BBQ: Elastic MapReduce over Cloud Platforms

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Abstract—Cloud infrastructure services such as Amazon EMR allow users to have access to tailor-made Big Data processing clusters within a few clicks from their web browser, thanks to the elastic property of the cloud. In virtual cloud environments, resource management is desired to be performed in a way which optimizes utilization, thus maximizing the value of the resources acquired. As cloud infrastructures become increasingly popular for Big Data analysis, the execution of programs with respect to user selected performance goals, such as job completion deadlines, remains a challenge. In this work we present BARBECUE (job Aware Big-data Elasticity Cloud management System), a system that allows a Hadoop MapReduce virtual cluster to automatically adjust its size to the workload it is required to execute in order to respect individual jobs’ completion deadlines without acquiring more resources than the least necessary. To that end, BBQ’s Decision Making module uses a Performance Model for MapReduce jobs which can express cluster resources (i.e., YARN Container capacity) and execution time as a function of the number of nodes in the cluster. BBQ leverages the abstraction of YARN, making it feasible for integration with other execution frameworks, such as Spark, with the necessary changes to its pluggable Decision Making module. We also add a new feature to Hadoop MapReduce which can now dynamically, on-the-fly update the number of selected ReduceTasks in cases where the cluster is expanded, so that our system makes full use of the resources it has acquired during the reduce phase of the execution. BBQ uses an adaptation of the hill climbing algorithm to estimate the optimal combination of number of nodes and reduce waves given a known job, its data input and an execution deadline. The attendees be able to watch the system perform cluster resizes in real-time in order to execute its assigned jobs in time.

I. INTRODUCTION

Cloud computing [14] becoming a mainstream trend about a decade ago, changed the way big data is processed and stored. Having access to unlimited computing power and storage resources, users and organizations are now able to respond to the ever growing need of processing huge amounts of data. According to IBM, approximately 2.5 quintillion bytes are created every day [2]. This increasing data production forces the use of cloud computing as a popular practice but also brings new challenges, concerning the way cloud cluster infrastructures are being managed and provisioned. Virtual cloud environments are an agile solution for Big Data analysis systems thanks to elasticity [5], [9]. The elastic property of the cloud allows administrators to manage the computing resources available to them according to their needs with minimal effort. Resource management in virtual cloud environments is an area with a lot of research potential, since the line between good and bad practices is extremely thin. Currently, many users handle their clusters’ provisioning needs by using rules of thumb and personal experience with specific frameworks. As big data analysis solidifies its status as an indispensable tool for cross-field academic as well as innovative entrepreneurial research and cloud services accessible to a large non-expert user base, there can be cases where users lack the background to make cluster provisioning decisions. Recent research projects have tried to explore the factors which influence such complex problems and suggest solutions.

In this work we introduce BARBECUE (a job Aware Big-data Elasticity Cloud management system – BBQ), a system that allows a Hadoop MapReduce [4] virtual cluster to automatically adjust its size to submitted jobs under a completion deadline. BBQ supports automated cluster deployment, provisioning and on-the-fly, per-job elasticity for the execution of MapReduce programs. BBQ’s backbone is a modified version of the Apache Hadoop project [1], an extremely popular platform which is especially designed for Big Data processing. BBQ allows the automatic a) deployment and b) expansion of a Hadoop cluster on the cloud to improve performance while processing huge amounts of data in order to meet execution time goals set by the user. Additionally, BBQ introduces a reduce phase optimization to improve the use of its elastic properties, by allowing the number of reduce tasks to be dynamically set to achieve better performance.

II. SYSTEM ARCHITECTURE

BBQ features an architecture that is illustrated in Fig. 1. It can be used to set up a new virtual Hadoop cluster from scratch and manage its resources taking into account the submitted jobs and their execution deadlines. When a new job is submitted, BBQ’s Decision Making module decides on cluster resize operations, if those are required for the execution to successfully meet the deadline. The Decision Making module then interacts with the Cloud Management module which contacts the cloud vendor to adjust the cluster’s physical resources by acquiring more virtual machines if necessary. The Cluster Coordinator module executes higher level add and remove node commands to modify cluster size.

A. Cloud Management

This module is responsible for the interaction with the cloud vendor whenever cluster nodes are to be acquired or released upon request from the Decision Making module. Our cloud management platform is a private OpenStack installation. BBQ can be deployed in Amazon’s EC2 or in any EC2-compliant IaaS cloud. To set up new clusters, we have created an Amazon

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Machine Image (AMI) that contains a pre-cooked version of BBQ-flavored Hadoop.

