Title

Zhouwang Fu[1] and Zhengwei Qi[1]
[1]*Shanghai Jiao Tong University*

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 network transfer overhead. Due to the dependency constrains, execution of those descendant tasks could be delayed by logy shuffles. To reduce shuffle overhead, we present *SCache*, a plugin system that particularly focuses on shuffle optimization in frameworks defining jobs as *directed acyclic graphs* (DAGs). By extracting and analyzing the job DAGs prior to the actual job execution, SCache can take full advantage of the system memory to accelerate the shuffle process. Meanwhile, it adopts heuristic-MinHeap scheduling to balance the total size of data that will be processed by each descendant task. We have implemented SCache and customized Spark to use it as the external shuffle service and co-scheduler. The performance of SCache is 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 90%.

1 Introduction

2 Motivation

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 Shuffle Characteristics

In large scale data parallel computations, large datasets are partitioned into pieces to fit into the memory of each node since the very beginning of MapReduce[15]. Meanwhile, complicated application procedures are divided into steps. The succeeding steps take the output of the ancestors as the computation input. Shuffle occurs when each successor needs part of data from all ancestors' outputs. It is designed to achieve an all-to-all data blocks transfer among nodes in the cluster. It exists in both MapReduce models and DAG computation models.

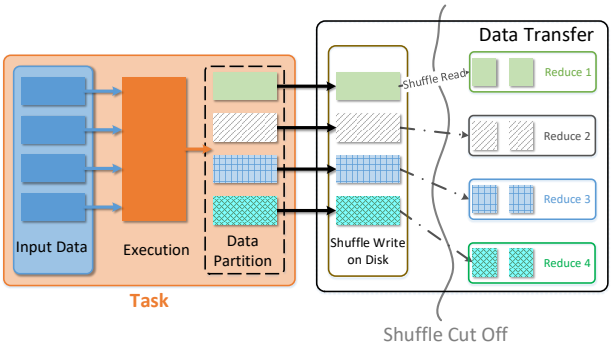


Figure 1: Shuffle Overview

Overview of shuffle process. As shown in Figure 1, shuffle mainly contains two phases itself: *data partition* and *data transfer*. For *data partition*, each map task will partition the result data (key, value pair) into several buckets according to the partition function. The total number of buckets is equal to the number of tasks in the next step. When the map tasks finish, all the shuffle output data will be written into local persistent storage for fault tolerance [15, 32]. *Data transfer* can be further divided into two parts: *shuffle write* and *shuffle read*. *Shuffle write* starts after execution of map tasks and intermediate tasks. Partitioned data will be stored on disk during *shuffle write*. *Shuffle read* starts at the beginning of reduce tasks. These tasks might fetch the data that belong to their corresponding partitions from both remote nodes and local storage.

Impact of shuffle process. Shuffle process 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 intensive [8]. For those shuffle intensive 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, and in shuffle intensive jobs that is up to even 70% [13]. Meanwhile, the completion time of shuffle correlates with the performance of storage, network, and even applications. This variation may bring a huge challenge for operators to find the correct configuration of the DAG framework.

