



PROJECT NO. 50
NKR: ON TOP SCHEDULER FOR APACHE MESOS

MS.PASINEE SANTIVORRANANT
MR.SUPAPAT SRI-ON
MS.PARATTHA WEERAPONG

A PROJECT SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR
THE DEGREE OF BACHELOR OF ENGINEERING (COMPUTER ENGINEERING)
FACULTY OF ENGINEERING
KING MONGKUT'S UNIVERSITY OF TECHNOLOGY THONBURI
2020

Project No. 50
NKR: On top scheduler for Apache Mesos

Ms.Pasinee Santivorrnanant
Mr.Supapat Sri-on
Ms.Parattha Weerapong

A Project Submitted in Partial Fulfillment
of the Requirements for
the Degree of Bachelor of Engineering (Computer Engineering)
Faculty of Engineering
King Mongkut's University of Technology Thonburi
2020

Project Committee

..... (Asst Prof.Rajchawit Sarochawikasit)	Project Advisor
..... (Asst Prof. Dr. Khajonpong Akkarajitsakul)	Committee Member
..... (Asst Prof. Dr. Phond Phunchongharn)	Committee Member
..... (Asst Prof. Sanan Srakaew)	Committee Member

Copyright reserved

Project Title	Project No. 50 NKR: On top scheduler for Apache Mesos
Credits	3
Member(s)	Ms.Pasinee Santivorranant Mr.Supapat Sri-on Ms.Parattha Weerapong
Project Advisor	Asst Prof.Rajchawit Sarochawikarit
Program	Bachelor of Engineering
Field of Study	Computer Engineering
Department	Computer Engineering
Faculty	Engineering
Academic Year	2020

Abstract

In a multihop ad hoc network, the interference among nodes is reduced to maximize the throughput by using a smallest transmission range that still preserve the network connectivity. However, most existing works on transmission range control focus on the connectivity but lack of results on the throughput performance. This paper analyzes the per-node saturated throughput of an IEEE 802.11b multihop ad hoc network with a uniform transmission range. Compared to simulation, our model can accurately predict the per-node throughput. The results show that the maximum achievable per-node throughput can be as low as 11% of the channel capacity in a normal set of α operating parameters independent of node density. However, if the network connectivity is considered, the obtainable throughput will reduce by as many as 43% of the maximum throughput.

Keywords: Multihop ad hoc networks / Topology control / Single-Hop Throughput

ACKNOWLEDGMENTS

Acknowledge your advisors and thanks your friends here..

CONTENTS

	PAGE
ABSTRACT	ii
THAI ABSTRACT	iii
ACKNOWLEDGMENTS	iv
CONTENTS	vi
LIST OF TABLES	vii
LIST OF FIGURES	viii
LIST OF SYMBOLS	ix
LIST OF TECHNICAL VOCABULARY AND ABBREVIATIONS	x
 CHAPTER	
1. INTRODUCTION	1
1.1 Problem Statement and Approach	1
1.2 Objectives	1
1.3 Scope	1
1.4 Tasks and Schedule	2
 2. BACKGROUND KNOWLEDGE AND LITERATURE REVIEW	4
2.1 Knowledge Background	4
2.2 Theoretical and Core Concepts	5
2.2.1 Tasks Failures Detection	5
2.2.2 Container Technology	6
2.2.3 Overview of machine learning	6
2.2.4 AI - Artificial Neural network	6
2.2.5 Deep learning	7
2.3 Technologies survey	8
2.3.1 Apache Mesos	8
2.3.2 Zookeeper	9
2.3.3 Elasticsearch	9
2.3.4 Chronos	10
2.3.5 Marathon	10
2.3.6 Spark	11
2.3.7 Apache Kafka	12
2.4 Related Research	12
 3. METHODOLOGY AND DESIGN	13
3.1 Project Functionality	13
3.1.1 Sequence diagram	13
3.1.2 Hypothesis testing	14
3.2 System Architecture	14
3.2.1 Architecture diagram	14
3.2.2 Policy	14
3.2.3 Database Schema	17
3.3 Data management	18
3.3.1 Which dataset is use for training?	18
3.3.2 Transform data pipeline	19
 4. IMPLEMENTATION RESULTS	20
4.1 Mesos Cluster Setup	20

4.2	Active Framework	20
4.3	Submit task	21
5.	CONCLUSIONS	23
5.1	Problems and Solutions	23
5.2	Future Works	23
	REFERENCES	24

LIST OF TABLES

TABLE	PAGE
1.1 Semester 1's Gantt chart	2
1.2 Semester 2's Gantt chart	3
2.1 Example of running 2 frameworks.	9
3.1 Variable description.	14
3.2 Variable description.	14
3.3 Variable description.	14
3.4 Description of Architecture diagram.	15
3.5 Parameter Formula and Description.	16
3.6 Decision Matrix.	16
3.7 Field name and description.	18
3.8 Framework of Apache Mesos.	18
3.9 Application Data.	19

LIST OF FIGURES

FIGURE	PAGE
2.1 TaskTracker Failure Detection Model in Hadoop Framework [15]	5
2.2 Virtual machine vs Container [2]	6
2.3 Neural networks.	7
2.4 The Mesos architecture consists of one or more masters, slaves, and frameworks. [8]	8
2.5 Mesos and Chronos provide a dynamic, fault-tolerant environment to run time-based jobs. [8]	10
2.6 Mesos managing cluster resources for two applications. [8]	11
2.7 Overview of Kafka. [18]	12
3.1 Sequence diagram of Apache Mesos	13
3.2 Architecture diagram.	15
3.3 Architecture diagram.	15
3.4 Flow Diagram of Predicting success rate.	16
3.5 database schema.	17
3.6 Data pipeline.	19
4.1 Cluster Information	20
4.2 Active Framework	21
4.3 Active Framework	22

LIST OF SYMBOLS

SYMBOL		UNIT
α	Test variable	m^2
λ	Interarival rate	jobs/ second
μ	Service rate	jobs/ second

LIST OF TECHNICAL VOCABULARY AND ABBREVIATIONS

ABC	=	Adaptive Bandwidth Control
MANET	=	Mobile Ad Hoc Network

CHAPTER 1 INTRODUCTION

1.1 Problem Statement and Approach

Nowadays, several different types of applications, which are short or long-lived jobs, container orchestration, or MPI jobs, are executed in clouds or large computer clusters. Multiple users can demand different resources to execute their tasks. Apache Mesos is a Middleware for the data center by introducing an abstraction layer that provides an entire data center as a single large server. Instead of focusing on one application that runs on a specific server. Mesos resource-isolation allows multi-tenant — the ability to run multiple applications on a single machine. Default sharing for multiple resources in this multi-tenant environment is defined by the Dominant Resource Fairness (DRF). Mesos receives the resources based on their current usage, which are responsible for scheduling their tasks within the allocation. In multiple schedulers can cause the fairness-imbalance in a multi-user environment, like a greedy scheduler. It consumes more than its share of resources. Running multiple small tasks is better than launching large ones in terms of time spent waiting for enough resources.

Therefore, this project aims to improve the fairness of the scheduler by reducing the unfair waiting time due to higher resource demand in a pending task list and use log data to improve the whole cluster.

