Predictive Pod Autoscaling in the Kubernetes Container Cluster Manager

by

Matt McNaughton

Professor Jeannie Albrecht, Advisor

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Abstract

Acknowledgments

Chapter 1

Introduction

Over the past few decades, an explosion in the need for computing resources, and the existence of cheap, interconnected computers, has driven a significant increase in the feasibility and benefits of distributed systems. [18, pg. 1]

First, we consider the origin of distributed systems as a field of computer science. Before the availability of cheap, powerful microprocessors and reliable, efficient local-area networks (LANs), computational tasks could only be performed on a singular computer. [18, pg. 1] If a task was too computationally expensive for a commodity PC, the only solution was to run it on a larger, more powerful supercomputer. However, as cheap microprocessors increased computers' availability, and LANs fostered quick inter-computer communication, a new model of performing resource intensive computation, distributed systems, arose. In the distributed systems model, a collection of individual computers function as a single computer to solve a given computational task. [18, pg. 2]

Second, we consider the ever-growing interest in unlocking and implementing the benefits of distributed systems. A number of forces drove, and continue to drive, increased interest in distributed systems over the past decade. The first, and most obvious, factor is the Internet. As more people connected to the Internet, through computers, mobile phones, and tablets, an increasing number of human interactions became computerized. Consumption, communication, research, and more all became possible on the Internet. Naturally, large amounts of computing resources were needed to store the data, and perform the computational tasks, related to these interactions. Closely coupled with this trend is the rise of "Big Data". In 2013, the digital universe contained 4.4 zettabytes of data.[1] [11] Naturally, without multiple computers working together it would be impossible to store and process this incredible volume of data. Today, it is nearly impossible to do anything in modern society without interacting with a distributed system and creating new digital data. Driving a car, trading a stock, visiting a doctor, checking an email, and even playing a simple video game, are all activities that distributed systems facilitate and improve. [12, pg. 4] As life becomes more computerized, and as the volume of data humans generate and hope to process grows, distributed systems will only increase in importance. Furthermore, research into distributed systems makes it possible to continue to unlock, and make available to the general public, the

[1] A zettabyte equals 10^{21} bytes, which equals 1 billion terabytes.

incredible power of networked, cooperating computers. As the distributed systems supplying massive computational power become more accessible, both because of decreased cost and increased ease of use and reliability, we can computationally address an ever increasing number of challenging, important problems.

There are a number of different models for computing tasks requiring high levels of computing resources, including supercomputing, cluster computing, and grid computing. In this thesis, we focus on cluster computing. Cluster computing groups together similar commodity PCs on the same LAN to offer a singular mass of computing resources. Specifically, we focus on the cluster manager, an integral component of cluster computing. Cluster managers are responsible for abstracting all of the management details of the distinct nodes in the cluster, and instead presenting a single mass of computing resources on which the user can run jobs or applications. In other words, a cluster manager "admits, schedules, starts, restarts, and monitors the full range of applications" on the cluster. [21, pg. 1] There are a variety of different cluster managers, the most important of which will be discussed in the background chapter, each pursuing different objectives. This thesis will ultimately focus on Kubernetes, an open-source cluster manager from Google. [8]

Cluster managers seek to accomplish a number of different goals, and as a result, multiple metrics indicate success. For example, Microsoft's Autopilot is predominantly concerned with application uptime, and thus success is measured with respect to reliability and downtime. [14, pg. 1] Alternatively, a number of cluster managers measure themselves based on efficient resource utilization (ERU). [21, pg. 7] Essentially, efficient resource utilization relates to the percent of cluster resources which are actually being used. One such measurement of this goal, cluster compaction, examines how many computers could be removed from the cluster, while still comfortably running the cluster's current application load. [20, pg. 5] This metric is particularly important, because the more efficient the cluster management is at utilizing resources, the less clusters cost, and the more accessible cluster computing becomes to the general public. A final important cluster management metric is quality of service (QOS). Quality of service measures the ability of an application to function at a specified performance level, despite ever-changing external factors. Again, this metric is particularly important because increasing the robustness of applications run on cluster managers means these applications can be trusted with increasingly important tasks. Cluster managers predominantly differ with respect to which metrics they optimize for, and the process by which this optimization occurs.