B. Cluster Coordinator

VM coordination is performed with the remote execution of shell scripts and the injection of on-the-fly created Hadoop-specific configuration files to each VM upon creation. Every time the Cloud Management module allocates new VMs, the Cluster Coordinator module is responsible for their integration with the existing nodes of the cluster. Similarly, when nodes are decommissioned, they are first removed from the cluster and then released.

C. Decision Making Module

This module is responsible for deciding the appropriate cluster resize action and number of reduce waves. Its decision depends on the submitted job, input data size and user defined execution time goal. The decision making module is pluggable and can be replaced by a different implementation of BBQ’s functionality. The implemented Decision Making module for the purposes of this demonstration uses hill climbing to solve the optimization problem of estimating the least nodes necessary to complete a submitted MapReduce job within a given deadline as well as the number of reduce waves of the job which will be executed. To model execution time, we have used the approach thoroughly presented in Section III. Hill climbing traverses a space of possible solutions, starting off of the initial state of the cluster, in order to converge to the one which gives us the best approximation of the optimal solution that our model can achieve. Upon reaching a resize decision, the module requests the addition or removal of a number of VMs using the Cloud Management and Cluster Coordinator modules. Once the MapReduce program has been executed and no other job has been submitted for a certain period, the Decision Making Module forces the cluster to gradually shrink by releasing unnecessary idle nodes. Other possible approaches to the problem in hand are presented in works mentioned in Section VI.

D. Hadoop

BBQ uses a modified, cloud aware version of Hadoop. Every time a new job is submitted for execution, Hadoop notifies BBQ, giving it information on the map reduce program to be executed, input data size and maximum desired execution time. Subsequently, the submitted job is paused until the Decision Making module has discovered the optimal cluster configuration and the resizing – if necessary – has been completed. Additional code has been injected in specific classes of the Hadoop framework to communicate with BBQ to notify it of incoming jobs, then wait for the Decision Making module to respond with the number of ReduceTasks to be scheduled and launched and, finally, make the necessary changes before the job is executed.

III. MODEL AND ALGORITHM

A. Performance Model

In order to be able make the required provisioning decisions which will allow Hadoop to complete MapReduce jobs in a specified time window, BBQ’s decision making model needs to be able to predict job execution time given a MapReduce program and its input. To accomplish that, we use a Hadoop MapReduce Performance Model, which can express the execution time of MapReduce jobs as a function of those features [16]. To construct our model, we analyze Hadoop’s internal functions. To fit the model to specific MapReduce programs, on the other hand, we use performance metrics from past executions – we record the execution time, number of nodes and number of reduce waves the job launched.

There is a set number of YARN MapTask and ReduceTask Containers which can co-exist in a Hadoop cluster at any given point in time. This number depends on cluster size, i.e., the number and size of the cluster’s nodes. Let’s assume there can be at most \( m \) Map Containers and \( r \) Reduce Containers distributed over all cluster nodes. By default, in Hadoop each Map process handles a single block of input data. Therefore, if we have \( M \) blocks, \( M \) MapTasks in total will be scheduled and assigned to \( m \) Containers. In the ideal case, exactly \( m \) MapTasks occupy the \( m \) Containers and run in parallel, resulting in a single wave of Map processes. If \( M > m \), which is usually the case for large datasets, \( \lceil M/m \rceil \) Map waves are needed. In contrast to the total number of Map processes, the number of Reduce processes, \( R \), can be set by the user and is determined by the application requirements. Similarly, if \( R > r \), more than one wave of ReduceTasks are scheduled. In addition to the cost of the Map and Reduce phases, we should also take into account the tasks of managing and scheduling the \( M \) MapTasks and \( R \) ReduceTasks.

1) Map Phase: The Map phase is divided into four sequential operations: Read, Map, Sort/Partition, and optionally Combine. Each task’s first operation is to Read a block of data from the disk – either a local or a remote data block.
We assume the average cost is a function of the size of data block, $b : i(b)$. Map is the execution of user defined Map function using the data block read in Read, the complexity of which is determined by the input data size $b$, denoted as $f(b)$. The Map function output data $o_m(b)$ is often a linear function to the input size $b$. The output will be a list of $(key, value)$ pairs which will be Sorted by the key and Partitioned into $R$ shares for the $R$ Reduce processes. We denote the cost of partitioning and sorting with $s(o_m(b))$. Since the partitioning process uses a hash function to map the keys, the cost $s(o_m(b))$ is independent of $R$. The overall cost of a Map process is the sum of the costs mentioned above – without the Combiner component, which will be discussed later:

$$\Phi_m = i(b) + f(b) + s(o_m(b)).$$

(1)

This cost is only related to the size of the data block $b$ and the complexity of the Map function. It is independent of the parameters $M, R$ and $r$.

