Efficient Shuffle Management for DAG Computing Frameworks Based on the FRQ Model

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ABSTRACT

In large-scale data-parallel analytics, shuffle, or the cross-network read and aggregation of partitioned data between tasks with data dependencies, usually brings in large overhead. Due to the dependency constraints, execution of those descendant tasks could be delayed by logy shuffles. To reduce shuffle overhead, we present *SCache*, an open source plug-in system that particularly focuses on shuffle optimization. During the shuffle optimization process, we propose a new performance model called *Framework Resources Quantification* (FRQ) model. The FRQ model quantifies the utilization of resources and predicts the execution time of each phase of computing jobs. We use the FRQ model to analyze DAG frameworks and evaluate the SCache shuffle optimization by mathematics. By extracting and analyzing shuffle dependencies prior to the actual task execution, SCache can adopt heuristic pre-scheduling combining with shuffle size prediction to pre-fetch shuffle data and balance load on each node. Meanwhile, SCache takes full advantage of the system memory to accelerate the shuffle process. We have implemented SCache as the external shuffle service and co-scheduler on both Apache Spark and Apache Hadoop MapReduce. The performance of SCache has been evaluated with both simulations and testbed experiments on a 50-node Amazon EC2 cluster. Those evaluations have demonstrated that, by incorporating SCache, the shuffle overhead of Spark can be reduced by nearly 89%, and the overall completion time of TPC-DS queries improves 40% on average. On Apache Hadoop MapReduce, SCache optimizes end-to-end Terasort completion time by 15%.

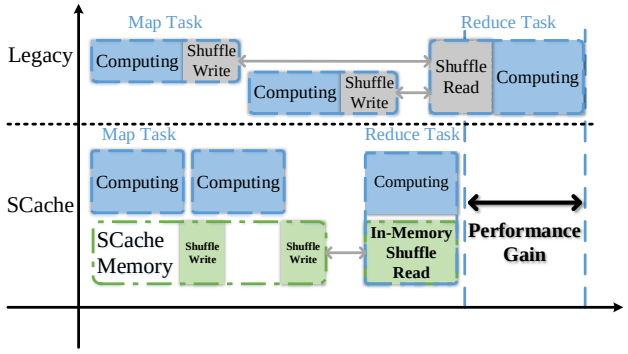

Figure 1: Workflow Comparison between Legacy DAG Computing Frameworks and Frameworks with SCache

1. Introduction

Recent years have witnessed the widespread use of sophisticated frameworks, such as Hadoop MapReduce[1], Dryad [1], Spark [2], and Apache Tez [3]. Most of them define jobs as directed acyclic graphs (DAGs), such as map-reduce pipeline in Hadoop MapReduce, lineage of resilient distributed datasets (RDDs) in Spark, vertices and edges in Dryad and Tez, etc. Despite the differences among data-intensive frameworks, their communication is always structured as a shuffle phase, which takes place between successive computation stages. Such shuffle phase places a significant burden for both the disk and network I/O, thus heavily affecting the end-to-end application performance. For instance, a MapReduce trace analysis from Facebook shows that shuffle accounts for 33% of the job completion time on average, and up to 70% in shuffle-heavy jobs [4].

Various efforts of performance optimization have been made among computing frameworks, both at the software and hardware levels [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]. However, the shuffle phase is often poorly optimized in practice. In particular, we observe that one major deficiency lies in the lack of fine-grained, coordinated management among different system resources. As Figure 1 shows, the *shuffle write* is responsible for writing intermediate results to disk, which is attached to the tasks in ancestor stages (i.e., map task). And the *shuffle read* fetches intermediate results from remote disks through network, which is commonly integrated as part of the tasks in descendant stages (i.e., reduce task). Once scheduled, a fixed bundle of resources (i.e., CPU, memory, disk, and network) named *slot* is assigned to a task, and the resources are released only after the task finishes. Such task aggregation together with the coarse-grained scheduling effectively simplifies task management. However, since a cluster has a limited number of slots, attaching the I/O intensive shuffle phase to the CPU/memory intensive computation phase results in a poor multiplexing between computational and I/O resources.

Moreover, the shuffle read phase introduces all-to-all communication pattern across the network, and such network I/O procedure is also poorly coordinated. Note that the shuffle read phase starts fetching data only after the corresponding reduce task starts. Meanwhile, the reduce tasks belonging to the same execution phase are scheduled at the same time by default. As a result, all the corresponding reduce tasks

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start fetching shuffle data almost simultaneously. Such synchronized network communication causes a burst demand for network I/O, which in turn greatly enlarges the shuffle read completion time. To desynchronize the network communication, an intuitive way is to launch some tasks in the descendent stage earlier, such as "slow-start" from Hadoop MapReduce. However, such early-start is by no means a panacea. This is because the early-start always introduces an extra early allocation of the slot leading to a slow execution of the current stage.

To make things worse, we note that the above deficiencies generally exist in most of the DAG computing frameworks. As a result, even we can effectively resolve the above deficiencies by modifying one framework, updating one application at a time is impractical given the sheer number of computing frameworks available today.

To analyze resources scheduling strategies as mentioned above, we propose a new performance model called *Framework Resources Quantification* (FRQ) model. The FRQ model quantifies computing and I/O resources and visualizes the resources scheduling strategies of DAG frameworks in the time dimension. We use the FRQ model to assist in analyzing the deficiencies of resources scheduling and optimize it. The FRQ model has five parameters: *Input Data Size, Data Conversion Rate, Computation Round Number, Computation Speed,* and *Shuffle Speed*. According to the above five parameters and the scheduling strategy of the DAG framework, the FRQ model is able to predict the execution time of each phase of a computing job. Taking Apache Hadoop MapReduce as a simple DAG computing example, we model each phase of the computing by the FRQ model, including Map, Shuffle, and Reduce. By revealing the relationships between the various phases, the FRQ model assists us in discovering the irrationality of resource scheduling during computing.

Can we efficiently optimize the data shuffling without significantly changing DAG frameworks? In this paper, we answer this question in the affirmative with S(huffle)Cache, an open source[2] plug-in system which provides a shuffle-specific optimization for different DAG computing frameworks. Specifically, SCache takes over the whole shuffle phase from the underlying framework by providing a cross-framework API for both shuffle write and read. SCache's effectiveness lies in the following two key ideas. First, SCache decouples the shuffle write and read from both map and reduce tasks. Such decoupling effectively enables fine-grained resource management and better multiplexing between the computational and I/O resources. In addition, SCache pre-schedules the reduce tasks *without launching* them and pre-fetches the shuffle data. Such pre-scheduling and pre-fetching effectively overlap the network transfer time, desynchronize the network communication, and avoid the extra early allocation of slots.

The workflow of a DAG framework with SCache is presented in Figure 1. SCache replaces the disk operations of shuffle write by the memory copy in map tasks. The slot is released after the memory copy. The shuffle data is stored in the reserved memory of SCache until all reduce tasks are pre-scheduled. Then the shuffle data is pre-fetched according to the pre-scheduling results. The application-context-aware memory management caches the shuffle data in memory before launching the reduce task. By applying these optimizations, SCache can help the DAG framework achieve a significant performance gain.

The main challenge to achieve this optimization is *pre-scheduling reduce tasks without launching*. First, the complexity of DAG can amplify the defects of naïve scheduling schemes. In particular, randomly assigning reduce tasks might result in a collision of two heavy tasks on one node. This collision can aggravate data skew, thus hurting the performance. Second, pre-scheduling without launching violates the design of most frameworks that launch a task after scheduling. To address the challenges, we propose a heuristic task pre-scheduling scheme with shuffle data prediction and a task co-scheduler (Section 3).

Another challenge is the *in-memory data management*. To prevent shuffle data touching the disk, SCache leverages extra memory to store the shuffle data. To minimize the reserved memory while maximizing the performance gain, we propose two constraints: all-or-nothing and context-aware (Section 4.2).

We have implemented SCache on both Apache Spark [16] and Hadoop MapReduce. We have also designed a performance model called FRQ model to analyze the shuffle optimization of SCache and predict the execution time of each phase of a computing job. The performance of SCache is evaluated with both simulations and testbed experiments on a 50-node Amazon EC2 cluster on both Apache Spark and Apache Hadoop. On Apache Spark, we conduct a basic test - *GroupByTest*. We also evaluate the system with Terasort[3] benchmark and standard workloads like TPC-DS[4] for multi-tenant modeling. On Apache Hadoop, we focus on Terasort benchmark. In a nutshell, SCache can eliminate explicit shuffle time by at most 89% in varied applications. More impressively, SCache reduces 40% of overall completion time of TPC-DS queries on average on Apache Spark. On Apache Hadoop, SCache optimizes end-to-end Terasort completion time by 15%.

2. Background and Observations

In this section, we first study the typical shuffle characteristics (2.1), and then spot the opportunities to achieve shuffle optimization (2.2).

2.1. Characteristic of Shuffle

In large scale data parallel computing, shuffle is designed to achieve an all-to-all data transfer among nodes. For a clear illustration, we use *map tasks* to define the tasks that produce shuffle data and use *reduce tasks* to define the tasks that consume shuffle data.

[2] https://github.com/frankfzw/SCache

[3] https://github.com/ehiggs/spark-terasort

[4] http://www.tpc.org/tpcds/

Overview of shuffle process. Each map task partitions the result data (key, value pair) into several buckets according to the partition function (e.g., hash). The total number of buckets equals the number of reduce tasks in the successive step. The shuffle process can be further split into two parts: *shuffle write* and *shuffle read*. Shuffle write starts at the end of a map task and writes the partitioned map output data to local persistent storage. Shuffle read starts at the beginning of a reduce task and fetches the partitioned data from remote as its input.

Impact of shuffle process. Shuffle is I/O intensive, which might introduce a significant latency to the application. Reports show that 60% of MapReduce jobs at Yahoo! and 20% at Facebook are shuffle-heavy workloads [17]. For those shuffle-heavy jobs, the shuffle latency may even dominate Job Completion Time (JCT). For instance, a MapReduce trace analysis from Facebook shows that shuffle accounts for 33% JCT on average, up to 70% in shuffle-heavy jobs [4].

