptual design of the Apache Spark cluster is introduced in Section 5.3. It consists of a single master node, a dynamic number of worker nodes, and *spark-submit* nodes. A *spark-submit* node is deployed whenever an application is submitted to the cluster. All master and worker nodes are deployed in standalone mode (described in Section 4.2.3).

6.4.1 Apache Spark Base Image

All services in the Apache Spark cluster share the same dependencies. To simplify the creation of the Docker images, a base image is created. This base image serves as the parent image for all other images. Listing C.1 provides the implementation of the *base-image* Dockerfile. To install a specific Apache Spark version on the Docker image, the `SPARK_VERSION`, and `HADOOP_VERSION` build arguments are provided. The build process of the images is explained in Section 6.4.5. The base image uses the `nvidia/cuda:11.0-devel-ubuntu16.04` Docker image as the parent image. This image is

provided by NVIDIA and has already installed the NVIDIA GPU driver and the CUDA toolkit dependencies. Additionally, the *spark-base* Dockerfile installs all required dependencies to run a standalone Apache Spark node with GPU acceleration introduced in Section 4.3.3. This includes Apache Spark, JRE 1.8, Python3, GPU discovery script, RAPIDS Java binary, cuDF Java binary, XGBoost4j binary, and XGBoost4j-spark binary.

6.4.2 Apache Spark Master Image

The Apache Spark master node Docker image is created from a custom Dockerfile (see Listing C.2). This image is built on top of the *spark-base* image and therefore already has all dependencies installed. It configures the Apache Spark master port to 7077 and the port for the web user interface to 4040. Additionally, the `start-master.sh` script is set as the entrypoint. Therefore, when a service is built from this image, it will automatically start an Apache Spark master node in standalone mode.

6.4.3 Apache Spark Worker Image

The Apache Spark worker image is created from a custom Dockerfile as well. This Dockerfile uses the *spark-base* image as the parent. As mentioned in Section 2.1.1, the horizontal scaling approach is more effective with homogeneous nodes. Each Apache Spark worker node is being created from the same Docker image given the same resources. Therefore, no additional dependencies have to be installed. To configure the worker nodes' resources, the `spark-env.sh` is copied to the Apache Spark `conf/` folder. Listing 6.10 shows the configuration file. It sets the number of GPUs for each executor and the path to the GPU discovery script on the node host. The entrypoint is set to `start-slave.sh` to start an Apache Spark worker in standalone mode. To connect to the Apache Spark master node, the URI has to be set as an environment variable.

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

Listing 6.10: Environment configuration for all worker nodes

6.4.4 Apache Spark Submit Image

The *spark-submit* Docker image is responsible for executing the spark-submit executable (introduced in Section 4.2.3) to run an Apache Spark application on the cluster. The spark-submit Dockerfile uses the *spark-base* image as parent. It copies a custom submit script to the image filesystem which is used as the image entrypoint. When a *spark-submit* container is started, it executes the custom submit script with all provided arguments.

Custom Submit Script

The custom submit script is provided at Listing C.5. It provides a simplified interface for the spark-submit executable. Furthermore, it includes all necessary configuration parameters to perform an application with GPU-acceleration enabled. Additionally, if the `CPU_ONLY` environment variable is set to *true*, the script will disable GPU-acceleration for the given application. This feature is useful when algorithms optimized for task-parallelism are being executed. Listing 6.11 demonstrates a usage example of the custom submit script. As arguments, the script takes the path of the application executable file and all needed application arguments as input. All arguments are forwarded to the spark-submit executable, which executes the applications using the configuration provided by all environment variables. In the example, the `train.py` application is executed with a `max-depth` argument.

```
$ sh submit.sh train.py --max-depth=50
```

Listing 6.11: Usage of the submit script

Environment Variables

The configuration of the underlying spark-submit executable can be configured by providing the environment variables listed in Table 6.2. The table shows the environment variable name and the default value if given. The only environment variable which is required is `SPARK_MASTER_URI`. This variable needs the URI of the Apache Spark master node. If the `CPU_ONLY` variable is set to *true*, the custom submit script executes the spark-submit executable without enabling GPU-acceleration using the RAPIDS plugin. `DRIVER_MEMORY` sets the available memory for the driver process, and `EXECUTOR_MEMORY` sets the memory for each executor process. The RAPIDS environment variables are described in detail in the online documentation[6].

Name	Default Value
`SPARK_MASTER_URI`	*required*
`CPU_ONLY`	false
`DRIVER_MEMORY`	4g
`EXECUTOR_MEMORY`	8g
`RAPIDS_GPU_ALLOC_FRACTION`	1
`RAPIDS_INCOMPATIBLE_OPS`	false
`RAPIDS_DEBUG`	NONE
`RAPIDS_GPU_POOL`	ARENA

Table 6.2: *spark-submit* image environment variables

6 spark-rapids Configuration - `https://nvidia.github.io/spark-rapids/docs/configs.html` (Accessed: 2021-02-09)

Executing an Application with the spark-submit Image

Listing 6.12 provides an example of how to perform an Apache Spark application using the *spark-submit* Docker image. The `SPARK_MASTER_URI` and `EXECUTOR_MEMORY` environment variables are set using the `-e` flag. It is important to set the `-rm` flag, which automatically removes the Docker container after submitting the script.

```
$ docker run \
  --rm \
  --network computing_net \
  -e SPARK_MASTER_URI=spark://spark-master:7077 \
  -e EXECUTOR_MEMORY=16g \
  spark-submit:latest \
  train.py \
  --max-depth=50
```

Listing 6.12: Example of the spark-submit image

6.4.5 Building the Apache Spark Docker Images

A script is used to automate the build process of all images. The source code of the build script is provided at Listing C.6. To specify which Apache Spark version is installed on all images, the script takes the Apache Spark and Hadoop version as input arguments which are required by the *spark-base* image. Additionally, the build script tags each image with the provided Apache Spark and Hadoop version. An example of the usage is provided in Listing 6.13. To build the images, the example uses Apache Spark version 3.0.1 and Hadoop 2.7.

```
$ sh build-images.sh 3.0.1 2.7
```

Listing 6.13: Example of the spark-submit image

6.5 GitLab CI/CD Pipeline for Automated Deployment of Machine Learning Applications

The CI pipeline is responsible to automatically validate, and submit an application to the Apache Spark cluster whenever a change has been committed to the source code of the application. It is important to notice, that Python is an interpreted programming language and does not need to be compiled into a binary file. However, Apache Spark supports `.zip`, `.egg`, and raw `.py` files when submitting a Python application. To keep the implementation simple, only raw `.py` files are submitted to the Apache Spark cluster. Therefore, there is no build stage in this CI pipeline architecture. The CI pipeline is implemented using GitLab CI/CD (introduced in Section 4.7). To perform CI/CD jobs on the host machine, a GitLab runner (introduced in Section 4.7.3) instance has to run on the same machine.

6.5.1 GitLab Runner

To deploy a *spark-submit* container to the Apache Spark cluster's swarm network through a CI/CD job, the GitLab Runner needs to run on the same host with access to the overlaying Docker engine.

In this implementation, a GitLab Runner is deployed inside a Docker container. The Docker container is built from the `gitlab/gitlab-runner:latest` image. To enable Docker support in the context of the GitLab Runner Docker container, the Docker socket has to be mounted to the container. The *socket-binding* approach is explained in detail on the GitLab online documentation[7].

Create a GitLab Runner Instance

Listing 6.14 shows the command to create a GitLab runner in a Docker container. The command creates a Docker container using the `gitlab/gitlab-runner:latest` image. This image provides an installation of the GitLab runner service and CLI. Additionally, the Docker Engine and the `/build` directory are mounted to the container. The reason to mount the `/build` directory to the host filesystem is explained in Section 6.5.3. Next, the `gitlab-runner register` command is performed in the context of the Docker container. To enable Docker access for the GitLab Runner, various settings have to be set. First, the docker executor has to be activated. This enables the runner to perform jobs with access to user defined Docker images, which is required to deploy a *spark-submit* Docker container from a CI/CD job. Second, the `docker:latest` image is set as Docker image for CI/CD job containers which enables to perform Docker CLI commands from CI/CD job containers. The support of the Docker CLI within CI/CD jobs is required to deploy a *spark-submit* container.

7 Building Docker images with GitLab CI/CD - `https://docs.gitlab.com/ee/ci/docker/using_docker_build.html#use-docker-socket-binding` (Accessed: 2021-01-31)

```
$ docker run -d \
    --name gitlab-runner \
    --restart always \
    -v /var/run/docker.sock:/var/run/docker.sock \
    -v /builds:/builds \
    gitlab/gitlab-runner:latest \
    gitlab-runner register \
    -n \
    --name "Spark-Cluster Runner" \
    --executor docker \
    --docker-image docker:latest \
    --docker-volumes /var/run/docker.sock:/var/run/docker.
   sock \
    --docker-volumes /builds:/builds \
    --docker-privileged=true
    --url https://gitlab.com/ \
    --registration-token mpCBWzZzhaaJrdqjXYZq \
    --tag-list spark-submit
```

Listing 6.14: CLI command to start a GitLab runner in a Docker container

6.5.2 Pipeline Architecture

As explained in Section 4.7.1, a GitLab CI/CD pipeline is configured by a `.gitlab-ci.yml` file in the source code repository's root directory. Listing C.7 shows the `.gitlab-ci.yml` configuration file of this implementation. The pipeline consists of a *test* and a *train* stage, as explained in the conceptual design in Section 5.6.

Test Stage

The first stage is the test stage, which consists of a single job called *unit-tests*. It uses the `python:3.8-slim` Docker image, which already has Python 3.8 installed. To perform the tests, first a Python virtual environment with all dependencies is created. Lastly, all tests in the `tests/` directory are performed using the pytest[8] library.

It is important to mention that the test stage depends on the application. This implementation focuses on simplicity and provides a general concept of a test stage that can be used and extended for other projects.

Train Stage

After the test stage has been performed successfully, the train stage is responsible for submitting the Apache Spark application to the Apache Spark cluster. The train stage consists of a single job called *train-model*. This job executes the `submit.sh` build script (see Listing 6.15), which is

8 pytest - `https://docs.pytest.org/en/latest/` (Accessed: 2021-02-01)

located in the repository root directory. The script executes the `docker run` command to deploy a *spark-submit* Docker container in the Apache Spark cluster. It takes the path to the application Python file and all needed parameters as input and forwards them to the `docker run` command. To configure the *spark-submit* container, all configuration parameters listed in Table 6.2 can be set as environment `variables` in the CI/CD job variables section. To perform this job with the in Section 6.5.1 created runner, the *train-model* job has to be tagged with the *spark-submit* tag.

```
#!/bin/bash

DRIVER_MEMORY=${DRIVER_MEMORY-4g}
EXECUTOR_MEMORY=${EXECUTOR_MEMORY-8g}
RAPIDS_GPU_ALLOC_FRACTION=${RAPIDS_GPU_ALLOC_FRACTION-1}
RAPIDS_INCOMPATIBLE_OPS=${RAPIDS_INCOMPATIBLE_OPS-"false"}
RAPIDS_DEBUG=${RAPIDS_DEBUG-"NONE"}
RAPIDS_GPU_POOL=${RAPIDS_GPU_POOL-"ARENA"}

docker run \
  --rm \
  --network $NETWORK \
  -v "${MOUNT_POINT}:/mnt" \
  -e SPARK_MASTER_URI=$SPARK_MASTER_URI \
  -e CPU_ONLY=$CPU_ONLY \
  -e DRIVER_MEMORY=$DRIVER_MEMORY \
  -e EXECUTOR_MEMORY=$EXECUTOR_MEMORY \
  -e RAPIDS_GPU_ALLOC_FRACTION=$RAPIDS_GPU_ALLOC_FRACTION \
  -e RAPIDS_INCOMPATIBLE_OPS=$RAPIDS_INCOMPATIBLE_OPS \
  -e RAPIDS_DEBUG=$RAPIDS_DEBUG \
  -e RAPIDS_GPU_POOL=$RAPIDS_GPU_POOL \
  local/cci/distributed-computing-framework/spark-images/
   spark-submit:3.0.1-hadoop2.7 \
  $@
```

Listing 6.15: Submit script to execute `docker run` with all needed configuration parameters

To mount the application source code to the spark-submit container, it has to be available to the host file system. This is explained in Section 6.5.3. The application source code is located at `/builds/<GITLAB_USERNAME>/<PROJECT_NAME>` on the *train-model* job Docker container, where *GITLAB_USERNAME* is the name of the project's developer and *PROJECT_NAME* the name of the project on GitLab. This directory has to be shared with the *spark-submit* container. In the submit script at Listing 6.15, this directory is saved as an environment variable called `MOUNT_POINT` and mounted to the `/mnt` directory on the *spark-submit* container. Then, inside the *spark-submit* container, the application source code is located at `/mnt`. This concept is discussed on the GitLab website[9].

9 Docker volumes not mounted when using docker:dind - `https://gitlab.com/gitlab-org/gitlab-foss/-/issues/41227` (Accessed: 2021-02-01)

6.5.3 Sharing the Applications Source Code between Docker Containers

Docker containers run in isolation and do no share their local filesystem with other containers. When the *train-model* job performs the `docker run` command to deploy a *spark-submit* container, it runs the command in the context of its container but deploys the container using the host Docker engine. Therefore, the `/builds` directory where the source code is located cannot be shared as a volume with the *spark-submit* container. To overcome this problem, the `/builds` directory has to be mounted to the host filesystem. The *train-model* job can then mount the `/builds` directory from the host filesystem to the *spark-submit* container. To make the `/builds` directory available on the host filesystem, the *train-model* job mounts the directory to the GitLab runner container filesystem when the GitLab runner starts the job in a separate Docker container. The GitLab runner container mounts the `/builds` directory to the host filesystem, as explained in Section 6.5.1.

Chapter 7

Evaluation

In this chapter, the implementation of Chapter 6 is evaluated in various experiments. Further, the experimental results are summarised and discussed.

7.1 Experimental Environment

The experiments are conducted on the DGX introduced in Section 6.1. As for the implementation, 2 GPUs have been available for the experiments.

7.2 Experiments

The performance of the computing environment is measured on two widely used machine learning algorithms. In both experiments, a machine learning model is trained on the computing environment using Apache Spark. Furthermore, each benchmark is evaluated using three different configurations:

1. Using a static number of CPU-only Apache Spark workers (Section 7.3)
2. Using a static number of GPU-accelerated Apache Spark workers (Section 7.4)
3. Dynamically scaling the replicas of CPU-only Apache Spark workers using the *Auto-Scaler* (Section 7.5)

For each configuration, the experiment is conducted ten times. The spark-job execution time mean value over all ten iterations per experiment is used as the result. The performance difference between GPU-accelerated worker nodes, and CPU-only worker nodes are explored using a CPU-only and a GPU-only version of the benchmark implementation.