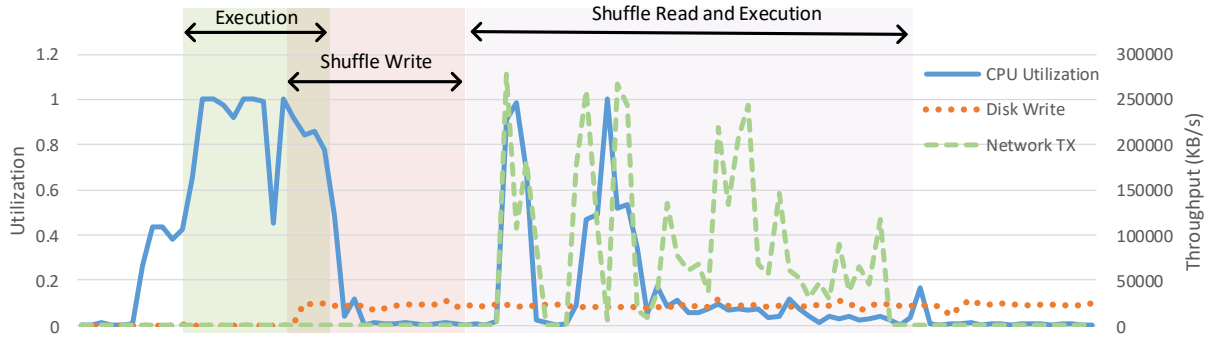


Figure 2: CPU utilization and I/O throughput of a node during a Spark single shuffle application

2.2 Observations

Of course, shuffle is unavoidable in a DAG computing process. But *can we mitigate or even remove the overhead of shuffle?* To find the answers, we run some typical Spark applications in a 5-node Amazon EC2 cluster with `m4.xlarge` instances. We then measure the CPU utilization, I/O throughput and tasks execution information of each node. Take the trace of Spark *GroupByTest* job in Figure 2 as an example. This job has 2 rounds of tasks for each node. We have marked out the execution phase as from the launch time of the first task of this node to the execution finish timestamp of the last one. The *shuffle write* phase is marked from the timestamp of the beginning of the first partitioned data write. The *shuffle read* and *execution* phase is marked from the start of the first reduce launch timestamp. Figure 2 reveals the performance information of two stages that are connected by shuffle. By analyzing the trace combing with Spark, we propose following observations.

2.2.1 Multi-rounds tasks in each stages

Both experience and DAG framework manuals recommend that multi-round execution of each stage will benefit the performance of applications. For example, Hadoop MapReduce Tutorial [2] suggests that *10-100 maps per-node* and *0.95 or 1.75 × no. of nodes × no. of maximum container per node* seem to be the right level of parallelism. Spark Configuration also recommends 2-3 tasks per CPU core in the cluster [4]. We have two rounds of tasks in job of Figure 2 to process data of about 70GB. Figure 2 shows that the second phase of shuffle—*data transfer*—will start until the reduce stage starts. But the shuffle data will become available as soon as the execution of one task is finished. Though in the context of Spark, the reduce task can do computation while fetching data, the uncontrolled network congestion may still hurt the performance. We have observed that, however, if the destination of the shuffle output of each task can be known in priori, the property of multi-rounds can be leveraged to do *data transfer* ahead of reduce stage.

2.2.2 Tight Couple between Shuffle and Computation

Another information we get from the trace is that, the shuffle process shall be decoupled from task execution. In general, CPU and memory are binded as a computing *slot* by the cluster resource scheduler. When a task is scheduled to a slot, it won't release that slot before completion. In Figure 2, the resource of Spark executor will be released at the ending of *shuffle write*. But CPU becomes idle almost as soon as the *execution* is finished. On the other hand, shuffle is I/O intensive. It doesn't involve CPU and application context. If the shuffle can be decoupled from task, the slot can be released after *execution* phase. The early release can benefit other tasks to achieve better overall performance of the DAG framework.

2.2.3 Variance of I/O Performance

When we look into the performance of disk and network in our test case, there is huge variance. Since we use the standard EBS as our backend storage for the EC2 instances, the I/O performance of the disk is poor. At the same time, the bandwidth of each instance is not specified from Amazon. But the utilization in Figure2 refers that the bandwidth is about 300Mbps. In this case, the bottleneck of shuffle is disk, which introduces a significant latency for the application. Vice versa, in some cases, the congestion of network may also become the bottleneck of shuffle [14]. The uncertainty about the I/O performance causes a huge challenge for optimizing the DAG computing in the cluster. For network latency, the most we can do is to mitigate the transfer delay. As for disk write, we believe it's not necessary for today's cluster. Recall that the persistence of shuffle data is used only for reduce fault tolerance, but the *mean time to failure* (MTTF) for a server is counted in the scale of year [24]. The MTTF is exponen-

tial compared with the duration of a shuffle, so we believe the disk write is unnecessary in today's data center.