1.1 Goals

This thesis is most concerned with maximizing the efficient resource utilization (ERU) and quality of service (QOS) metrics with respect to the Kubernetes cluster manager. As such, this thesis pursues three goals:

1. Given an application running on a Kubernetes cluster, we seek to determine a method which ensures quality of service stays consistently high regardless of external factors. While it is difficult to make guarantees regarding quality of service, because application performance is

dependent on a number of uncontrollable, varying external factors, it is possible to ensure each application has, and is utilizing, the resources it needs to function property. Given the cluster manager grants the application the resources it needs to function given the current external load, the cluster manager has done all it can to ensure a high quality of service.

2. A simplistic solution to the first goal of ensuring a high application quality of service is to just give each application many more resources than it requests. Yet, this overallocation is inefficient and costly. Thus, our methods for ensuring a high quality of service must also ensure the maintenance, or improvement, of the efficient resource utilization metric. Thus, we add an additional goal: given a certain number of applications running on a Kubernetes cluster, we seek to determine a method which ensures the cluster is as small as possible, while still comfortably supporting the application's current, and future, resource needs.

3. Given Kubernetes is an open-source project, we seek to implement, test, and evaluate a proposed enactment of the previous two goals. Thus, the methods we pursue will in part be dictated by the current structure and implementation of Kubernetes. Tests will be conducted using the Google Compute Engine [4] on both simulated and real Kubernetes user data. The eventual goal is for this thesis' improvements to be merged into the production version of Kubernetes used to run 1000s of applications at Google everyday.

1.2 Contributions

This thesis presents our given contributions to Kubernetes. Kubernetes seeks to ensure high application quality of service and efficient resource utilization, and our contributions look to further its ability to accomplish these goals. As such, we present not only new methodology, but also new, working implementations with the accompanying evaluation. We demonstrate the effectiveness of our modifications in comparison to the non-modified Kubernetes using both simulated and real-world datasets. Finally, we discuss the experiences of making these modifications to Kubernetes, as well as avenues for future improvements with respect to Kubernetes and cluster managers in general.

1.3 Contents

@TODO - This section cannot be written until the thesis is completed.

Chapter 2

Background

2.1 Resource Intensive Computing Paradigms

As was briefly mentioned in the introduction, a number of different paradigms exist for undertaking computing tasks too resource intensive for a single computer. They are discussed in detail below:

1. Supercomputing: The supercomputing model responds to increased demands for computing resources by increasing the technical specifications of the computer far beyond the range of the traditional commodity PC. While supercomputers are able to avoid the majority of the complications resulting from the introduction of networks, most prominently reliability and security, there are naturally limits on the power of supercomputers. Importantly, constructing supercomputers is extremely expensive, and thus their computing power is not available to the general public. Furthermore, it is difficult to scale a supercomputer should the need arise. Finally, supercomputers offer a single point of failure, meaning they are not particularly robust to error. These limitations have decreased the usage of supercomputers to provide the mass of computing power needed in the "Big Data" era.

2. Cluster Computing: Cluster computing is defined as utilizing "a collection of similar workstations of PCs, losely connected by means of a high-speed local-area network [where] each node runs the same operating system." [18, pg. 17-18] Cluster computing can provide a mass of computing power similar to that contained in a supercomputer. Cluster computing also offers many advantages over the single supercomputer. First, and perhaps most importantly, they are much more cost-efficient, and thus much more accessible. Second, clusters are easy to scale by simply adding new commodity PCs as nodes. Finally, cluster computing is much more fault tolerant, as a single failing commodity computer will simply be removed from the cluster. Cluster computing is used in the implementation of what is colloquially referred to as *Cloud computing*, in which large amounts of computing resources are offered on a per-usage basis. [12, pg. 13] Cloud computing, as implemented by Amazon Web Services, [2] Microsoft Azure, [9] and Google Compute Engine, [4] continue to revolutionize the development and

deployment of computing applications, as developers gain access to cheap, easily accessible, and quickly scalable computing power.