1.2 Objectives

- To study about job scheduling in Apache Mesos
- To study how to develop an algorithm to improve performance of scheduler in large-scale clustered environments.
- To evaluate result and compare with Apache Mesos scheduler by using different job types in the list (short job, long job, MPI)

1.3 Scope

- This project focuses on the reduction of job failed.
- Design and develop an add-on architecture on top of the Apache Mesos scheduler, to track and distribute the incoming tasks.
- What are the limitations of existing approaches?

CHAPTER 2 BACKGROUND KNOWLEDGE AND LITERATURE REVIEW

2.1 Knowledge Background

In 2009, Apache Mesos [6] was a research project at the University of California in Berkeley. Benjamin, et al. wanted to improve datacenter efficiency by allowing multiple applications to share a single computing cluster across the many servers that make up a modern datacenter. So, multiple applications can share the processor, memory, and hard drive with any laptop or workstation. In 2010, the Mesos project entered the Apache Incubator, an arm of the Apache Software Foundation, so this project can gain the full support of the ASF's efforts. In 2013, The Apache Mesos project graduated from the incubator and founded Mesosphere. Mesosphere's flagship product, the Datacenter Operating System (DCOS), commercializes the open-source project by providing a turnkey solution to enterprises looking to deploy applications and scale infrastructure as effortlessly as other companies using Mesos, such as Airbnb, Apple, and Netflix.

Meanwhile, most such operating systems only fairly divide and account for CPU cycles. So, performance isolation is essential to operating systems shared by dependable services. These dependable services require specifying and enforcing policies for all resources, and that current metrics for evaluating fair sharing are insufficient. In 2006, Aage Kvalnes et al. researched new policy specifications and metrics, and illustrated these with the help of a new operating system that supports holistic resource sharing. [17]

In data centers and clouds, where applications could be co-scheduled on the same physical nodes, resource fairness needs to extend to multiple resource types such as memory, disk I/O, and network bandwidth. Ali, et al. considered the problem of fair resource allocation in a system containing different resource types, where each user may have different demands for each resource and researched about a new generalization of max-min fairness to multiple resource types called Dominant Resource Fairness (DRF). [5]

2.2 Theoretical and Core Concepts

2.2.1 Tasks Failures Detection

Hadoop usually uses JobTracker to detect failures of the TaskTracker nodes. It detects with heartbeat-based failure detection. The TaskTracker will send heartbeat message to JobTracker and JobTracker will declare a TaskTracker as dead only when it does not receive heartbeat for a limited time. It cannot quickly detect the failures and it may assign task to dead nodes. This can increase the number of failure tasks in Hadoop. [15]

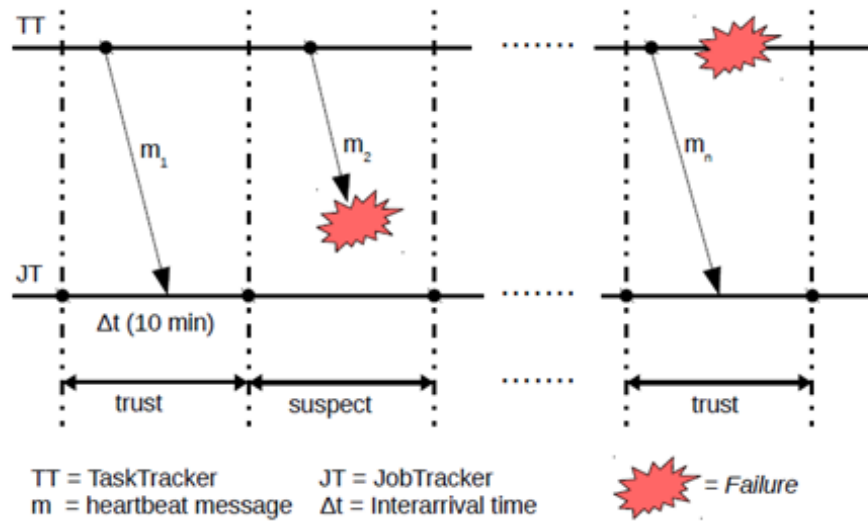


Figure 2.1 TaskTracker Failure Detection Model in Hadoop Framework [15]

For example, active TaskTracker send heartbeat messages to JobTracker every 3 seconds. While JobTracker check the timeout condition every 200 seconds. And there are network delays or messages losses, so some heartbeat may arrive late or loss. The JobTracker may consider that TaskTracker as dead node even it is available as shown in **Figure 2.1**. that heartbeat message m_2 does not arrive and the JobTracker consider this TaskTracker as dead.

2.2.2 Container Technology

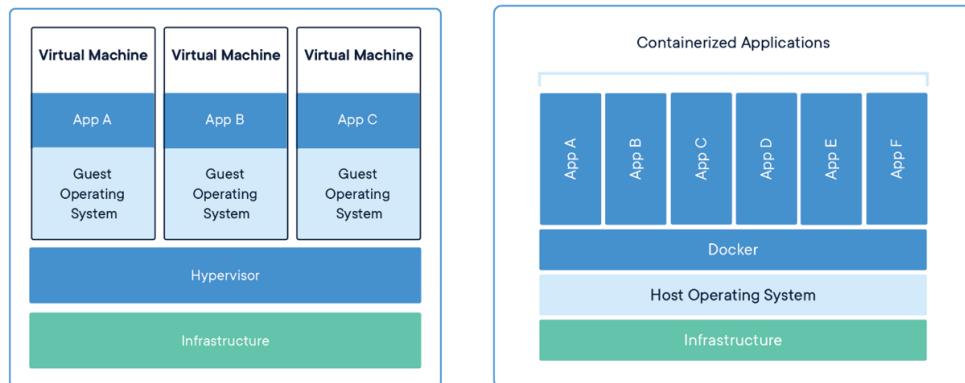


Figure 2.2 Virtual machine vs Container [2]

Container Technology is a method to package up code and all its dependencies, so the application runs quickly and reliably from one computing environment to another, with container software having names including the popular choices of Docker, Apache Mesos, RKT, and Kubernetes. The virtual machine contains the entire operating system. Therefore, the physical server that runs several virtual machines is running several operating systems' simultaneously as shown in **Figure 2.2**. [2]

There is a lot of overhead on virtual machine. In contrast, with container technology, the server runs a single operating system. Each container can share this single operating system with other containers on server. Containers require less resource of server with less overhead and more efficient than virtual machines. [1] Containers are set up to accomplish work in a multiple container architecture (container cluster). They also enable a program to be broken down into smaller pieces, which are known as microservices. So, the program can work on each of the containers separately.

2.2.3 Overview of machine learning

Machine learning is a branch of artificial intelligence (AI). It is the machine's ability to learn from data provided without human intervention and able to improve decision from experience. Without human directed programming instructions, the machine accesses data, observes and finds data pattern. The more data input the better data pattern learning and better decision making.[3]

2.2.4 AI - Artificial Neural network

An artificial neural network (ANN) is a computational model imitates the natural human brain. The network consists of hundreds or thousands small neuron nodes. Those numerous neuron nodes communicate to each other in the web form. The neuron node is called processing unit. Each of processing unit is interconnected by nodes. Each processing unit comprises of input unit and output unit. Input unit receives various type of data format. It also has an internal weighting system. The neural network learns from the input and produce output result.