2.2. Observations

Can we mitigate or even remove the overhead of shuffle? To find the answers, we ran some typical Spark applications on a 5-node `m4.xlarge` EC2 cluster and analyzed the design and implementation of shuffle in some DAG frameworks. Here we present the hardware utilization trace of one node running Spark's *GroupByTest* in Figure 2a as an example. This job has 2 rounds of tasks for each node. The *Map Execution* is marked from the launch time of the first map task to the execution end time of the last one. The *Shuffle Write* is marked from the beginning of the first shuffle write in the map stage. The *Shuffle Read and Reduce Execution* is marked from the launch time of the first reduce task.

2.2.1. Coarse Granularity Resource Allocation

When a slot is assigned to a task, it will not be released until the task completes (i.e., the end of shuffle write in Figure 2a). On the reduce side, the network transfer of shuffle data introduces an explicit I/O delay during shuffle read (i.e., the beginning of shuffle read and execution in Figure 2a). Meanwhile, both shuffle write and shuffle read occupy the slot without significantly involving CPU as presented in Figure 2a. The current coarse slot-task mapping results in an imbalance between task's resource demand and slot allocation thus decreasing the resource utilization. Unfortunately this defect exists not only in Spark [16] but also Hadoop MapReduce and Apache Tez [3]. A finer granularity resource allocation scheme should be provided to reduce these delays.

2.2.2. Synchronized Shuffle Read

Almost all reduce tasks start shuffle read simultaneously. The synchronized shuffle read requests cause a burst of network traffic. As shown in Figure 2a, the data transfer causes a high demand of network bandwidth, which may result in network congestion and further slow down the network transfer. It also happens in other frameworks that follow Bulk Synchronous Parallel (BSP) paradigm, such as Hadoop MapReduce, Dryad [1], etc.

2.2.3. Inefficient Persistent Storage Operation

At first, both shuffle write and read are tightly coupled with task execution, which results in a blocking I/O operation. This blocking I/O operation along with synchronized shuffle read may introduce significant latency, especially in an I/O performance bounded cluster. Besides, the legacy of storing shuffle data on disk is inefficient in modern clusters with large memory. Compared to input dataset, the size of shuffle data is relatively small. For example, the shuffle size of Spark Terasort is less than 25% of input data. The data reported in [18] also show that the amount of data shuffled is less than the input data by as much as $10\% - 20\%$. On the other hand, memory based distributed storage systems have been proposed [19, 6, 20] to move data back to memory, but most of the DAG frameworks still store shuffle data on disks (e.g., Spark [16], Hadoop MapReduce, Dryad [1], etc). We argue that the memory capacity is large enough to store the short-living shuffle data with cautious management.

2.2.4. Multi-round Tasks Execution

Both experience and DAG framework manuals(e.g., Hadoop[5] and Spark[6]) recommend that multi-round execution of each stage will benefit the performance of applications. For a cluster with n slots, the number of tasks should be $n \times k$ ($k \geq 1$). Since the shuffle data becomes available as soon as the end of a task's execution, and the network is idle during the map stage ("Network TX" during map stage in Figure 2a), the property of multi-round tasks can be leveraged to hide the cost by starting shuffle data transfer at the end rounds of map tasks.

To mitigate the shuffle overhead, we propose an optimization that starts shuffle read ahead of reduce stage to overlap the I/O operations in multi-round map tasks, and uses memory to store the shuffle data. To achieve this optimization:

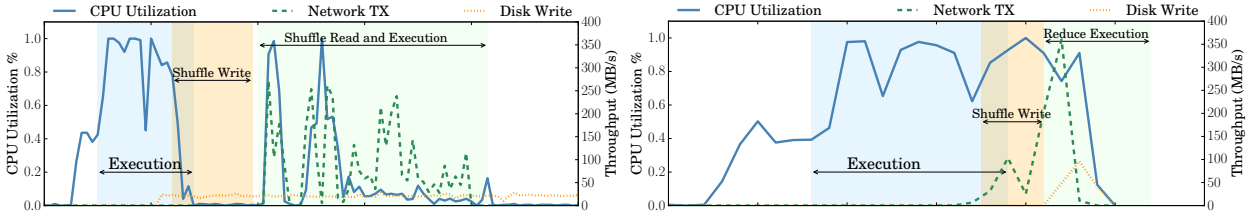
- Shuffle process should be decoupled from task execution to achieve a fine granularity scheduling scheme.
- Reduce tasks should be pre-scheduled without launching to achieve shuffle data pre-fetching.
- Shuffle process should be taken over and managed outside DAG frameworks to achieve a cross-framework optimization.

3. Shuffle Optimization

This section presents the detailed methodologies to achieve the three design goals. The out-of-framework shuffle data management is used to decouple shuffle from execution and provide a cross-framework optimization. Two heuristic algorithms (Algorithm 1, 2) and a co-scheduler is used to achieve shuffle data pre-fetching without launching tasks.

[5] http://hadoop.apache.org/docs/current/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial.html

[6] http://spark.apache.org/docs/1.6.2/configuration.html



(a) Original Spark (b) Spark With SCache

Figure 2: CPU utilization and I/O throughput of a node during a Spark single shuffle application

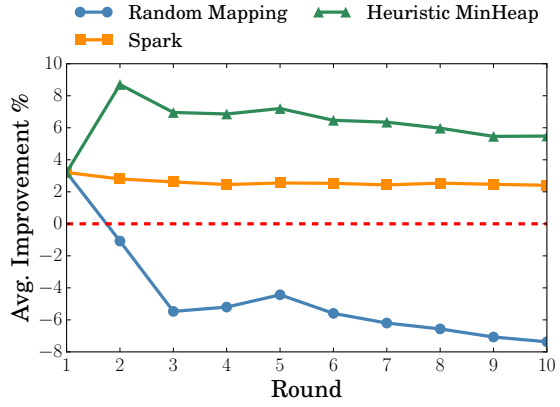


Figure 3: Stage Completion Time Improvement of OpenCloud Trace

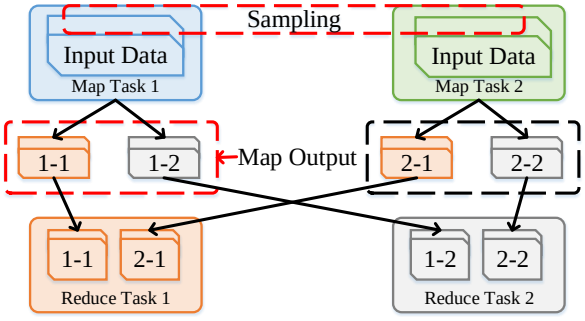


Figure 4: Shuffle Data Prediction

3.1. Decouple Shuffle from Execution

To achieve the decoupling of map tasks and reduce tasks, the original shuffle write and read implementation in the current frameworks should be modified to apply the API of SCache. To prevent the release of a slot being blocked by shuffle write, SCache provides a disk-write-like API named *putBlock* to handle the storage of partitioned shuffle data blocks produced by a map task. Inside the *putBlock*, SCache uses memory copy to move the shuffle data blocks out of map tasks and store them in the reserved memory. After the memory copy, the slot will be released immediately.

From the perspective of reduce task, SCache provides an API named *getBlock* to replace the original implementation of shuffle read. With the precondition of shuffle data pre-fetching, the *getBlock* leverages the memory copy to fetch the shuffle data from the local memory of SCache.

3.2. Pre-schedule with Application Context

The pre-scheduling and pre-fetching are the most critical aspects of the optimization. The task-node mapping is not determined until tasks are scheduled by the scheduler of DAG framework. Once the tasks are scheduled, the slots will be occupied to launch them. On the other hand, the shuffle data cannot be pre-fetched without the awareness of task-node mapping. We propose a co-scheduling scheme with two heuristic algorithms (Algorithm 1, 2). That is, the task-node mapping is established a priori, and then it is enforced by the co-scheduler when the DAG framework starts task scheduling.

3.2.1. *Problem of Random Mapping*

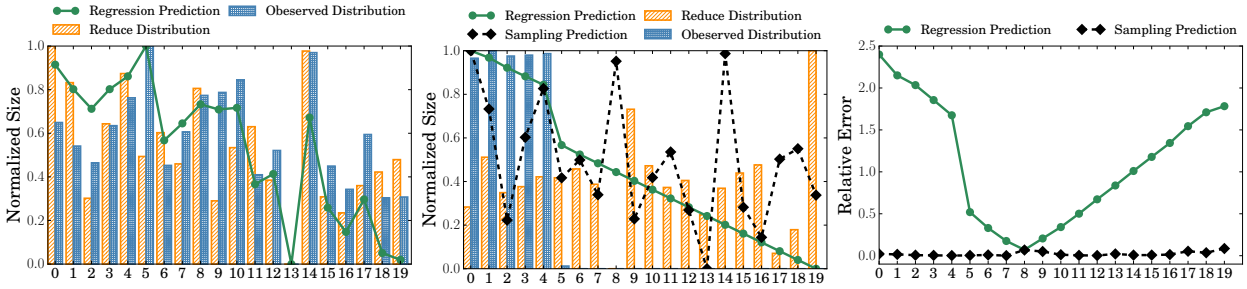
The simplest way of pre-scheduling is mapping tasks to nodes randomly and evenly. In order to evaluate the effectiveness of random mapping, we use traces from OpenCloud[7] for the simulation. The average shuffle read time is 3.2% of total reduce completion time.

As shown in Figure 3, the baseline (i.e., red dotted line) is the stage completion time with Spark FIFO scheduling algorithm. We then remove the shuffle read time of each task and run the simulation under three scheduling schemes: random mapping, Spark FIFO, and our heuristic MinHeap. Random mapping works well when there is only one round of tasks, but the performance drops as the round number grows. This is because that data skew commonly exists in data-parallel computing [21, 22, 23]. Several heavy tasks may be assigned to the same node, thus slowing down the whole stage. In addition, randomly assigned tasks also ignore the data locality between shuffle map output and reduce input, which may introduce extra network traffic in cluster.

3.2.2. *Shuffle Output Prediction*

The problem of random mapping is obviously caused by application context (e.g., shuffle data size) ignorance. Note that a balanced schedule decision can be made under the consideration of the size of each reduce task, and the size of a reduce task produced by one shuffle $reduceSize_i = \sum_{j=0}^{m} BlockSize_{ji}$, where the m is the number of map tasks that can be easily extracted from DAG information; $BlockSize_{ji}$ represents the size of block which is produced by map $task_j$ for reduce $task_i$ (e.g., block '1-1' in Figure 4). The final sizes of reduce tasks can be calculated by aggregating $reduceSize_i$

[7] http://ftp.pdl.cmu.edu/pub/datasets/hla/dataset.html



(a) Linear Regression Prediction of Hash Partitioner

(b) Linear Regression and Sampling Prediction of Range Partitioner2222

(c) Prediction Relative Error of Range Partitioner

Figure 5: Reduction Distribution Prediction

by reduce ID among all shuffle dependencies. So the pre-scheduling can be made if the "prediction" of size of shuffle block is practical.