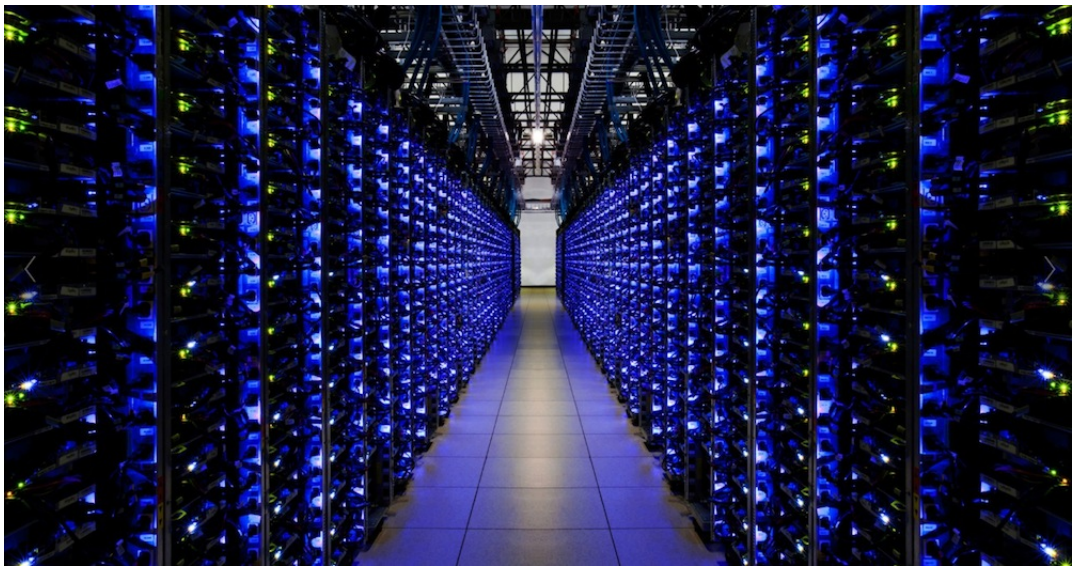

Figure 2.1: A Google Computing Cluster. [10]

3. Grid Computing: Grid computing is similar to concept in cluster computing, except it foregoes the requirement that all computers within the grid be relatively homogeneous. As such, the grid computing model accounts for a large degree of heterogeneity with respect to network membership, operating system, hardware, and more. [18, pg. 18] While grid computing systems lack of homogeneity requirements increase flexibility, the resulting heterogeneity introduces significant complexity.

Ultimately, because of simplicity, cost, and scalability, cluster computing is the most prominent resource intensive computing paradigm. Thus, cluster computing, and the accompanying cluster manager, is the focus of this thesis.

2.2 Cluster Management Paradigms

As was briefly mentioned in the introduction, cluster managers are responsible for admitting, scheduling, running, maintaining, and monitoring all applications and jobs a user wishes to run on the cluster. Naturally, cluster managers are extremely diverse, both in the types of applications and jobs they are most suited to running, and the method in which they seek execute their duties. At the most basic level, there are two types of workload that may be submitted to a cluster manager: production and batch. Production tasks are long-running with strict performance requirements and penalties to downtime. Batch tasks are more flexible in their ability to handle short-term performance variance. In the context of a large company like Google, a production task would be serving

a large website like Gmail, which must be continuously accessible with low-latency and little downtime. A batch task would be analysing advertising analytics data with MapReduce, which can fail or slow without significant external costs. [21, pg. 1] The type of tasks a cluster management system predominantly seeks to run dictate the cluster manager's implementation details.

