Moving Hadoop into the Cloud with Flexible Slots

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Abstract

Load imbalance is considered a major source of overhead in parallel programs. Hadoop workloads are in particular susceptible to such imbalance (a.k.a, skew) due to the uneven distribution of input data among tasks. As a result, tasks with more data run significantly slower (known as stragglers) than others, delaying the overall job completion. Although data skew can be mitigated by using customized, job-specific data partitioners, this increases the burden on users. Running Hadoop in a virtual private cloud opens up opportunities for elastic resource allocations, where stragglers are expedited with more resources. However, virtualized environments introduce problems that often cancel out the performance gain: (1) besides data skew, performance interference from co-running jobs may create new stragglers; (2) there exist a semantic gap between Hadoop task management and resource pool-based virtual cluster management preventing tasks from using resources efficiently.

In this work, we strive to make Hadoop more resilient to data skew and more efficient in cloud environments. We present *FlexSlot*, a user-transparent task slot management scheme that automatically identifies map stragglers and resizes their slots accordingly to accelerate task execution. FlexSlot also adaptively changes the number of slots on each virtual node to balance the resource usage so that the pool of resources can be efficiently used by the virtual cluster. Experimental results with representative benchmarks show that FlexSlot effectively reduces job completion time by as much as 46% compared with stock Hadoop and outperforms a recent proposed skew mitigation approach.

1 Introduction

Hadoop, the open source implementation of the MapReduce programming model [7], has become increasingly popular in Big Data analytics due to its simplicity of use and the scalability to large clusters. However, studies have shown that current use of Hadoop in enterprises and research stay in an ad hoc manner, leaving advanced features underused [19], potential performance unexploited [16, 25, 26], and resources in Hadoop clusters inefficiently utilized [18]. In particular, load imbalance (a.k.a. skew) among Hadoop tasks poses significant challenges on achieving good performance and high resource utilization [12, 15, 17]. Skew that could come from uneven data distribution or non-uniform data processing cost [16] creates *stragglers*. Such sluggish tasks can take more than five times longer to complete than the fastest task [16], slowing the overall job completion significantly.

To address hardware failure and misconfiguration, Hadoop *speculatively* runs a backup copy of a slow task on a different machine. Besides fault-tolerance, speculative execution is able to expedite stragglers due to skew to a certain extent as the backup copy may run on a better performing machine. However, the differences in machines are not significant enough to mitigate skew and job performance is still bottlenecked by stragglers. Although skew can be eliminated by using customized and job-specific data partitioners for balancing workload among tasks [15], this approach requires domain knowledge on the structure of input data and imposes burdens on users. To this end, researchers propose to mitigate skew by dynamically re-partitioning data during job execution [16]. Nevertheless, re-distributing data at runtime introduces overhead of moving data between machines.

In this work, we look at the skew problem in Hadoop applications from a different perspective. Rather than mitigating skew among tasks, we try to balance the processing time of tasks even with the presence of data imbalance. Specifically, tasks with more data or more expensive data records are accelerated by having more resources. We purposely create heterogeneous clusters and match different machine capabilities with the actual processing demands of unbalanced tasks. Cloud comput-

ing, unlocked by virtualization, allows the creation of dynamic virtual clusters with elastic resource allocations. Hadoop clusters can be easily scaled out by adding virtual nodes with a latency of several minutes. More importantly, individual nodes can also be scaled up with more resources. Recent study has found that the ability to scale-up leads to better Hadoop performance in a virtual cluster compared to a native cluster with the same settings [4].

However, moving Hadoop into the cloud introduce additional problems that can outweigh the benefit of flexible resource management. First, clouds are usually shared by multiple users in order to increase hardware utilization. Interferences from co-located users may create new stragglers in Hadoop applications [6, 14]. Second, to reduce the resources required to run a virtual cluster, private clouds often multiplex a pool of shared resources among virtual nodes [20]. Virtual cluster management such as VMware DRS (Distributed Resource Manager) [10] and OpenStack Utilization-based Scheduling [2] dynamically allocates resources to individual nodes according to their estimated demands. This eliminates the need of proactively allocating resource for slave nodes. Surprisingly, we find that there exists a semantic gap between demand-based resource allocation and the actual needs of Hadoop tasks. The virtual nodes that receive disproportionately more resources due to high demands actually run fast tasks, leaving nodes with stragglers deprived of resources. Our study find that running unmodified Hadoop in such a cloud does not mitigate skew instead aggravates the imbalance.

In this paper, we explore the possibility of using elastic resource allocation in the cloud to mitigate skew in Hadoop applications. We propose, *FlexSlot*, a simple extension to the slot-based Hadoop task scheduling framework. FlexSlot automatically identifies stragglers and resizes their slots. Slot resizing not only allows stragglers to receive more resources but also alleviates the interference between co-running jobs. To expose the actual demands of tasks, FlexSlot co-locates stragglers with fast tasks on a node by dynamically changing the number of slots on the node. As fast tasks finish quickly and the node is allocated a large amount of resources, stragglers in fact receive more resources and their executions are accelerated.

We implemented FlexSlot on a 32-node Hadoop virtual cluster and evaluated its benefits using the Purdue MapReduce Benchmark Suite (PUMA) [3] with datasets collected from real applications. We compared the performance of FlexSlot running different workloads with that of the stock Hadoop and a recently proposed skew mitigation approach SkewTune [16]. Experimental results show that FlexSlot reduces job completion time by 30% and 22% compared with stock Hadoop and SkewTune, respectively. FlexSlot also achieves better resource utilization with both the flexible slot size and flexible number of slots.

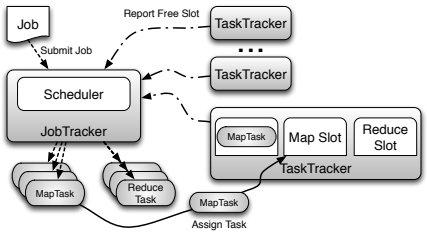


Figure 1: The slot-based task scheduling in Hadoop.