The *Auto-Scaler* is not evaluated using GPU-accelerated worker nodes. As mentioned, for this experiment, only 2 GPUs are available. The RAPIDS plugin allocates a GPU exclusively for each executor. When the *Auto-Scaler* creates a new worker node, the worker allocates a random available GPU.

However, the host machine is a live system. It is not possible to allocate a random GPU that may be in use by another application. Furthermore, the *Auto-Scaler* does not support allocating a specific GPU for each newly created worker. An approach to overcome this problem is introduced in Section 8.2.3.

The two benchmarks to evaluate the performance are:

- XGBoost classification model using the *Fannie Mae's Single-Family Historical Loan Performance Dataset*[1] [Fan]
- XGBoost regression model using a Taxi fare dataset[2]

The source code and the dataset used in these experiments are available on Github on the *spark-xgboost-examples*[3] repository from NVIDIA. The repository provides a *mortgage* and a *taxi* application. Both applications provide a CPU and a GPU configuration.

Classification and regression algorithms are supervised machine learning algorithms. The classification algorithm identifies the category of a label. A regression algorithm predicts a continuous numeric value. The goal of supervised machine learning algorithms is to train a model by finding patterns in labeled data. The trained model is then used to predict labels on newly observed data based on the learned labels [McD20].

7.3 Static CPU-Only Workers

The first experiment is conducted using a fixed number of CPU-only Apache Spark workers to evaluate both benchmarks' performance. The performance data of each iteration for the classification benchmark is available at Section C.2.1, and for the regression benchmark at Section C.2.2.

Figure 7.1 illustrates the mean execution time of both benchmarks for different numbers of worker nodes. The best performance for the classification benchmark was achieved with 247 seconds using 30 workers with an improvement of 7.04x compared to 1 worker. The regression benchmark performed best with 102 seconds using 10 workers with an improvement of 3.21x in comparison to 1 worker. It achieved a mean execution time of 102 seconds with 30 workers as well. However, using 10 workers is considered the best result for the regression benchmark because fewer workers are used.

1 Downloaded from: `https://docs.rapids.ai/datasets/mortgage-data` (Accessed: 2021-02-06)

2 The Taxi dataset is available at: `https://github.com/NVIDIA/spark-xgboost-examples/tree/spark-3` (Accessed: 2021-02-06)

3 spark-xgboost-examples - `https://github.com/NVIDIA/spark-xgboost-examples/tree/spark-3` (Accessed: 2021-02-06)

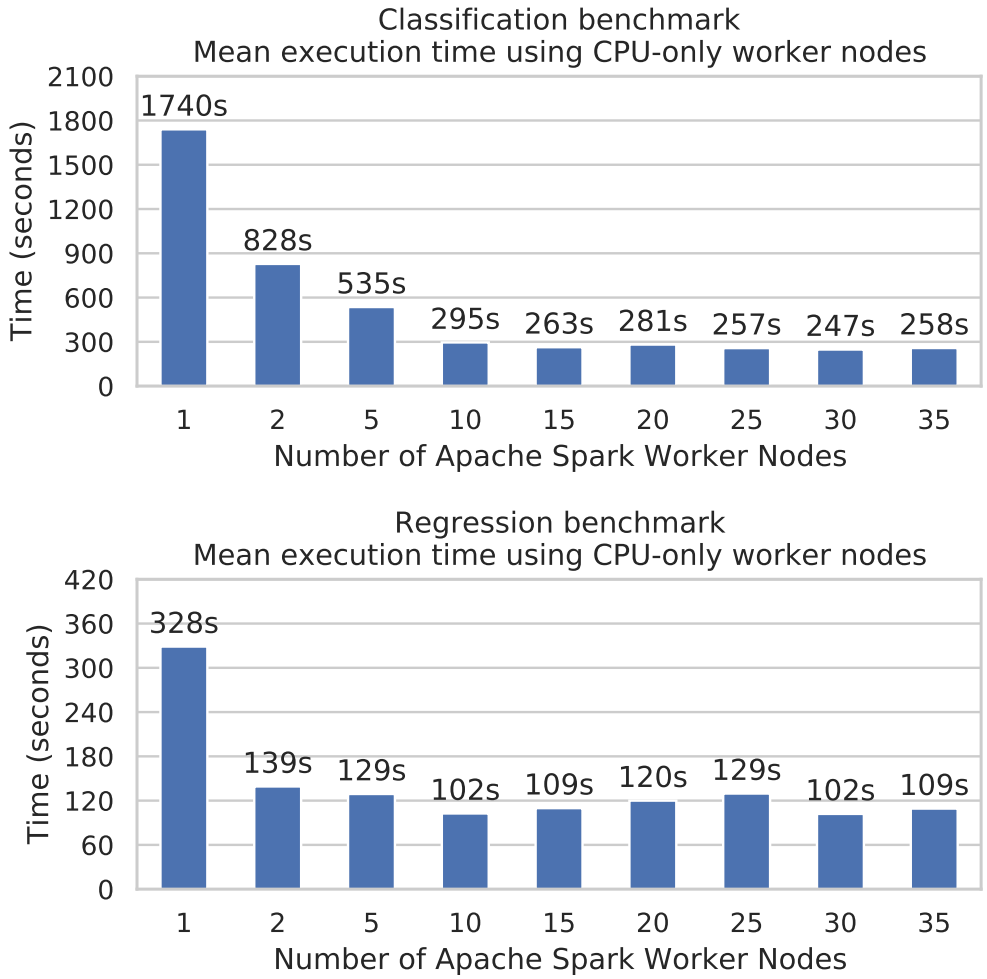

Figure 7.1: Mean execution time using CPU-only worker nodes

In addition, Figure 7.1 shows that from a specific number of workers onwards, no significant improvement is made. For the classification benchmark, this point is reached at 15 workers. A similar result can be seen for the regression benchmark. From 10 workers onward, the execution time does not improve anymore. This result shows that over-provisioning the Apache Spark cluster by simply adding more workers does not improve the performance.

7.4 GPU-Accelerated Workers

The impact of GPU-accelerated Apache Spark worker nodes for both benchmarks have been evaluated using 2 configurations: Using one and two GPU-accelerated worker nodes respectively. The GPU-experiment performance data for the classification benchmark is available in Figure C.10, and Figure C.11., for the regression benchmark at Figure C.22, and Figure C.23.

The results of the experiment are illustrated in Figure 7.2. The mean

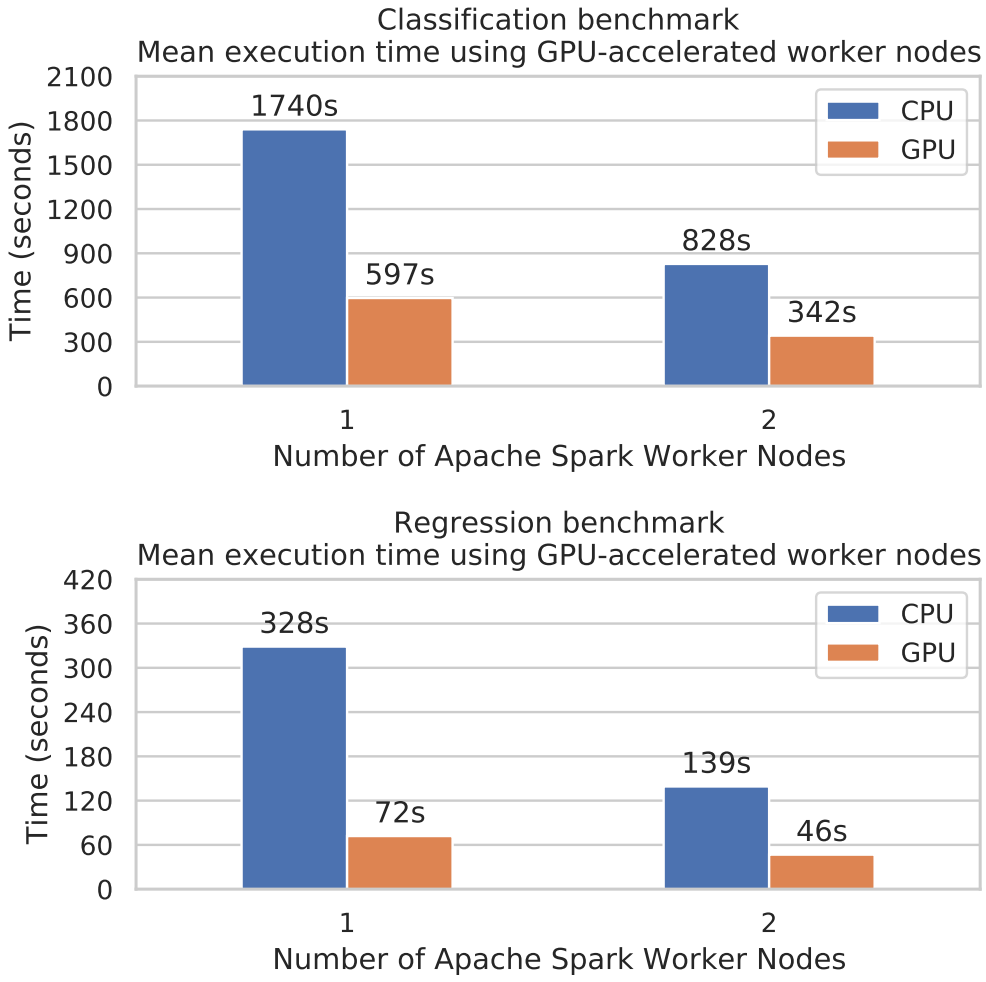

Figure 7.2: Mean execution time of GPU-accelerated worker nodes vs. Mean execution time of CPU-only worker nodes

execution times using GPU-accelerated worker nodes are plotted against the mean execution times using CPU-only worker nodes. Overall, GPU-accelerated worker nodes significantly outperformed the equivalent number of CPU-only worker nodes. For the classification benchmark, the best execution time was achieved using 2 GPU-accelerated worker nodes with an improvement of 2.42x compared to 2 CPU-only worker nodes. Using 1 GPU-accelerated worker node achieved an improvement of 2.91x compared to 1 CPU-only worker node. The regression benchmark performed best with 2 GPU-accelerated worker nodes improving the execution by 3.02x in comparison to 2 CPU-only worker nodes. Using 1 GPU-accelerated worker node achieved an improvement of 4.55x in comparison to 1 CPU-only worker node.

Table 7.1 shows the overall results by comparing CPU-only and GPU-accelerated results for each benchmark. For the classification benchmark, 5 CPU-only worker nodes outperformed 1 GPU-accelerated worker node,

and 10 CPU-only worker nodes performed better than 2 GPU-accelerated worker nodes. However, for the regression benchmark, CPU-only worker nodes could not outperform GPU-accelerated worker node performance.

	Classification		Regression	
Number of workers	CPU	GPU	CPU	GPU
1	1740s	597s	328s	72s
2	828s	**342s**	139s	**46s**
5	535s	-	129s	-
10	295s	-	**102s**	-
15	263s	-	109s	-
20	281s	-	120s	-
25	257s	-	129s	-
30	**247s**	-	102s	-
35	258s	-	109s	-

Table 7.1: Mean execution time of all CPU-only and GPU-accelerated experiments for both benchmarks

7.5 Auto-Scaler

To test the impact of the *Auto-Scaler* while training machine learning applications, both benchmarks have been tested with different *Auto-Scaler* configurations. The performance data for the classification benchmark is available in Figure C.12, and for the regression benchmark in Figure C.24.

7.5.1 Auto-Scaler Benchmark Configurations

The configuration parameters are chosen according to the results of the static worker experiment (Section 7.3). The *Auto-Scaler* configuration parameters for each benchmark are shown in Table 7.2. To prevent cluster over-provisioning, the maximum number of worker nodes for the classification benchmark is set to 15, and 10 for the regression benchmark respectively. Figure 7.3 shows all 10 iterations of the CPU-only experiment for both benchmarks. It shows that, while the machine learning model is trained, only 2 performance spikes occurred at the beginning and at the end during a short period. To scale while these performance spikes occur, the recurrence factor is set to 1. Additionally, the maximum CPU utilization for both benchmarks is set according to the maximum CPU utilization during the performance spikes.

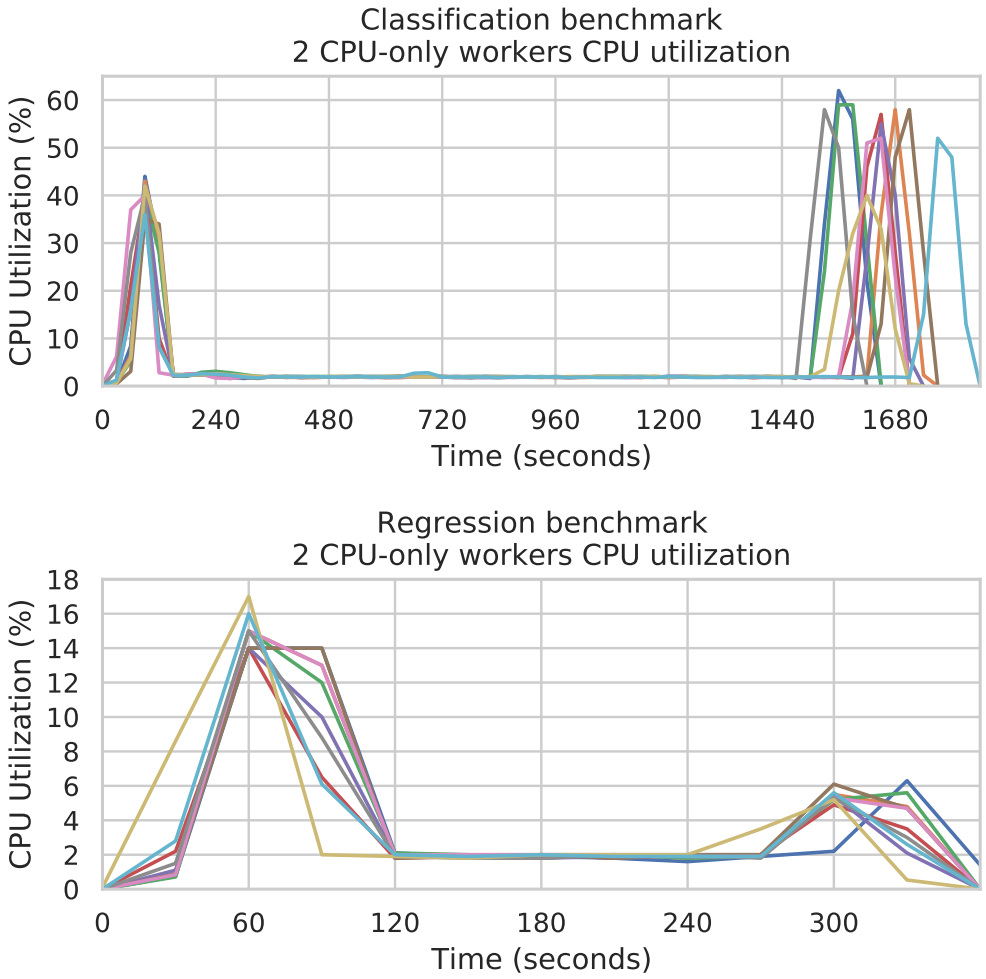

Figure 7.3: CPU utilization during all iterations of both benchmarks with 2 CPU-only workers

7.5.2 Execution Time Evaluation

Figure 7.4 illustrates the results of the *Auto-Scaler* experiment. The mean execution time of 2 CPU-only worker nodes is plotted against the mean execution with the *Auto-Scaler* enabled. The results show that no improvement was achieved using the *Auto-Scaler* implementation. For the classification benchmark, the execution time increased by 228 seconds when enabling the *Auto-Scaler* in comparison to 2 CPU-only worker nodes. Furthermore, the execution time is 38 seconds higher with *Auto-Scaler* enabled than 2 CPU-only worker nodes.