ANN use rules and guidelines to generate result/ output. The set of these learning rules is called backpropagation because it uses backward propagation of error to learn or improve the better result. ANN learns data patterns in training phase. It compares actual output with the desired output that is expected result in supervised phase. The difference between actual and expected result are worked backward to adjust the weight of its connections between the units. The purpose is to make the lowest possible error. [4]

2.2.5 Deep learning

Nowadays, there are collections of vast unlabeled and unstructured data gathering from various sources that is difficult to analyse useful information by traditional programs in a linear way. The hierarchical level of artificial neural network that work in web form to process data with a nonlinear approach is called Deep Learning. The first layer of the neural network processes a raw data and pass output on to the next layer. The second layer processes first layer output plus additional information and pass output to next layer again. This continues across all levels of the neuron network to make information more meaningful information. [12]

Deep learning models can achieve high accuracy, sometimes exceeding human-level performance. “Deep” refers to the powerful number of hidden layers in the neural network. However, it needs lots of labeled data and high-performance machines to analyze. The organized layers of interconnected nodes can be tens or hundreds of hidden layers. [16] as shown in **Figure 2.3**.

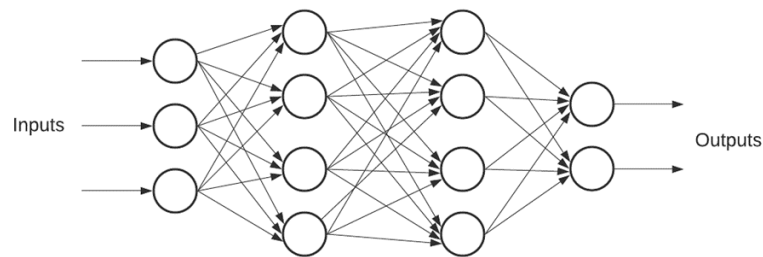


Figure 2.3 Neural networks.

2.3 Technologies survey

2.3.1 Apache Mesos

Mesos consists of a master, agent daemons running on each cluster node, and Mesos frameworks that run task on these agents as shown in **Figure 2.4**. Architecture consist of three components: masters, slaves, and the frameworks that run on them. Mesos relies on Apache ZooKeeper, a distributed database used specifically for coordinating leader election within the cluster, and for leader detection by other Mesos masters, slaves, and frameworks. [8]

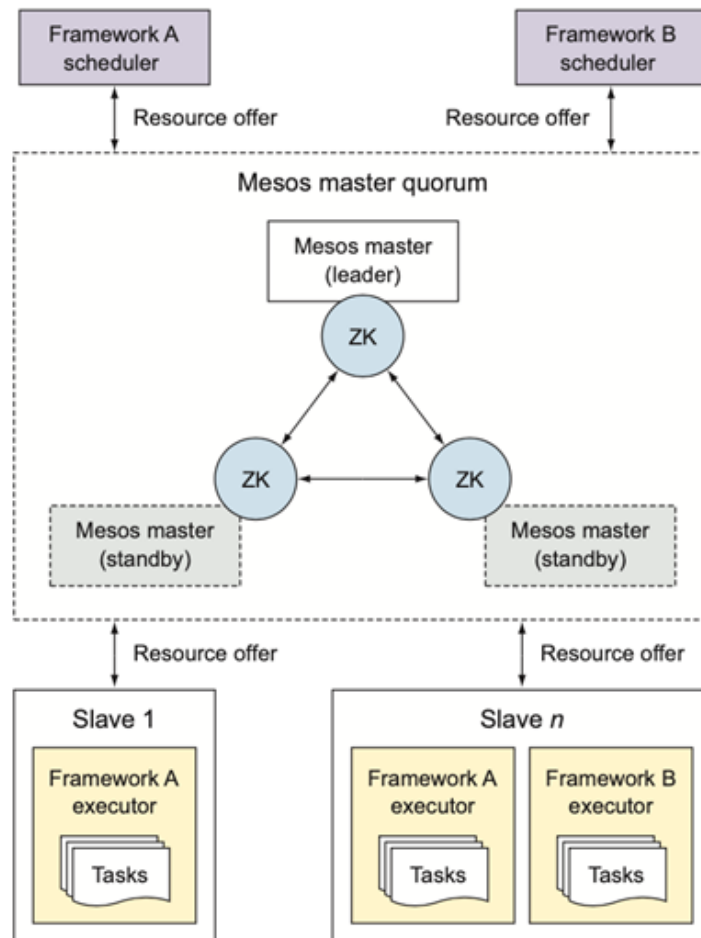


Figure 2.4 The Mesos architecture consists of one or more masters, slaves, and frameworks. [8]

1. **Masters:** Mesos masters are responsible for managing the Mesos slave daemons running on each machine in the cluster. Using Zookeeper, they coordinate which node will be the leading master, and which masters will be on standby, and ready to take over if the leading master goes offline. A Mesos cluster requires minimum one master, and three or more are recommended for production deployments. Zookeeper can run on the same machines as the Mesos masters themselves or use a standalone Zookeeper cluster.
2. **Slaves:** The machines in a cluster responsible for executing a framework's tasks.
3. **Frameworks:** Mesos application that's responsible for scheduling and executing tasks on a cluster. A framework is made up of two components: a scheduler and an executor.

- **Schedulers** A scheduler is a long-running service responsible for connecting to a Mesos master and accepting or rejecting resource offers. Mesos delegates the responsibility of scheduling to the framework, instead of attempting to schedule all the work for a cluster itself. The scheduler can then accept or reject a resource offer based on whether it has any tasks to run at the time of the offer.
- **Executor** An executor is a process launched on a Mesos slave that runs a framework's tasks on a slave.

Dominant resource is a resource of specific type (CPU, memory, disk, ports) which is most demanded by given framework among other resources it needs. DRF computes the share of resource allocated to a framework (dominant share) and tries to maximize the smallest dominant share in the system. for next round offers the resources first to the one with smallest dominant share, then to the second smallest one and so on. [9] Example with 9 CPUs and 18 GB RAM to two frameworks running task that require <1 CPU, 4GB> and <3CPUs, 1GB> shown in **Table 2.1**.

Table 2.1 Example of running 2 frameworks.

Schedule	Framework A		Framework B		total	
	Resource Share	Dominant Share	Resource Share	Dominant Share	CPU	RAM
B	<0, 0>	0	<3/9, 1/18>	1/3	3/9	1/18
A	<1/9>, <4/18>	2/9	<3/9, 1/18>	1/3	4/9	5/18
A	<2/9>, <8/18>	4/9	<3/9>, <1/18>	1/3	5/9	8/18
B	<2/9>, <8/18>	4/9	<6/9>, 2/18>	2/3	8/9	10/18
A	<3/9>, <12/18>	2/3	<6/9>, 2/18>	2/3	1	14/18

2.3.2 Zookeeper

ZooKeeper is an open-source Apache project that provides a centralized service for providing configuration information, naming, synchronization, and group services over large clusters in distributed systems. The goal is to make these systems easier to manage with improved, more reliable propagation of changes. ZooKeeper provides an infrastructure for cross-node synchronization by maintaining status type information in memory on ZooKeeper servers. A ZooKeeper server keeps a copy of the state of the entire system and persists this information in local log files. Large Hadoop clusters are supported by multiple ZooKeeper servers, with a master server synchronizing the top-level servers. [7]

2.3.3 Elasticsearch

Elasticsearch is an open-source search and analytics engine built on Apache Lucene and developed in Java. Elasticsearch can be used to store and search all kinds of documents, analyze huge volumes of data in near real-time and give back answers in milliseconds, and supports multitenancy. It's able to achieve fast search responses because it searches an index directly instead of searching the text. Related data is often stored in the same index, which consists of one or more primary shards, and zero or more replica shards. Once an index has been created, the number of primary shards cannot be changed. It uses a structure based on documents and comes with extensive REST APIs for storing and searching the data.