The rest of this paper is organized as follows. Section 2 introduces the background of Hadoop, discusses existing issues, and presents a motivating example. Section 3 elaborates FlexSlot's architecture and key designs. Section 4 gives the testbed setup and experimental results. Related work is presented in Section 5. We conclude this paper in Section 6.

2 Background and Motivation

In this section, we first describe the basics of the Hadoop MapReduce framework and discuss the causes of skew in Hadoop tasks. Then, we show that elastic resource allocation in a cloud and an ideal task scheduling in Hadoop together help balance task execution time and improve the overall job performance significantly. Finally, we demonstrate that a trivial migration of Hadoop to the cloud does not mitigate skew instead aggravates task imbalance.

2.1 Hadoop MapReduce Framework

The data processing in MapReduce is expressed as two functions: *map* and *reduce*. The map function takes an input pair and produces a list of intermediate key/value pairs. The reduce function processes the intermediate key with the list of its values and generates the final results. In the implementation of Hadoop, the *map* and *reduce* functions are implemented in `MapTask` and `ReduceTask`. Each MapReduce job is divided into multiple map tasks and reduce tasks.

Figure 1 shows the MapReduce execution environment in Hadoop with one master node and multiple slave nodes. The master node runs `JobTracker` and manages the task scheduling on the cluster. Each slave node runs `TaskTracker` and controls the execution of individual tasks. Hadoop uses a slot-based task scheduling algorithm. Each `TaskTracker` has a preconfigured number of map slots and reduce slots. Task trackers report their

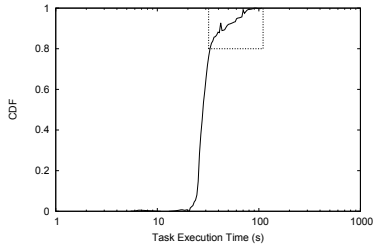


Figure 2: The skewed task execution time of *wordcount*.

number of free slots to the job tracker through heartbeat [1]. The job tracker then assigns a task to each free slot.

Ideally, each task should take approximately the same time to complete if it is assigned the same amount of data. However, there is no guarantee that data is evenly distributed among tasks or the same amount of input data will take the same time to process. Hadoop tries to divide the input data set into a collection of input splits, ideally each matching the block size of HDFS. Map tasks usually process block of input at a time using the default `FileInputFormat`. If the input data contains file with various sizes (e.g., files smaller or larger than the HDFS block size), taking one block of data as input inevitably leads to input skew in map tasks. Although it is possible to combine small blocks into a map input (e.g., using a custom input reader), study shows that only a small portion of Hadoop users customizes input handling and data skew in map tasks is quite common in production Hadoop clusters [19]. Similarly, reduce tasks may also have imbalanced input size as the partitions generated by map tasks can contain different number of key/value pairs [8, 15, 16]. Moreover, the same input size can lead to distinct task execution time as some records are inherently more expensive to process. As a result, unbalanced task runtime is prevalence in Hadoop applications [19].

Figure 2 shows an example of skewed task execution in the `wordcount` benchmark. The job was run on a homogeneous cluster with 32 nodes. From the figure, we can see that nearly 20% of tasks run at least 20% longer than the others. Such an imbalance leads to prolonged job completion time and wasted cluster resources on nodes that were idle waiting for the stragglers. Next, we show that how a re-organization of cluster resources, i.e., using a heterogeneous cluster, improves Hadoop performance.

2.2 Mitigating Skew with Heterogeneous Resource Allocation

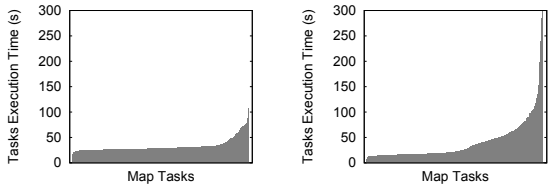
In this subsection, we study how does heterogeneous resource allocation to map tasks help the overall job performance. The data skew in reduce tasks can be mitigated by repartitioning and rebalancing intermediate data [11, 15, 16]. But similar approach cannot be easily applied to map tasks. We show that purposely allocating more resources to nodes that run stragglers effectively mitigates map input skew. If not otherwise stated, tasks refer to map tasks throughout this paper.

Table 1: Task skewness of *wordcount* on three clusters.

	Homo.	Heter.	Heter. + Skew-Sched
Skewness	2.65	2.25	0.31

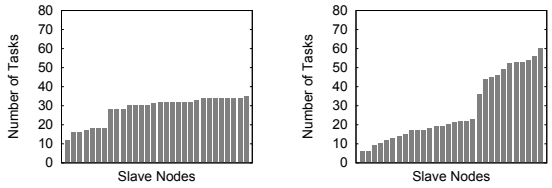
We created three 32-node Hadoop clusters, each with a total capacity of 153.6 GHz CPU resource and 128 GB memory in our university cloud. The first cluster (denoted as `Homo.`) emulates a physical cluster with homogeneous configurations on each node. The resources were evenly distributed to nodes, resulting in a uniform node capacity of 4.8 GHz CPU and 4 GB memory. Cluster `Heter.` contained nodes with heterogeneous resource allocations. We profiled the resource demands of individual Hadoop tasks and created powerful nodes for stragglers. We first ran a job in a homogeneous cluster and determined the stragglers. We then scaled up the nodes running stragglers according to their runtime statistics. Specifically, we increased the CPU resources and memory sizes of these nodes proportionally based on their CPU time and I/O wait time in the last run. We then re-ran the job on the adjusted cluster. Although stragglers had their input data on the powerful nodes, Hadoop's task scheduler may still launch them remotely on less powerful nodes if there are no available slots on the powerful ones. In the third cluster (denoted as `Heter. + Skew-sched`), we forced that stragglers only run on powerful nodes.