One important decision in the implementation of a cluster manager is the manner by which the cluster manager schedules jobs.[1] There exist three different methods of scheduling: monolithic, two-level, and shared state. With monolithic scheduling, a single algorithm is responsible for taking the resource requests of all jobs and assigning them to the proper machine. With two-level scheduling, the cluster manager simply offers resources, which can then be accepted or rejected by the distributed computing frameworks.[2] Finally, with shared state scheduling, multiple different algorithms concurrently work to schedule jobs on the cluster. [17, pg. 1] Naturally, all of these methods have positives and negatives. While monolithic scheduling is simple to initially, a single-threaded monolithic scheduler does not allow nuanced processing of jobs. Attempts to add this nuance can create an incredibly complicated algorithm that is difficult to extend. [17, pg. 353-354] While two-level scheduling is lightweight, simple, and offers advantages with respect to data locality, it is not effective for long-running, production jobs. Finally, while shared state scheduling removes the scheduler as both a computational and complexity bottleneck, yet must take steps to guarantee global properties of the cluster. [17, pg. 363] The ultimate determined method of assigning a job resources effects the type of applications and distributed computing frameworks runnable on the cluster manager and the efficiency with which these applications and frameworks run.

A final distinction is licensing and availability of the cluster manager's code. Because entities need cluster managers only to process and store massive amounts of data and human-computer interaction, mainly large corporations develop and utilize cluster managers. Often these cluster managers are kept within the confines of the corporation, or only explained by a brief paper or conference talk, with little source code available. In more unique cases, the company will open-source the source code, allowing anyone to view, modify, and run the cluster manager. Such open-sourcing presents a unique opportunity for researchers wishing to experiment with cluster managers, yet without the resources to create their own from scratch. In rarer instances, a fully-developed cluster manager will originate from academic research. In unique scenarios, a large corporation will use this cluster manager and the full code will be open-sourced. The availability of source code directly impacts the feasibility of pursuing experiments with an already existing cluster management system.

Naturally, cluster managers can vary in multiple additional ways. However, the previous three differences recognize the most important distinctions in this thesis' context. Given this understanding, we can know begin to examine specific cluster management implementations and defend our choice of Kubernetes as the cluster manager on which we will ask and answer our research question.

[1] Scheduling jobs on machines simply equates to assigning jobs to resources on a machine.

[2] Distributed computing frameworks are frameworks built to function over multiple machines: Apache Hadoop, Apache Spark...

Table 2.1: Overview of Cluster Management Paradigms.

	Job Type	**Scheduling Model**	**Open Source**
Borg	Both	Monolithic	No
Omega	Both	Shared state	No
Mesos	Batch	Two-level	Yes
YARN	Batch	Monolithic	Yes
Kubernetes	Production	Monolithic	Yes

2.2.1 Borg

While just recently described to the public in a 2015 paper, the *Borg* cluster manager from Google has been in use for over a decade. [21, pg. 14] Borg incorporates many different objectives, seeking to abstract resource management and failure handling, maintain high availability, and efficiently utilize resources on the cluster. [21, pg. 1] It is responsible for managing the hundreds of thousands of batch and production jobs run everyday at Google. Additionally, Borg utilizes a monolithic scheduler, as jobs specify the resources they need, and a single Borg scheduler decides whether to admit and schedule said jobs. Finally, Borg is not open-source. In fact, it was not even publicly announced or described until 2015, despite running at Google for over a decade. However, Kubernetes, Google's open-source cluster manager, incoporates much of the work done to implement and improve Borg.

2.2.2 Omega

Also originating at Google, *Omega* is a cluster manager seen as the current-day extension of Borg. While retaining the mission and goals of Borg, Omega differs in implementation. Specifically, it considers a new method of assigning jobs the resources they need on the cluster by implementing shared state, instead of monolithic, scheduling. As mentioned in the general overview, shared state scheduling allows multiple scheduling algorithms to work in parallel to assign tasks the resources they request. Research on Omega shows this parallel scheduling implementation both eases the complexity of adding new scheduling behaviors and offers competitive scaling performance. [17, pg. 358-359] Additionally, in Omega, all schedulers are aware of the entire state of the cluster, meaning that the resource allocation to a job can be varied after the job begins to execute. This flexibility offers significant performance improvements. [17, pg.352] Like Borg, Omega is not open-source. However, like Borg, much of the work done on Omega is incorporated into Kubernetes, Google's open-source cluster manager.