Elasticsearch is the component of the Elastic Stack, a set of open-source tools for storage, analysis, and visualization. The four components, Elasticsearch, Logstash, Kibana and Beats, are designed for use as an integrated solution. It is commonly referred to as the "ELK" stack.[13]

2.3.4 Chronos

Chronos is the Mesos Cron system. It handles time-based scheduling of jobs on a Mesos cluster. Chronos can be used to schedule commands or scripts. The Chronos feature set is easily and reliably to create standalone schedule-based jobs, as well as complex dependency-based jobs and pipelines, simply by specifying the schedule and resources that the job requires. This guarantees that time-based jobs are running on time while continuing to use datacenter resources as efficiently as possible. In **Figure 2.5**, it shows about the differences between running Cron jobs on a single machine and running them on a Mesos cluster.[8]

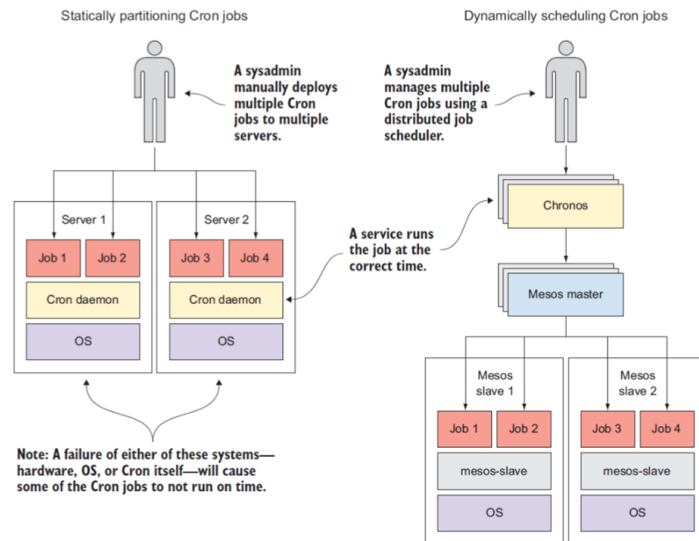


Figure 2.5 Mesos and Chronos provide a dynamic, fault-tolerant environment to run time-based jobs. [8]

2.3.5 Marathon

Marathon is a popular open source Mesos framework developed by Mesosphere. Marathon is used for deploying long-running services and applications, both in Linux cgroups and Docker containers. It can also be considered a private platform as a service (PaaS) on which to deploy applications. Marathon can specify the resources needed for each instance of an application and number of running instances. If a Mesos slave fails, or an instance of application crashes or exits, Marathon will automatically start a new instance to replace the failed one.

Marathon also allows users to specify dependencies on other services and applications during deployment, so an application instance can't start before its database instance is up and passing health checks. Marathon contains a list of features that should satisfy the needs of most application management scenarios such as managing applications and groups of applications with dependencies and health checks, rolling application upgrades with specific capacity requirements, a powerful web interface and REST API, and high availability (using ZooKeeper for leader election and coordination).[8]

2.3.6 Spark

Apache Spark, unified analytics engine for large-scale data processing, runs on Hadoop, Apache Mesos, Kubernetes, standalone, or in the cloud. It can access diverse data sources. Spark perform task faster and more efficiently than Hadoop's MapReduce, both in memory and on disk in many cases. Spark also provide API for several programming language, including Python, Scala and Java and support streaming workloads, interactive queries and machine learning libraries, in addition to MapReduce-like batch processing. Spark can run locally. But that is useful only for development purpose, the number of CPU cores limits the number of executors. When setting up a production Spark cluster, there are two option.

When setting up statically partitioned cluster on an Infrastructure as a Service (IaaS) provider. It will be wasting money due to cloud instances sitting idle. Find-grained resource sharing can help increase system's utilization. For example, if there are two applications likes in **Figure 2.6**, Spark and Jenkins that need to run on multiple servers. Each of these system atop a general-purpose cluster manager like Mesos that allows for this sort of fine-grained resource sharing. It can share compute resources and run multiple workloads on a single Mesos slave. This will lead to better resource utilization across many machines within a modern datacenter.[8]

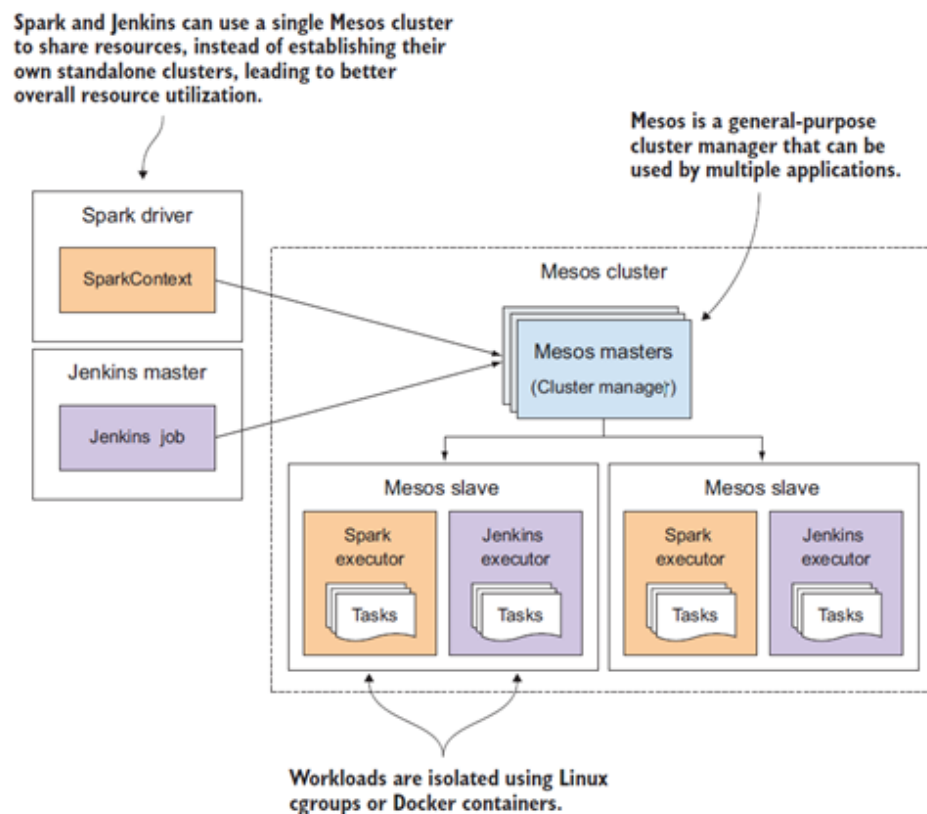


Figure 2.6 Mesos managing cluster resources for two applications. [8]