We calculated the skewness in task runtimes in a job J as $\sum_{i \in J} \frac{(x_i - \mu)^3}{\sigma^3}$, where x_i is the runtime of individual tasks, μ and σ represent the average and deviation, respectively. The lower the skewness, the more balanced task execution. Table 1 lists the task skewness of *wordcount* on the three clusters. As expected, cluster `Homo.` show significant skew in task completion with a skewness of 2.65. We can also see that creating a heterogeneous cluster alone only mitigated the skew to a certain extent (e.g., reducing skewness to 2.25) because Hadoop task scheduler may not run stragglers on powerful nodes. In contrast, strictly requiring stragglers be run on powerful nodes significantly improved task balance with a skewness of 0.30. This confirms previous findings [26] that allocating more data and work on powerful nodes optimizes Hadoop performance in a heterogeneous environment.



(a) Static cluster. (b) Dynamic cluster.

Figure 3: Task runtime of *wordcount* on two clusters.



(a) Static cluster. (b) Dynamic cluster.

Figure 4: Task distribution of *wordcount* on two clusters.

Unfortunately, it is difficult to predict which tasks will be the stragglers and determine their resource demands before actually running these tasks. There is a need for dynamic resource allocations in Hadoop clusters in response to stragglers.

2.3 Automatically Tuning Hadoop with Demand-based Resource Allocation

Modern cloud management middleware, such as VMware DRS, XenServer and OpenStack, supports demand-based resource allocation, where a virtual cluster shares a resource pool and individual nodes receive resources according to their estimated demands. Ideally, if nodes running stragglers show high demands, demand-based resource allocation is able to automatically tune a Hadoop cluster into a heterogeneous cluster that accelerates stragglers. However, we found that there exists a semantic gap between demand-based resource allocation and the actual needs of Hadoop tasks, making incorrect decisions in resource allocations.

We created a resource pool of 153.6 GHz CPU resources and 128 GB memory, which is shared by a 32-node Hadoop cluster. VMware DRS was used to automatically allocate resources on these virtual nodes. Figure 3(a) and (b) show the execution time of individual map tasks on a static homogeneous cluster and the dynamic cluster with demand-based resource allocation, respectively. From the figure, we can see that demand-based resource allocation unexpectedly aggravated skewness in task execution time. Although the tasks on the left of Figure 3(a) ran faster than those in the static cluster, stragglers in the dynamic cluster (tasks on the right tail) appeared to be significant slower.

Figure 4 shows the number of finished tasks on each virtual node in the two clusters. We find that in the dynamic cluster, some nodes ran 10X more tasks than the nodes with fewest tasks. An examination of the Hadoop execution log and the VMware resource allocation log revealed that these "hot spot" nodes ran mostly fast tasks and received disproportionate more resources than the "idle" nodes, which turned out to host straggler tasks. We attribute the counterintuitive resource allocations to the semantic gap between the resource demands estimated by the cloud management and the actual Hadoop task demands. VMware DRS computes a node's CPU demand based on its recent actual CPU consumption and estimates the memory demand according to the ratio of touched pages in a set of randomly-selected pages.

However, the demand-based allocation do not meet stragglers' needs. Study has shown that production Hadoop clusters are still dominated by I/O intensive jobs [19] and stragglers with more data are likely to spend a significant amount of time waiting for disk I/O. Thus, nodes running stragglers appear to be less busy than nodes with fast tasks and are allocated few resources by the demand-based cloud management. For memory, a straggler is unable to use the additional memory allocated as its memory usage is upper bounded by the JVM heap size of its slot. The heap size of a slot is statically set in the cluster configuration file. The selection of the heap size is usually conservative to prevent a node from memory thrashing.

[**Summary**] We have shown that skew in Hadoop map tasks can be effectively mitigated by accelerating stragglers with more resources. However, demand-based dynamic resource allocation in a cloud does not meet stragglers' needs and the fixed slot configuration in Hadoop prevents a flexible use of dynamic resources. These findings motivated us to make Hadoop run more efficiently in the cloud in the presence of skew and the in place cloud management. We found that a simple extension to Hadoop's map slot management effectively directs resource to map stragglers in a cloud environment. Next, we present FlexSlot, a user-transparent flexible slot management scheme for Hadoop.

3 FlexSlot Design

We aim to mitigate skew in Hadoop applications by leveraging the dynamic resource allocation in the cloud. We focus on a private cloud platform in which dynamic resource allocation to virtual clusters is automated by estimating the demands of individual virtual nodes and adjusting their resources accordingly. In this section, we present *FlexSlot*, a simple extension to the Hadoop's slot

management scheme that automatically identifies map stragglers at run-time and adjusts both the map slot size and number on the nodes hosting the stragglers. The dynamic adjustment to slot configurations effectively exposes the actual demands of stragglers to the low-level virtual resource management and guides the demand-based allocation to efficiently allocate resources to stragglers.

3.1 Overview

FlexSlot provides two key functionalities: on-the-fly straggler identification and automated slot reconfiguration.

Identifying Stragglers. FlexSlot continuously monitors two task-specific metrics during task execution: *progress rate* and *input processing speed*. Based on a synthesis of these metrics, FlexSlot is able to identify tasks that are abnormally slower than their peers due to either uneven data distribution, expensive record or cloud interference. Once determining stragglers, FlexSlot infers their resource bottlenecks based on resource usages obtained on the straggler nodes.

Proactively changing the size of slots . If FlexSlot determines that a straggler's performance is bottlenecked by I/O operations, it proactively terminates the straggler and restarts it with a larger slot size. Since it is hard to predict the memory requirement of a task, FlexSlot uses a trial-and-error approach to change the slot size at incremental steps. The increment continues until the overhead of task restarting outweighs the improvement on task processing speed.

Adaptively adjusting the number of slots. FlexSlot bridges the semantic gap between Hadoop tasks and the demand-based resource allocation by adaptively changing the number of slots on Hadoop nodes. Contrary to intuition, FlexSlot adds more slots to straggler nodes in order to expose the actual straggler demand to the resource management.