Parameter	Classification	Regression
Interval	5 seconds	5 seconds
Recurrence factor	1	1
Cooldown period	60 seconds	60 seconds
Target CPU utilization	10%	5%
Minimum CPU utilization	5%	2%
Maximum CPU utilization	25%	10%
Minimum worker nodes	2	2
Maximum worker nodes	15	10

Table 7.2: *Auto-Scaler* configuration parameters for both benchmarks

	Classification		Regression	
Iteration	Time	Nodes	Time	Nodes
1	**840s**	15	168s	5
2	960s	7	**150s**	2
3	1020s	15	186s	6
4	1140s	15	180s	6
5	1080s	15	180s	6
6	1140s	15	180s	6
7	1140s	15	180s	6
8	1080s	15	180s	6
9	1140s	7	180s	6
10	1020s	15	186s	6

Table 7.3: Results of each iteration during the *Auto-Scaler* experiment for both benchmarks

Table 7.3 summarizes the results for all 10 iterations of each benchmark. For the classification benchmark, the best result was achieved in the first iteration with an execution time of 960 seconds and a maximum number of 15 worker nodes during the execution. The regression benchmark performed best in the second iteration, with an execution time of 150 seconds and a maximum number of 2 worker nodes during this iteration. The results show that, during the classification benchmark, the *Auto-Scaler* scaled upon the maximum number of allowed worker nodes in 8 out of 10 iterations. During the regression benchmark experiment, the maximum number of worker nodes was never reached. Furthermore, in the second iteration, the *Auto-Scaler* had not scaled the number of worker nodes when the best result was achieved.

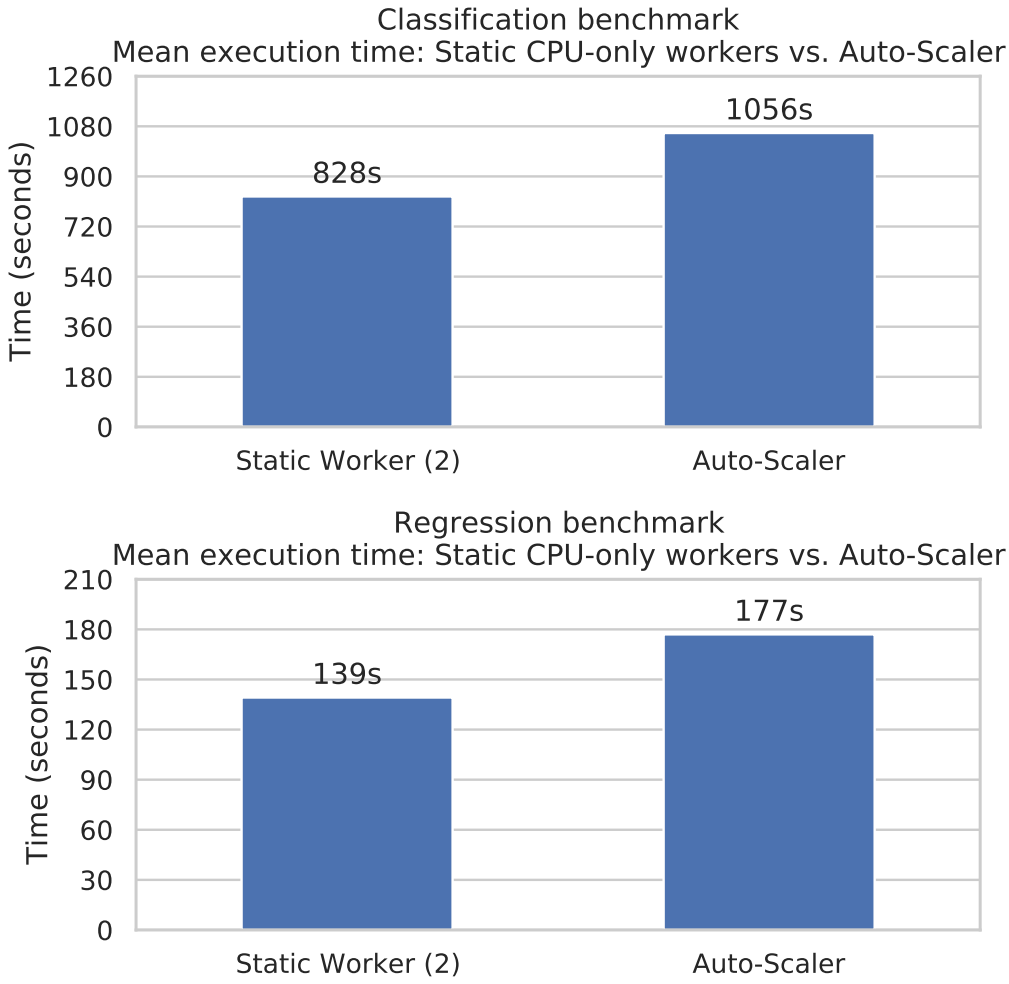

Figure 7.4: *Auto-Scaler* experiment mean execution time of both benchmarks

7.6 Experimental Results Summary

Overall, three different experiments have been conducted to evaluate the implementation of this thesis. The results of the first experiment show that over-provisioning the Apache Spark cluster does not improve the performance significantly and can negatively impact the performance. The second experiment shows that GPU-accelerated worker nodes significantly outperformed CPU-only worker nodes. However, CPU-only workers achieved a better performance in the classification benchmark than GPU-accelerated workers with 5x the amount. For the last experiment, the results show that enabling the *Auto-Scaler* during the training of machine learning models increases the execution time compared with a fixed number of worker nodes.

Chapter 8

Conclusion and Outlook

In this chapter, an outlook is given for further research based on the results of Chapter 7.

8.1 Conclusion

In this thesis, a scalable computing environment for training machine learning models using Apache Spark was implemented. In addition, the training process is automated using an automated deployment pipeline. In Chapter 1, three research questions for this thesis are defined.

The first research question is about implementing a solution to automatically scale the number of workers in an Apache Spark cluster. For this research question, a computing environment is implemented according to the autonomic computing architecture. It consists of an autonomic manager and an Apache Spark cluster. For simplicity, all components of the computing environment were deployed with Docker. The autonomic manager is implemented according to the MAPE architecture and responsible for monitoring and automatically scaling the Apache Spark workers. For the implementation of the autonomic manager, Prometheus, cAdvisor, and DCGM-Exporter are used to create a monitoring system. In addition, an *Auto-Scaler* is implemented using Python 3 that automatically fetches performance metrics from the monitoring system and scales the Apache Spark worker nodes. The decision to use Docker for containerization contributed to the simplicity of the implementation. Additionally, using Docker Swarm significantly simplified the scaling process of worker nodes. The *Auto-Scaler* is able to fetch meaningful performance metrics from the monitoring system and make scaling decisions in real-time.

The second research question is about how to accelerate the Apache Spark cluster's computational power using GPUs. This research question is implemented by extending the existing Apache Spark cluster with the NVIDIA RAPIDS plugin. Using the RAPIDS plugin to accelerate the Apache Spark cluster, achieved the expected results. Furthermore, the installation process is very intuitive to enable Apache Spark to leverage

GPUs. However, the RAPIDS plugin lacks in available features. Firstly, only XGBoost is GPU accelerated and it cannot accelerate Apache Spark's ML library. Second, RAPIDS allocates GPUs exclusively for an executor which caused problems during the implementation on a shared host.

The final research question is about how to automate the training of a machine learning model. To accommodate this research question, a CI pipeline is implemented using GitLab CI/CD. The CI pipeline triggers when a change is committed to the application source code. It consists of a *train-stage* that automatically deploys a *spark-submit* Docker container to the Apache Spark cluster. The *spark-submit* container executes the spark-submit executable to perform the application on the Apache Spark cluster. To deploy a *spark-submit* container from the *train-stage* inside the Apache Spark cluster, a GitLab Runner is created, which runs on the same host. With GitLab CI/CD, the automation of the Machine Learning model training using a CI pipeline is a straightforward process. However, it requires to implement the CI pipeline separately for each project. Therefore, developers will probably end up coping and pasting boilerplate code to setup the pipeline, which can be further simplified.

The implementation is evaluated with a variety of experiments using a classification and regression machine learning algorithm. The GPU-accelerated Apache Spark cluster significantly outperformed a CPU-only cluster. However, the *Auto-Scaler* implementation is not able to improve the performance of the Apache Spark cluster. Furthermore, it increases the overall execution time. In order to scale GPU-accelerated worker nodes, the *Auto-Scaler* implementation requires further work. Instead of horizontal-scaling, the *Auto-Scaler* can be extended using different approaches to automatically scale the environment's computational power.

Overall,

8.2 Outlook

Mentioned in Section 8.1, the *Auto-Scaler* implementation was not able to improve the performance of training machine learning models on the Apache Spark cluster. A possible reason for the execution time increase is that Apache Spark is not able to efficiently distribute the workload of an application while workers are added to the cluster during the execution of an application. Additionally, mentioned in Section 8.1 as well, the setup process of the CI pipeline can be simplified to reduce the amount of boilerplate code. Therefore, different *Auto-Scaler* and CI pipeline implementation approaches for further research are introduced.

8.2.1 Proactive Auto-Scaler Approach

The current implementation of the *Auto-Scaler* follows a reactive approach. It uses static threshold-based rules (e.g., maximum and minimum CPU utilization) to define when a scaling action is necessary. The *Auto-Scaler*

can be optimized using a proactive approach. A proactive *Auto-Scaler* tries to predict the computing environment's future state (e.g., reinforcement learning) using historical data. The MAPE architecture can be extended with a knowledge source (MAPE-K), which provides data about the computing environment [Sin06]. The autonomic manager can use the knowledge to try to predict when a scaling action is necessary.

8.2.2 Vertical-Scaling Approach

The evaluation of the static CPU-only worker experiments showed that from a specific number of workers, no significant performance improvement was made. Therefore, instead of scaling the replicas of worker nodes, a vertical-scaling approach, where the *Auto-Scaler* scales the available computing resources of a worker node, should be explored. Providing more powerful resources, increases the computational power of the Apache Spark cluster and could lead to lower execution times for training machine learning models.

8.2.3 Scaling GPU-accelerated Workers

Due to the lack of implementation, the *Auto-Scaler* can not keep track of available GPUs in the cluster. Therefore, it was not possible to evaluate the *Auto-Scalers* impact on GPU-accelerated worker nodes. Extending the *Auto-Scaler* to keep track of GPUs which are free or already allocated by a worker should be explored. Auto-scaling GPU-accelerated worker nodes can improve the spark-job execution time.

8.2.4 Save Temporary Data on an External Service

With the current *Auto-Scaler* implementation, it is not possible to remove worker nodes while an application is actively performing because worker nodes save important temporary data. The worker nodes can be extended to save temporary data on an external storage service, which enables the *Auto-Scaler* to remove nodes while an application performs. The impact of removing nodes during the execution of an application should be explored. In the evaluation of this thesis, only the impact of adding worker nodes is explored.

8.2.5 Train-Stage Docker Image

GitLab CI/CD requires to setup a pipeline for each project additionally using a `.gitlab-ci.yml` configuration file. Therefore, the developer has to implement the process to share the source code between multiple Docker containers everytime a new project is created. Additionally, the custom submit script needs to be added to the project source code. This process can be automated using a custom Docker image, which is then used for the *train-stage* implementation. The image automatically copies the source code to a *mount-point* and integrates the custom submit script.

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Appendix A

Attached CD

The source code of this implementation is available to the CD attached to this thesis. It includes the following directories:

- auto-scaler: Source code of the Auto-Scaler implementation
- computing_framework: Source code of the computing environment
- spark-images: Source code of the Apache Spark images
- ci-pipeline: Source code of the CI pipeline

Appendix B

Implementation

B.1 Computing Environment

```
version: "3.7"

networks:
    computing-net:
        name: computing_net
        attachable: true

services:
    spark-master:
        image: spark-master:3.0.1-hadoop2.7
        networks:
            - computing-net
        ports:
            - 4040:4040
            - 7077:7077
        volumes:
            - ./conf/spark-master/metrics.properties:/usr/bin/spark/conf/metrics.properties
            - ./conf/spark-master/spark-defaults.conf:/usr/bin/spark/conf/spark-defaults.conf

    prometheus:
        image: prom/prometheus
        networks:
            - computing-net
        volumes:
            - ./conf/prometheus/prometheus.yml:/etc/prometheus/prometheus.yml
            - ./conf/prometheus/recording_rules.yml:/etc/prometheus/recording_rules.yml
        command:
            - "--config.file=/etc/prometheus/prometheus.yml"
        ports:
            - "9090:9090"
        depends_on:
            - cadvisor

```

```
34     cadvisor:
35         image: google/cadvisor
36         networks:
37             - computing-net
38         ports:
39             - "8080:8080"
40         volumes:
41             - "/:/rootfs:ro"
42             - "/var/run:/var/run:ro"
43             - "/sys:/sys:ro"
44             - "/var/lib/docker/:/var/lib/docker:ro"
45             - "/dev/disk/:/dev/disk:ro"
46         command:
47             - "--docker_only=true"
48             - "--logtostderr=true"
49         depends_on:
50             - spark-master
51             - spark-worker
52
53     auto-scaler:
54         image: auto-scaler:latest
55         networks:
56             - computing-net
57         volumes:
58             - "/var/run/docker.sock:/var/run/docker.sock:ro"
59             - ./conf/auto-scaler/config.yml:/etc/autoscaler/
   config.yml
60         command:
61             - '--config=/etc/autoscaler/config.yml'
62         depends_on:
63             - prometheus
```

Listing B.1: Computing environment docker-compose file

Appendix C

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 C.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 C.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 C.3: Apache Spark worker image Dockerfile