For the most DAG applications with random large scale input, the $BlockSize_{ji}$ in a particular shuffle can be predicted accurately by liner regression model (i.e., equation 1) based on observation that the ratio of map output size and input size are invariant given the same job configuration [24, 25]:

$$BlockSize_{ji} = a \times inputSize_j + b \tag{1}$$

The $inputSize_j$ is the input size of jth map task. The a and b can be determined using the observed $inputSize_j$ and $BlockSize_{ji}$.

Though the linear regression is stable in most scenarios, it can fail in some uncertainties introduced by sophisticated frameworks like Spark [16]. For instance, the customized partitioner may result in large inconsistency between observed map output blocks distribution and the final reduce input distribution. We present two particular examples with 20 tasks respectively in Figure 5a and Figure 5b. The data in are normalized to $0-1$ because the prediction of SCache only produces the data distribution instead of the real size. The observed map outputs are randomly picked. With a random input and a hash partitioner in Figure 5a, the distribution of observed map output is close to the final reduce input distribution. The prediction results also fit them well. However, the data partitioned by Spark RangePartitioner [16] in Figure 5b results in a deviation from the linear regression model, because the RangePartitioner might introduce an extreme high data locality skew. That is, for one reduce task, almost all of the input data are produced by a particular map task (e.g., the observed map tasks only produce data for reduce task 0-5 in Figure 5b). The data locality skew results in a missing of other reduce tasks' data in the observed map outputs.

Algorithm 1 Heuristic MinHeap Scheduling for Single Shuffle

```
1:  procedure SCHEDULE(m, host_ids, p_reduces)
2:      m ← partition number of map tasks
3:      R ← sort p_reduces by size in non-increasing order
4:      M ← min-heap {host_id → ([reduces], size)}
5:      idx ← 0
6:      while idx < len R do
7:          M[0].size += R[idx].size
8:          M[0].reduces.append(R[idx])
9:          R[idx].assigned_id ← M[0].host_id
10:         Sift down M[0] by size
11:         idx ← idx − 1
12:     end while
13:     max ← maximum size in M
14:     for all reduce in R do          ▷ Heuristic locality swap
15:         if reduce.assigned_id ≠ reduce.host_id then
16:             p ← reduce.prob
17:             norm ← (p − 1/m) / (1 − 1/m) /10
18:             upper_bound ← (1 + norm) × max
19:             SWAP_TASKS(M, reduce, upper_bound)
20:         end if
21:     end forreturn M
22: end procedure
23: procedure SWAP_TASKS(M, reduce, upper_bound)
24:     Swap tasks between node host_id and node
    assigned_id
25:     of reduce without exceeding the upper_bound
26:     of both nodes.
27:     Return if it is impossible.
28: end procedure
```

To handle this corner case, we introduce another methodology, named *weighted reservoir sampling*, as a substitution of linear regression. Note that linear regression will be replaced only when a RangePartitioner or a customized non-hash partitioner occurs. For each map task, we use classic reservoir sampling to randomly pick $s \times p$ of samples, where p is the number of reduce tasks and s is a tunable number. After that, the map function is called locally to process the sampled data (*Sampling* in Figure 4). Finally, the partitioned outputs are collected with the $InputSize_j$ as the weight of the samples. Note that sampling does not consume the input

data of map tasks. The $BlockSize_{ji}$ can be calculated by:

$$BlockSize_{ji} = InputSize_j \times \frac{sample_i}{s \times p} \quad (2)$$
$$sample_i = \text{number of samples for } reduce_i$$

In Figure 5b, when s is set to 3, the result of sampling prediction is much better than linear regression. The variance of the normalization between sampling prediction and reduce distribution is because the standard deviation of the prediction results is relatively small compared to the average prediction size, which is 0.0015 in this example. Figure 5c further proves that the sampling prediction can provide precise result even in the dimension of absolute input size of reduce task. On the other hand, the result of linear regression comes out with a large relative error. Though the weighted reservoir sampling is precise, it also introduced extra overhead. We will show the overhead evaluation of sampling in Section 6.

During both of the predictions, the composition of each reduce partition is calculated as well. We define $prob_i$ as

$$prob_i = \max_{0 \le j \le m} \frac{BlockSize_{kji}}{reduceSize_i} \quad (3)$$
$$m = \text{number of map tasks}$$

This parameter is used to achieve a better data locality while performing shuffle pre-scheduling.

3.2.3. Heuristic MinHeap Scheduling

As long as the input sizes of reduce tasks are available, the pre-scheduling is a classic scheduling problem without considering the data locality. But ignoring the data locality can introduce extra network transfer. In order to balance load while minimizing the network traffic, we present the Heuristic MinHeap scheduling algorithm (Algorithm 1).

For the pre-scheduling itself (i.e., the first *while* in Algorithm 1), the algorithm maintains a min-heap to simulate the load of each node and applies the longest processing time rule (LPT) [26] to achieve $4/3$-*approximation* optimum. Since the sizes of tasks are considered while scheduling, Heuristic MinHeap can achieve a shorter makespan than Spark FIFO which is a 2-*approximation* optimum. Simulation of OpenCloud trace in Figure 3 also shows that Heuristic MinHeap has a better improvement (average 5.7%) than the Spark FIFO (average 2.7%). After pre-scheduling, the task-node mapping will be adjusted according to the locality. The $SWAP\_TASKS$ will be triggered when the *host_id* of a task does not equal the $assigned\_id$. Based on the *prob*, the normalized probability *norm* is calculated as a bound of performance degradation. Inside the $SWAP\_TASKS$, tasks will be selected and swapped without exceeding the *upper_bound*.

3.2.4. Cope with Multiple Shuffle Dependencies

A reduce stage can have more than one shuffle dependencies in the current DAG computing frameworks. The technique mentioned in Section 3.2.2 can only handle an ongoing shuffle. For those pending shuffles, it is impossible to predict their sizes. This problem can be solved by having all map tasks of pending shuffles launched simultaneously. But doing this introduces large overhead such as extra task serialization. To avoid violating the optimization from framework, we present the Accumulated Heuristic Scheduling algorithm to cope with multiple shuffle dependencies.

As illustrated in Algorithm 2, the sizes of previous *shuffles* scheduled by Heuristic MinHeap are counted. When a new shuffle starts, the predicted *size*, *prob*, and *host_id* in *p_reduces* are accumulated with previous *shuffles*. After scheduling, if the new $assigned\_id$ of a reduce task did not equal the original one, a re-shuffle will be triggered to transfer data to the new host. This re-shuffle is rare since the previous shuffle data contributes a huge composition (i.e., high *prob*) after the accumulation, which leads to a higher probability of tasks swap in $SWAP\_TASKS$.

Algorithm 2 Accumulated Heuristic Scheduling for Multi-Shuffles

```
1:  procedure M_SCHEDULE(m, host_id, p_reduces, shuffles)
2:      m ← partition number of map tasks   ▷ shuffles are the
    previous schedule result
3:      for all r in p_reduces do
4:          r.size += shuffles[r.rid].size
5:          new_prob ← shuffles[r.rid].size/r.size
6:          if new_prob ≥ r.prob then
7:              r.prob ← new_prob
8:              r.host_id ← shuffles[r.rid].assigned_host
9:          end if
10:     end for
11:     M ← SCHEDULE(m, host_id, p_reduces)
12:     for all host_id in M do                    ▷ Re-shuffle
13:         for all r in M[host_id].reduces do
14:             if host ≠ shuffles[r.rid].assigned_host then
15:                 Re-shuffle data to host
16:                 shuffles[r.rid].assigned_host ← host
17:             end if
18:         end for
19:     end forreturn M
20: end procedure
```

4. Implementation

This section presents an overview of the implementation of SCache. We first present the system overview and the detail of sampling in Subsection 4.1. The following 4.2 subsection focuses on two constraints on memory management. In Subsection 4.3, we evaluate the cross-framework capability of SCache. At last, we discuss the cost of adapting SCache and fault tolerance.

4.1. System Overview

SCache consists of three components: a distributed shuffle data management system, a DAG co-scheduler, and a worker daemon. As a plug-in system, SCache needs to rely on a DAG framework. As shown in Figure 6, SCache employs the legacy master-slaves architecture like GFS [27] for the shuffle data management system. The master node of

SCache coordinates the shuffle blocks globally with application context. The worker node reserves memory to store blocks. The coordination provides two guarantees: (a) data is stored in memory before tasks start and (b) data is scheduled on-off memory with all-or-nothing and context-aware constraints. The daemon bridges the communication between DAG framework and SCache. The co-scheduler is dedicated to pre-schedule reduce tasks with DAG information and enforce the scheduling results to original scheduler in framework.

When a DAG job is submitted, the DAG information is generated in framework task scheduler. Before the computing tasks begin, the shuffle dependencies are determined based on DAG. For each shuffle dependency, the shuffle ID, the type of partitioner, the number of map tasks, and the number of reduce tasks are included. If there is a specialized partitioner, such as range partitioner, in the shuffle dependencies, the daemon will insert a sampling application before the computing job. We will elaborate the sampling procedure in the Section 4.1.1.

When a map task finishes computing, the shuffle write implementation of the DAG framework is modified to call the SCache API and move all the blocks out of framework worker through memory copy. After that, the slot will be released (without being blocked on disk operations). When a block of the map output (i.e., "map output" in Figure 4) is received, the SCache worker will send the block ID and the size to the master. If the collected map output data reach the observation threshold, the DAG co-scheduler will run the scheduling Algorithm 1 or 2 to pre-schedule the reduce tasks and then broadcast the scheduling result to start pre-fetching on each worker. SCache worker will filter the reduce tasks' IDs that are scheduled on itself and start pre-fetching shuffle data from the remote. In order to force the DAG framework to run according to the SCache pre-scheduled results, we insert some lines of codes in framework scheduler. After modification, DAG scheduler consults SCache co-scheduler to get the preferred location for each task.