3.2 Identifying Stragglers

There are three causes of straggler tasks in a cloud environment: (1) uneven data distribution among tasks; (2) non-uniform data processing time; and (3) performance interferences from co-running jobs. We measure two performance metrics during task execution. Hadoop provides *progress score* to represent the fraction of work completed. It is computed as the ratio of finished input size and the original input size. *Progress rate* [26], which is defined as the change in progress score in unit time, is a good online measure of task performance. If all tasks process input data at the same speed, the tasks with smaller progress rates are likely to have large input sizes. Another important metric is the *input processing speed D*. It counts how many bytes are processed in unit time. Ideally, all tasks should have the same input processing speed given that the data distribution is uniform across tasks and it takes the same amount time to process the same amount of data. If some tasks exhibit apparently slower processing speed, it is likely that their record are more expensive to process or they are experiencing interferences.

Neither of the two metrics alone can reliably determine stragglers. Thus, we create a composite metric based these two. We normalize both metrics against their maximum values (both in the range of 0 to 1) among all tasks and simply use their sum as a heuristic to identify stragglers. Since progress rate can be expressed $\frac{D}{S}$, where S is the input data size and D is the input processing speed. Therefore, we use $P = (1 + \frac{1}{S}) \cdot D$ to measure task performance.

We consider straggler tasks as outliers compared to regular tasks. For every measurement interval, we calculate the value of P for all tasks and perform a *k-means* clustering algorithm on the P values. The clustering algorithm divides all tasks into two clusters and the cluster with smaller P values are considered significant different from the rest of tasks.

3.2.1 Determining Performance Bottlenecks

Having stragglers identified by the proposed heuristic, FlexSlot then determines how to accelerate the execution of stragglers. Depending on the cause of straggler, these tasks can be bottlenecked either by disk I/O performance or insufficient CPU resources.

Disk I/O bottleneck due to Data Skew. Previous studies show that the number of input records can largely affect the task completion time even with the same amount of input data [23, 24, 27]. The *expensive record* is a major type of data skew in map tasks. A map task processes a collection of key value pairs, each pair as one record. Due to data skew, some records may require more resources to process than others, leading to more processing time. These expensive records can simply contain large data that fills the output buffer quickly. When the output buffer is full, intermediate results need to be written to disk. Thus, expensive record cause more frequent disk I/O operations.

The *inverted-index* benchmark contains non-uniform records and incurs skewed task processing time. Figure 5 shows the breakdown of task execution time for all tasks. Since expensive records incur excessive I/O operations, we are interested in how much does I/O time (e.g., `I/O wait`) contribute to the total task completion time. Tasks are sorted in the ascending order of their completion time, with tasks on the right tail considered

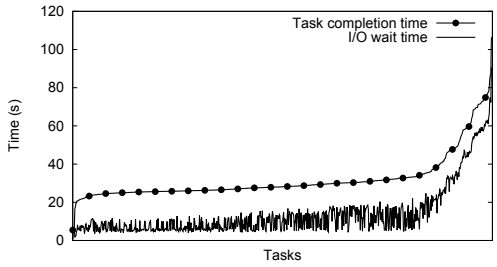


Figure 5: Task completion time and `iowait` time.

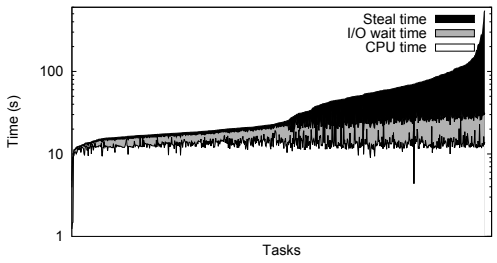


Figure 6: Task completion time and the `cputime`.

as stragglers. We find that `I/O wait` contributed most to the prolonged completion time in stragglers. We observed as much as 8X more `I/O wait` time than that of regular tasks. Thus, a large portion of time spending in waiting for I/O is a good indicator of stragglers with I/O bottleneck. A larger slot memory size, e.g., a larger output buffer, can effectively reduce I/O operations.

CPU Starvation due to Inaccurate Demand Estimation. As discussed in Figure 4, demand-based resource allocation incurs severe imbalance on task distribution, with some nodes heavily loaded and some hosting only a few stragglers. The culprit is that nodes running faster tasks received more resources from cloud resource management. It enters a loop that nodes with more resources ran tasks even faster. Stragglers usually incur more I/O operations and appear to be less busy in terms of CPU usage. Thus, such tasks may become victims of CPU starvation in demand-based resource allocation. Figure 6 shows the breakdown of task runtime of benchmark *wordcount*. It plots each task's actual `cputime`, `I/O wait` and `steal time`, which is the time that a task's node is ready to run but fails to get scheduled by the hypervisor. In the figure, we can see that `steal time` contributed most to the straggler runtime. If given sufficient CPU, these stragglers can be effectively accelerated. Thus, a large portion of time being ready but not running is a good indicator of insufficient CPU resources. Next, we show that purposely coupling stragglers with faster tasks exposes the demands of stragglers to the cluster-level resource manager.

3.3 Resizing Slot Memory

Increasing the memory size of a slot can reduce the number of I/O operations and effectively expedites stragglers caused by data skew. However, the memory that can be used by a slot is limited by the heap size of its JVM and the output buffer size of the task running on it. Although the JVM heap size can be dynamically changed through JVM memory ballooning, the output buffer size of a task cannot be altered without restarting the task. Thus, it is difficult to increase a slot's memory size during task execution. We rely on the straggler identification to determine stragglers in a timely manner. As such, we can afford to kill stragglers and restart them with a larger slot size.