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

#
```

```
# Licensed to the Apache Software Foundation (ASF) under one or more
# contributor license agreements.  See the NOTICE file distributed with
# this work for additional information regarding copyright ownership.
# The ASF licenses this file to You under the Apache License, Version 2.0
# (the "License"); you may not use this file except in compliance with
# the License.  You may obtain a copy of the License at
#
#    http://www.apache.org/licenses/LICENSE-2.0
#
# Unless required by applicable law or agreed to in writing, software
# 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 C.4: GPU discovery script - Source: `https://github.com/apache/spark/blob/v3.0.1/examples/src/main/scripts/getGpusResources.sh` (Accessed: 2021-01-03)

```
#!/bin/bash

DRIVER_MEMORY=${DRIVER_MEMORY-4g}
EXECUTOR_MEMORY=${EXECUTOR_MEMORY-8g}
```

```
5
6  if [ "$CPU_ONLY" == "true" ]
7      then
8      echo "Submit Spark app with CPU only"
9
10     $SPARK_HOME/bin/spark-submit \
11         --master $SPARK_MASTER_URI \
12         --driver-memory $DRIVER_MEMORY \
13         --executor-memory $EXECUTOR_MEMORY \
14         --conf spark.driver.extraClassPath=${SPARK_CUDF_JAR
       }:${JAR_RAPIDS}:${LIBS_PATH}/xgboost4j_3.0-1.3.0-0.1.0.
       jar:${LIBS_PATH}/xgboost4j-spark_3.0-1.3.0-0.1.0.jar \
15         --conf spark.executor.extraClassPath=${
       SPARK_CUDF_JAR}:${JAR_RAPIDS}:${LIBS_PATH}/xgboost4j_3
       .0-1.3.0-0.1.0.jar:${LIBS_PATH}/xgboost4j-spark_3
       .0-1.3.0-0.1.0.jar \
16         --jars ${SPARK_CUDF_JAR},${LIBS_PATH}/xgboost4j-
       spark_3.0-1.3.0-0.1.0.jar,${LIBS_PATH}/xgboost4j_3
       .0-1.3.0-0.1.0.jar,${JAR_RAPIDS} \
17         --py-files ${LIBS_PATH}/xgboost4j-spark_3
       .0-1.3.0-0.1.0.jar,/tank/data/users/chh-ms/spark-xgboost-
       examples/examples/apps/python/samples.zip \
18         $@
19 else
20     echo "Submit Spark app with GPU acceleration"
21
22     RAPIDS_GPU_ALLOC_FRACTION=${RAPIDS_GPU_ALLOC_FRACTION-1}
23     RAPIDS_INCOMPATIBLE_OPS=${RAPIDS_INCOMPATIBLE_OPS-"false
       "}
24     RAPIDS_DEBUG=${RAPIDS_DEBUG-"NONE"}
25     RAPIDS_GPU_POOL=${RAPIDS_GPU_POOL-"ARENA"}
26
27     $SPARK_HOME/bin/spark-submit \
28         --master $SPARK_MASTER_URI \
29         --driver-memory $DRIVER_MEMORY \
30         --executor-memory $EXECUTOR_MEMORY \
31         --conf spark.plugins=com.nvidia.spark.SQLPlugin \
32         --conf spark.rapids.memory.gpu.pool=$RAPIDS_GPU_POOL
       \
33         --conf spark.rapids.memory.gpu.allocFraction=
       $RAPIDS_GPU_ALLOC_FRACTION \
34         --conf spark.rapids.sql.incompatibleOps.enabled=
       $RAPIDS_INCOMPATIBLE_OPS \
35         --conf spark.rapids.memory.gpu.debug=$RAPIDS_DEBUG \
36         --conf spark.task.resource.gpu.amount=1 \
37         --conf spark.executor.resource.gpu.amount=1 \
38         --conf spark.driver.extraClassPath=${SPARK_CUDF_JAR
       }:${JAR_RAPIDS}:${LIBS_PATH}/xgboost4j_3.0-1.3.0-0.1.0.
       jar:${LIBS_PATH}/xgboost4j-spark_3.0-1.3.0-0.1.0.jar \
39         --conf spark.executor.extraClassPath=${
       SPARK_CUDF_JAR}:${JAR_RAPIDS}:${LIBS_PATH}/xgboost4j_3
       .0-1.3.0-0.1.0.jar:${LIBS_PATH}/xgboost4j-spark_3
       .0-1.3.0-0.1.0.jar \
40         --jars ${SPARK_CUDF_JAR},${LIBS_PATH}/xgboost4j-
       spark_3.0-1.3.0-0.1.0.jar,${LIBS_PATH}/xgboost4j_3
       .0-1.3.0-0.1.0.jar,${JAR_RAPIDS} \
```

```
        --py-files ${LIBS_PATH}/xgboost4j-spark_3.0-1.3.0-0.1.0.jar,/tank/data/users/chh-ms/spark-xgboost-examples/examples/apps/python/samples.zip \
        $@
fi
```

Listing C.5: Custom submit script

```
#!/bin/bash

if [ $# -ge 2 ]
  then
    SPARK_VERSION=$1
    HADOOP_VERSION=$2

    PWD=$(pwd)

    IMAGE_TAG_PATH="local"

    echo
    echo "# Image tag-path: ${IMAGE_TAG_PATH}"
    echo

    echo "# STEP(1/4) - Building spark-base"
    docker build \
      -t $IMAGE_TAG_PATH/spark-base:$SPARK_VERSION-hadoop$HADOOP_VERSION \
      --build-arg SPARK_VERSION=$SPARK_VERSION \
      --build-arg HADOOP_VERSION=$HADOOP_VERSION \
      $PWD/spark-base/

    echo "# STEP(2/4) - Building spark-master"
    docker build \
      -t $IMAGE_TAG_PATH/spark-master:$SPARK_VERSION-hadoop$HADOOP_VERSION \
      --build-arg IMAGE_TAG_PATH=$IMAGE_TAG_PATH \
      --build-arg SPARK_VERSION=$SPARK_VERSION \
      --build-arg HADOOP_VERSION=$HADOOP_VERSION \
      $PWD/spark-master/

    echo "# STEP(3/4) - Building spark-worker"
    docker build \
      -t $IMAGE_TAG_PATH/spark-worker:$SPARK_VERSION-hadoop$HADOOP_VERSION \
      --build-arg IMAGE_TAG_PATH=$IMAGE_TAG_PATH \
      --build-arg SPARK_VERSION=$SPARK_VERSION \
      --build-arg HADOOP_VERSION=$HADOOP_VERSION \
      $PWD/spark-worker/

    echo "# STEP(4/4) - Building spark-submit"
    docker build \
      -t $IMAGE_TAG_PATH/spark-submit:$SPARK_VERSION-hadoop$HADOOP_VERSION \
      --build-arg IMAGE_TAG_PATH=$IMAGE_TAG_PATH \
      --build-arg SPARK_VERSION=$SPARK_VERSION \
      --build-arg HADOOP_VERSION=$HADOOP_VERSION \
      $PWD/spark-submit/
```

```
  else
    echo "No arguments supplied\n"
    echo "Use the script as follows:"
    echo "build-images.sh <SPARK_VERSION> <HADOOP_VERSION>"
    exit 1
fi
```

Listing C.6: Build script for all Apache Spark images

C.1 GitLab CI/CD Pipeline Implementation

```
stages:
    - test
    - train

unit-tests:
    stage: test
    image: python:3.8-slim
    tags:
        - spark-submit
    script:
        - pip3 install -e .
        - cd tests
        - pytest

train-model:
    stage: train
    tags:
        - spark-submit
    variables:
        TMP_MOUNT_POINT: /tmp/_mnt
        NETWORK: "computing_net"
        CPU_ONLY: "true"
        DRIVER_MEMORY: "4g"
        EXECUTOR_MEMORY: "8g"
        SPARK_MASTER_URI: "spark://spark-master:7077"
    script:
        - pwd
        - mkdir -p "$TMP_MOUNT_POINT"
        - mv -v * $TMP_MOUNT_POINT
        - 'export MOUNT_POINT="$(dirname $CI_PROJECT_DIR)/shared"'
        - rm -rf $MOUNT_POINT
        - mkdir -p "$MOUNT_POINT"
        - cp -R $TMP_MOUNT_POINT/* $MOUNT_POINT/
        - rm -rf $TMP_MOUNT_POINT
        - chmod -R 777 $MOUNT_POINT
        - sh $MOUNT_POINT/submit.sh /mnt/train.py --max-depth=50
    only:
        - master
```