2.3.7 Apache Kafka

Apache Kafka is an open-source stream-processing software platform. Apache Kafka is providing a unified, high-throughput, low-latency platform for handling real-time data feeds. Kafka allows user to subscribe itself and publish data to any number of systems or real-time applications. In **Figure 2.7**, producers are processes that send message to Kafka. Then, Kafka stores these messages in key-value. The data can be partitioned into different topic. And Consumers are process that can read messages from partitions. Kafka runs on a cluster of one or more server, And the topics are distributed across the cluster nodes. And partitions are replicated to multiple servers.[18]

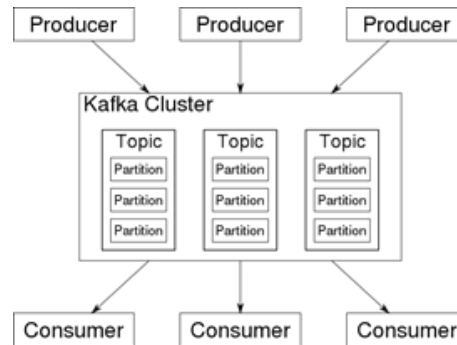


Figure 2.7 Overview of Kafka. [18]

2.4 Related Research

The current data center management is a representative large-scale resource management and scheduling framework for clusters, liked the open-source project Mesos [8]. However, the data center environment are cluster systems and variety of submitted tasks, such as Hadoop clusters that support big data processing and Spark clusters that support in-memory computing. Mesos is a resource allocation method with no differential task type and scheduler does not consider the overall resource demand or workload, which leads to low average resource utilization and starve were a framework with a high demand on queue. Moreover, Mesos uses the DRF (Dominant Resource Fairness) algorithm for resource allocation. The DRF algorithm is the default scheduling algorithm of Mesos, the algorithm still has the disadvantage of not considering the machine performance and task type.

Many researchers have conducted relevant work. For example, in 2016, Li Y et al [10] introduced the fish swarm intelligence algorithm to dynamically adjusting the Mesos cluster resources to improve the Mesos load imbalance and resource utilization. The DRF scheduling algorithm of Mesos is extended, and in 2018, Wenbin Liu et al. proposed A X-DRF algorithm [11] based on building classifies the performance of physical machines and job type judgment classification is proposed to solve the problem of machine performance in literature, but the task type is not considered and not consider the waiting time. Compared with the original DRF algorithm, the X-DRF algorithm has higher system resource utilization rate, which is in line with the actual production rules of data centers, and provides new ideas for heterogeneous cluster multi- resource management for data center managers. In 2019, Pankaj Saha et al. developed Tromino [14], a policy driven queue manager. Tromino allows task from individual frameworks to be scheduled based on each framework's overall resources requirement and current resources consumption. Tromino reduce the impact of unfairness due to framework specific configuration and unfair waiting time due to higher resource demand in a pending task queue.

CHAPTER 3 METHODOLOGY AND DESIGN

We explained a background knowledge that important to use in this project in the previous chapter. Now it is the time to know an overall of our project how this project is designed a meta-scheduler, functionality lists, and hypothesis that this project needs to answer.

3.1 Project Functionality

This project is based on the hypothesis If the dominant share and demand awareness is known by meta-scheduler, the failure job in each framework will be reduced.

This project aims to design separated architecture from previous Apache Mesos to prove the hypothesis above. This architecture accepts tasks, aggregates all tasks that user submits directly into it, and keeps track information from cluster master for a better fairness and utilization.

3.1.1 Sequence diagram

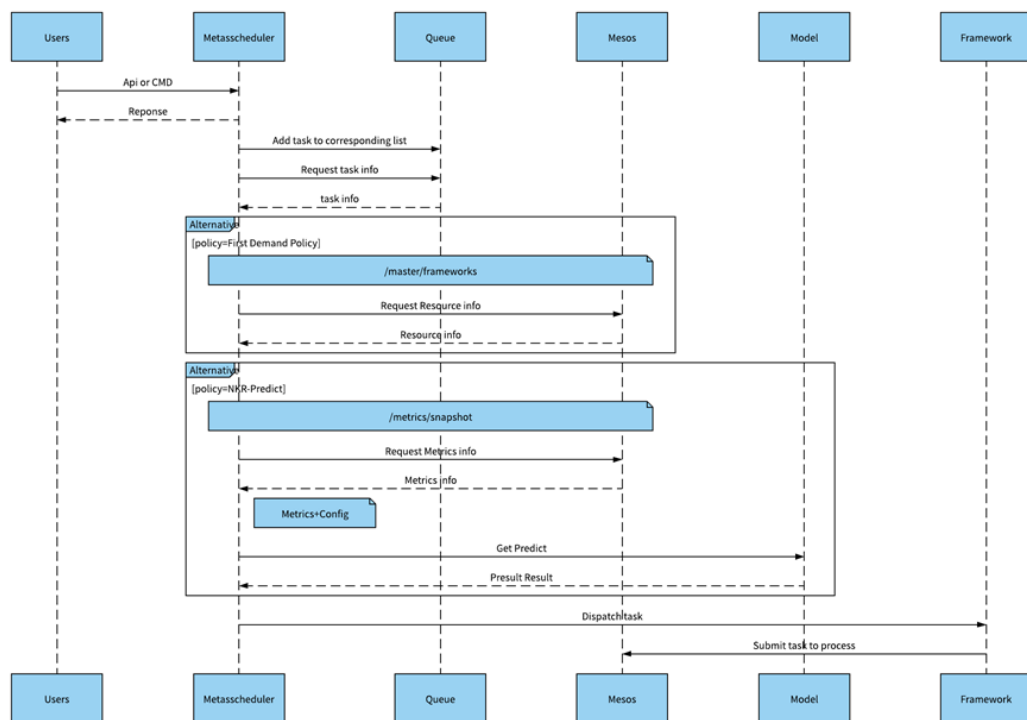


Figure 3.1 Sequence diagram of Apache Mesos

According to **Figure 3.1** shows sequence diagram that user submits a job via command line or Application Programming Interface (API), and also specifies their framework, resources requirement, configuration script, and command to the meta-scheduler. Meta-scheduler, called NKR-scheduler, keeps track of incoming task from user and distributes each task to the queue. NKR-scheduler periodically fetches cluster and task information from Mesos Master to make a decision for scheduling task based on policy. After NKR-scheduler finishes a decision making, then it will dispatch task directly to corresponding framework.

3.1.2 Hypothesis testing

Hypothesis testing is to verify reduction of failure task in each framework. This project separates into 2 experiments because it considers both Dominant share and Demand awareness which describes more detail in **Table 3.1**. This project uses three frameworks which are Marathon, Chronos, along with spark for the test. Comparing results from execute these frameworks with normal clustering setting, and our NKR-scheduler which apply one or two policies.

Table 3.1 Variable description.

Variable	Description
Dominant share	The resource that each framework now uses in cluster
Demand awareness	resource requirement of each framework

Experiment 1: Framework with different arrival rate and all tasks are identical in a resource consumption as shown in **Table 3.2**. This experiment will run 3 times consist of 1) First Demand Share Policy, 2) Success rate prediction, and 3) Both policies.

Table 3.2 Variable description.

	Number os tasks	Arrival rate (sec)
Marathon	100	5
Chronos	100	2
Spark	100	1

Experiment 2: Framework with different arrival rate and all tasks are vary in a resource consumption as shown in **Table 3.3**. This experiment will run 3 times consist of 1) First Demand Share Policy, 2) Success rate prediction, and 3) Both policies.

Table 3.3 Variable description.