Algorithm 1 Flexible slot size.

```
1:  Variables: Heartbeat interval T; Data spilt size S;
2:
3:  The killcount of task k is initialized to 0.
4:  /* Only apply to stragglers */
5:  function RESIZESLOTMEM(k)
6:      get current input processing speed D
7:      if k.killcount == 0 or S/(D−k.D_prev) > T then
8:          kill k, free slot s
9:          s.size = s.size * (1 + α)
10:         launch k on slot s
11:         k.killcount = k.killcount + 1
12:     end if
13:     k.D_prev = D
14: end function
```

Another question that needs to be answered is how to determine the slot size for straggler tasks. We propose an algorithm that is automatically invoked on all straggler tasks at every heartbeat. It determines the slot memory size for a straggler task. The pseudo-code for this algorithm is shown in Algorithm 1. The goal of this algorithm is to increase the slot memory size for straggler tasks so that the performance of these tasks becomes close to that of regular tasks. For some straggler tasks, it may require multiple iterations to reach the desired slot memory size.

Once a straggler is identified, the function `ResizeSlotMem` is called to determine the appropriate memory size of the task. If the task has not gone through a memory resizing (i.e., first time killing and $killcount = 0$), we kill it immediately and increase the memory size of the slot at a step of α (empirically set to 0.2). Otherwise, we test if an additional round of killing and memory resizing is needed. Suppose a task k's input data size is S. For each round (at heartbeat intervals), we keep increasing the memory size of the slot until the resulting decrease in the input processing time (i.e., $\frac{S}{D-k.D_{prev}}$) no longer outweighs the wasted processing

time due to task killing (i.e., the last heartbeat interval T). Then, the slot resizing process is stopped.

3.4 Adjusting Slot Number

The key rationale behind adjusting slot number on Hadoop nodes is to couple stragglers with fast tasks and expose stragglers' demand to cloud management. Once stragglers are identified and their bottlenecks are determined as insufficient CPU resource, FlexSlot tries to move slots from nodes running faster tasks to straggler nodes. We design a greedy algorithm for automating the slot adjustment. The pseudo-code is shown in Algorithm 2. The objective is to minimize the steal time (defined in Section 3.2.1) on the Hadoop cluster. To reduce the steal time on straggler nodes, which are either caused by CPU starvation or interference, we increase the slot number on these nodes in hopes that the additional slots will bring faster tasks and finally increase the nodes' CPU allocation. We follow a simple heuristic of moving slots from the node with the smallest steal time to the nodes with the largest. We ensure that the number of total task slots in the cluster remain the same. The algorithm keeps calculating the average node steal time μ and its standard deviation σ. When σ is greater than the threshold λ, the algorithm decides that the imbalance of CPU resource needs to be adjusted. Changing the λ allows us to trade-off between the resource imbalance and the converging speed of the algorithm.

Changing the slot number on nodes not only affects cloud resource allocation but also influences Hadoop task scheduling, leading to a better coordination between the two. Without slot adjustment, each Hadoop node is configured with the same number of slots but is allocated imbalanced resources. Dynamically changing slot number on each node direct both task and resources to the same node. For example, adding slots to a node brings more resources and tasks. The performance interference from co-running jobs is also mitigated as the objective of the algorithm is to minimize steal time.

One concern of this algorithm is that newly added slots can be assigned with a straggler task, aggravating the skew and worsening the starvation on straggler nodes. However, as majority of the tasks are regular tasks, the new slot is likely to be assigned to a regular task. Currently, all nodes are monitored for the automated slot memory resizing. If we find that the newly scheduled task is a straggler task, we kill it and try to reassign it to another node that has no stragglers.

Algorithm 2 Flexible slot number.

```
1: Variables: list of node L; list of steal time ST on these nodes
2:
3: while true do
4:     calculate the average steal time μ
5:     calculate the standard deviation of steal times σ
6:     if σ ≤ λ then
7:         break
8:     end if
9:     for st_i in ST do
10:        Δst_i = st_i − μ
11:    end for
12:    sort list ΔST in ascending order
13:    find node l_max that has the maximum Δst
14:    find node l_min that has the minimum Δst
15:    l_min.removeMaxMapSlots(1)
16:    l_max.addMaxMapSlots(1)
17: end while
```

4 Evaluation

4.1 Testbed Setup

We performed evaluations of FlexSlot on our university cloud. It consists of 8 HP BL460c G6 blade servers. Each server is equipped with 2-way Intel quad-core Xeon E5530 CPUs and 64GB memory. The servers are connected with 10 Gbps Ethernet. VMware vSphere 5.1 is used to provide the server virtualization.

We used a 32-node virtual Hadoop cluster to evaluate FlexSlot. Each node was initially configured with 4 VCPU and 4 GB memory. Depending on different experiments, the resource allocation to individual Hadoop nodes can be fixed or managed by the demand-based resource allocation in VMware DRS. We deployed Hadoop stable release version 1.1.1 and each VM ran Ubuntu Linux with kernel 2.6.24. Two nodes were configured as the `JobTracker` and `NameNode`, respectively. The rest 30 nodes ran as slave nodes for HDFS storage and MapReduce task execution. We set the HDFS block size to its default value 64 MB. Each slave node was initially configured with 4 map slots and 2 reduce slots and parameters `io.sort.mb` and `mapred.child.jvm.opts` were set to 100 MB and 200 MB, respectively. These Hadoop task settings were dynamically adjusted by FlexSlot during task execution.

For comparison, we also implemented a recently proposed skew mitigation approach SkewTune [16]. SkewTune parallelizes a straggler task by repartitioning and redistributing its input data. It mitigates the data skew and improves the job completion time. It assumes that all the slave nodes have the same processing capacity. SkewTune evenly distributes the unprocessed data across all available nodes to mitigate the data skew. However,

Table 2: Benchmark details.

Benchmark	Input Size (GB)	Input Data
tera-sort	150	TeraGen
inverted-index	150	Wikipedia
term-vector	150	Wikipedia
wordcount	150	Wikipedia
grep	150	Wikipedia
k-means	30	Netflix data, $k = 6$
histogram-movies	100	Netflix data
histogram-ratings	100	Netflix data

in virtualized environment, the resource allocation of different slave nodes can be different, especially in demand-based resource allocation. Evenly distributing the unprocessed data may not the best option. The existing of hotspot nodes also incurs unnecessary data movements.