2) Reduce Phase: The Reduce phase is broken into the following operations: Copy, MergeSort, Reduce and WriteResult. To simplify our model we will assume the $k$ keys of the Map result are equally distributed to the $R$ Reduce processes. During Copy, each ReduceTask pulls its shares, i.e., $k/R$ keys and the corresponding records, from the $M$ Map phase outputs. Thus, the total amount of data in each Reduce will be:

$$b_R = M \cdot o_m(b) \cdot k/R.$$  

(2)

The Copy cost is linear to $b_R$, denoted as $c(b_R)$. A MergeSort follows to merge the $M$ shares from the Map results while keeping the records sorted, which has the complexity $O(b_R \log b_R)$, denoted as $ms(b_R)$. The Reduce function processes the data with some complexity $g(b_R)$ that depends on the application. Assume the output data of the Reduce function has an amount $o_r(b_R)$, which is often less than $b_R$. Finally, the result is duplicated and Written back to multiple nodes, with the complexity linear to $o_r(b_R)$, denoted as $wr(o_r(b_R))$. In summary, the cost of the Reduce process is the sum of the component costs,

$$\Phi_r = c(b_R) + ms(b_R) + g(b_R) + wr(o_r(b_R)).$$  

(3)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$</td>
<td>single MapTask input size</td>
</tr>
<tr>
<td>$b_R$</td>
<td>single ReduceTask input size</td>
</tr>
<tr>
<td>$M$</td>
<td>total MapTasks</td>
</tr>
<tr>
<td>$R$</td>
<td>total ReduceTasks</td>
</tr>
<tr>
<td>$m$</td>
<td>single wave cluster MapTask capacity</td>
</tr>
<tr>
<td>$r$</td>
<td>single wave cluster ReduceTask capacity</td>
</tr>
<tr>
<td>$w_r$</td>
<td>number of ReduceTask waves</td>
</tr>
<tr>
<td>$N$</td>
<td>number of cluster nodes</td>
</tr>
</tbody>
</table>

TABLE I: Symbols used in this section and their meanings.

3) Full Model: Replacing from the equations above, we can see that the overall time complexity $T$ depends on the number of Map waves and Reduce waves. By including the cost of managing and scheduling the Map and Reduce processes $\Theta(M, R)$, which is assumed to be linear to $M$ and $R$, we represent the overall cost as:

$$T = \left\lceil \frac{M}{m} \right\rceil \Phi_m + \left\lceil \frac{R}{r} \right\rceil \Phi_r + \Theta(M, R).$$  

(4)

We want to focus on the relationship that connects the total time complexity $T$, the input data size $M \times b$, the number of ReduceTasks $R$, and the number of YARN Containers, $m$ and $r$. Using a fixed block size $b$ in the analysis, we observe that the cost of each Map process, $\Phi_m$, is fixed. The cost of each Reduce process, $\Phi_r$, is subject to the factor $M$ and $R$. After replacing and keeping only the variables $M, R$ and $m$ in the model, get:

$$T_1(M, m, R, r) = \beta_0 + \beta_1 \left\lceil \frac{M}{m} \right\rceil + \beta_2 \left\lceil \frac{R}{r} \right\rceil$$

$$\frac{M}{R} + \beta_3 \frac{M}{R} \log\left(\frac{M}{R}\right) + g\left(\frac{M}{R}\right)$$

$$+ \beta_4 M + \beta_5 R + \epsilon,$$

(5)

where $\beta_i$ are the parameters describing the constant factors. $T_1(M, m, R)$ is not linear to its variables, but it is linear to the transformed components: $M/m, M/R, M/R \log(M/R)$, $g(M/R)$, $M$, and $R$. The parameter $\beta_0$ defines the contribution of each fine grain operation of either phase in the model. Concretely, $\beta_1$ represents the fixed Map cost $\Phi_m$; $\beta_2$ represents the parameter associated with the cost of Copy and WriteBack in the Reduce phase; $\beta_3$ represents the parameter associated with the MergeSort component in the Reduce phase; $\beta_4$ and $\beta_5$ represent the parameters for the cost associated with the management cost $\Theta()$, i.e., we assume the cost is linearly associated with the number of Map and Reduce tasks: $\Theta(M, R) = \beta_4 M + \beta_5 R$. $\beta_0$ represents some constant, and $\epsilon$ represents the noise component that covers the unknown or unmodeled factors in the system. We discuss the impact of $g(M/R)$ in the model later.