4.1.1. *Reservoir Sampling*

If the submitted shuffle dependencies contained a RangePartitioner or a customized non-hash partitioner, the SCache master will send a sampling request to the framework master. The sampling job uses a reservoir sampling algorithm [28] on each partition. For the sample number, it can be tuned to balance the overhead and accuracy. The sampling job randomly selects some items and performs a local shuffle with partitioner (see Figure 7). At the same time, the items number is counted as the weight. These sampling data will be aggregated by reduce task ID on SCache master to predict the reduce partition size. After the prediction, SCache master will call Algorithm 1 or 2 to do the pre-scheduling.

4.2. Memory Management

As mentioned in Section 2.2, though the shuffle size is relatively small, memory management should still be cautious enough to limit the effect of performance of DAG framework. When the size of cached blocks reaches the limit of

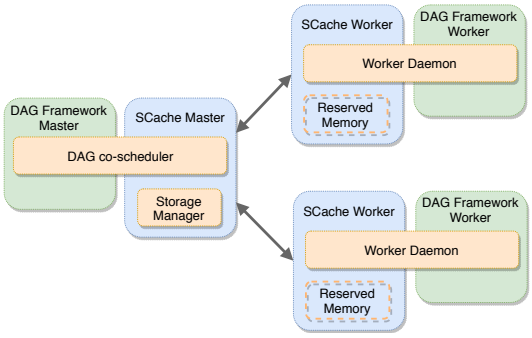


Figure 6: SCache Architecture

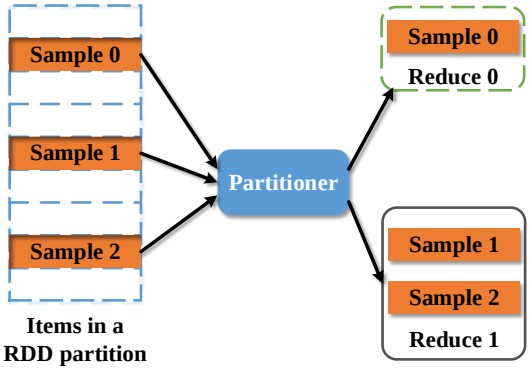


Figure 7: Reservoir Sampling of One Partition

reserved memory, SCache flushes some of them to the disk temporarily, and re-fetches them when some cached shuffle blocks are consumed or pre-fetched. To achieve the maximum overall improvement, SCache leverages two constraints to manage the in-memory data-all-or-nothing and context-aware-priority.

4.2.1. *All-or-Nothing Constraint*

This acceleration of in-memory cache of a single task is necessary but insufficient for a shorter stage completion time. Based on the observation in Section 2.2.4, in most cases one single stage contains multi-rounds of tasks. If one task missed a memory cache and exceeded the original bottleneck of this round, that task might become the new bottleneck and then slow down the whole stage. PACMan [29] has also proved that for multi-round stage/job, the completion time improves in steps when $n \times number\ of\ tasks\ in\ one\ round$ of tasks have data cached simultaneously. Therefore, the cached shuffle blocks need to match the demand of all tasks in one running round at least. We refer to this as the all-or-nothing constraint.

According to all-or-nothing constraint, SCache master leverages the pre-scheduled results to determine the bound of each round, and sets blocks of one round as the minimum unit of storage management. For those incomplete units, SCache marks them as the lowest priority.

4.2.2. *Context-Aware-Priority Constraint*

Unlike the traditional cache replacement schemes such as MIN [30], the cached shuffle data will only be used once

(without failure), but the legacy cache managements are designed to improve the hit rate. SCache leverages application context to select victim storage units when the reserved memory is full.

At first, SCache flushes blocks of the incomplete units to disk cluster-widely. If all the units are completed, SCache selects victims based on two factors-*inter-shuffle* and *intra-shuffle*.

- Inter-shuffle: SCache master follows the scheduling scheme of Spark to determine the inter-shuffle priority. For example, Spark FIFO scheduler schedules the tasks of different stages according to the submission order. So SCache sets the priorities according to the submission time of each shuffle.
- Intra-shuffle: The intra-shuffle priorities are determined according to the task scheduling inside a stage. For example Spark schedules tasks with smaller ID at first. Based on this, SCache can assign the lower priority to storage units with a larger task ID.

4.3. Analysis of cross-framework capability

Shuffle optimization of SCache inevitably requires the modification on the DAG frameworks. SCache provides APIs through RPC, such as *putBlock (blockId)*, *getBlock (blockId)*, and *getScheduleResult (shuffleId)*. In order to use SCache, we mainly need to modify two parts of the frameworks: (a) The DAG scheduler should provide the DAG information and follow the pre-scheduled result of SCache; (b) The shuffle data should be transferred to SCache Storage Management.

To prove the cross-framework capability of SCache, we adapt SCache on Hadoop MapReduce and Spark respectively. In Hadoop MapReduce, we modify codes in ResourceManager, MapTask, and ReduceTask to call SCache APIs through RPC. It takes about 380 lines of code. In Spark, we mainly modify DAGScheduler and the corresponding data fetcher. It only takes about 500 lines of code. Such hundreds of lines of code modification are very small compared to the hundreds of thousands of lines of code in DAG framework. We believe that the costs of enabling SCache on other DAG computing frameworks, such as Tez [3], are also low.

4.4. Fault tolerance

Due to the characteristic of shuffle data (e.g., short-lived, write-once, read-once), we believe fault tolerance is not a crucial goal of SCache at present. We plan to implement SCache master with Apache ZooKeeper [31] to provide constantly service. If a failure happens inside the SCache worker, SCache daemon can block the shuffle write/read operations until the worker process restarts without violating the correctness of the DAG computing. A possible way to handle this failure is selecting some backup nodes to store replications. But the replications can introduce a significant network overhead [32]. Currently, we leave the sever faults (e.g., the failure of a node) to the DAG frameworks. We believe it is a more promising way because most DAG frameworks have more advanced fast recovery schemes on the application layer, such as paralleled recovery of Spark. Meanwhile, SCache can still provide shuffle optimization during the recovery.

5. Framework Resources Quantification Model

In this section, we introduce *Framework Resources Quantification* (FRQ) model to describe the performance of DAG frameworks. The FRQ model quantifies computing and I/O resources and visualizes them in the time dimension. According to the FRQ model, we can calculate the execution time required by the application under any circumstances, including different DAG frameworks, hardware environments, and so on. Therefore the FRQ model is able to help us analyze the resources scheduling of DAG framework and evaluate their performance. We will first introduce the FRQ model in Subsection 5.1. In the following Subsection 5.2, we will use the FRQ model to describe three different computation jobs and analyze their performance. In the last Subsection 5.3, we will use the actual experimental results to verify the FRQ model.

5.1. The FRQ Model

The current distributed computing frameworks mostly use DAGs to describe computation logic. A shuffle phase is required between each adjacent DAG computation phases. To better analyze the relationship between the computation phase and the shuffle phase, we propose the FRQ model. After quantifying computing and I/O resources, the FRQ model can describe different resource scheduling strategies. For convenience, we introduce the FRQ model by taking a simple MapReduce job as an example in this section.

Figure 8 shows how the FRQ model describes a MapReduce task. The FRQ model has five input parameters:

- Input Data Size (D): The data size of the computation phase.
- Data Conversion Rate (R): The conversion rate of the input data to the shuffle data during a computation phase. This rate depends on the algorithm used in the computation phase.
- Computation Round Number (N): The number of rounds needed to complete the computation phase. These rounds depend on the current computation resources and the configuration of the framework. Take Hadoop MapReduce as an example. Suppose we have a cluster with 50 CPUs and enough memory, the map phase consists of 200 map tasks, and each map requires 1 CPU. Then we need 4 rounds of computation to complete the map phase.
- Computation Speed (V_i): The computation speed for each computation phase. This speed depends on the algorithm used in the computation phase.

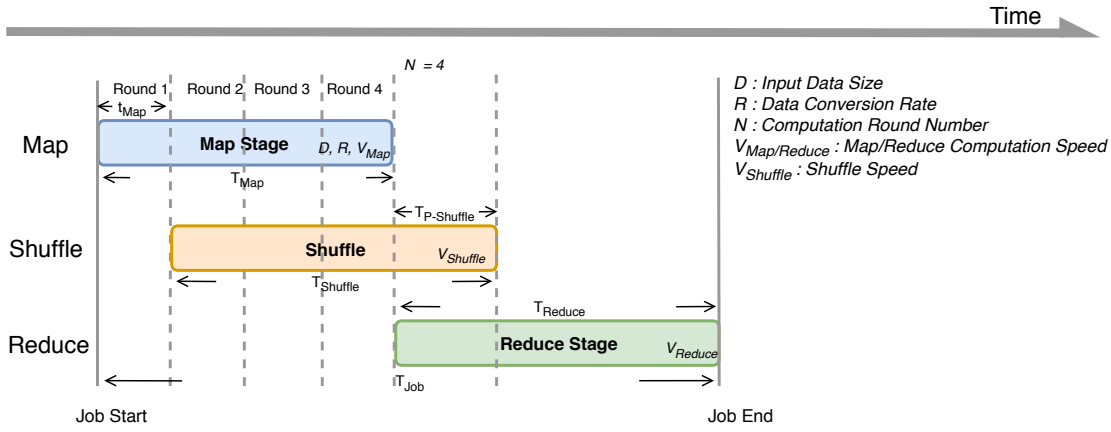


Figure 8: Framework Resources Quantification (FRQ) Model with Full Parallel MapReduce

- Shuffle Speed ($V_{Shuffle}$): Transmission speed in the shuffle phase. This speed depends on network and storage device bandwidth.

The FRQ model calculates the execution time of each phase of the job with these five parameters. As shown in Figure 8, the total execution time of a job is the sum of the map phase time and reduce phase time:

$$T_{Job} = T_{Map} + T_{Reduce} \tag{4}$$

Map phase time depends on input data size and map computation speed:

$$T_{Map} = \frac{D}{V_{Map}} \tag{5}$$

The reduce phase time formula is as follows:

$$T_{Reduce} = \frac{D \times R}{V_{Reduce}} + K \times T_{P\_Shuffle} \tag{6}$$

$\frac{D \times R}{V_{Reduce}}$ represents the ideal computation time of a reduce phase, and $(K \times T_{P\_Shuffle})$ represents the computing overhead. We use $T_{P\_Shuffle}$ to represent the overlap time between shuffle phase and reduce phase. $T_{Shuffle}$ represents the total time of the shuffle phase. The relationship between $T_{P\_Shuffle}$ and $T_{Shuffle}$ is determined by the resources scheduling strategy of DAG frameworks. This relationship will be shown in the following Subsection 5.2. K is an empirical value. Because the computation of the reduce phase relies on the data transfer results of the shuffle phase, a portion of the computation in the reduce phase needs to wait for the transfer results. This waiting causes the overhead. The FRQ model uses K to indicate the extent of the waiting.