Listing C.7: texttt.gitlab-ci.yml configuration file

C.2 Evaluation Data

C.2.1 Classification Benchmark

Static CPU-only Workers

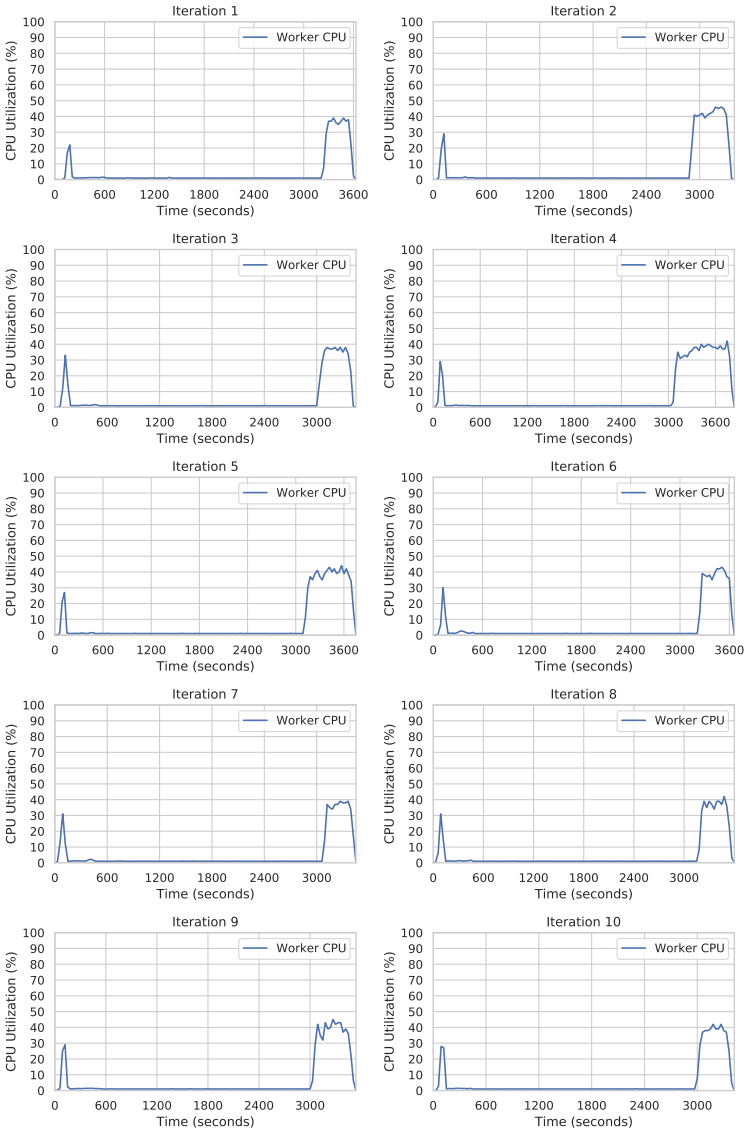

Figure C.1: Performance data of all iterations with 1 worker

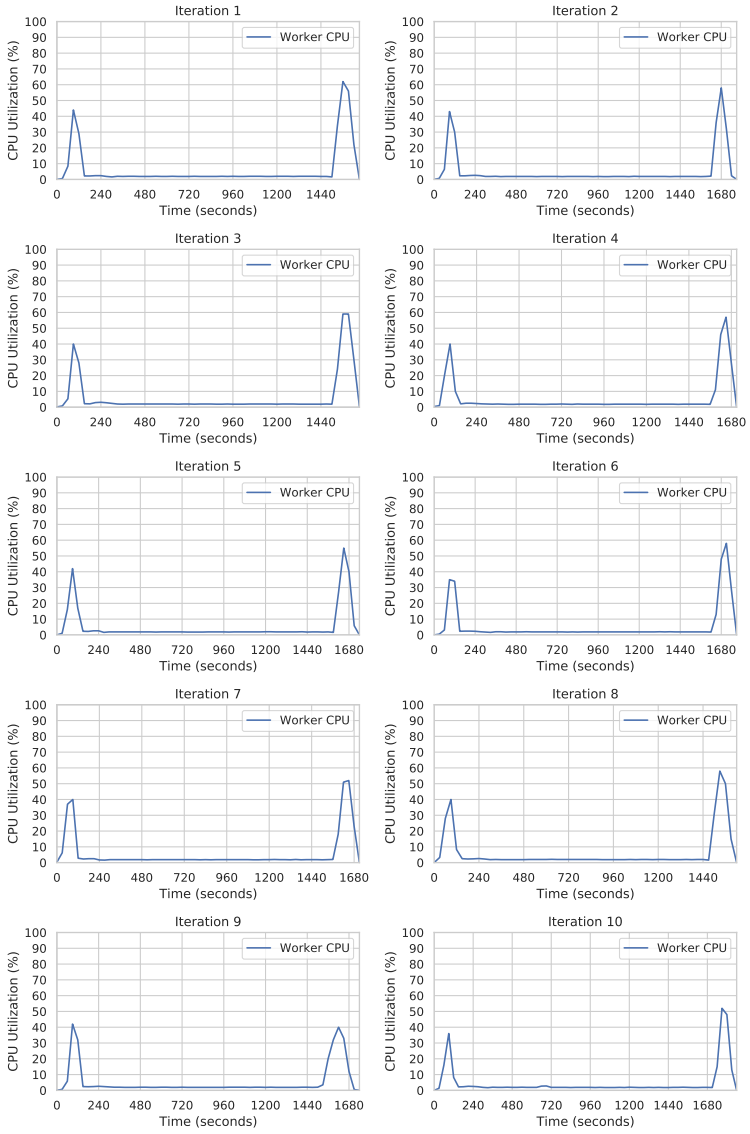

Figure C.2: Performance data of all iterations with 2 worker

GPU-Accelerated Workers

Auto-Scaler

C.2.2 Regression Benchmark

Static CPU-only Workers

GPU-Accelerated Workers

Auto-Scaler

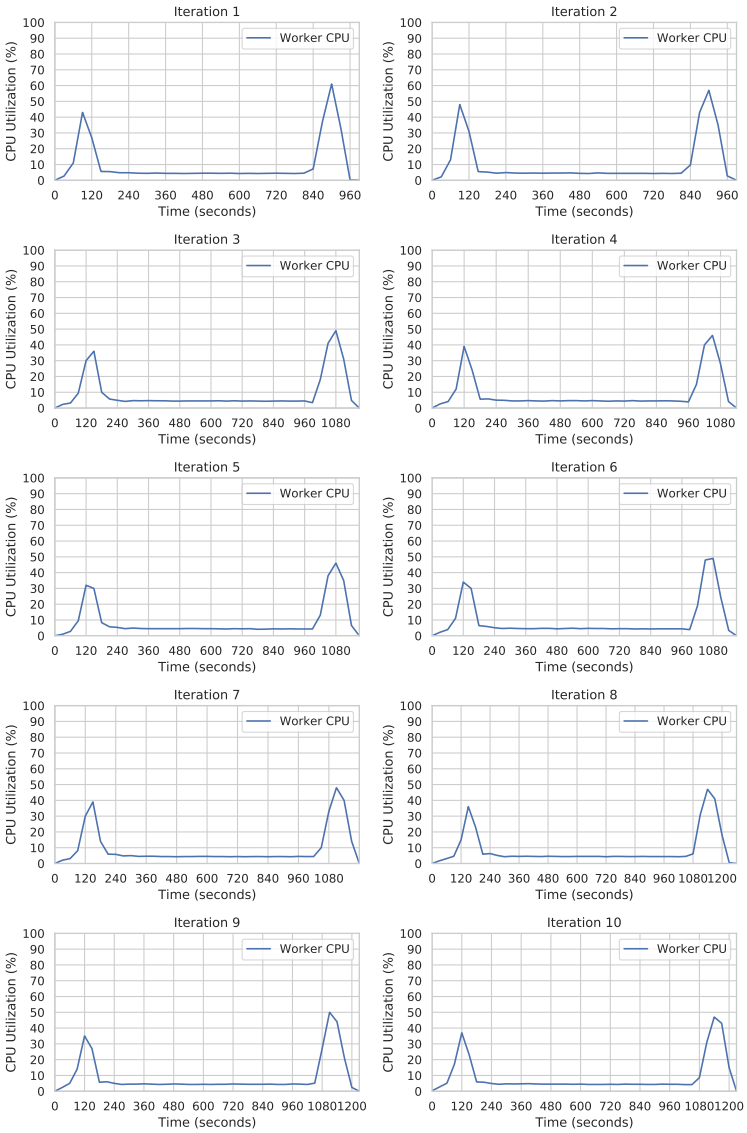

Figure C.3: Performance data of all iterations with 5 worker

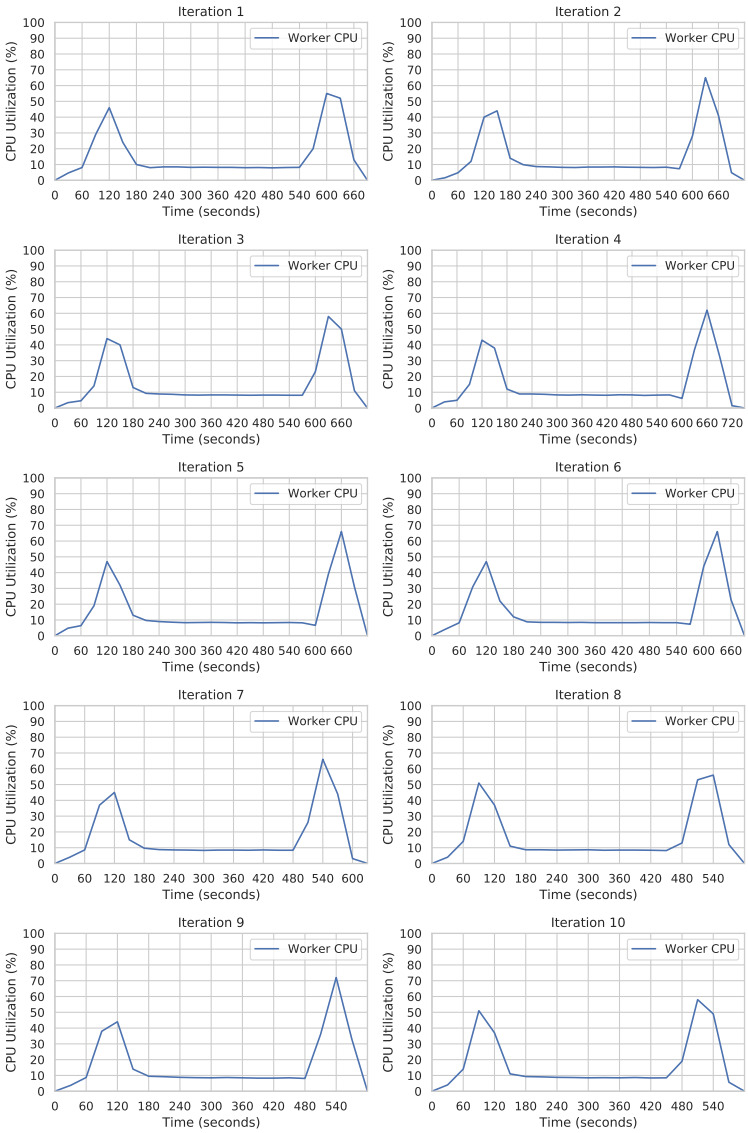

Figure C.4: Performance data of all iterations with 10 worker

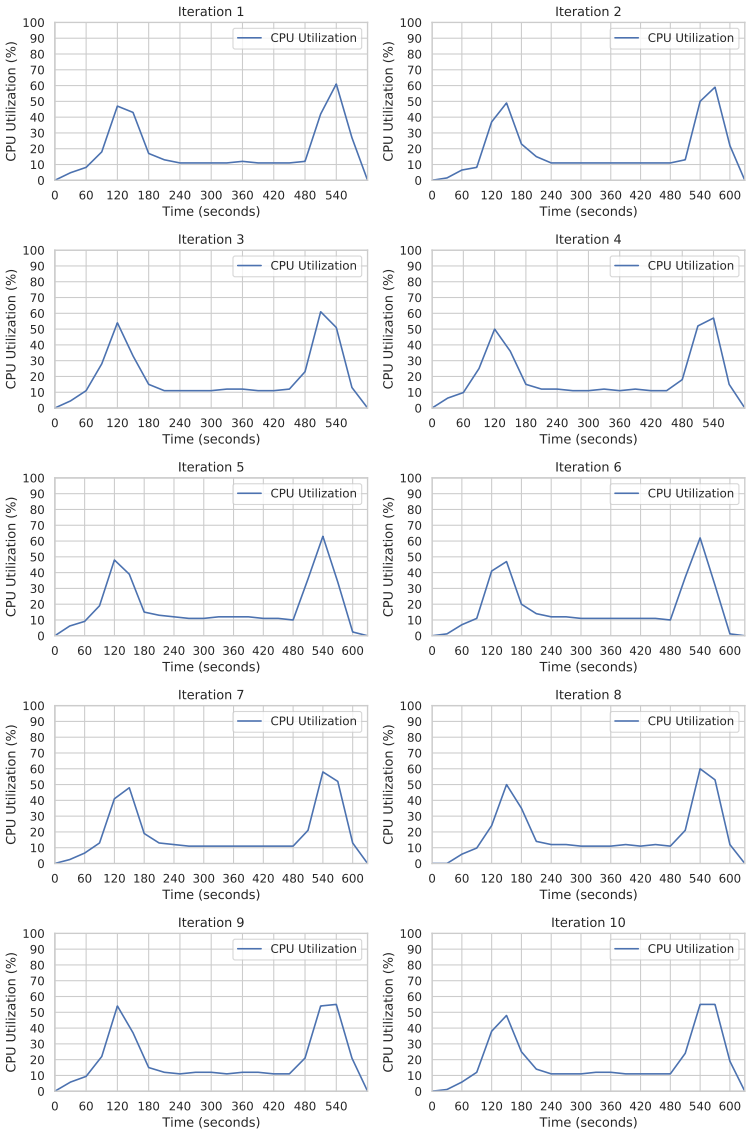