2.2.3 Mesos

Lest we think all cluster managers originate at Google, we now examine Apache Mesos, a cluster manager originating at University of California, Berkeley, and currently at use at a number of prominent corporations including Twitter. Mesos is much more lightweight than either Borg or Omega, and simply seeks to offer resources to distributed computing frameworks (i.e. Apache Hadoop, Apache Spark...) which can decide to accept or reject these resources. It does not seek to monitor the health of jobs or provide user-interfaces for viewing the current state of a job, leaving

those tasks to the distributed computing framework. Additionally, Mesos predominantly focuses on quick-running, high-volume batch jobs, and is not particularly suited to long-running, high-availability production jobs. [17, pg. 358] In part, Mesos' job scheduling implementation specifics the singularity of the job types Mesos efficiently processes. Mesos utilizes two-level scheduling, in which the cluster management system simply offers, not assigns, available resources to the distributed computing framework. Predominantly, this decision is made to ensure data locality. [13, pg. 1] Data locality is a measure of if the task has the necessary data on its machine, or if it must make a costly request across the network for the data. Mesos works to ensure data locality by allowing multiple frameworks to function on the same machines, and thus share data, and also for frameworks to dictate their own resources, such that they can work to ensure data locality. If running a large number of data processing tasks, with extremely high volumes of data, data locality can be essential to efficient cluster operation. Finally, Mesos is interesting in that it is entirely open-source, yet still in use at some of the largest tech companies.

2.2.4 YARN

We now briefly discuss Apache Hadoop YARN. YARN, an acronym for *Yet Another Resource Negotiator*, is a cluster manager initially built for use with Apache Hadoop. [19, pg. 1] However, it is now possible to use YARN with a variety of distributed computing frameworks. Unsurprisingly given YARN's initial use case, YARN is predominantly used for running batch jobs.[3] Like Mesos, YARN aims to support data-locality, again a predominant advantage for batch processing. [19, pg. 3] YARN schedules resources by allowing per distributed computing framework application masters to request resources from a single resource master. [19, pg. 5] As a single resource master is assigning all of these resources, YARN is a monolithic scheduler. Similar to Mesos, YARN is both entirely open-source and in use at major corporations like Yahoo. [19, pg. 9]

2.2.5 Kubernetes

Finally, we arrive at the cluster management that is the focus of this thesis: Kubernetes. Kubernetes also originates, although it is open source, meaning anyone is free to modify and deploy Kubernetes. Kubernetes is also the most recent of the cluster managers we consider in this background research section.[4] The recent explosion in popularity of containerization[5] heavily impacts the development and implementation of Kubernetes. Specifically, Kubernetes is seen as part of a new paradigm of developing applications through the use of microservices.[6] Kubernetes predominantly focuses on effectively running service jobs. As previously mentioned, these jobs require high-availability and potentially varying amounts of resources. Additionally, Kubernetes currently utilizes a monolithic,

[3] At the time of the publication, YARN was just beginning to be used for production jobs; however, its main focus from creation has been batch processing. [19, pg. 11]

[4] Kubernetes became public in the summer of 2014.

[5] We discuss both the motivations and technology behind containerization in the Appendix. Briefly, containerization is packing everything an application needs to run into a single *container* and then running that container on any desired computer.

[6] Again, we will discuss microservices in greater detail in the Appendix. Essentially, microservices are the division of applications into small, easily scalable services which communicate with each other across the network.

fairly simple scheduler, although there are plans to grow the scheduler in the future. [6] Finally, Kubernetes is an open source project, yet is also used in production at Google, and available to the public through the Google Container Engine. [5]

We choose Kubernetes as the cluster manager on which to conduct our experiments for a number of reasons. First, Kubernetes focuses on service jobs. Services jobs have particularly stringent requirements for availability and are also the most likely to have varying resource needs. Both these conditions are closely linked with the previously stated goals of this thesis, and Kubernetes is the cluster manager that stands to benefit the most if we achieve our goals. Additionally, Kubernetes is the only cluster manager focusing on long-running services that is open source. Focusing on a open source cluster manager allows us to benefit from the previous work of others, as well as expand the potential benefits of any successful work.