2.2.4 Relatively Small Size of Shuffle Data

In order to accelerate computation, Spark will put all the input data set for a task into memory. Compared to the input dataset, size of shuffle data is relatively small. We present two typical applications on Spark to compare size of the shuffle data with that of the input data in Figure 3. Although TeraSort [26] is known as a shuffle intensive job, in a 10GB input TeraSort, the shuffle size is less than 3GB. When it's mapped to a 5-node cluster, it only takes about 500MB memory (25% of input size for each node) to cache the shuffle data in memory. The data reported in [25] also shows that the amount of data shuffled is less than the input, by as much as a factor of $5 - 10$. This is another reason that disk should not be involved in the whole shuffle procedure.

Based on these observations, it's straightforward to come up with an optimization that uses memory to store the shuffle data and overlap the I/O operations of shuffle by leveraging *multi-round* property of DAG computing. In order to achieve this optimization, we have to decouple shuffle from task and perform pre-fetch as soon as each output of map task and intermediate task is available. But is this feasible? We try to answer this question in the following sections.

3 Achieve Shuffle Optimization

In this section, we try to achieve shuffle optimization by applying

- Decouple shuffle from task
- Pre-fetch shuffle to reduce node

on the DAG computing framwork. We choose Spark as the representative of DAG computing framwork to implement our optimization.

3.1 Decouple shuffle from task

On the map task side of shuffle, it's used to partition the output of map task according to the pre-defined partitioner. More specifically, shuffle takes a set of key-value pairs as input. And than it calculates the partitioner number of a key-value pait by applying pre-defined the partition function to the key. At last it put the key-value pair into the corresponding partition. The output at last is a set of blocks. Each of them contains the key-value pairs for one partition. For those application context unrelated blocks, they can be easily hijacked in the memory of Spark executor and moved out of JVM space via memory mapping. Meanwhile, we have to prevent the memory spill during the shuffle partition procedure, so that the shuffle data can never touch the disk. The default shuffle spill threshold in Spark is 5GB[3], which is big enough in most scenarios according to Section 2.2.4.

3.2 Pre-schedule with Application Context

When the shuffle output blocks are available in memory, they can be pre-fetched to the remote hosts to hide the network transfer time. But at that time, the reduce tasks taking shuffle as input are still pending. In other word, the remote hosts of those blocks keep unknown until the reduce tasks are scheduled by the DAG framework. In order to break this serialization between map tasks and shuffle, we have to first pre-schedule the task-node mapping ahead of DAG framework scheduler. We explore several pre-scheduling schemes in different scenarios, and evaluate the performance of pre-scheduling and prediction by calculating the improvement of reduce tasks completion time with trace of OpenCloud[5]. We first emulate the scheduling algorithm of Spark to schedule the reduce tasks of one job, and take the bottleneck of the task set as the completion time. Then we remove the shuffle read time as the assumption of shuffle data pre-fetch and emulate under different schemes. The result is shown in 4b. Note that since most of the traces from OpenCloud is shuffle-light workload as shown in Figure 4a. The average shuffle read time is 2.3% of total reduce completion time. So we will only use this trace to evaluate the pre-scheduling.

3.2.1 Random Task-Node Mapping

The simplest way of pre-scheduling is mapping tasks to different nodes evenly. As shown in Figure 4b, Random mapping works well when there is only one round of tasks in cluster. But multi-round in cluster is overwhelming according to Section 2.2.1. The performance of random mapping collapses as the round number grows. After analyzing the trace, we find out that it's caused by data-skew. Reports in these papers[23, 10, 18] also claim that data-skew is commonly exist in data-parallel computing. When we apply a random mapping, it's probable to assign several slow tasks on one node. The collision than slow down the the whole stage, which make the performance even worse than those without shuffle-prefetch. In addition, randomly assigned tasks also ignore the data locality between shuffle map output and shuffle reduce input, which can bring extra network traffic in cluster.