4.2 Workloads

We used the PUMA benchmark suite for evaluation. It contains various MapReduce benchmarks and real-world test inputs. Table 2 shows the benchmarks and their configurations used in our experiments.

These benchmarks are divided into three categories based on the content of their input data. The *tera-sort* benchmark uses a data set that is generated by *TeraGen*. The data has a relatively uniform distribution due to the randomized generation process. The *inverted-index*, *term-vector*, *wordcount* and *grep* benchmarks use the data extracted from Wikipedia. The data contains records with different sizes. Some of them are significantly larger than the average. This provides a good example of data skew. The *k-means*, *histogram-movies* and *histogram-ratings* benchmarks use the data from Netflix. They are good examples of expensive records. The content of the records can significantly affect input processing time even with the same record size.

4.3 Mitigating Data Skew

In this subsection, we study the effectiveness of FlexSlot in mitigating data skew. If tasks take about the same time to finish even in the presence of skew, we consider that the skew has been mitigated. We measured the distribution of the task completion time of different benchmarks. We used the stock Hadoop with demand-based resource allocation in the cloud as the baseline. The total number of task slots in FlexSlot is set to be the same as that in stock Hadoop and SkewTune for a fair comparison.

Figure 7 shows the distribution of the task completion time of the *inverted-index* benchmark due to three different approaches. The skewness of the task execution time due to the stock Hadoop, SkewTune, and FlexSlot

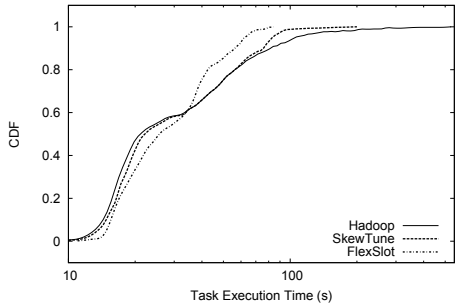


Figure 7: The CDF of task completion time.

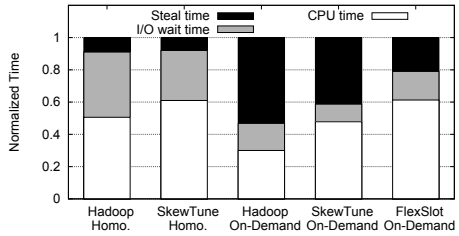


Figure 8: Breakdown of task runtime of *inverted-index*.

are 4.98, 1.68 and 0.96, respectively. The result shows that FlexSlot is the most effective in mitigating data skew in all three approaches. FlexSlot significantly reduced the task completion time of straggler tasks than SkewTune. FlexSlot and SkewTune have similar performance on these regular tasks, but FlexSlot brings more improvement to the performance of straggler tasks than SkewTune.

FlexSlot outperformed SkewTune for two reasons. First, FlexSlot continuously detects straggler tasks and reduces the execution time of straggler tasks with automated slot memory resizing. On the other hand, SkewTune only mitigates a straggler task when there are free slots to parallel the straggler task. Second, SkewTune does not have the coordination between the Hadoop task scheduler and the cloud infrastructure. It does not eliminate the hotspot nodes. SkewTune tends to use the hotspot nodes to parallelize the execution of a straggler task because these nodes hold more resources. This introduces additional data movement for the straggler tasks that can be finished quickly with simply more resource. FlexSlot does not have these problems mainly because it moves slots, instead of tasks, across slave nodes. It preserves the data locality and minimizes the data movement for mitigating data skew.

The results in Figure 7 also show that FlexSlot has longer completion time for fast tasks than stock Hadoop. It is because running stock Hadoop with demand-based resource allocation created “hot spot” nodes that boost

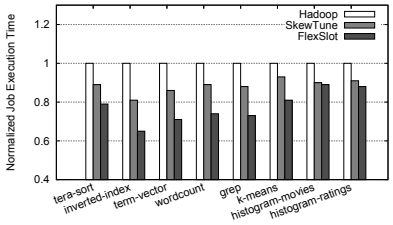


Figure 9: The normalized job completion time.

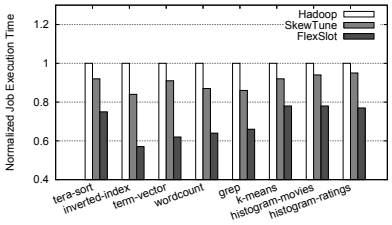


Figure 10: The normalized job completion time with co-running jobs.

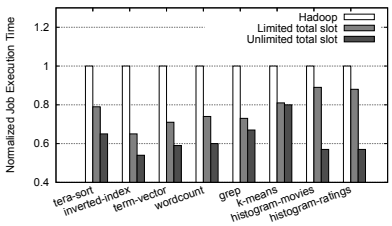


Figure 11: Job completion time with an unlimited number of slots.

these fast tasks. FlexSlot avoided "hot spot" nodes from receiving disproportional more resources. Note that making fast tasks run even faster does not help improve overall job completion time, which is bottlenecked primarily by stragglers.

To further study how skew is mitigated, we show detailed breakdown of task completion time. For comparison, we also ran benchmarks in Hadoop and SkewTune on static homogeneous virtual clusters (denoted as `Homo.`). Figure 8 shows the breakdown of average task execution time of *inverted-index* on different clusters. FlexSlot reduced the portion of steal time by 60.5% and 49.1% when compared to stock Hadoop and SkewTune in demand-based resource allocation. The huge steal time of stock Hadoop and SkewTune with demand-based resource allocation is the sign of imbalanced CPU resource allocation between fast tasks and straggler tasks. The reduction of steal time suggests that FlexSlot was effective in preventing CPU starvation on straggler. Moreover, FlexSlot reduced the I/O wait time compared to stock Hadoop and SkewTune in homogeneous clusters. FlexSlot achieved 39.7% and 26.7% lower I/O wait time than stock Hadoop and SkewTune, respectively. It suggests that FlexSlot reduce the I/O operations for straggler tasks with larger slot memory size.