Figure C.5: Performance data of all iterations with 15 worker

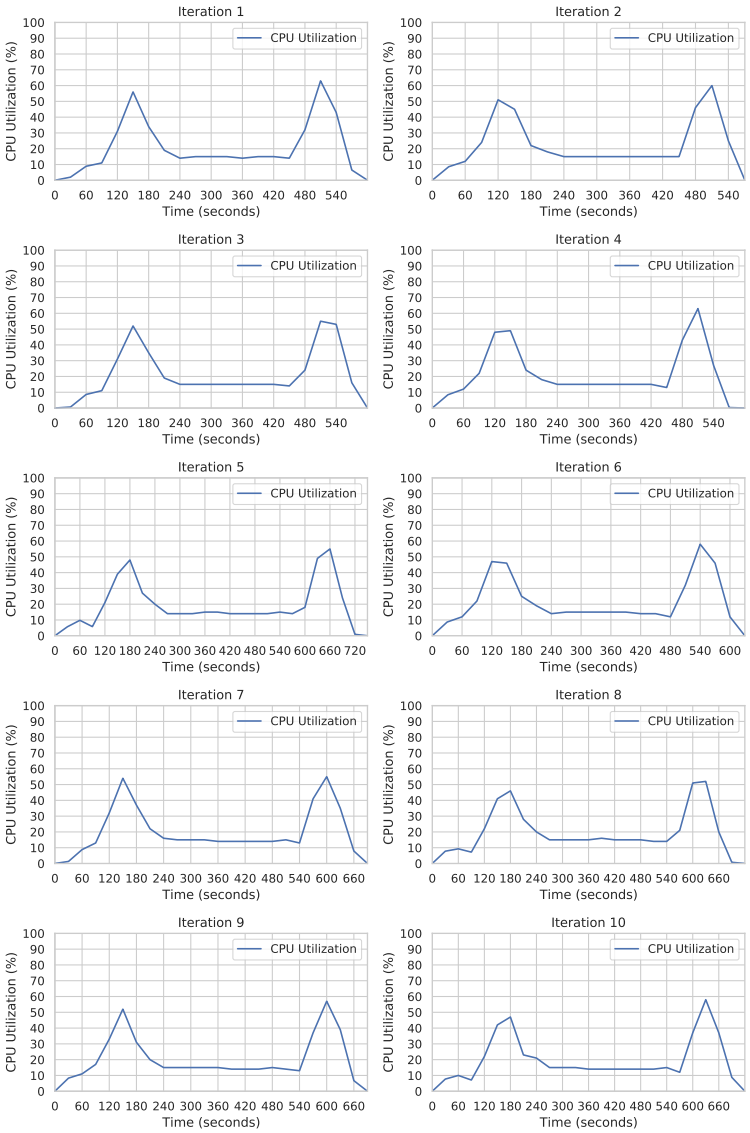

Figure C.6: Performance data of all iterations with 20 worker

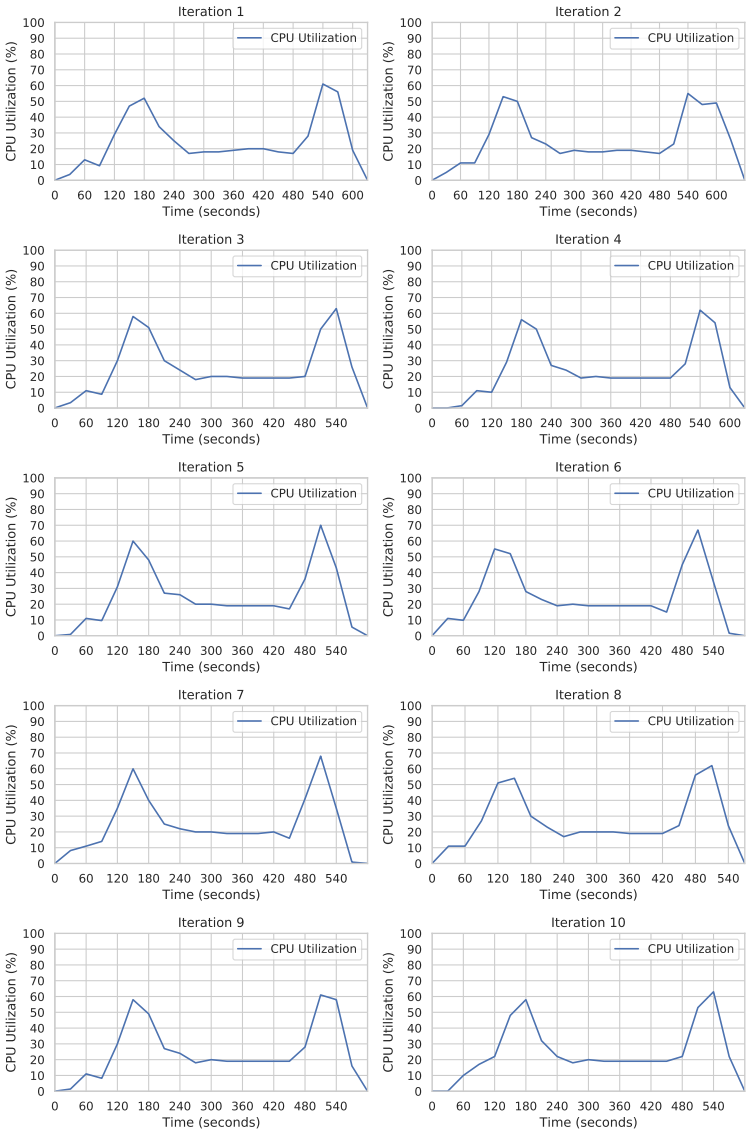

Figure C.7: Performance data of all iterations with 25 worker

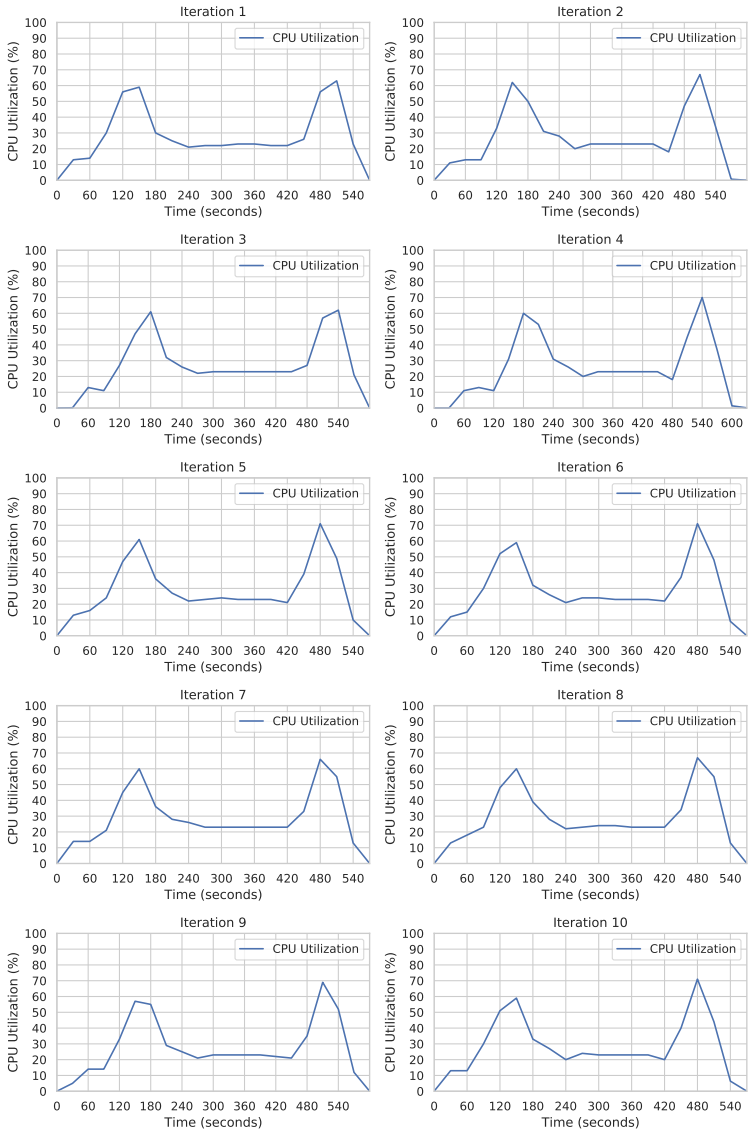

Figure C.8: Performance data of all iterations with 30 worker

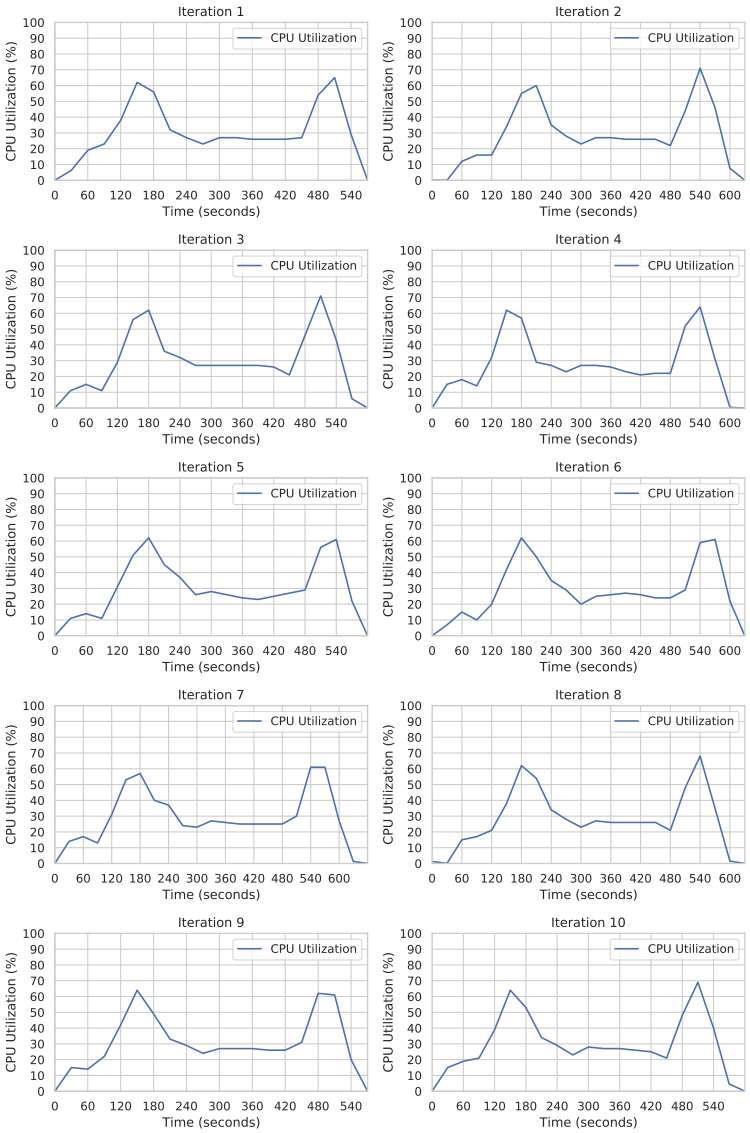

Figure C.9: Performance data of all iterations with 35 worker

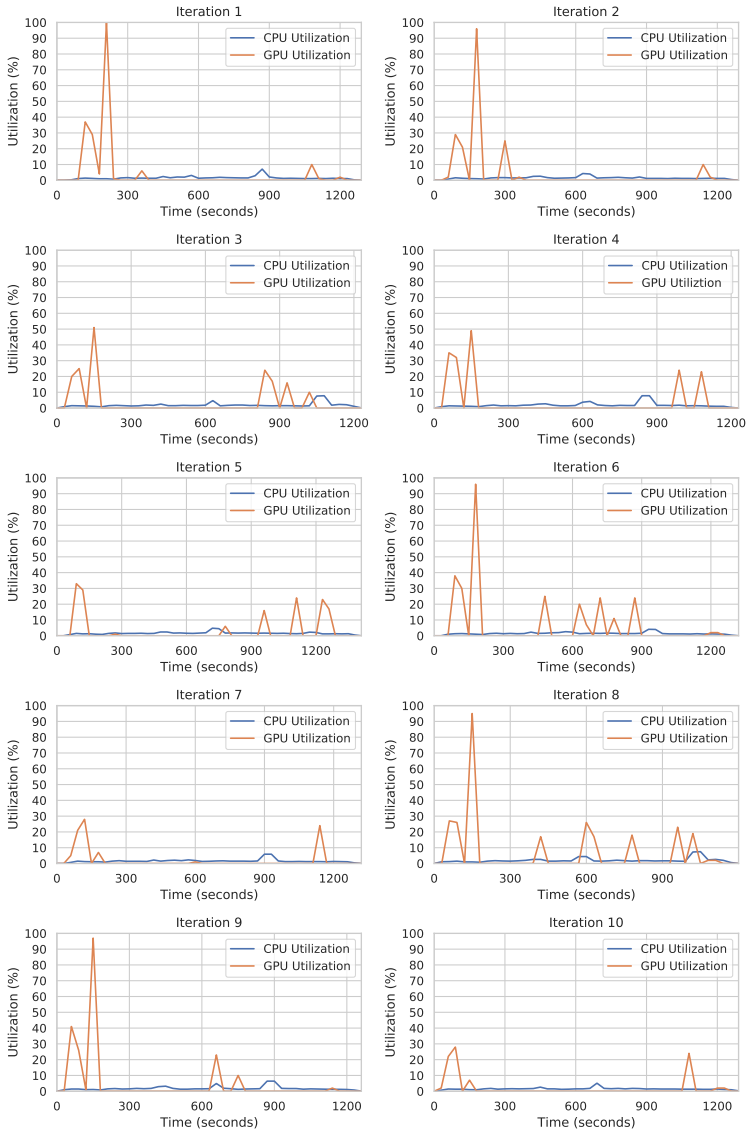

Figure C.10: Performance data of all iterations with 1 GPU-accelerated worker

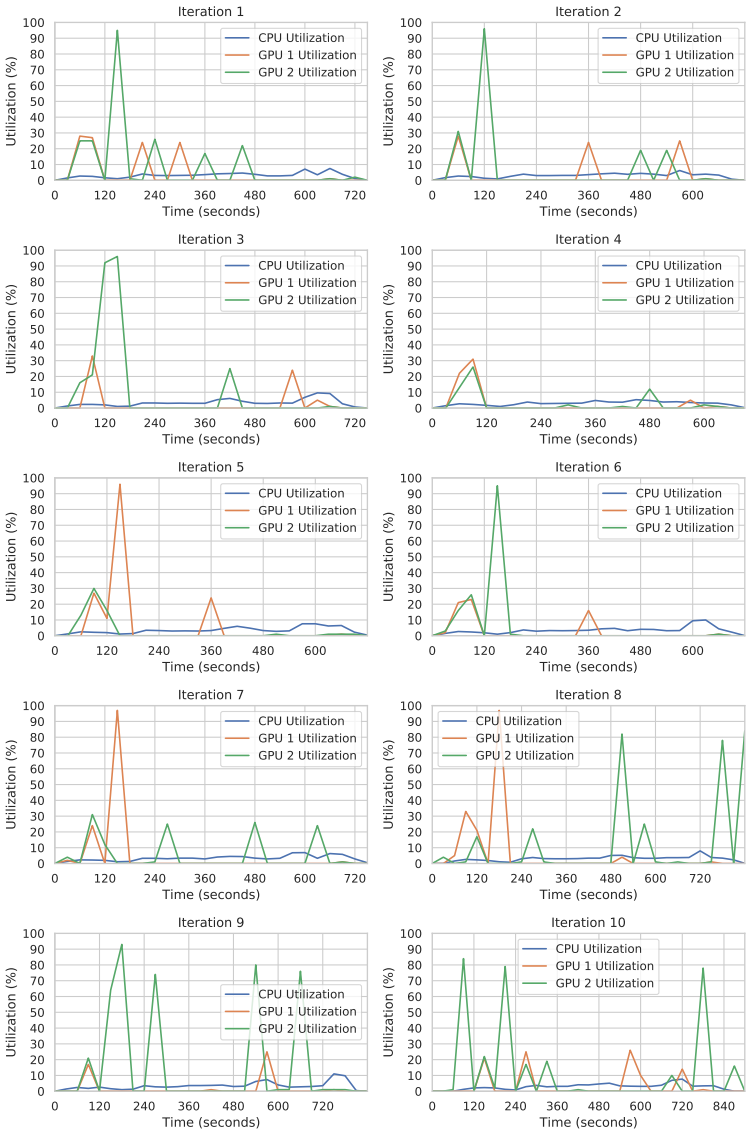

Figure C.11: Performance data of all iterations with 2 GPU-accelerated workers