	Number os tasks	Arrival rate (sec)
Marathon	100	5
Chronos	100	2
Spark	100	1

3.2 System Architecture

3.2.1 Architecture diagram

According to **Figure 3.2** shows architecture diagram, there are many components that this project implements. NKR-scheduler consists of three major elements 1) Client Receiver, 2) Queue, and 3) Scheduler and the other components describe below in **Table 3.4**.

3.2.2 Policy

This project designs two policies for the Meta-scheduler: 1) First Demand Policy (FDP), and 2) Success rate prediction. These policies can be extended further based on scheduling needs of users.

1. **First Demand Share Policy** We explain how FDP policy work by considering, a cluster with a total of 8 CPU and 64 GB of memory, where two frameworks (A and B) are shared completing shared resources. Each framework be able to have a different number of tasks in their list. In example, framework a has 4 tasks each task consumes (2 CPU, 0.5GB memory) as a resource demand, and Framework B has 2 tasks with (0.5 CPU, 1 GB memory) and task still running on cluster. Framework A has 1 task (2CPU, 0.5

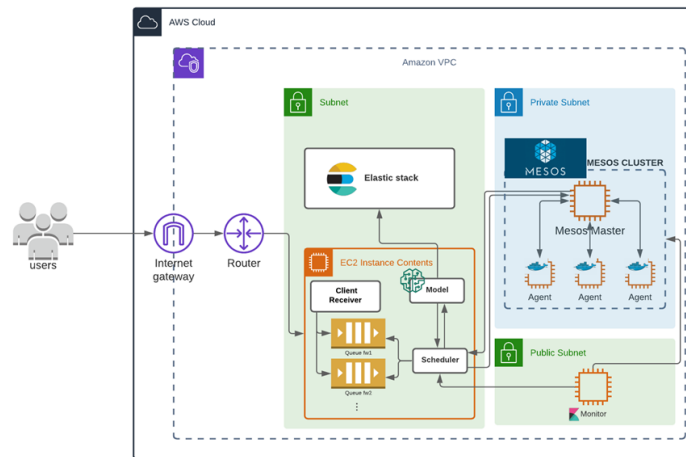


Figure 3.2 Architecture diagram.

Table 3.4 Description of Architecture diagram.

Components	Description
Client Receiver	Interface for user to submit task to cluster.
Queue	The list that stores task, and information about resources requirement in each framework that register into the Apache Mesos.
Scheduler	The adaptive policy that configured by user and keeps track information about cluster from Apache Mesos.
Elasticsearch	Elasticsearch stores previous data from Apache Mesos and periodically train a new model.
Monitor	Monitor keeps track abnormality and another metrics.
Model	It stores model for predicting in case user want to use AI to schedule tasks.

GB memory), and Framework B has 2 task (1CPU, 2 GB memory) the dominants share of framework A = $\max(2/8, 0.5/64) = 25\%$ and Framework B = 12.5%. In this case if we apply normal scheduling policy it will dispatch task from framework B as shows in **Figure 3.3**.

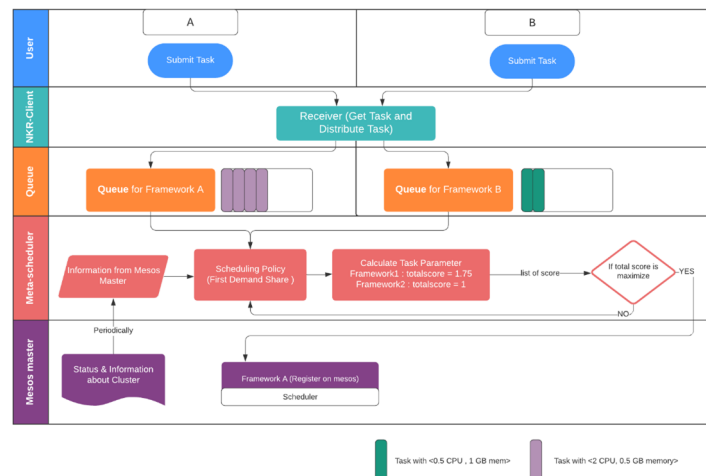


Figure 3.3 Architecture diagram.

In FDP policy, we consider both the demands of each framework and their dominant share that come from cluster monitor. Scheduling based just on the demand may cause unfairness. A framework could end up consuming the entire cluster due to its higher demand while another framework that has significantly fewer number of tasks to execute could starve for resources. Therefore, we combine both as a factor and use decision matrix in each cycle to decide which task to be dispatched. We present how to calculate each parameter in **Table 3.5**. according to **Table 3.6**, We can see highly total factor in framework A, therefore program assign a higher priority and let its corresponding dispatcher release a task

Table 3.5 Parameter Formula and Description.

Parameter name	Formula	Description
Demand Dominant (DD)	$DD_i = \max_{j=1}^m (\frac{n_i r_{d_{i,j}}}{r_j})$	m available types of resources
		n_i number of tasks on list i
		$r_{d_{i,j}}$ resource demand of type j being demand by framework rd_i
		r_j total resource of type j
Demand Share (DS)	$DS_i = \max_{j=1}^m (\frac{n_i}{r_j})$	m available types of resources
		n_i number of tasks on list i
		r_j total resource of type j

Table 3.6 Decision Matrix.

Framework	DD	(1-DS)	TOTAL
A	1	0.75	1.75
B	0.125	0.875	1

2. **Success rate prediction** There are many metrics in this policy that affect system or task performance, such as CPU utilization, free memory, storage in use, message send information, message queue length, average execution time, etc. These metrics are able to identify anomalies (task failed, task killed, etc.) by using the pipeline provided in **Topic 3.3.2**

Firstly, the log data need to be pre-processed by transforming and cleansing. Secondly, the log data are clustered by K-means algorithm to separate the data that point into different metric groups or different machines. The success rate prediction of given task will use the Random Forest. Random Forest is a set of interconnected decision tree that uses the majority voting to provide classification or regression result. It is robust to noise and able to provide highly accurate prediction. [15] In each cluster, the model will be trained by active and terminated tasks information.

In each cluster, data will be divided into 80% training dataset and remaining 20% testing dataset. The measure metric is accuracy, precision, recall and error. When users submit task, NKR-scheduler will request metric information from Mesos, allocate resource to run tasks, profile the task to cluster and use that cluster's model to predict success rates of this task shown in **Figure 3.4**.

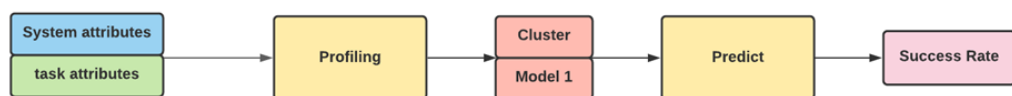


Figure 3.4 Flow Diagram of Predicting success rate.