2.3 Auto-scaling Paradigms

We now proceed to consider a subset of cluster management closely related to this thesis' goal of ensuring high quality of service in the face of changing external factors and efficient resource utilization. Specifically, we introduce auto-scaling, a method of ensuring each application has the necessary amount of resources to handle its varying load.[7]

To better understand both the implementation and benefits of auto-scaling, let us consider a simple scenario. Imagine you have an application running on a cluster for a week. On Monday, it will need x resources.[8] On Tuesday through Thursday, the application will need $2x$ resources. Finally, on Friday the application will again need x resources. Without auto-scaling, we are forced to assign a constant amount of resources to the application running on our cluster. However, there is no constant amount of resources that can meet the two goals of efficiently utilizing the cluster's resources and ensuring the application has the resources it needs to maintain a high-level of service. If we assign the application x resources, then on Tuesday through Thursday the application will not have the amount of resources it needs to handle its load, and quality of service will deteriorate. Alternatively, if we assign the application $2x$ resources on the cluster, than on Monday and Friday we will essentially be wasting x resources on the cluster, as they are assigned to an application that does not need them. This waste prevents reaching our goal of efficiently utilizing the cluster's resources.

We address the inability to find a static amount of resources efficiently handling all the variances in application load through auto-scaling. Auto-scaling allows us to assign an application more or less resources on the cluster based on varying external factors. In our previous example, auto-scaling would allow us to assign the cluster x resources on Monday and Friday and $2x$ resources on Tuesday through Thursday. Through auto-scaling, we accomplish both goals: our application has the resources it needs to ensure a high quality of service, and our application is not inefficiently

[7] Importantly, auto-scaling is made possible by current models of clustercloud computing, in which it is possible to automatically obtain and relinquish computing resources within a very short time frame. Obviously, if adding computing resources required buying a new physical server, as was the case before the advent of cloud computing, auto-scaling becomes impossible.

[8] By *resources*, we mean CPU, memory...

holding cluster resources that it does not need. Overall, Auto-scaling can make applications on a cluster more cost-effective and more performant.

Given an understanding of the importance of auto-scaling, we now begin the examine the differing implementations of auto-scaling. Auto-scaling implementations differ in how they assign an application the new resources it needs[9] and how they decide to assign the application the resources it needs. There are two predominant characteristics shaping the nature of an autoscaling implementation. The first is if the auto-scaling is horizontal or vertical. The second is if the auto-scaling is reactive or predictive.

We begin by examining the difference between horizontal and vertical scaling. Let us begin by assuming there is an application running on a virtual machine instance assigned by the cluster with x amount of resources. The application now faces external load such that the current amount of resources assigned to the application is not sufficient. Rather, let us assume the application now needs $2x$ resources to function efficiently. There are now two options. In *vertical* auto-scaling, the cluster manager will attempt to assign the virtual machine instance running the application the needed $2x$ resources without halting the execution of the application. In *horizontal* auto-scaling, the cluster manager will create another instance of the virtual machine running the application, so that there are now two machines each with x resources ($2x$ resources in summation). The load will now be split between the two new instances of the application, meaning each machine must only handle requests requiring the x resources each individual virtual machine instance has. [16, pg. 4] While both of these variations of auto-scaling accomplish the same purpose, horizontal auto-scaling is much simpler. Given we know how to create an instance of a virtual machine running the application, which is an entirely safe assumption considering we already created one such instance, it is fairly trivial to create another instance, and then split the load between these two instances using standard methods of load balancing. This statement of simplicity of course assumes the application is written in a scalable manner such that it can be replicated with no unexpected modifications on operation. Contrast this well-defined with more questionable, difficult process of changing the resources given to a virtual machine without stopping the application from executing. Importantly, there exists no consistent, cross-platform method of modifying the amount of resources granted to a virtual machine instance without stopping the execution of the virtual machine. As a result, every method of auto-scaling we examine focuses on horizontal auto-scaling. [16, pg. 4]

We continue by examining the distinction between reactive and predictive auto-scaling. At the simplest level, *reactive* auto-scaling reacts to the current state of the application and cluster, while *predictive* auto-scaling predicts the current state of the application and cluster. [16, pg. 12] Predictive auto-scaling can be based on a number of different metrics and methods of prediction, which highlights some of the inherent complexity of predictive auto-scaling. While reactive auto-scaling must only consider one method of gathering and interpreting information, when attempting predictive auto-scaling there are many decisions that must be made with respect to the most accurate method of projecting past metrics into future metrics. However, predictive auto-scaling has the advantages both of incorporating greater amounts of past information which may be able to provide historical insight and allowing the cluster manager to decrease the time-costs of certain actions by

[9] Auto-scaling implementations can also take away resources from an application running on a cluster.