Combiner function. In the Map phase, the Combiner function is used to aggregate the results by key. If there are
The Combiner function reduces the output data of the Map process and thus affects the cost of the Reduce phase as well. When using a Combiner function, the data that a Reduce process needs to consume from the Map output shrinks to:

\[ b_R = \frac{M}{R} \]

on average – assuming normal distribution. Since the factor \( M/R \) is already present in (5), the cost model applies without changes.

**Function \( g() \).** The complexity of the Reduce function has to be estimated each time for the given application. There are some special cases where \( g() \) can be removed from (5). If \( g() \) is linear to the size of the input data, then its contribution can be merged to the factor \( \beta_2 \), because \( g(M/R) \sim M/R \). Similarly, if its complexity is \( O\left(\frac{M}{R} \log M \right) \), its contribution can be merged to \( \beta_3 \).

In those two special cases, the cost model can be simplified to:

\[
T_2(M, m, R, r) = \beta_0 + \beta_1 \left( \frac{M}{m} \right) + \beta_2 \left( \frac{R}{r} \right) \left( \frac{M}{R} \right) + \beta_3 \frac{R}{r} \log \left( \frac{M}{R} \right) + \beta_4 M
\]

Similarly, the complexity of the Reduce function has to be estimated each time for the given application. There are some special cases where \( g() \) can be removed from (5). If \( g() \) is linear to the size of the input data, then its contribution can be merged to the factor \( \beta_2 \), because \( g(M/R) \sim M/R \). Similarly, if its complexity is \( O\left(\frac{M}{R} \log M \right) \), its contribution can be merged to \( \beta_3 \). In those two special cases, the cost model can be simplified to:

**VM creation overhead.** The time required for the new VMs to be created, configured and integrated in the cluster is calculated by adding the average time for new VM creation in our cloud infrastructure to the average configuration and integration time for the working cluster. These metrics have been collected through experimentation. Since all VM instances are launched in parallel, we only need to take this term into account once per cluster resize action. According to Mao et al. [12], VM startup time can be considered of trivial cost and should not cause substantial problems. They claim that launching VMs in a cloud environment should not be a bottleneck, as long as the precooked images of their hard drives are not extremely large. In this case these images only include an installation of the operating system and Hadoop. Lagar-Cavilla et al. [10] also made a strong case of VM launch time becoming more and more insignificant.

**Data Locality.** The time required for the new VMs’ file system to be populated by the data which will be processed by the Map function is modeled to be linear to the number of new nodes BBQ has added to the cluster. This overhead also depends on the speed of data transfer within the cloud infrastructure and its architecture.

\[
T_{\text{init}} = \beta_6 (N - N_{\text{init}}).
\]

**Training.** BBQ uses regression and performance metrics from previous executions of instances of a MapReduce program with various values for \((M, R, m, r)\) to calculate \( \beta_i \). These model coefficients are stored in a local database and can be updated in regularly for improved fitting.

### B. Algorithm

Having access to Performance Models for MapReduce programs, our system uses an implementation of hill climbing (algo. 1) to solve the optimization problem of minimizing the cluster resources while ensuring job execution time will not exceed its limit. In this case we search in a two dimensional space for pairs of \((N, w_r)\). Starting from the current state, we examine whether increasing the candidate number of reduce waves without adding any nodes can have a positive effect to the performance predicted by our model. As long as it does, we keep increasing the number of reduce waves until the point where that increase has a negative effect in execution time (i.e., the scheduling and networking cost overhead dominates any possible gain) or the model responds with an acceptable execution time. In the case it does not, we increase the candidate number of cluster nodes and reset the reduce waves to one. We repeat the process until either the model responds with an acceptable execution time or the upper limit for cluster nodes is reached. That limit guarantees that the algorithm will eventually finish. If the algorithm finishes without finding a solution within our cluster’s maximum nodes, BBQ deploys the maximum number of nodes allowed. The cost of the algorithm is linear to the number of \( N \) values it examined as possible solutions despite the fact that we are in fact searching in a bi-dimensional space, since the number of Reduce waves \( w_r \) usually takes a small value over a few iterations – which is expected, since increasing the number of Reduce waves out of proportions can cause a significant overhead in resource managing and data transfer through the web. Hill climbing’s overhead is insignificant in comparison to the processing time for meaningfully large datasets.