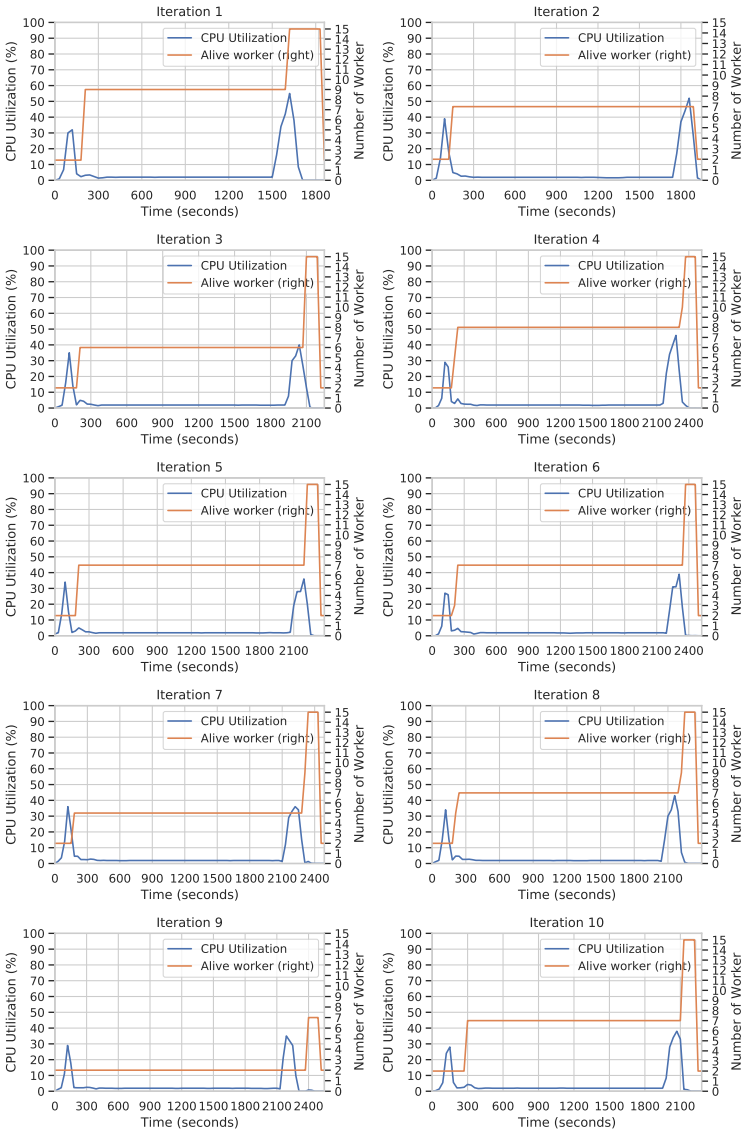

Figure C.12: Performance data of all iterations with the *Auto-Scaler* enabled

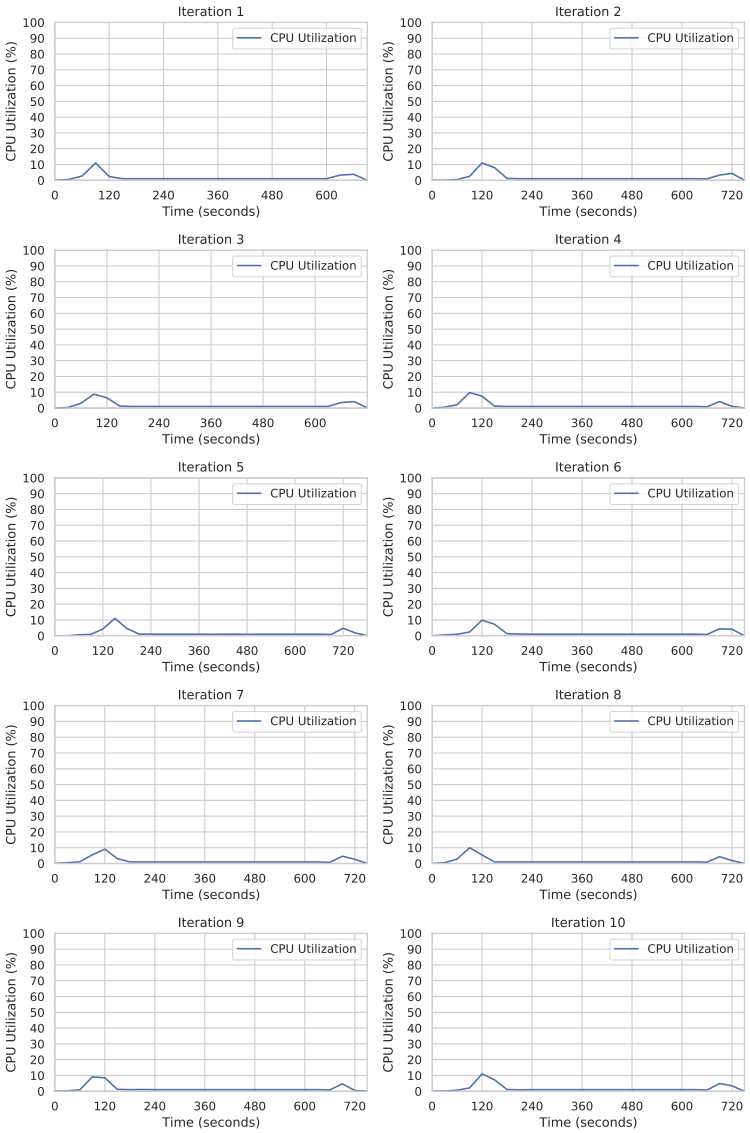

Figure C.13: Performance data of all iterations with 1 worker

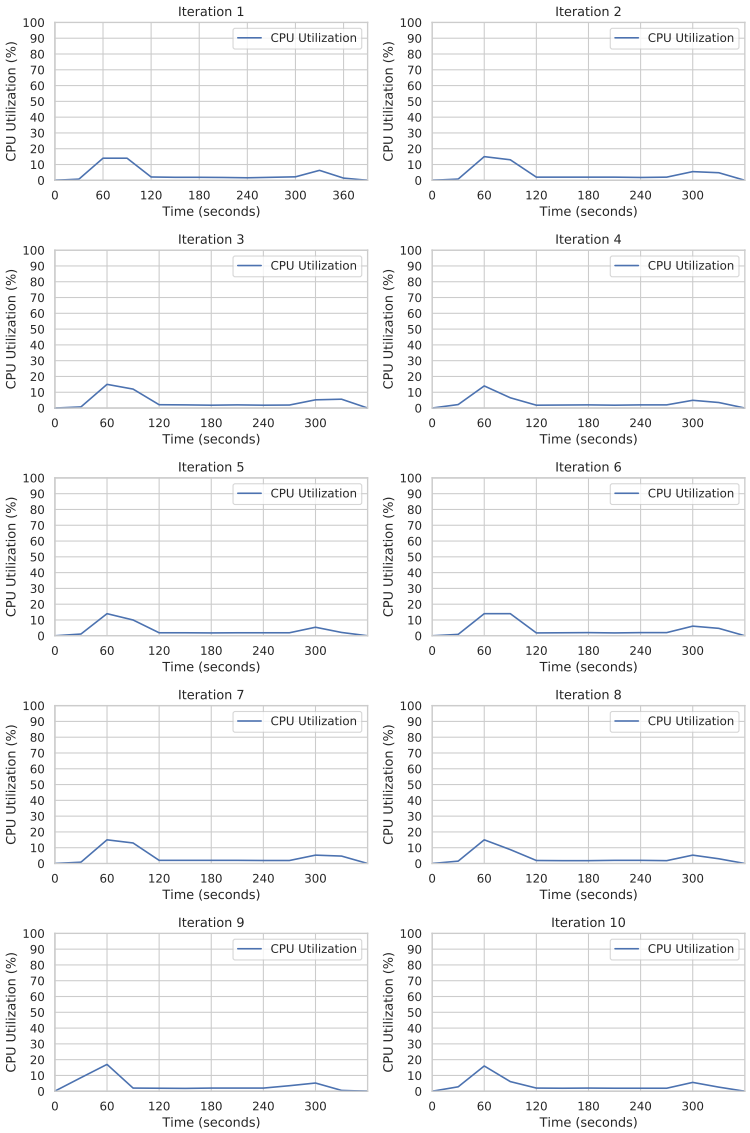

Figure C.14: Performance data of all iterations with 2 worker

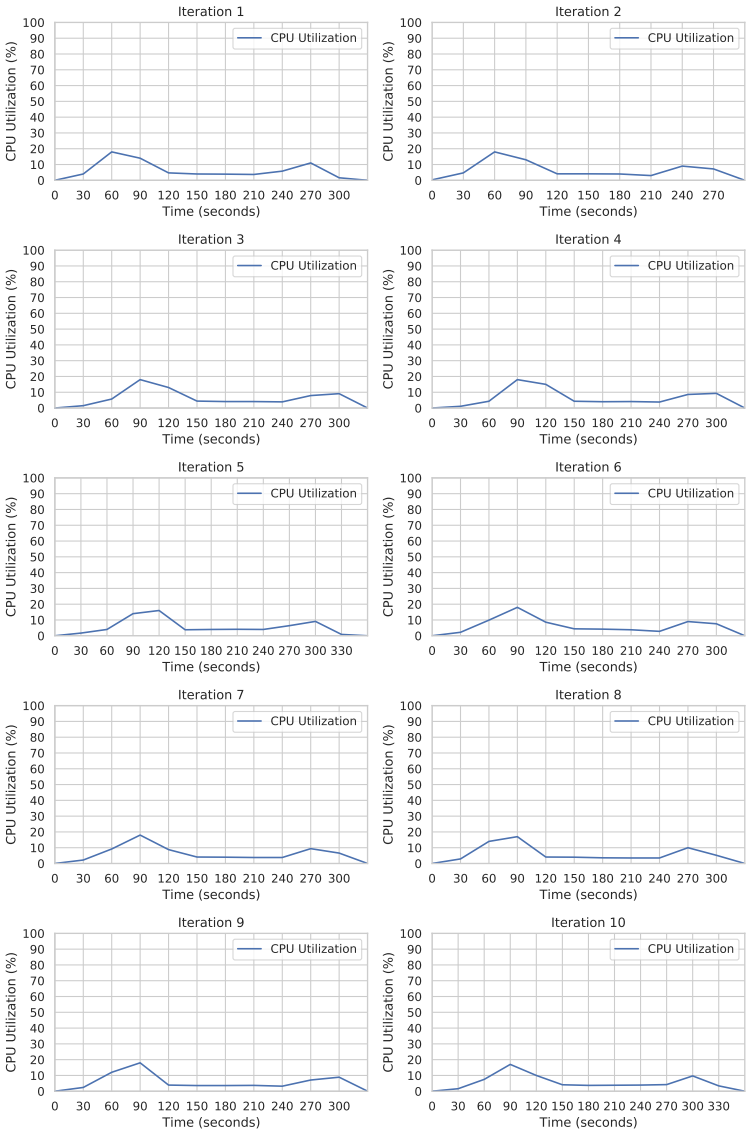

Figure C.15: Performance data of all iterations with 5 worker

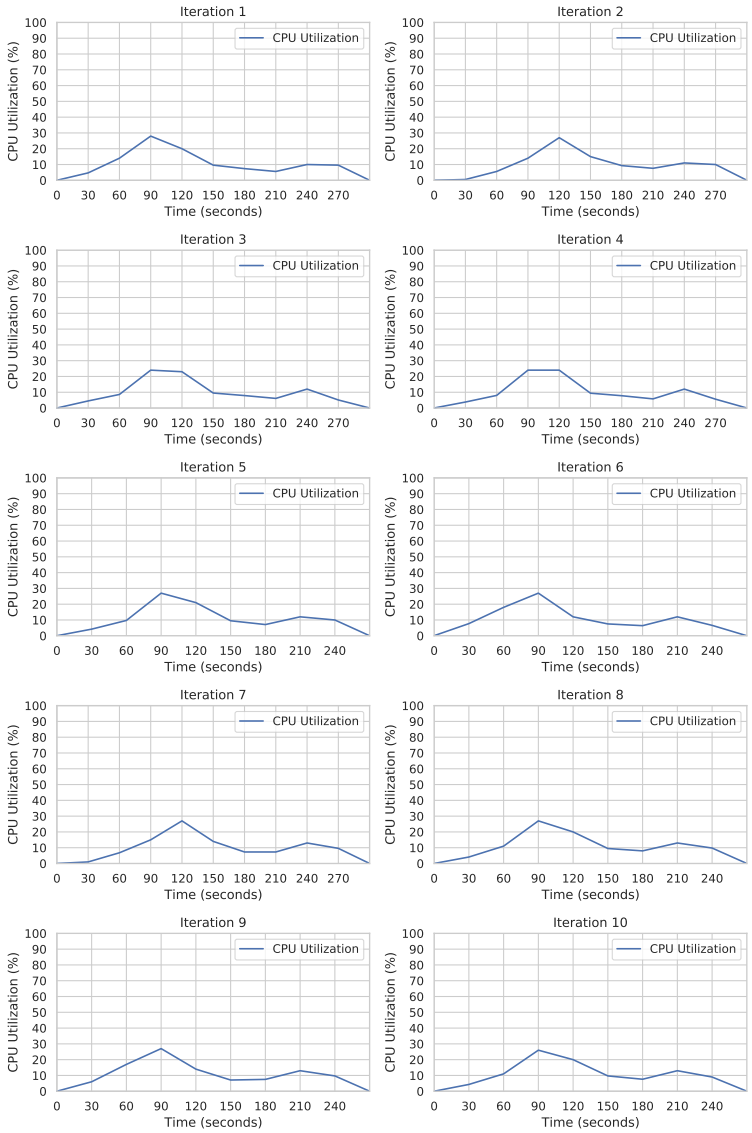

Figure C.16: Performance data of all iterations with 10 worker

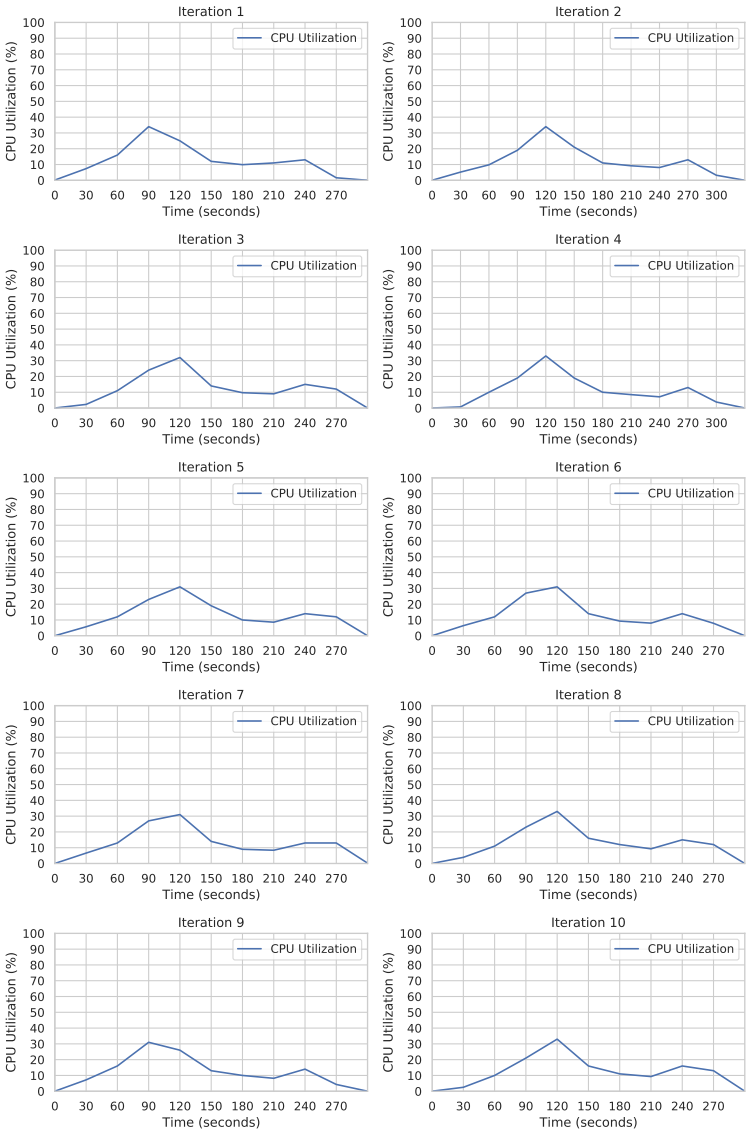

Figure C.17: Performance data of all iterations with 15 worker

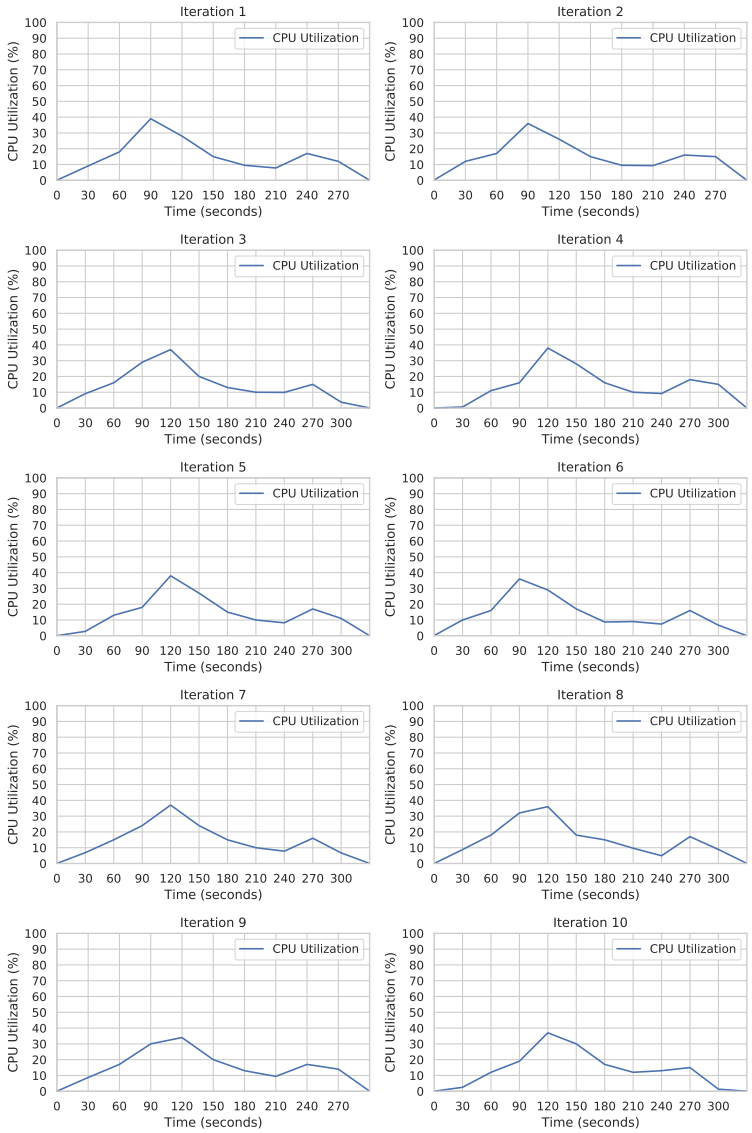