Table 2.2: Overview of Auto-scaling Paradigms.

	Reactive vs Predictive	**Implementors**
Threshold	Reactive	Amazon Web Services
Time-Series Analysis	Predictive	Netflix
Control-Theory	Both (currently reactive)	Kubernetes

performing them before a reactive cluster manager would suggest.[10] Finally, techniques for auto-scaling can be both reactive and predictive as they incorporate both current and projected cluster and application information to make auto-scaling decisions.

A number of the major providers of cloud computing resources offer auto-scaling. The most prominent of these providers is Amazon, which supports threshold-based horizontal auto-scaling on EC2 virtual machine instances. [3] Furthermore, Netflix implements time-series analysis auto-scaling to help it respond to the varying demand placed on its services throughout the day. [15] Finally, Kubernetes implements control-theory auto-scaling. [7] We will examine threshold, time-series analysis, and control-theory auto-scaling in detail in the remainder of this section.

2.3.1 Threshold-based Rule Policies

The simplest method of auto-scaling is threshold-based rule policies. Threshold-based rule policies are reactive, as they perform scaling behaviors if the current system is not in accordance with predefined rules. The rules predominantly relate to per machine resource utilization levels. For example, a rule could be that if the average percent CPU utilization for all the machines is above 80%, then a new machine should be created. This rule would be accompanied with an additional scale-down rule stating that if the average percent CPU utilization for all of the machines is below 20%, then a machine should be deleted. The most popular implementation of threshold-based rule policies for auto-scaling comes from Amazon Web Services.[11] [3]

Threshold-based rule policies offer both advantages and disadvantages with respect to auto-scaling. Predominantly, the origin of these qualifiers is threshold=based rule policies' conceptual simplicity. Because threshold-based rule policies are reactive and based on simple metrics like percent cpu utilization and memory usage, they are simple to write. However, they are difficult to write well, as it is difficult to predict how certain rules will respond to the varying external circumstances. One particular difficulty arises with respect to handling the nebulous time between when the threshold is crossed and auto-scaling triggers the creation of a new application, and when the newly created application can start running and balancing the load.

Overall, there are a number of variables that must be considered, reinforcing that while it is easy to conceive of a threshold-based rule for auto-scaling, if an application will face varying external

[10] We will spend considerable time later in this concept. Basically, predictive auto-scaling makes it easier to account for the amount of time necessary to perform horizontal auto-scaling (i.e. creating a new virtual machine instance running the application). If we know we need a machine in the future, we can start creating it now, so it is ready by the time it is needed. With reactive auto-scaling, we do not know we need the replication until the current state of the application and cluster indicates it. Thus, we must wait for the auto-scaling to occur, all the while the application will be operating with sub-optimal resources.

[11] More specifically, Amazon Web Services uses threshold-based rule policies for auto-scaling with respect to EC2 instances. EC2 instances are essentially rentable cloud servers. [1]

circumstances it can be difficult to write a threshold-based rule having the desired effect.

2.3.2 Time-series Analysis

We now examine an additional, substantially more complex, form of auto-scaling situated upon predictive time-series analysis. Time-series analysis seeks to find a repeating pattern in application load, and then horizontally auto-scale the application based on these patterns. [16, pg. 29] For example, if time-series analysis indicated a pattern in which every Friday at 5pm, the application needed $2x$ resources, it would be possible to auto-scale the application to $2x$ resources at this time. If we are able to compose a number of these observations, we can create a policy for the entire auto-scaling behavior of the given application by taking the application's predicted external environment and determining the resources the application will need as a response.