3.2.2 Shuffle Output Prediction

The failure of random mapping was obvious caused by application context (e.g. Shuffle input of each task) un-

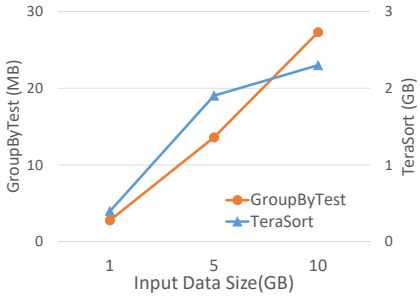
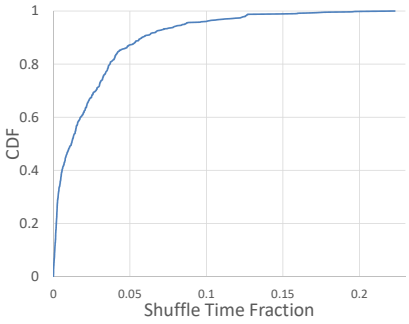
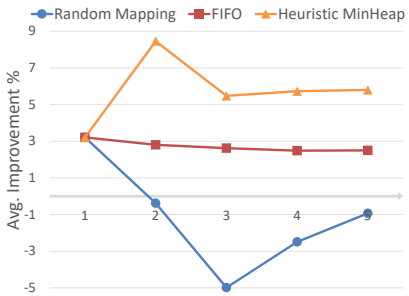


Figure 3: Shuffle Size Comparing with Input Size



(a) Shuffle Time Fraction CDF



(b) Stage Completion Time Improvement

Figure 4: Emulate Result of OpenCloud Trace

awareness, which results in a severe data skew. To avoid the 'bad' schedule results, we have to leverage the application context as assistance. The optimal schedule decision can be made under the awareness of shuffle dependencies number with input size for each task. Unfortunately these data is unavailable when the shuffle-prefetch starts. But the approximate size of each reduce task can be predicted during the initial phase of map tasks with DAG context, so that the scheduling can approaching a more uniform load for each node.

According to the DAG computing process, the shuffle size of each reduce task is decided by input data, map task computation and hash partitioner. And for each map task, it will produce a data block for each reduce tasks, like '1-1' in Figure 5. '1-1' means it's produced by 'Map Task 1' for 'Reduce Task 1'. For Hadoop MapReduce, the shuffle input for each reduce task can be predicted with decent accuracy[12]. They propose a liner regression model based on Verma et al.[28] that the ratio of map output size and input size is invariant given the same job configuration. Several map outputs (marked as Map Output in Figure 5) are picked as observation objects to train the model and than predict the final reduce distribution. But in the more sophisticated DAG computing framework like Spark, this model can't fit. For instance, the reduce stage in Spark has more number of tasks that consume shuffle data instead of Hadoop MapReduce. More importantly, the customized partitioner can bring huge inconsistency between observed map output blocks distribution and the final reduce distribution, as we presented in Figure 6. We use different datasets with different partitioners to find the connection among three factors. We normalize threes sets of data to [0,1] to fit in one figure. In Figure 6a, we use a random input dataset with the Hash Partitioner of Spark[3]. In Figure 6b, we use a skew dataset with the Range Partitioner of Spark[3]. We randomly pick one observation map output and plot. As we can see, in hash partitioner, the distribution of each map(blue area) is close to the final reduce distribution(orange boxes). The prediction results also turns out well fitted. As we apply linear regression model to predict the final reduce distribution of Range Partitioner. The prediction is severely effected by the skew observed map output distribution.