The shuffle phase time formula is as follows:

$$T_{Shuffle} = \frac{D}{V_{Shuffle}} \tag{7}$$

According to Equation 4&6, we can optimize the job completion time by reducing $T_{P\_Shuffle}$. Improving I/O speed is an effective way to reduce shuffle time. Another optimization method is to use the idle I/O resources in the map phase for pre-fetching (see Figure 8). Both of the above methods can effectively reduce $T_{P\_Shuffle}$. By using the FRQ model to describe a MapReduce job, the users can analyze the resource scheduling strategy of the computation framework.

5.2. Model Analysis

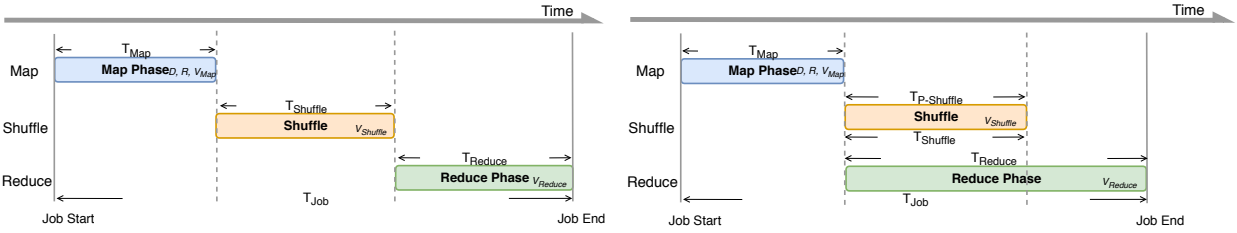
The FRQ model can describe a variety of resource scheduling strategies. First, we analyze a simple scheduling strategy which used by Apache Spark by default. As shown in Figure 9a, the FRQ model describes a MapReduce job that is entirely serially executed. The overlap time between the shuffle phase and the reduce phase is 0, in which case $T_{P\_Shuffle}$ is 0. Therefore, the overhead of the reduce phase is 0. The total execution time of a job is also different from the above:

$$T_{Job} = T_{Map} + T_{Shuffle} + T_{Reduce} \tag{8}$$

Due to serialization, the I/O resource is idle during the reduce phase and map phase. This scheduling strategy is simple and has much room for optimization.

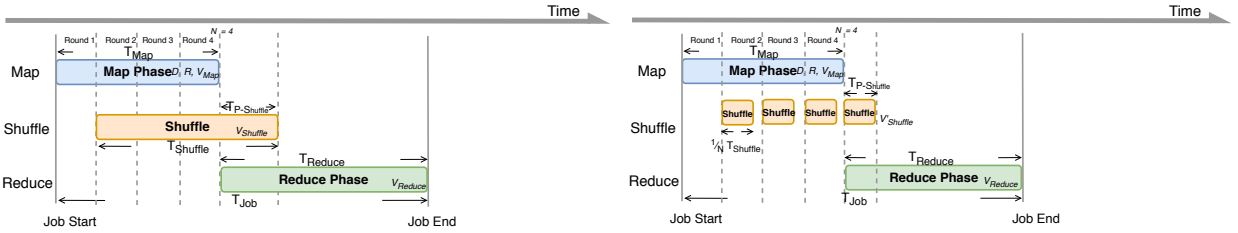
Figure 9b shows a more efficient scheduling strategy which is used by Hadoop MapReduce. In this scheduling strategy, shuffle phase and reduce phase start at the same time. In this case, $T_{P\_Shuffle}$ is equal to $T_{Shuffle}$. Due to the increase in $T_{P\_Shuffle}$, the time of reduce phase increases (according to Equation 6). Because the shuffle phase and the computation phase are executed in parallel, the total execution time of a job is the sum of T_{Map} and T_{Reduce} (see Equation 4). The execution time of the shuffle phase is hidden in the reduce phase. However, we also found that the I/O resource in the map phase is still idle. This scheduling strategy can still be optimized.

Hadoop MapReduce overlaps shuffle phase with reduce phase and utilizes idle resources. We intuitively think that we can also overlap shuffle phase one and map phases. We implemented this idea with SCache. Figure 10 shows the scheduling strategy for Hadoop MapReduce with SCache (Suppose N is 4). SCache starts pre-fetching and pre-scheduling



(a) Full Serial MapReduce (b) Half Parallel MapReduce

Figure 9: Framework Resources Quantification (FRQ) Model with Different Scheduling Strategies



(a) If $V_{Map} \times R \geq V_{Shuffle}$ (b) If $V_{Map} \times R < V_{Shuffle}$

Figure 10: Framework Resources Quantification (FRQ) Model with Full Parallel MapReduce in Different Environments

in the map phase. This scheduling strategy can make better use of resources and avoid the I/O resource being idle in the map phase. According to the design of SCache pre-fetching, we found that using the FRQ model to describe the scheduling strategy of SCache needs to distinguish two situations:

1. $V_{Map} \times R \geq V_{Shuffle}$ (Figure 10a): The meaning of the inequality is that the speed of generating shuffle data ($V_{Map} \times R$) is greater than or equal to the shuffle speed ($V_{Shuffle}$). In this situation, the shuffle phase is uninterrupted. The I/O resource will be fully utilized during the whole shuffle phase. As a result, the formula of $T_{PShuffle}$ is as followed:

$$T_{P\_Shuffle} = T_{Shuffle} - \frac{(N-1) \times T_{Map}}{N} \quad (9)$$

2. $V_{Map} \times R < V_{Shuffle}$ (Figure 10b): When the shuffle speed ($V_{Shuffle}$) is faster, SCache needs to wait for shuffle data to be generated. As Figure 10b shown, the shuffle phase will be interrupted in each round. In this case, the formula of $T_{PShuffle}$ is as followed:

$$T_{P\_Shuffle} = T_{Shuffle} \times \frac{1}{N} \quad (10)$$

Compared to the original Hadoop MapReduce resource scheduling strategy, Hadoop MapReduce with SCache shortens $T_{P\_Shuffle}$ and thus shortens T_{Reduce}. This is how pre-fetching optimizes the total execution time of a job.

5.3. Model Verification

To verify the FRQ model, we run experiments on two environments: (a) 50 Amazon EC2 m4.xlarge nodes cluster as shown in Subsection 6.1. (b) 4 in-house nodes cluster with 128GB memory and 32 cores per node. To simplify the calculation of the FRQ model, we run the Terasort as an experimental application on a Hadoop MapReduce framework. We deployed Hadoop with SCache and without SCache in both environments.

Table 1 shows the calculational results of the FRQ model in the in-house environment. The workload is from 16 GB to 64 GB. D and N are set according to the application parameters. $R, V_{Map}, V_{Shuffle}$,and V_{Reduce} are calculated based on experimental results. K is the empirical value, we set K to 0.5 and 0.6, which reflects that $T_{P\_Shuffle}$ has less impact on the reduce phase in the case of SCache. In the Hadoop with SCache, Terasort satisfies the situation in Figure 10a ($V_{Map} \times R \geq V_{Shuffle}$). In the original Hadoop, since pre-fetching is not used, $T_{P\_Shuffle}$ is equal to $T_{Shuffle}$(see Equation 7). $ExpT_{Job}$ represents the actual experiment data, we calculate $Error$ according to T_{Job} and $ExpT_{Job}$.

Table 2 shows the calculational results of the FRQ model in Amazon EC2 environment. $V_{Map}, V_{Shuffle}$, and V_{Reduce} are modified because of the different hardware devices. We also set K to the same empirical value. The formulas in the table are all the same except $T_{P\_Shuffle}$. In this environment, Terasort on Hadoop MapReduce satisfies the situation in Figure 10b ($V_{Map} \times R < V_{Shuffle}$), thus the formula of $T_{P\_Shuffle}$ is Equation 10.

In order to verify the two cases as mentioned above when using SCache, we monitor the network utilization as Figure 11. Figure 11a shows that, in the in-house environment, the network utilization remains high until the shuffle phase is completed. On the other hand, Figure 11b shows that the network utilization has 5 regular peaks in Amazon EC2 environment. Both these two situations are consistent with the FRQ model in Figure 10.

	D	R	N	V_{Map}	V_{Reduce}	$V_{Shuffle}$	K	T_{Map}	$T_{Shuffle}$	$T_{P\_Shuffle}$	T_{Reduce}	T_{Job}	$ExpT_{Job}$	$Error$
SCache	16	1	2	0.65	1	0.47	0.5	24.62	34.04	21.73	26.87	51.48	55	6.39%
	32	1	4	0.65	1	0.47	0.5	49.23	68.09	31.16	47.58	96.81	104	6.91%
	48	1	6	0.65	1	0.47	0.5	73.85	102.13	40.59	68.29	142.14	151	5.87%
	64	1	8	0.65	1	0.47	0.5	98.46	136.17	50.02	89.01	187.47	193	2.87%
Legacy	16	1	2	0.65	1	0.47	0.6	24.62	34.04	34.04	36.43	61.04	73	16.38%
	32	1	4	0.65	1	0.47	0.6	49.23	68.09	68.09	72.85	122.08	135	9.57%
	48	1	6	0.65	1	0.47	0.6	73.85	102.13	102.13	109.28	183.12	188	2.59%
	64	1	8	0.65	1	0.47	0.6	98.46	136.17	136.17	145.70	244.16	249	1.94%

D: GB, V_i: GB/s, T_i: s

Table 1
Hadoop MapReduce on 4 nodes cluster in the FRQ model

	D	R	N	V_{Map}	V_{Reduce}	$V_{Shuffle}$	K	T_{Map}	$T_{Shuffle}$	$T_{P\_Shuffle}$	T_{Reduce}	T_{Job}	$ExpT_{Job}$	$Error$
SCache	128	1	5	1.15	1.46	1.4	0.5	111.30	91.43	18.29	96.81	208.12	232	10.29%
	256	1	5	1.15	1.46	1.4	0.5	222.61	182.86	36.57	193.63	416.24	432	3.65%
	384	1	5	1.15	1.46	1.4	0.5	333.91	274.29	54.86	290.44	624.36	685	8.85%
Legacy	128	1	5	1.15	1.46	1.4	0.6	111.30	91.43	91.43	142.53	253.83	266	4.57%
	256	1	5	1.15	1.46	1.4	0.6	222.61	182.86	182.86	285.06	507.67	524	3.12%
	384	1	5	1.15	1.46	1.4	0.6	333.91	274.29	274.29	427.59	761.50	776	1.87%

D: GB, V_i: GB/s, T_i: s

Table 2
Hadoop MapReduce on 50 AWS m4.xlarge nodes cluster in the FRQ model

Regarding accuracy, the experimental values are all larger than the calculated values. This is because the application has some extra overhead at runtime, such as network warm-up, the overhead of allocating slots, and so on. This overhead will be amplified when the input data is small or the total execution time is short. Overall, the error between T_{Job} and $ExpT_{Job}$ is mainly below 10%, such errors are acceptable. Therefore, we believe that the FRQ model can accurately describe DAG frameworks.