There are a variety of techniques for conducting time-series analysis auto-scaling including pattern matching, signal processing, and auto-correlation.[12] [16, pg. 32] Like threshold-based rules for auto-scaling, there are significant advantages and disadvantages to time-series analysis. Unlike threshold-based rules which are marked by simplicity, time-series analysis is significantly more complex. Time-series analysis can be particularly effective at responding to external changes when said changes have a pattern.[13] However, time-series analysis requires a large amount of data and also substantial mathematical knowledge; it certainly cannot be implemented as easily as specifying a few simple thresholds. Additionally, while time-series analysis works well for auto-scaling with respect to patterns, it does not work well the external application load differs from the pattern. As such, predictive time-series analysis is often combined with reactive threshold-based rule auto-scaling to combine the benefits of both.[14]

2.3.3 Control theory

We continue on to examining a new auto-scaling technique predicated on control theory. Control theory is normally used for reactive auto-scaling, although it can also be used in a predictive context. The simplest implementation of a control system with respect to auto-scaling utilizes feedback controllers. [16, pg. 25] Abstractly, a feedback model functions by continuously examining a set of output parameters, and then tweaking a set of desired input parameters in an attempt to ensure the output parameters maintain some desired state. More concretely with respect to auto-scaling, the output parameters would be the current state of the application instances, such as the percent CPU utilization or the amount of memory the instances were using. Additionally, the input parameters would be the number of instances of the application currently being run. A feedback model can implement auto-scaling as the number of application instances will vary in accordance to the external load on the application, which will ensure that the application instances maintain certain operation

[12] Netflix utilizes a combination of methods with respect to their predictive time-series analysis auto-scaler, Scryer. [22]

[13] An example of a change with a pattern would be Netflix users who are more likely to watch TV at 10pm than 10am.

[14] Netflix's Scryer implements this combination of time-series analysis and threshold-based rule auto-scaling. [22]

metrics. For example, we could specify that the feedback controller should auto-scale applications such that all application instances utilize 70% of the CPU.

Done correctly, feedback control theory offers substantial advantages over threshold-based rules. Specifically, it is equally simple to write auto-scaling specifications for each. Yet, it is easier to determine the effects of feedback control systems. When a new instance is created as the result of the violation of a threshold-based rule, we do not exactly know what the result will be with respect to the metrics we care about. However, with a feedback control system, we are certain about the results of the auto-scaling, as we auto-scale specifically to ensure the maintenance of certain metrics.

Kubernetes currently implements auto-scaling through a feedback control system. While we will spend substantially more time discussing Kubernetes auto-scaling implementation later, the basics are as follows. The user specifies a target resource metric, for example CPU utilization. At a specified time interval, Kubernetes then examines the current values of the resource metric, and updates the number of application instances to ensure the actual current actual value equals the target value. [7]

Predictive Feedback Control

As previously mentioned, feedback control systems are typically reactive, meaning that the metrics used are based on the current state of the system. However, we can also consider a feedback control system that is predictive. We call this Model Predictive Control. [16, pg. 27] Again, we will spend significantly more time discussing predictive feedback control later, but at its simplest, it is an implementation of feedback control based auto-scaling, but the outputs are predictions about the future state of the application instance, instead of the current state of the application instance.

Adding prediction to feedback control offers significant benefits. The most significant benefit is accounting for the pod's creation time when auto-scaling. With predictive feedback control, we can create pods so they are ready as soon as they are needed. Ultimately, we hypothesize adding a predictive component to Kubernetes current feedback control auto-scaling will allow us to auto-scale in a manner that ensures both quality of service and efficient resource utilization.

2.4 Summary

Overall, there are a number of lessons to be learned in this section. In summation, we discussed the variety of methods for performing resource intensive computational tasks, before focusing on cluster computing. We examined a variety of popular cluster managers, before focusing on Kubernetes. Finally, we examined a variety of methods of auto-scaling applications running on cluster managers, before focusing on model predictive control. The remainder of this thesis will seeks to show the effectiveness of model predictive control in modifying the current implementation of auto-scaling in Kubernetes, such that we will improve both quality of service and efficient resource utilization.

Chapter 3

Appendix

3.1 Technologies Underlying Kubernetes

3.1.1 Containerization

Virtualization

Containerization

Docker

3.2 Trends Motivating Kubernetes

3.3 Microservices

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