4.4 Reducing Job Completion Time

We have shown that FlexSlot is effective in mitigating skew. In this subsection, we study how does the mitigation help improve overall job completion time. Similarly, we use the job completion time in the stock Hadoop as the baseline and compare the normalized job completion time of FlexSlot and SkewTune. Figure 9 shows the normalized job completion time of all benchmarks due to these three approaches. The results show that for benchmarks with expensive records, e.g., *inverted-index*, *term-vector*, *wordcount* and *grep*, FlexSlot outperforms stock Hadoop by 35.1%, 29.3%, 26.7% and 27.4%, respectively. FlexSlot also outperformed SkewTune by 19.8%, 17.1%, 16.9% and 17.1% in these benchmarks.

Benchmarks such as *k-means*, *histogram-movies* and *histogram-ratings* use data from Netflix. The input data is relatively uniform in record size. In the experiments with these benchmarks, FlexSlot outperformed the stock Hadoop by 25%, 13% and 12%, respectively. However, FlexSlot has less performance improvement on *histogram-movies* and *histogram-ratings* than *k-means*, because those benchmarks have small memory demand due to the small volume of their intermediate results. The default configuration of slot memory size already provides sufficient output buffer.

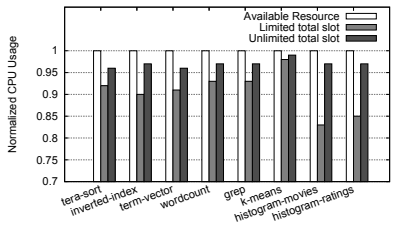
The *k-means* benchmark has a large volume of intermediate data. It requires large output buffer and more memory to reduce I/O operations. It contains computation intensive tasks that requires a lot of CPU resource. FlexSlot achieved much shorter job completion time than stock Hadoop because FlexSlot was able to improve both the slot memory size and CPU resource allocation for *k-means*.

FlexSlot achieved 17.5%, 1.2% and 3.3% shorter job completion time than SkewTune in *k-means*, *histogram-movies* and *histogram-ratings* benchmarks, respectively. FlexSlot only had marginal performance improvement over SkewTune in *histogram-movies* and *histogram-ratings* benchmarks because their data skew is not severe and the CPU requirement is also low. But for the job with significant data skew and high CPU consumption, FlexSlot clearly showed a significant advantage compared to SkewTune.

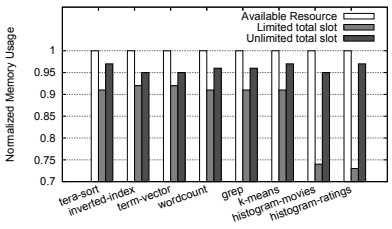
4.5 Mitigating Performance Interference

Note that adjusting slot size and number can possibly resolve the interference between co-running jobs. To create interferences, we consolidated two clusters with the same configuration (see Section 4.1 for details) to the shared physical infrastructure. We submitted the same jobs to these two clusters and calculated their average job completion times. We used the job completion time in stock Hadoop as the baseline, and normalized FlexSlot and SkewTune's performance against it.

Figure 10 shows the normalized job completion time of all benchmarks due to three approaches with per-



(a) CPU



(b) Memory

Figure 12: Resource consumption of FlexSlot.

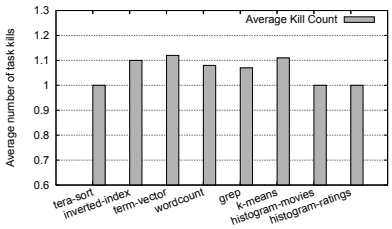


Figure 13: Average number of task kills per straggler.

formance interference from co-running jobs. The results show that FlexSlot outperformed stock Hadoop and SkewTune by as much as 43.8% and 33.2%, respectively. FlexSlot achieved $34.2-43.8\%$ shorter job completion time than stock Hadoop in the *inverted-index*, *term-vector*, *wordcount* and *grep* benchmarks. FlexSlot also outperformed SkewTune by $24.3-33.2\%$ in these benchmarks. Due to the performance interference from co-running jobs, the difference of job completion time between FlexSlot, SkewTune, and stock Hadoop is larger than the results in Figure 9.

For benchmarks with less data skew, *histogram-movies* and *histogram-ratings*, FlexSlot outperformed SkewTune and stock Hadoop by 22%, 23% and 17.1%, 18%, respectively. The difference of job completion time between SkewTune and stock Hadoop is around 5%, because there is no much data skew to mitigate. The results clearly show that FlexSlot can further improved the job completion time by mitigating the performance interference from co-running jobs.

4.6 Improving Resource Utilization

By default, FlexSlot keeps the total number of task slots unchanged in a Hadoop cluster. Thus, any addition of task slots on one node should be coupled with the removal of slots on another node. As discussed in previous experiments, the flexible slot movement effectively mitigates skew and improves job performance. In this subsection, we extend FlexSlot to handle unlimited number of slots. That is, FlexSlot adds or removes slot to/from a node only based on the performance of tasks running on the node, without the constraint of maintaining the total of slots in the cluster. Although it is a common practice to match the map slot number with the number of CPUs on a node, it is not considered the optimal configuration. With this experiment, we study if a even more flexible slot management could further improve cluster resource utilization and job performance.

We compare two FlexSlot variations (i.e., with `limited slots` and `unlimited slots`) and stock Hadoop. Figure 11 shows the normalized job completion time of all benchmarks due to the three approaches. FlexSlot with an unlimited number of slots achieved up to 46% shorter job completion time than the stock Hadoop. It also outperformed the FlexSlot with a limited number of slots by 35%. The improvement varies depending on the job characteristics. For most jobs, using an unlimited number of slots can bring approximately 17% shorter job completion time than with a limited number of slots. But for CPU intensive jobs like *k-means*, removing the limitation on slots makes no major differences because the job performance is bottlenecked by the number of physical CPUs. Adding more slots does not allow more tasks to run concurrently. In contrast, job such as *histogram-movies* and *histogram-ratings* have a significant portion of I/O time. With a limited number of slots, the resources of the virtual cluster , especially the CPU resource, are not fully utilized. Figure 11 shows that FlexSlot with unlimited slots achieved on average 35% short job completion time compared to the one with limited slots.