6. Evaluation

This section reveals the evaluation of SCache with comprehensive workloads and benchmarks. First we run a job with single shuffle to analyze hardware utilization and see the impacts of different components from the scope of a task to a job. Then we use a recognized shuffle intensive benchmark — Terasort to evaluate SCache with different data partition schemes.

In order to prove the performance gain of SCache with a real production workload, we also evaluate Spark TPC-DS[8] and present the overall performance improvement. To prove the compatibility of SCache as a cross-framework plug-in, we implemented SCache on both Hadoop MapReduce and Spark. Due to the simple DAG computing in Hadoop MapReduce, we only use Terasort as a shuffle-heavy benchmark to evaluate the performance of Hadoop MapReduce with SCache.

Finally, we measure the overhead of weighted reservoir sampling. In summary, SCache can decrease 89% time of Spark shuffle without introducing extra network transfer. More impressively, the overall completion time of TPC-DS can be improved 40% on average by applying the optimization from SCache. Meanwhile, Hadoop MapReduce with SCache optimizes job completion time by up to 15% and an average of 13%

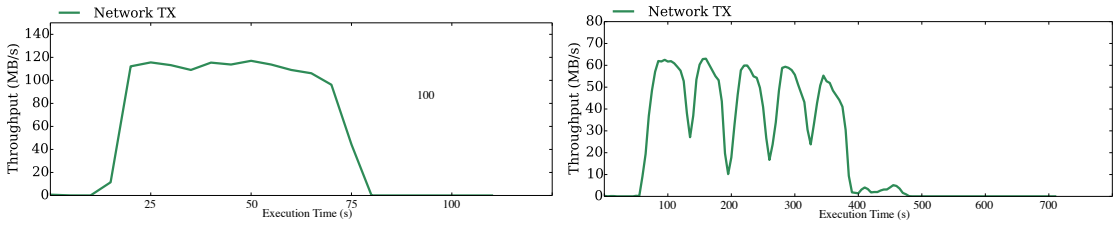
6.1. Setup

We modified Spark to enable shuffle optimization of SCache as a representative. The shuffle configuration of Spark is set to the default[9]. We run the experiments on a 50-node m4.xlarge cluster on Amazon EC2[10]. Each node has 16GB

[8] https://github.com/databricks/spark-sql-perf

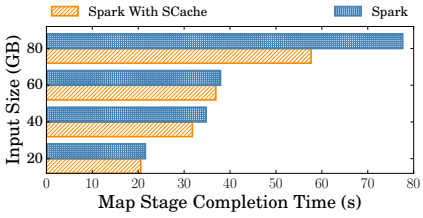
[9] http://spark.apache.org/docs/1.6.2/configuration.html

[10] http://aws.amazon.com/ec2/

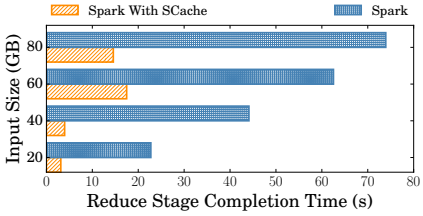


(a) If $V_{Map} \times R \geq V_{Shuffle}$ (b) If $V_{Map} \times R < V_{Shuffle}$

Figure 11: Network utilization on Hadoop MapReduce with SCache

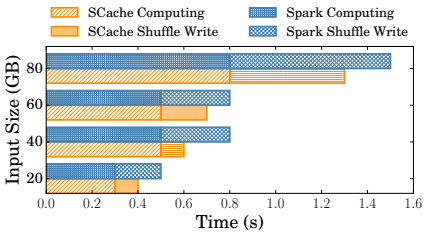


(a) Map Stage Completion Time

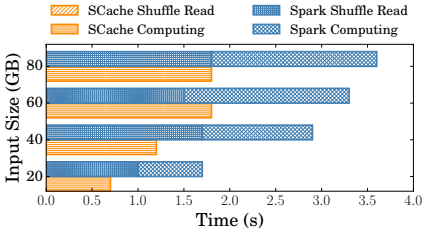


(b) Reduce Stage Completion Time

Figure 12: Stage Completion Time of Single Shuffle Test

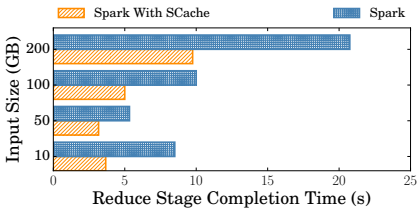


(a) Median Task in Map Stages

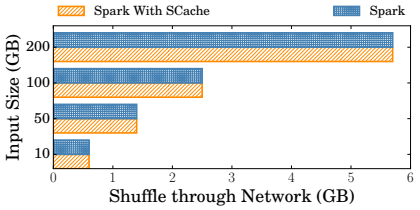


(b) Median Task in Reduce Stages

Figure 13: Median Task Completion Time of Single Shuffle Test



(a) Reduce Stage of First Shuffle



(b) Network Traffic of Second Shuffle

Figure 14: Terasort Evaluation

memory and 4 CPUs. The network bandwidth provided by Amazon is insufficient. Our evaluations reveal the bandwidth is only about 300 Mbps (see Figure 2a).

6.2. Simple DAG Analysis

We first run the same single shuffle test shown in Figure 2a. For each stage, we run 5 rounds of tasks with different input size. As shown in Figure 2b, the hardware utilization is captured from one node during the job. Note that since the completion time of whole job is about 50% less than Spark without SCache, the duration of Figure 2b is cut in half as well. An overlap among CPU, disk, and network can be easily observed in Figure 2b. It is because the decoupling of shuffle prevents the computing resource from being blocked by I/O operations. On the one hand, the decoupling of shuffle write helps free the slot earlier, so that it can be re-scheduled to a new map task. On the other hand, with the help of shuffle pre-fetching, the decoupling of shuffle read significantly decreases the CPU idle time at the beginning of a reduce task. At the same time, SCache manages the hardware resources to store and transfer shuffle data without interrupting the computing process. As a result, the utilization and multiplexing of hardware resource are increased, thus improving the performance of Spark.

The performance evaluation in Figure 13 shows the consistent results with our observation of hardware utilization. For each stage, we pick the task that has median completion time. In the map task, the disk operations are replaced by the memory copies to decouple the shuffle write. It helps eliminate 40% of shuffle write time (Figure 13a), which leads to a 10% improvement of map stage completion time in Figure 12a. Note that the shuffle write time can be observed even with the optimization of SCache. The reason is that before moving data out of Spark's JVM, the serialization is inevitable and CPU intensive [18].

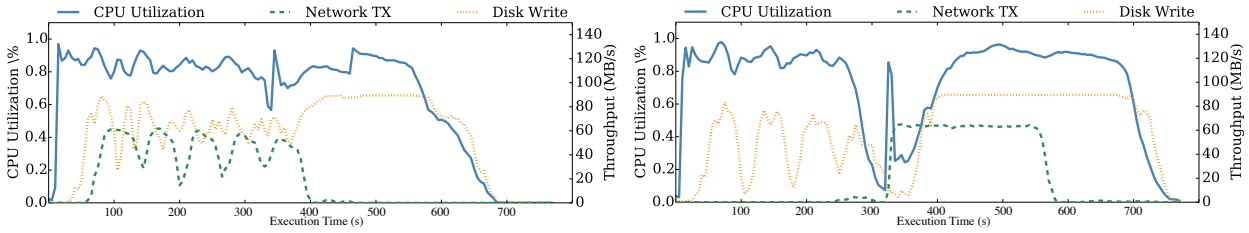
In the reduce task, most of the shuffle overhead is introduced by network transfer delay. By doing shuffle data pre-fetching based on the pre-scheduling results, the explicit network transfer is perfectly overlapped in the map stage. With the help of the co-scheduling scheme, SCache guarantees that each reduce task has the benefit of shuffle pre-fetching. The in-memory cache of shuffle data further reduces the shuffle read time. As a result, the combination of these optimizations decreases 100% overhead of the shuffle read in a reduce task (Figure 13b). In addition, the heuristic algorithm can achieve a balanced pre-scheduling result, thus providing 80% improvement in reduce stage completion time (Figure 12b).

In overall, SCache can help Spark decrease by 89% overhead of the whole shuffle process.

6.3. Terasort

We also evaluate Terasort-a recognized shuffle intensive benchmark for distributed system analysis. Terasort consists of two consecutive shuffles. The first shuffle reads the input data and uses a hash partition function for re-partitioning. As shown in Figure 14a, Spark with SCache runs 2 × faster during the reduce stage of the first shuffle, which is consistent with the results in Section 6.2. It further proves the effectiveness of SCache's optimization.

The second shuffle of Terasort partitions the data through a Spark RangePartitioner. In the second shuffle, almost 93% of input data of a reduce task is produced by one particular map task. So we take the second shuffle as an extreme case to evaluate the heuristic locality swap of SCache. In this shuffle, Spark schedules a reduce task to the node that produces most input data. By doing this, Spark minimizes the shuffle data through network. At the same time, Figure 14b reveals that SCache produces exactly same network traffic as Spark. It implies that the heuristic locality swap of SCache can obtain the best locality while balancing the load.