Figure C.18: Performance data of all iterations with 20 worker

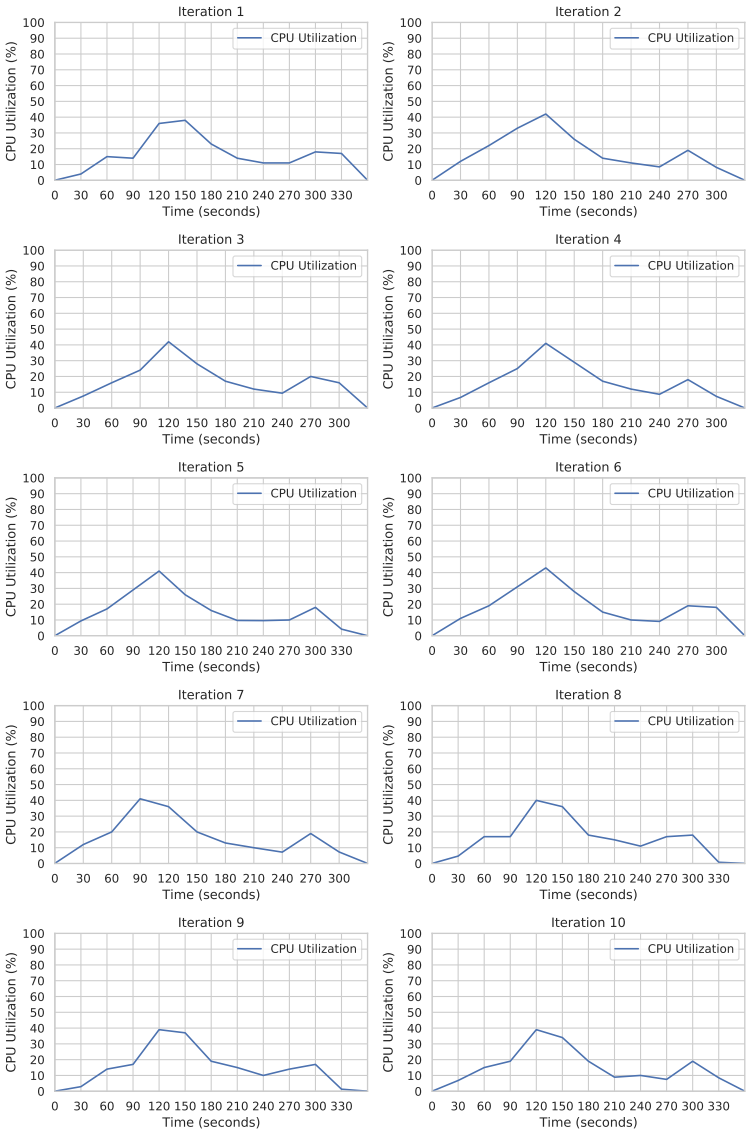

Figure C.19: Performance data of all iterations with 25 worker

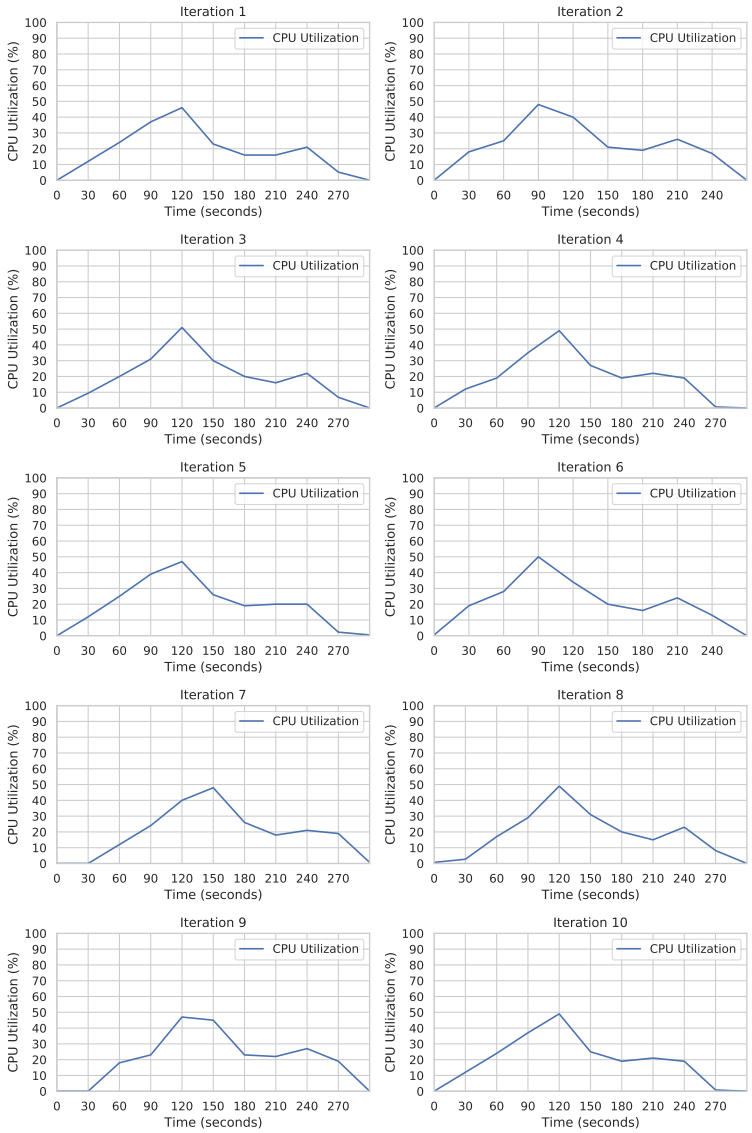

Figure C.20: Performance data of all iterations with 30 worker

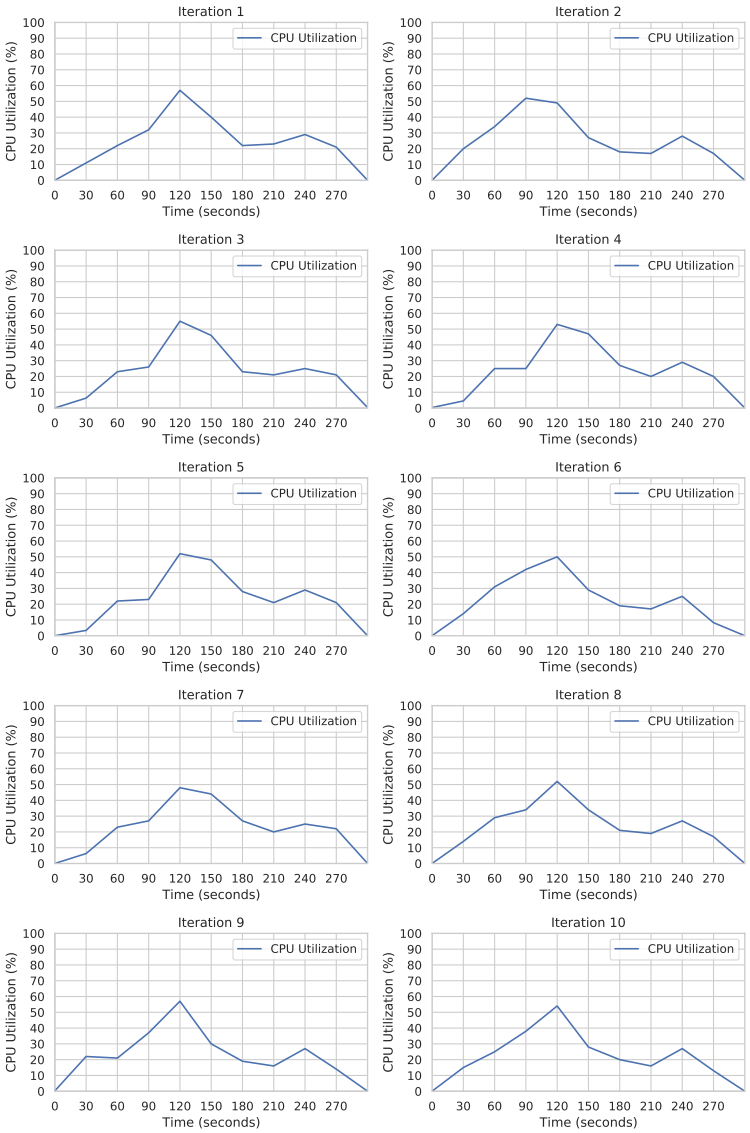

Figure C.21: Performance data of all iterations with 35 worker

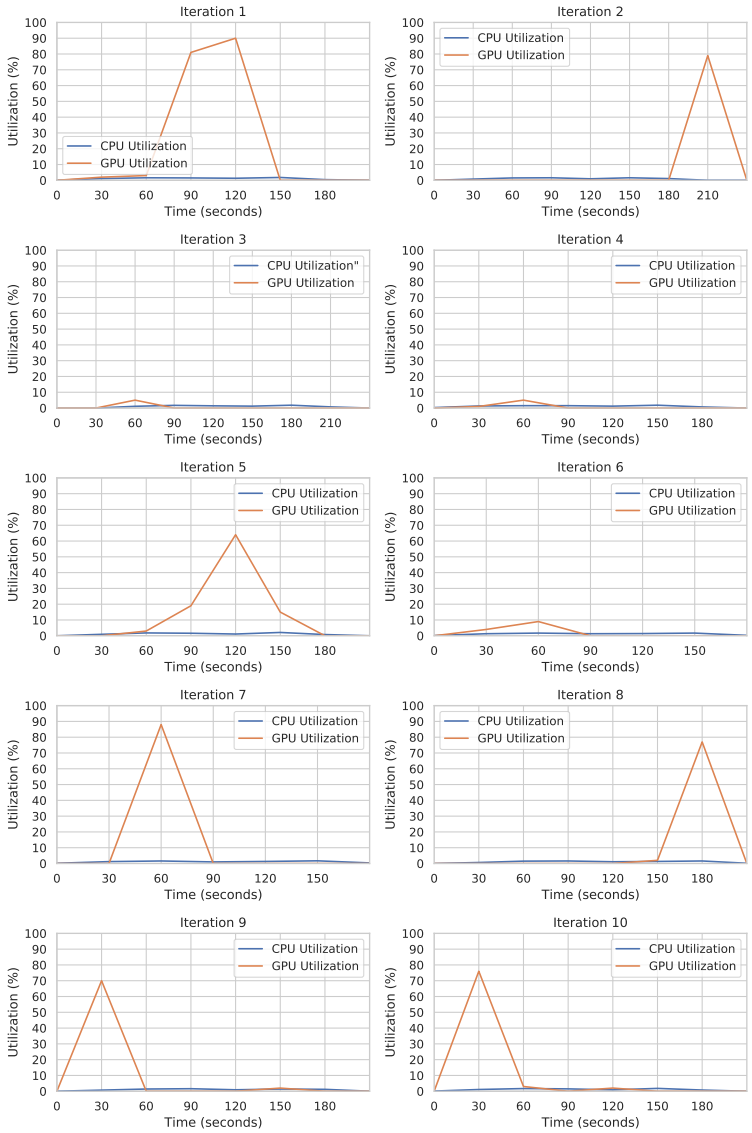

Figure C.22: Performance data of all iterations with 1 GPU-accelerated worker

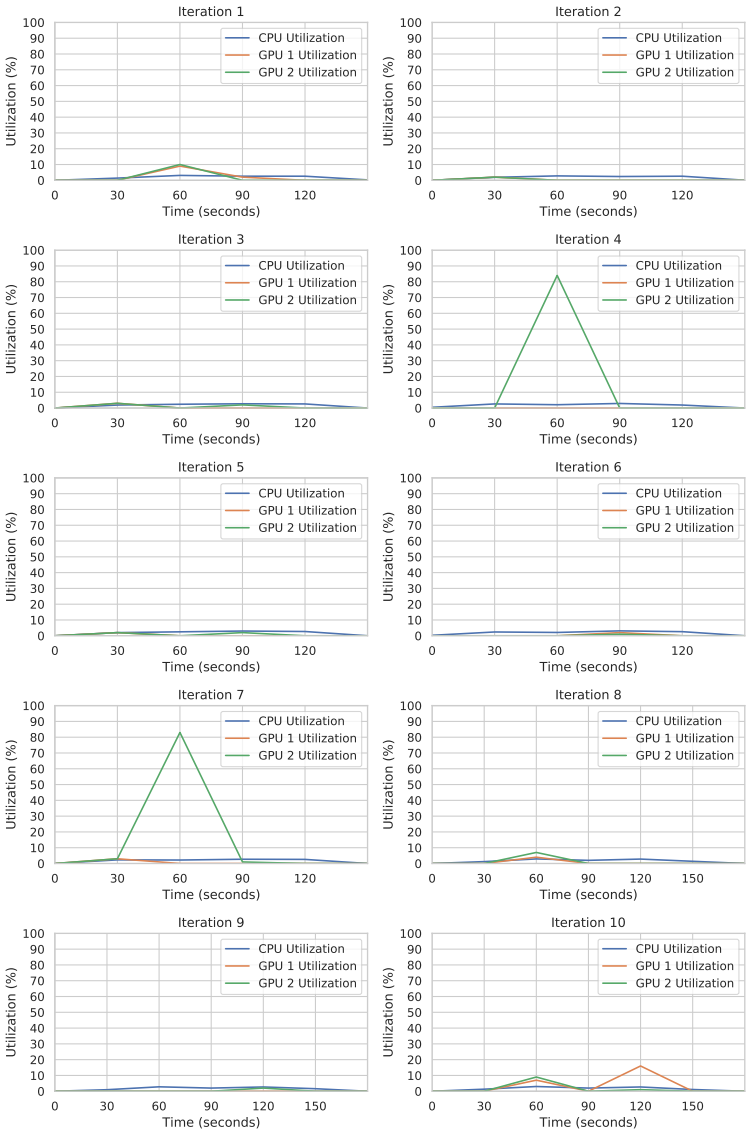

Figure C.23: Performance data of all iterations with 2 GPU-accelerated workers

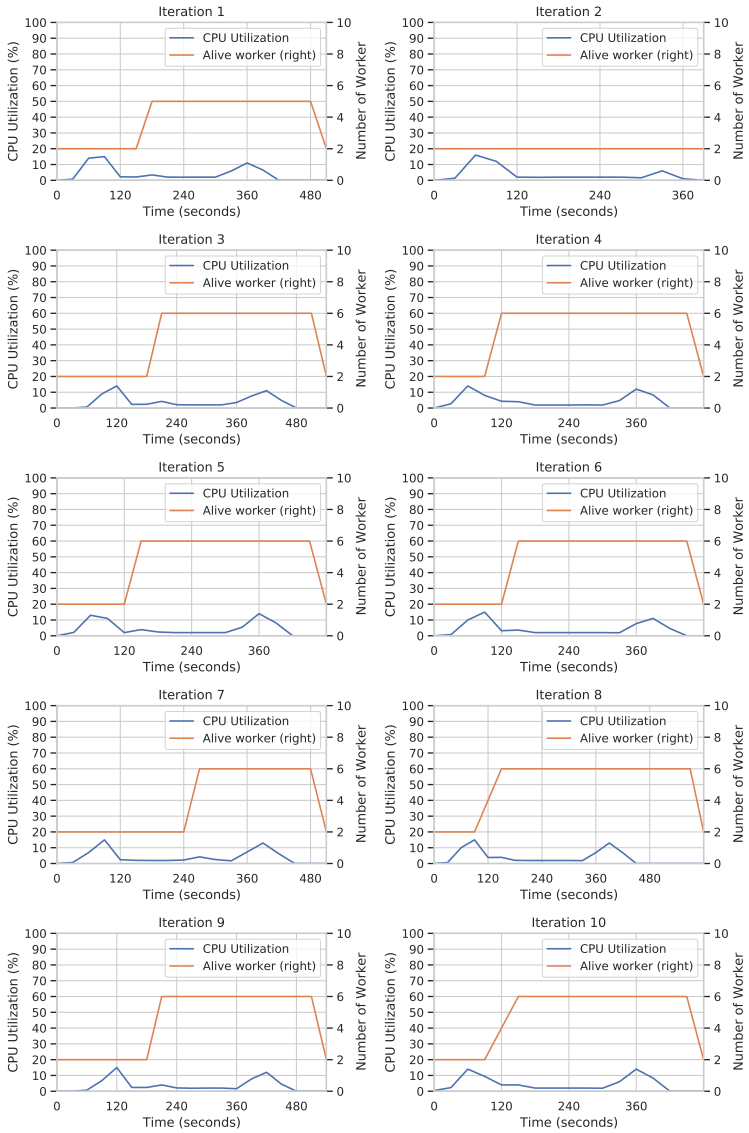

Figure C.24: Performance data of all iterations with the *Auto-Scaler* enabled