Next, we compare the resource utilizations in different FlexSlot variations. Figure 12(a) and 12(b) show the CPU and memory usage of FlexSlot with and without a limit on the number of total slots. The results show that FlexSlot without slot limit resulted in 10% and 11% higher in CPU and memory utilization, respectively. As discussed above, these resources were used to accelerate job execution. Note that due to the different job characteristics of *k-means*, *histogram-movies*, and *histogram-ratings* benchmarks, the changes in resource utilizations of these jobs were different. For the *k-means* benchmark, the resource utilization was high even with a limited number of total slots. For the *histogram-movies* and the *histogram-ratings* benchmarks FlexSlot with slot limit left roughly 15% and 26% CPU and memory resources unused, respectively. Removing the limit improved the resource utilization significantly.

These results suggest that FlexSlot with unlimited slots can be a viable approach for Hadoop in the cloud. It improves the performance by maximizing the resource utilization. It does not affect the performance of jobs that have high resource demand because the slots will only be

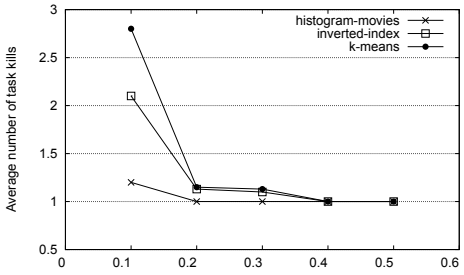


Figure 14: Average number of task kills per straggler due to different α.

added when there is available resource.

4.7 Slot Resizing Overhead

FlexSlot uses task-killing-based approach in the slot memory resizing and allows tasks to be killed multiple times. The killing inevitably incurs overhead as the killed stragglers lose already performed work. We measure the overhead using the number of kills per straggler tasks. The fewer the kills the smaller the overhead. Figure 13 shows the average number of kills of per straggler for different benchmarks. The results show that most straggler only required 1 kill to run normally as fast as other tasks.

The slot memory resizing algorithm increases a slot's memory size by α for each task kill. The average number of task kills is affected by the value of α. Figure 14 shows the average task kills due to different α values. For *inverted-index* and *k-means* benchmarks, increasing α resulted in a significant reduction in the average number of task kills. These benchmarks are every sensitive to the memory size because they have large intermediate data. Using a large α increases the amount of memory resource that will be allocated to them in each task kill. The *histogram-movies* benchmark, which does not have large intermediate data, is less sensitive to the memory size. Allocating more memory to it during task killing does not have a great impact on its task execution time. A large α value will lead to wasted memory resources. According to Figure 14, we empirically set α to 0.2 in FlexSlot because benchmarks with different types benefit from it while not incurring significant memory waste.

5 Related Work

MapReduce is a programming model for large-scale data processing [7]. Hadoop, the open-source implementation of MapReduce, provides a software framework to support the distributed processing of large datasets [1]. YARN [22] is the second generation of Hadoop. It uses containers to replace task slots and provides a finer granularity of resource management. But it only allows different jobs to have different containers. The tasks in one job still have the containers of one fixed size. Therefore, YARN cannot mitigate data skew with flexible size of containers.

There are a few studies on data skew mitigations. SkewReduce [15] alleviate the computational skew problem by applying a user-defined cost function on the input records. Partitioning across nodes relies on this cost function to optimize the data distribution. SkewTune [16] is a framework for data skew mitigation. It repartitioned long tasks to take the advantage of idle slots freed by short tasks. However, moving repartitioned data to idle nodes requires extra I/O operations, which could aggravate the performance interference. More importantly, these approaches do not have the coordination between Hadoop and the cloud infrastructure.

There are recent studies that focus on improving performance of applications in the cloud by dynamic resource allocation [13, 20, 21]. Bazaar is a cloud framework that predicts the resource demand of applications based on the high-level performance goals [13]. Bazaar translates the performance goal of an application into multiple combinations of resources and select the combination that most suitable for cloud provider. It determines the resource allocation of each application using a online resource demand prediction approach. One recent work focus on demand-based resource allocation [20].

A Hadoop cluster in the cloud can be seen as heterogeneous Hadoop clusters because the dynamic resource allocation. A number of studies proposed different task scheduling algorithms to improve Hadoop performance for heterogeneous environments [26, 5, 9]. PIKACHU focuses on achieving optimal workload balance for Hadoop [9]. It presents guidelines for the tradeoffs between the accuracy of workload balancing and the delay of workload adjustment. But, these studies focus on hardware heterogeneity of in physical machine based clusters. They are not designed for VM-based clusters where the computing capability of a slave node can be changed due to dynamic resource allocation.

6 Conclusions

Hadoop provides a open-source implementation of the MapReduce framework. But its design poses challenges to attain the best performance in the cloud environment due to the data skew. Moving Hadoop into the cloud offers the possibility of mitigating data skew with dynamic resource allocation. But Hadoop lacks of the coordination between its task scheduler and the cloud management, which brings new challenges due to the performance interference and demand-based resource alloca-

tion. In this paper, we propose *FlexSlot*, a simple extension to the Hadoop's slot management that provides the flexibility to change the slot memory size and the number of slots in a slave node online. We implement FlexSlot in Hadoop and evaluate its effectiveness on a 32-node virtual Hadoop cluster with various workloads. Experimental results show that FlexSlot is able to reduce job completion time by as much as 46% compared to stock Hadoop and a recently proposed skew mitigation approach. An extension to FlexSlot with unlimited slots further improves the resource utilization of the virtual cluster.

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