3.2.3 Database Schema

This project implement database as a Elasticsearch and keep log every minute. It allows storing, searching, and analyzing big volumes of data quickly and schema-less. It uses a default configuration to index the data. Database schema shows in **Figure 3.5** and describe each field in **Table 3.7**

Resources
master/cpus_used
master/cpus_total
master/disk_used
master/disk_total
master/mem_used
master/mem_total

System
system/load_15min
system/load_5min
system/load_1min

Slaves
master/slaves_active
master/slaves_connected

Tasks
master/tasks_error
master/tasks_failed
master/tasks_finished
master/tasks_killed
master/tasks_lost
master/tasks_running
master/tasks_staging
master/tasks_starting

Frameworks
master/frameworks_active
master/frameworks_connected
master/frameworks_disconnected
master/frameworks_inactive
master/outstanding_offers

Messages
master/invalid_framework_to_executor_messages
master/invalid_status_update_acknowledgements
master/invalid_status_updates
master/dropped_messages
master/messages_authenticate
master/messages_deactivate_framework
master/messages_exited_executor
master/messages_framework_to_executor
master/messages_kill_task
master/messages_launch_tasks
master/messages_reconcile_tasks
master/messages_register_framework
master/messages_register_slave
master/messages_reregister_framework
master/messages_reregister_slave
master/messages_resource_request
master/messages_revive_offers
master/messages_status_udpate
master/messages_status_update_acknowledgement
master/messages_unregister_framework
master/messages_unregister_slave
master/valid_framework_to_executor_messages
master/valid_status_update_acknowledgements
master/valid_status_updates

Figure 3.5 database schema.

Table 3.7 Field name and description.

Index Name	Description		
Resources index	The following metrics provide information about the total resources available in the cluster and their current usage.		
System index	The following metrics provide information about the resources available on this master node and their current usage.		
	Field name	Data type	Description
	Load_15min	Double	Load average for the past 15 minutes
	Load_5min	Double	Load average for the past 5 minutes
	Load_1min	Double	Load average for the past 1 minutes
Slave index	The following metrics provide information about slave events, slave counts, and slave states.		
Task index	The following metrics provide information about active and terminated tasks. A high rate of lost tasks may indicate that there is a problem with the cluster.		
	Field name	Data type	Description
	tasks_error	Double	Number of tasks that were invalid
	tasks_failed	Double	Number of failed tasks
	tasks_finished	Double	Number of finished tasks
	tasks_killed	Double	Number of killed tasks
	tasks_lost	Double	Number of lost tasks
	tasks_running	Double	Number of running tasks
	tasks_staging	Double	Number of staging tasks
	tasks_starting	Double	Number of starting tasks
Framework index	The following metrics provide information about the registered frameworks in the cluster.		
Message index	The following metrics provide information about messages between the master and the slaves and between the framework and the executors. A high rate of dropped messages may indicate that there is a problem with the network.		

3.3 Data management

3.3.1 Which dataset is use for training?

This project uses simulation to create a large dataset, and typical usage of Mesos cluster. This project divides types of framework into 3 parts 1) Application management and batch scheduling, 2) Data processing, and 3) Distributed databases and storage, but it will cover only 2 types of framework. This project implements a job simulator to submit 5 frameworks that work well with Apache Mesos and used by many organizations. Nowadays, the simulator simulates based on following example typically job, shown in **Table 3.8** and this project will run application job according to **Table 3.9** for one week, and the minimum task for a day is 50 for each framework.

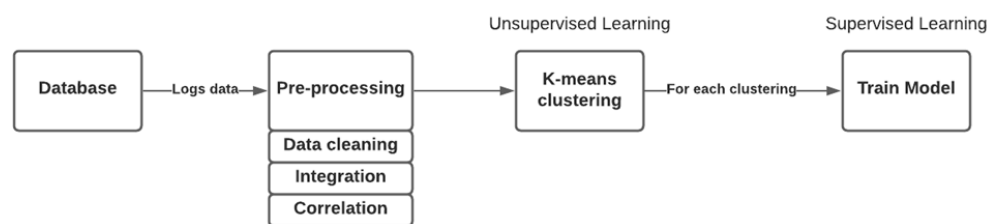
Table 3.8 Framework of Apache Mesos.

Type	Framework1	Framework2	Framework3
1. Application management and batch scheduling	Chronos	Marathon	
2. Data processing	Spark	Dpark	Kafka

Table 3.9 Application Data.

Framework	Application job
Chronos	Wordcount, Kmeans, Topk, InvertedIndex
Marathon	Inline Shell Script, Docker based Application https://mesosphere.github.io/marathon/docs/application-basics.html
Spark	Wordcount, Pi Estimation, Text search http://spark.apache.org/examples.html
Dpark	Wordcount, Python program for data analysis
Kafka	Broker, Topic, Producer, Consumer

3.3.2 Transform data pipeline

**Figure 3.6** Data pipeline.

This project uses log data that mentioned before, and then transforms log data to be a model by using the following step below.

1. **Database** Collecting logs data and sending out all of data from last week.
2. **Pre-processing**
 - **Data cleaning** Dropping entire row that if it has only one attribute missing.
 - **Integration** Summarizing resource utilization of task, and server.
 - **Normalization** Changing value of data into the same range, without distorting differences in the ranges of values.
 - **Data selection with correlation** Finding correlation of each attribute and selecting high correlation to build a model.
3. **Data Mining** Because there is plenty of data and cannot see relative of them, so this project plugs them all into K-means clustering algorithm. It will find patterns in data by grouping it into clusters. In each cluster is point to a subset of the same machines, task, or framework to investigate further. Then, input those same metrics into the machine learning model.

CHAPTER 4 IMPLEMENTATION RESULTS

In this chapter, we walk you through the setup, the configuration and the result we got from our policies, explain more in details.

4.1 Mesos Cluster Setup

For this section about Mesos setup, We setup 3 node of EC2 to be a cluster for each node have 2 GB of vCPU and 4 GiB of Memory, then totally calculate cluster should be 6 CPU and 8.4 Memory. We setup this cluster in medium performance of network and expose cluster to public via IP, Then we can submit task via API

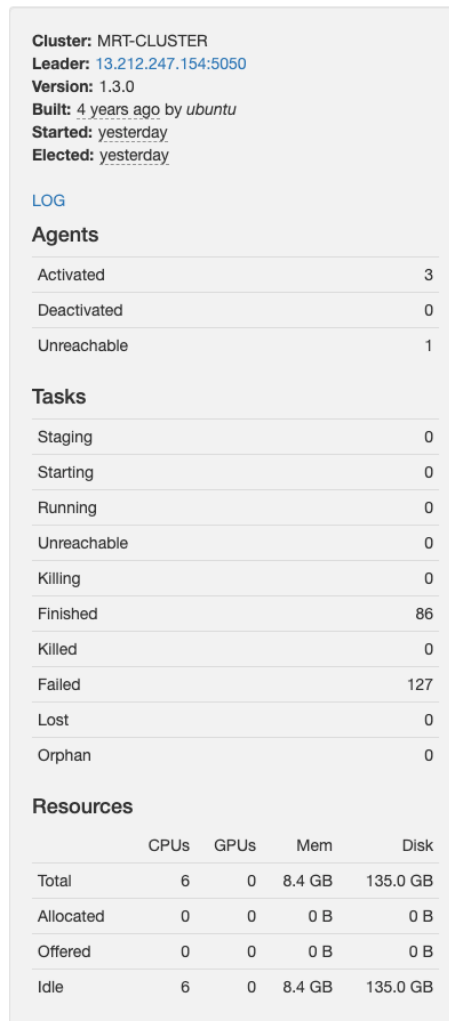


Figure 4.1 Cluster Information

4.2 Active Framework

There are consist of three widely known Mesos Frameworks, Spark Marathon and Chronos and use default setup for each Framework