To avoid this inconsistency in some cases, we introduce another methodology, weighted reservoir sampling, to mitigate this inconsistency. The classic reservoir sampling is designed for randomly choosing k samples from n items, where n is either a very large or unknown number[29]. For each partition of data that produce shuffle output, we use reservoir sampling to randomly pick $s \times p$ of samples, where p is the number of reduce tasks and s is a tunable number. The number of input data partition and reduce tasks can be easily obtained when the from the DAG information. In Figure 6b, we set $s = 3$. After that, the map function is called locally to process the sampled data. As the 'Sampling' part shown in Figure 5, the final sampling map outputs are collected with the size of each partition of input data which is used as weight for each set of sample. For each reduce, the predicted size $reduceSize_i$

$$reduceSize_i = \sum_{j=0}^{m} partitionSize_j \times \frac{sample_i}{s \times p} \quad (1)$$

$$(m = \text{partition number of input data})$$

As we can see in Figure 6b, the prediction result is much better even in a very skew scenario. The variance of the normalized data of sampling prediction is because the standard deviation of the prediction result is relatively small comparing to the average prediction size, which is 0.0015 in this example. Figure 6c further prove that the sampling prediction can provide precise results even in the absolute partition size of reduce tasks. On the opposite, the result of linear regression comes out with huge relative error com-

paring with the fact of partition size of reduce tasks.

Algorithm 1 Heuristic MinHeap Scheduling for Single Shuffle

```
1:  procedure SCHEDULE(m, h, p_reduces)
2:      R ← sort p_reduces by size
3:      M ← mapping of host id in h to reduce id and size
4:      rid ← len(R)                    ▷ Current scheduled reduce id
5:      while rid ≥ 0 do                ▷ Schedule redues by MinHeap
6:          Update M [0] .size
7:          Assign R (rid) to M [0]
8:          sift_down(M [0])
9:                          ▷ Use min-heap according to size in M
10:         rid ← rid − 1
11:     max ← maximum size in M
12:     rid ← len(R)
13:     while rid ≥ 0 do                ▷ Heuristic swap by locality
14:         prob ← max composition portion of rid
15:         nor ← (prob − 1/m) / (1 − 1/m) /10
16:           ▷ Use nor to limit the performance degradation in
    tasks swap
17:         t_h ← host that produces prob data of rid
18:         c_h ← current assigned host by MinHeap
19:         if t_h == c_h then
20:             Seal the assignment of rid in M
21:         else
22:             swap_tasks(rid, c_h, t_h, max, nor)
23:         rid ← rid − 1
        return M
24: procedure SWAP_TASKS(rid, c_h, t_h, max, nor)
25:     num ← number of reduces
26:     selected from t_h that total_size won't
27:     make both c_h and t_h exceed (1 + nor) ∗ max
28:     after swapping
29:     if num == 0 then
30:         return
31:     else
32:         # Swap nums of reduces with rid between c_h and
    t_h
33:         # Update size of t_h and c_h
```

But the sampling prediction may introduce a extra overhead in DAG computing process, we will evaluate the overhead in the Section 5. Though in most cases, the overhead is negligible, but we won't use sampling for every reduce prediction. Combing with the DAG context, the sampling prediction will be triggered only when the range partitioner or customized partitioner occurs.

3.2.3 Heuristic MinHeap Scheduling of Single Shuffle

For each predicted reduce size, a percentage array of total data composition among each map output is calculated. The highest percentage and it's corresponding host should be the best choice the dimension of locality. In order to achieve the uniform load on each node while reducing the network traffic and shuffle transmission time. With this composition array and the predicted size of reduce, we present a heuristic MinHeap as the scheduling algorithm for single shuffle.

This algorithm can be divided into two round of scheduling. For input of $schedule$, m is the partition number of input data, h is the array of nodes ID in cluster and $p\_reduces$ is the predicted reduce matrix. Each row in $p\_reduces$ contains r_id as reduce partition ID, $size$ as predicted size of this partition, $prob$ as the maximum composition portion of reduce data, and $host$ as the node ID that produce the maximum portion of reduce data. As for M, it's a matrix consists $hostid$, $size$(total size of reduce data on this node) and an array of reduce id.