(a) Hadoop MapReduce with SCache (b) Hadoop MapReduce without SCache

Figure 15: CPU utilization and I/O throughput of a node during a Hadoop MapReduce Terasort job

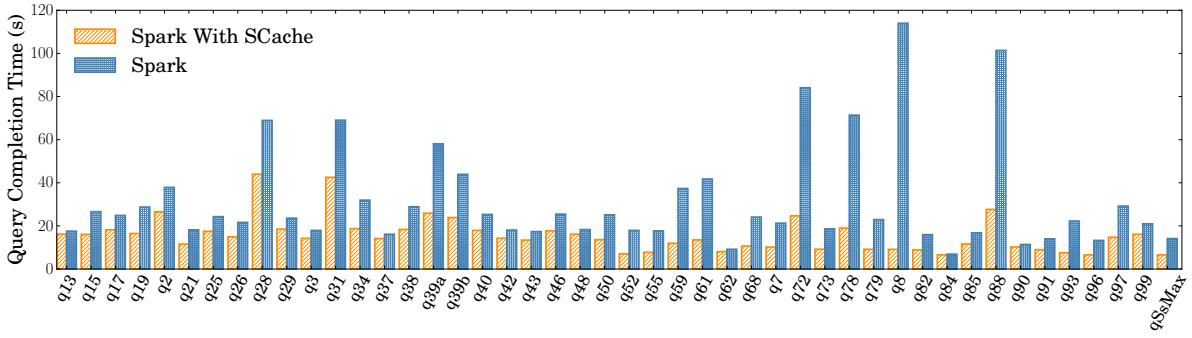


Figure 16: TPC-DS Benchmark Evaluation

6.4. Hadoop MapReduce with SCache

To prove SCache compatibility as a cross-framework plug-in, we also implemented SCache on Hadoop MapReduce. Although the simple DAG computing alleviates the effect of *pre-scheduling*, the shuffle-heavy jobs can still be optimized by the SCache shuffle data management.

As Figure 15 shows, Hadoop MapReduce with SCache brings 15% of total time optimization with 384GB input data size. As shown in Figure 15b, Hadoop MapReduce without SCache writes intermediate data locally in the map phase. The shuffle phase and the reduce phase start simultaneously. Because a large amount of shuffle data reaches the network bottleneck, the beginning part of reduce phase needs to wait for network transfer. This causes the CPU resources to be idle. On the other hand, in Figure 15a, Hadoop MapReduce with SCache starts pre-fetching in the map phase. This avoids the reduce phase waiting for the shuffle data. Furthermore, pre-fetching utilizes the idle I/O throughput in the map phase. As shown in Figure 17, after better fine-grained utilization of hardware resources, Hadoop MapReduce with SCache optimizes Terasort overall completion time by up to 15% and an average of 13% with input data sizes from 128GB to 512GB.

6.5. Production Workload

We also evaluate some queries from TPC-DS[11]. TPC-DS benchmark is designed for modeling multiple users submitting varied queries (e.g. ad-hoc, interactive OLAP, data mining, etc.). TPC-DS contains 99 queries and is considered as the standardized industry benchmark for testing big data systems. As shown in Figure 16, the horizontal axis is query name and the vertical axis is query completion time. Note that we skip some queries due to the compatible issues. Spark with SCache outperforms the original Spark in almost all tested queries. Furthermore, in many queries, Spark with SCache outperforms original Spark by an order of magnitude. It is because that those queries contain shuffle-heavy operations such as "groupby", "union", etc. The overall reduction portion of query time that SCache achieved is 40% on average. Since this evaluation presents the overall job completion time of queries, we believe that our shuffle optimization is promising.

[11] http://www.tpc.org/tpcds/

6.6. Overhead of Sampling

We evaluate the overhead of sampling with different input sizes and numbers of nodes. In Figure 18, the overhead of sampling only grows with the increase of input size on each node, but remains relatively stable when the cluster size scales up. Since the shuffle data is short-lived, write-once, and read-once, the central controller of SCache does not have to collect and manage complex metadata. Meanwhile, most of the optimizations such as fetching and storing shuffle data are finished by workers independently. So the cost of pre-scheduling algorithm and memory management are unlikely to make the master become the bottleneck of the scalability. Combined with the sampling overhead evaluation, we believe that SCache is scalable.

7. Related Work

Modeling: Most representative DAG computing frameworks use similar *Bulk Synchronize Parallel* (BSP)[33] model to control data synchronization in each computing phase, i.e., *stage* in Spark, *superstep* in Pregel[34] and so on. Verma

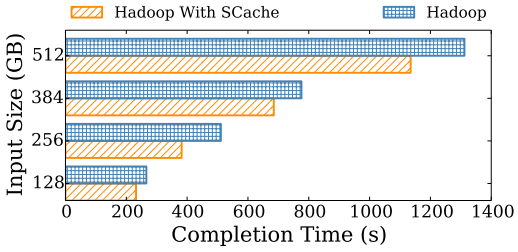


Figure 17: Hadoop MapReduce Terasort completion time

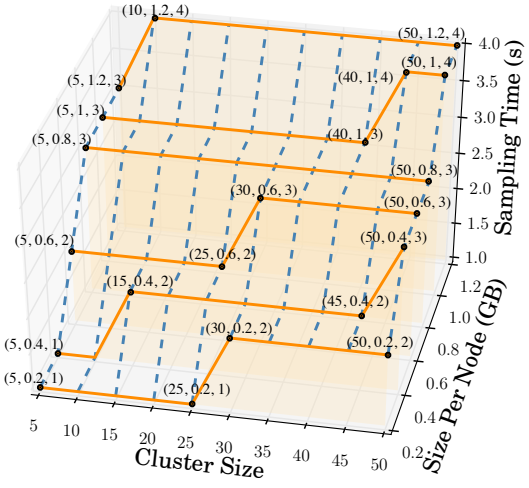


Figure 18: Sampling Overhead

et al. [35] proposed the ARIA model to estimate the required resources based on the job information, the amount of input data and a specified soft deadline. Khan et al. [36] proposed the HP model which extends the ARIA model. The HP model adds scaling factors and uses a simple linear regression to estimate the job execution time on larger datasets. In [37], Herodotou proposed a detailed set of mathematical performance models for describing the five phases of a MapReduce job and combine them into an overall MapReduce job model. Chen et al. [38] proposed the CRESP model which is a cost model that estimates the performance of a job then provisions the resources for the job. Farshid Farhat et al.[39] proposed a closed-form queuing model which focus on stragglers and try to optimize them. However, the above models are not able to accurately describe the overhead caused by the shuffle process under different scheduling strategies. The FRQ model focuses on describing the overhead caused by the shuffle process in different scheduling strategies, which satisfies our demand.

Pre-scheduling: Slow-start from Apache Hadoop MapReduce is a classic approach to handle shuffle overhead. Starfish [40] gets sampled data statics for self-tuning system parameters (e.g. slow-start, etc). DynMR [41] dynamically starts reduce tasks in late map stage. All of them have the explicit I/O time in occupied slots. SCache instead starts shuffle prefetching without consuming slots. iShuffle [24] decouples shuffle from reducers and designs a centralized shuffle controller. But it can neither handle multiple shuffles nor schedule multiple rounds of reduce tasks. iHadoop [42] aggressively pre-schedules tasks in multiple successive stages to start fetching shuffle. But we have proved that randomly assign tasks may hurt the overall performance in Section 3.2.1. Different from these works, SCache pre-schedules multiple shuffles without breaking load balancing.

Delay-scheduling: Delay Scheduling [43] delays tasks assignment to get better data locality, which can reduce the network traffic. ShuffleWatcher [17] delays shuffle fetching when the network is saturated. At the same time, it achieves better data locality. Both Quincy [44] and Fair Scheduling [45] can reduce shuffle data by optimizing data locality of map tasks. But all of them cannot mitigate explicit I/O in both map and reduce tasks. In addition, their optimizations fluctuate under different network performances and data distributions, whereas SCache can provide a stable performance gain by shuffle data pre-fetching and in-memory caching.

Network layer optimization: Varys [46] and Aalo [47] provide the network layer optimization for shuffle transfer. Though the efforts are limited throughout whole shuffle process, they can be easily applied on SCache to further improve the performance.

8. Conclusion

In this paper, we present SCache, a cross-framework shuffle optimization for DAG computing frameworks. SCache decouples the shuffle from computing tasks and leverages memory to store shuffle data. By task pre-scheduling and shuffle data pre-fetching with application context, SCache significantly mitigates the shuffle overhead. Our evaluations on Spark and Hadoop MapReduce with SCache show that SCache can provide a promising speedup. Furthermore, we propose *Framework Resources Quantification* (FRQ) model to assist in analyzing shuffle process of DAG computing frameworks. At last, we evaluate the SCache shuffle optimization by this practical model. Therefore, with the shared defects of shuffle among different frameworks, we believe that the optimization of SCache is general and easy to adapt.

9. Acknowledge

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References

[1] M. Isard, M. Budiu, Y. Yu, A. Birrell, and D. Fetterly, "Dryad: distributed data-parallel programs from sequential building blocks," in *ACM SIGOPS operating systems review*, vol. 41, no. 3. ACM, 2007, pp. 59–72.

[2] M. Zaharia, M. Chowdhury, T. Das, A. Dave, J. Ma, M. McCauley, M. J. Franklin, S. Shenker, and I. Stoica, "Resilient distributed

datasets: A fault-tolerant abstraction for in-memory cluster computing," in *Proceedings of the 9th USENIX conference on Networked Systems Design and Implementation*. USENIX Association, 2012, pp. 2–2.

[3] B. Saha, H. Shah, S. Seth, G. Vijayaraghavan, A. Murthy, and C. Curino, "Apache tez: A unifying framework for modeling and building data processing applications," in *Proceedings of the 2015 ACM SIGMOD international conference on Management of Data*. ACM, 2015, pp. 1357–1369.

[4] M. Chowdhury, M. Zaharia, J. Ma, M. I. Jordan, and I. Stoica, "Managing data transfers in computer clusters with orchestra," in *ACM SIGCOMM Computer Communication Review*, vol. 41, no. 4. ACM, 2011, pp. 98–109.

[5] C. Xie, R. Chen, H. Guan, B. Zang, and H. Chen, "Sync or async: Time to fuse for distributed graph-parallel computation," in *Proceedings of the 20th ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming*, ser. PPoPP 2015. New York, NY, USA: ACM, 2015, pp. 194–204. [Online]. Available: http://doi.acm.org/10.1145/2688500.2688508

[6] H. Li, A. Ghodsi, M. Zaharia, S. Shenker, and I. Stoica, "Tachyon: Reliable, memory speed storage for cluster computing frameworks," in *Proceedings of the ACM Symposium on Cloud Computing*. ACM, 2014, pp. 1–15.