Active Frameworks												Find...	
ID ▼	Host	User	Name	Roles	Principal	Active Tasks	CPUs	GPUs	Mem	Disk	Max Share	Registered	Re-Registered
...98e0-d57389bb61e5-0002	13.212.247.154	root	marathon	*		0	0	0	0 B	0 B	0%	yesterday	yesterday
...98e0-d57389bb61e5-0001	13.212.247.154	root	chronos	*		0	0	0	0 B	0 B	0%	yesterday	yesterday
...98e0-d57389bb61e5-0000	spark-mesos	root	spark	*		0	0	0	0 B	0 B	0%	yesterday	-

Figure 4.2 Active Framework

4.3 Submit task

We developed python code to help us submit work, with random pick on memory and cpu base on each task and also random framework to submit. This python code require 1 parameter to start work that is number of task.


```

=====
Random pick framework: marathon http://13.212.247.154:8080/v2/apps ( task no : 2 )
Finish submit -> marathon.
=====

Random pick framework: marathon http://13.212.247.154:8080/v2/apps ( task no : 0 )
Finish submit -> marathon.
=====

Random pick framework: chronos http://13.212.247.154:4400/v1/scheduler/iso8601 ( task no : 0 )
Finish submit -> chronos.
=====

Random pick framework: chronos http://13.212.247.154:4400/v1/scheduler/iso8601 ( task no : 0 )
Finish submit -> chronos.
=====

Random pick framework: spark http://13.212.247.154:7077/v1/submissions/create ( task no : 0 )
Finish submit -> spark.
=====

Random pick framework: chronos http://13.212.247.154:4400/v1/scheduler/iso8601 ( task no : 0 )
Finish submit -> chronos.
=====

Random pick framework: chronos http://13.212.247.154:4400/v1/scheduler/iso8601 ( task no : 0 )
Finish submit -> chronos.
=====

Random pick framework: marathon http://13.212.247.154:8080/v2/apps ( task no : 1 )
Finish submit -> marathon.
=====

Random pick framework: marathon http://13.212.247.154:8080/v2/apps ( task no : 1 )
Finish submit -> marathon.
=====

Random pick framework: spark http://13.212.247.154:7077/v1/submissions/create ( task no : 1 )
Finish submit -> spark.
=====

Random pick framework: marathon http://13.212.247.154:8080/v2/apps ( task no : 0 )
Finish submit -> marathon.
=====

Random pick framework: chronos http://13.212.247.154:4400/v1/scheduler/iso8601 ( task no : 0 )
Finish submit -> chronos.
=====

Random pick framework: chronos http://13.212.247.154:4400/v1/scheduler/iso8601 ( task no : 1 )
Finish submit -> chronos.
=====

Random pick framework: marathon http://13.212.247.154:8080/v2/apps ( task no : 1 )
Finish submit -> marathon.
=====

Random pick framework: chronos http://13.212.247.154:4400/v1/scheduler/iso8601 ( task no : 0 )
Finish submit -> chronos.
=====

Random pick framework: spark http://13.212.247.154:7077/v1/submissions/create ( task no : 1 )
Finish submit -> spark.
=====

Random pick framework: spark http://13.212.247.154:7077/v1/submissions/create ( task no : 0 )
Finish submit -> spark.
=====

Random pick framework: chronos http://13.212.247.154:4400/v1/scheduler/iso8601 ( task no : 1 )
Finish submit -> chronos.
=====

```

Figure 4.3 Active Framework

CHAPTER 5 CONCLUSIONS

This chapter is optional for proposal and progress reports but is required for the final report.

5.1 Problems and Solutions

State your problems and how you fixed them.

5.2 Future Works

What could be done in the future to make your projects better.

REFERENCES

1. Jonas DeMuro, 2019, "What is container technology?," www.techradar.com/news/what-is-container-technology, Accessed: 2020-08-30.
2. docker, 2020, "What is a Container?," www.docker.com/resources/what-container, Accessed: 2020-08-30.
3. expertsystem, 2020, "What is Machine Learning? A definition," <https://expertsystem.com/machine-learning-definition/>, Accessed: 2020-08-30.
4. Jake Frankenfield, 2020, "Artificial Neural Network (ANN)," <https://www.investopedia.com/terms/a/artificial-neural-networks-ann.asp>, Accessed: 2020-09-05.
5. Ali Ghodsi, Matei Zaharia, Benjamin Hindman, Andy Konwinski, Scott Shenker, and Ion Stoica, 2011, "Dominant resource fairness: fair allocation of multiple resource types," **8th USENIX conference on Networked systems design and implementation**, pp. 323–336, march 2011.
6. Ali Ghodsi, Matei Zaharia, Benjamin Hindman, Andy Konwinski, Scott Shenker, and Ion Stoica, 2011, "Mesos: A Platform for Fine-Grained Resource Sharing in the Data Center," **8th USENIX conference on Networked systems design and implementation**, April 2011.
7. IBM, 2020, "Apache ZooKeeper," <https://www.ibm.com/analytics/hadoop/zookeeper>, Accessed: 2020-09-05.
8. Roger Ignazio, 2016, **Mesos in Action**, Manning Publications Co.
9. Anton Kirillov, 2016, "Resource Allocation in Mesos: Dominant Resource Fairness," <http://datastrophic.io/resource-allocation-in-mesos-dominant-resource-fairness-explained>, Accessed: 2020-09-5.
10. Qing Liu, Tomohiro Odaka, Jousuke Kuroiwa, and Hisakazu Ogura, 2013, "A Fair Scheduling Algorithm for Adaptive Heterogeneous Resources in Data Centers," **IEICE**, pp. 872–885, April 2013.
11. Wenbin Liu, Ningjiang Chen, Hua Li, Yusi Tang, and Birui Liang, 2018, "A Fair Scheduling Algorithm for Adaptive Heterogeneous Resources in Data Centers," **the Tenth Asia-Pacific Symposium**, September 2018.
12. Hargrave Marshall, 2019, "Deep Learning," <https://www.investopedia.com/terms/d/deep-learning.asp>, Accessed: 2020-09-03.
13. Abueg Ralf, 2020, "Elasticsearch: What It Is, How It Works, And What It's Used For," <https://www.knowi.com/blog/what-is-elastic-search/>, Accessed: 2020-11-24.
14. Pankaj Saha, Angel Beltré, , and Madhusudhan Govindaraju, 2019, "Tromino: Demand and DRF Aware Multi-Tenant Queue Manager for Apache Mesos Cluster," **2018 IEEE/ACM 11th International Conference on Utility and Cloud Computing (UCC)** 63-72, May 2019.
15. Mbarka Soualhia, Foutse Khomh, and Sofiène Tahar, 2018, "Adaptive Failure-Aware Scheduling for Hadoop," **2015 IEEE 34th International Performance Computing and Communications Conference (IPCCC)**, February 2018.
16. TheMathWorks, 2020, "What Is Deep Learning?," <https://www.mathworks.com/discovery/deep-learning.html>, Accessed: 2020-09-03.
17. Robbert van Renesse, Aage Kvalnes, Dmitrii Zagorodnov, and Dag Johansen, 2006, "Policies and Metrics for Fair Resource Sharing," **University of Tromsø**, January 2006.
18. Wikipedia, 2020, "Apache Kafka," https://en.wikipedia.org/wiki/Apache_Kafka, Accessed: 2020-11-25.