### IV. Experiments

In this section we will describe our experimental testing of BBQ. In the first part of the our evaluation, we trained our model and tested its accuracy. For that purpose we used two popular Hadoop benchmarks, WordCount and TeraSort[15]. Both these programs’ Reduce method is linear to its input, as MapTasks read and parse all inputs and send them to reducers. Therefore, we can consider that our simplified model, presented in (7) stands. For the second part of the evaluation, we submitted WordCount and TeraSort MapReduce jobs to a small cluster with a deadline each, observed BBQ in action and recorded its performance.

**Experimental Testbed.** The experiments were conducted on a private OpenStack cloud. Each worker node had four processing cores and 4GB memory and uses the 2.6.0 version of Apache Hadoop. One node served as the master node and the others as slave nodes. The BBQ deamon ran on a separate dedicated machine. HDFS blocks were set to 256MB.
BBQ had been configured taking into consideration specific details of the cluster properties and configuration such as node capacity in terms of memory and cores and resources allocated to YARN Containers. MapTask and ReduceTask Containers have the same size and each node can host 3 in total at most. In these experiments for simplicity reasons we used an homogenous cluster but BBQ can also work for heterogenous clusters, since each node is treated as a container for YARN Containers. We performed our experiments in small clusters of 2-6 nodes.

A. Model Accuracy

The experimental evaluation of BBQ took place in two distinct steps, the first of which was the evaluation of the model’s accuracy. After calculating the model coefficients for the two benchmarks through a training procedure, we tested the Performance Model by estimating execution times for the following test sets: we used three sets of input data - a small (<30 blocks), a medium size (<100 blocks) and a large one (<200 blocks). We recorded the model’s performance and present it in Figure 2. Using $R^2$ as a measure of goodness of fit [3], we get an acceptable measure of 0.98% for both benchmarks.

B. Evaluating BBQ

We tested BBQ by submitting jobs to a small cluster of two nodes. We measured the execution times of these jobs and compared them to the desired execution times. BBQ’s provisioning actions and the actual execution times are presented in Table II.

We notice that in the cases where no cluster expansion is required, most of the times programs complete their execution significantly faster than required. We also observe that a few of the rest of the executions finish sooner than expected. Since each node can host multiple YARN Containers, even adding only one extra node can have a significant impact, even more so in small clusters like the one we experimented with. In most cases our system predicts the execution time quite well, despite missing the requested goal on a few occasions by a short margin. It is more likely for BBQ to miss a given deadline when the cluster resize action it is required to perform significantly changes the cluster size because of the overhead of the initial network data traffic.

V. DEMONSTRATION DESCRIPTION

The demonstration will allow attendees to observe BBQ while it is executing MapReduce programs. A simple comprehensive GUI enables users to enter the initialization parameters regarding cluster and VM size. Because the training process is a particularly long one, for the needs of this experiment we will have already completed it, so the BBQ cluster will already

<table>
<thead>
<tr>
<th>Program</th>
<th>BBQ action</th>
<th>Input Size (blocks)</th>
<th>Time goal (mins)</th>
<th>Actual Time (mins)</th>
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<tbody>
<tr>
<td>WordCount</td>
<td>-</td>
<td>27</td>
<td>30</td>
<td>19</td>
</tr>
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<td>18</td>
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<td>WordCount</td>
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<td>TeraSort</td>
<td>+4</td>
<td>90</td>
<td>40</td>
<td>44</td>
</tr>
</tbody>
</table>

TABLE II: BBQ resizing the cluster.
have access to the MapReduce Performance Models for the programs used as benchmarks here, WordCount and TeraSort. In order to launch an experiment on an existing cluster, users will be able to select the program they want to execute, data input size and execution time performance goal.

Attendees can observe how BBQ handles the job submission and resizes the cluster through the GUI provided and also compare the execution time goal with our system’s real execution time. They will also be able to access the cluster’s Hadoop web interface and monitor the cluster live using performance stats collected and visualized by Ganglia [13].

This system creates detailed job profiles from past executions introducing in this work to form our Performance Model. ARIA [11] uses a hill climbing algorithm in order to optimize and on-line fine tune a YARN cluster for the execution of a specific job and is applicable for jobs that even only run once.

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