[7] B. Heintz, A. Chandra, R. K. Sitaraman, and J. Weissman, "End-to-end optimization for geo-distributed mapreduce," *IEEE Transactions on Cloud Computing*, vol. 4, no. 3, pp. 293–306, 2016.

[8] Q. Zhang, M. F. Zhani, Y. Yang, R. Boutaba, and B. Wong, "Prism: fine-grained resource-aware scheduling for mapreduce," *IEEE Transactions on Cloud Computing*, no. 1, pp. 1–1, 2015.

[9] D. Cheng, J. Rao, Y. Guo, C. Jiang, and X. Zhou, "Improving performance of heterogeneous mapreduce clusters with adaptive task tuning," *IEEE Transactions on Parallel and Distributed Systems*, vol. 28, no. 3, pp. 774–786, 2017.

[10] C.-T. Chen, L.-J. Hung, S.-Y. Hsieh, R. Buyya, and A. Y. Zomaya, "Heterogeneous job allocation scheduler for hadoop mapreduce using dynamic grouping integrated neighboring search," *IEEE Transactions on Cloud Computing*, 2017.

[11] H. Yviquel, L. Cruz, and G. Araujo, "Cluster programming using the openmp accelerator model," *ACM Transactions on Architecture and Code Optimization (TACO)*, vol. 15, no. 3, p. 35, 2018.

[12] A. Kaitoua, H. Hajj, M. A. Saghir, H. Artail, H. Akkary, M. Awad, M. Sharafeddine, and K. Mershad, "Hadoop extensions for distributed computing on reconfigurable active ssd clusters," *ACM Transactions on Architecture and Code Optimization (TACO)*, vol. 11, no. 2, p. 22, 2014.

[13] M. Wasi-ur Rahman, N. S. Islam, X. Lu, and D. K. D. Panda, "A comprehensive study of mapreduce over lustre for intermediate data placement and shuffle strategies on hpc clusters," *IEEE Transactions on Parallel and Distributed Systems*, vol. 28, no. 3, pp. 633–646, 2017.

[14] M. Zhang, K. T. Lam, X. Yao, and C.-L. Wang, "Simpo: A scalable in-memory persistent object framework using nvram for reliable big data computing," *ACM Transactions on Architecture and Code Optimization (TACO)*, vol. 15, no. 1, p. 7, 2018.

[15] R. Chen and H. Chen, "Tiled-mapreduce: Efficient and flexible mapreduce processing on multicore with tiling," *ACM Transactions on Architecture and Code Optimization (TACO)*, vol. 10, no. 1, p. 3, 2013.

[16] M. Zaharia, R. S. Xin, P. Wendell, T. Das, M. Armbrust, A. Dave, X. Meng, J. Rosen, S. Venkataraman, M. J. Franklin, A. Ghodsi, J. Gonzalez, S. Shenker, and I. Stoica, "Apache spark: A unified engine for big data processing," *Commun. ACM*, vol. 59, no. 11, pp. 56–65, Oct. 2016. [Online]. Available: http://doi.acm.org/10.1145/2934664

[17] F. Ahmad, S. T. Chakradhar, A. Raghunathan, and T. Vijaykumar, "Shufflewatcher: Shuffle-aware scheduling in multi-tenant mapreduce clusters." in *USENIX Annual Technical Conference*, 2014, pp. 1–12.

[18] K. Ousterhout, R. Rasti, S. Ratnasamy, S. Shenker, B.-G. Chun, and V. ICSI, "Making sense of performance in data analytics frameworks." in *NSDI*, vol. 15, 2015, pp. 293–307.

[19] B. Fitzpatrick, "Distributed caching with memcached," *Linux J.*, vol. 2004, no. 124, pp. 5–, Aug. 2004. [Online]. Available: http://dl.acm.org/citation.cfm?id=1012889.1012894

[20] D. Ongaro, S. M. Rumble, R. Stutsman, J. Ousterhout, and M. Rosenblum, "Fast crash recovery in ramcloud," in *Proceedings of the Twenty-Third ACM Symposium on Operating Systems Principles*. ACM, 2011, pp. 29–41.

[21] Y. Kwon, M. Balazinska, B. Howe, and J. Rolia, "Skewtune: mitigating skew in mapreduce applications," in *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data*. ACM, 2012, pp. 25–36.

[22] G. Ananthanarayanan, S. Kandula, A. G. Greenberg, I. Stoica, Y. Lu, B. Saha, and E. Harris, "Reining in the outliers in map-reduce clusters using mantri." in *OSDI*, vol. 10, no. 1, 2010, p. 24.

[23] B. Gufler, N. Augsten, A. Reiser, and A. Kemper, "Load balancing in mapreduce based on scalable cardinality estimates," in *Data Engineering (ICDE), 2012 IEEE 28th International Conference on*. IEEE, 2012, pp. 522–533.

[24] Y. Guo, J. Rao, D. Cheng, and X. Zhou, "ishuffle: Improving hadoop performance with shuffle-on-write," *IEEE Transactions on Parallel and Distributed Systems*, vol. 28, no. 6, pp. 1649–1662, 2017.

[25] A. Verma, L. Cherkasova, and R. H. Campbell, "Resource provisioning framework for mapreduce jobs with performance goals," in *ACM/IFIP/USENIX International Conference on Distributed Systems Platforms and Open Distributed Processing*. Springer, 2011, pp. 165–186.

[26] D. P. Williamson and D. B. Shmoys, "The design of approximation algorithms. 2010," *preprint http://www. designofapproxalgs. com*, 2010.

[27] S. Ghemawat, H. Gobioff, and S.-T. Leung, "The google file system," in *ACM SIGOPS operating systems review*, vol. 37, no. 5. ACM, 2003, pp. 29–43.

[28] J. S. Vitter, "Random sampling with a reservoir," *ACM Transactions on Mathematical Software (TOMS)*, vol. 11, no. 1, pp. 37–57, 1985.

[29] G. Ananthanarayanan, A. Ghodsi, A. Wang, D. Borthakur, S. Kandula, S. Shenker, and I. Stoica, "Pacman: Coordinated memory caching for parallel jobs," in *Proceedings of the 9th USENIX conference on Networked Systems Design and Implementation*. USENIX Association, 2012, pp. 20–20.

[30] L. A. Belady, "A study of replacement algorithms for a virtual-storage computer," *IBM Systems journal*, vol. 5, no. 2, pp. 78–101, 1966.

[31] P. Hunt, M. Konar, F. P. Junqueira, and B. Reed, "Zookeeper: Wait-free coordination for internet-scale systems." in *USENIX annual technical conference*, vol. 8, 2010, p. 9.

[32] S. Y. Ko, I. Hoque, B. Cho, and I. Gupta, "On availability of intermediate data in cloud computations." in *HotOS*, 2009.

[33] L. G. Valiant, "A bridging model for parallel computation," *Communications of the ACM*, vol. 33, no. 8, pp. 103–111, 1990.

[34] G. Malewicz, M. H. Austern, A. J. Bik, J. C. Dehnert, I. Horn, N. Leiser, and G. Czajkowski, "Pregel: a system for large-scale graph processing," in *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*. ACM, 2010, pp. 135–146.

[35] A. Verma, L. Cherkasova, and R. H. Campbell, "Aria: automatic resource inference and allocation for mapreduce environments," in *Proceedings of the 8th ACM international conference on Autonomic computing*. ACM, 2011, pp. 235–244.

[36] M. Khan, Y. Jin, M. Li, Y. Xiang, and C. Jiang, "Hadoop performance modeling for job estimation and resource provisioning," *IEEE Transactions on Parallel & Distributed Systems*, no. 2, pp. 441–454, 2016.

[37] H. Herodotou, "Hadoop performance models," *arXiv preprint arXiv:1106.0940*, 2011.

[38] K. Chen, J. Powers, S. Guo, and F. Tian, "Cresp: Towards optimal resource provisioning for mapreduce computing in public clouds," *IEEE Transactions on Parallel and Distributed Systems*, vol. 25, no. 6, pp. 1403–1412, 2014.

[39] F. Farhat, D. Tootaghaj, Y. He, A. Sivasubramaniam, M. Kandemir, and C. Das, "Stochastic modeling and optimization of stragglers," *IEEE Transactions on Cloud Computing*, 2016.

[40] H. Herodotou, H. Lim, G. Luo, N. Borisov, L. Dong, F. B. Cetin, and S. Babu, "Starfish: A self-tuning system for big data analytics." in *Cidr*, vol. 11, no. 2011, 2011, pp. 261–272.

[41] J. Tan, A. Chin, Z. Z. Hu, Y. Hu, S. Meng, X. Meng, and L. Zhang, "Dynmr: Dynamic mapreduce with reducetask interleaving and maptask backfilling," in *Proceedings of the Ninth European Conference on Computer Systems*. ACM, 2014, p. 2.

[42] E. Elnikety, T. Elsayed, and H. E. Ramadan, "ihadoop: asynchronous iterations for mapreduce," in *Cloud Computing Technology and Science (CloudCom), 2011 IEEE Third International Conference on*. IEEE, 2011, pp. 81–90.

[43] M. Zaharia, D. Borthakur, J. Sen Sarma, K. Elmeleegy, S. Shenker, and I. Stoica, "Delay scheduling: a simple technique for achieving locality and fairness in cluster scheduling," in *Proceedings of the 5th European conference on Computer systems*. ACM, 2010, pp. 265–278.

[44] M. Isard, V. Prabhakaran, J. Currey, U. Wieder, K. Talwar, and A. Goldberg, "Quincy: fair scheduling for distributed computing clusters," in *Proceedings of the ACM SIGOPS 22nd symposium on Operating systems principles*. ACM, 2009, pp. 261–276.

[45] Y. Wang, J. Tan, W. Yu, L. Zhang, X. Meng, and X. Li, "Preemptive reducetask scheduling for fair and fast job completion." in *ICAC*, 2013, pp. 279–289.

[46] M. Chowdhury, Y. Zhong, and I. Stoica, "Efficient coflow scheduling with varys," in *ACM SIGCOMM Computer Communication Review*, vol. 44, no. 4. ACM, 2014, pp. 443–454.

[47] M. Chowdhury and I. Stoica, "Efficient coflow scheduling without prior knowledge," in *Proceedings of the 2015 ACM Conference on Special Interest Group on Data Communication*, ser. SIGCOMM '15. New York, NY, USA: ACM, 2015, pp. 393–406. [Online]. Available: http://doi.acm.org/10.1145/2785956.2787480

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