In the first round (i.e. The first while in Algorithm 1), the reduces are first sorted by size. And then, they are assigned to hosts in the descending order of size . For hosts, we use a min-heap to maintain the hosts array according to the scheduled size on each hosts. In other word, the heavy tasks can be distributed evenly in the cluster. After the scheduling, the completion time of reduce stage is close to the optimal. may need to add math prove between this and optimal. In the second round, the task-host mapping will be adjusted according to the locality. The closer $prob$ is to $1/m$, the more evenly this reduce is distributed in cluster. For a task which contains at most $prob$ data from $host$, the normalized probability nor is calculated as a bound of performance degradation. This normalization can ensure that the more performance can be traded when the locality level increases. But the degradation of performance will not exceed 10% since the maximum value of nor is 0.1 (in extreme skew scenarios). If the assigned host(c_h in algorithm 1) is not equal to the $host$ (t_h in algorithm 1), than it has the nor probability to trigger a tasks swap between two hosts. To maintain the scheduling mapping of first round, the tasks will only be swapped if the target hosts owns a set of tasks that has similar size totally. We use the OpenCloud[5] trace to evaluate Heuristic MinHeap. Without swapping, the Heuristic MinHeap can achieve a better performance improvement (average 5.7%) than the default Spark FIFO scheduling algorithm (average 2.7%). In the case of extreme skew scenario, such as Figure 6b, Heuristic MinHeap trades about 0.05% percent of stage completion time for 99% reduction of shuffle data transmission through network by heuristicly swapping tasks.

3.2.4 Cope with Multiple Shuffles

Unlike Hadoop MapReduce, multiple shuffles commonly exist in DAG computing. The techniques mention in Section 3.2.2 can only predict the ongoing shuffle. For those pending shuffle, it's impossible to predict their size because of lacking either observed map outputs or sampling data. Let all tasks of all shuffle to be scheduled by DAG framework simultaneously can relieve the

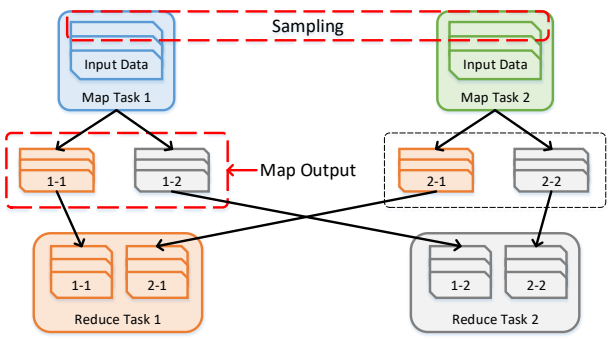


Figure 5: Shuffle Data Prediction

dilemma. But huge modification in DAG framework should be made by doing this. For example, Spark only supports one stage running at the same time for one application. To avoid this redundant workload, we provide the accumulating scheduling to cope with multiple shuffles.

Algorithm 2 Accumulate Scheduling for Multi-Shuffles

procedure MSCHEDULE($m, h, p\_reduces, shuffles$)
  ▷ $shuffles$ is the previous array of reduce partition ID, host ID and size
  for all r_id in $p\_reduces$ **do**
    $p\_reduce\,[r\_id]\,.size \leftarrow p\_reduce\,[r\_id]\,.size + shuffles\,[r\_id]\,.size$
    if $shuffles\,[r\_id]\,.size \geq p\_reduce\,[r\_id]\,.size * p\_reduce\,[r\_id]\,.prob$ **then**
      Update $prob$ set $host$ to $shuffles\,[r\_id]\,.host$
  $M \leftarrow$ schedule$(m, h, p_reduecs)$
  for all $host$ in M **do**
    for all r_id in $host$ **do**
      if $host \neq shuffles\,[r\_id]\,.host$ **then**
        Re-shuffle data to $host$
        $shuffles\,[r\_id]\,.host \leftarrow host$
  return M

When a new shuffle start, the $mSchedule$ is called to schedule the new one with previous $shuffles$. The size of reduce on each node of previous scheduled $shuffles$ are counted. Combined the with the predicted reduces size of the new start shuffle in $p\_reduces$, the $size$ of each reduce and its corresponding $porb$ and $host$ are updated. Then the $schedule$ is called to perform the shuffle scheduling. When the new host-reduce mapping is available, for each reduce task, if the new scheduled host in M is not equle to the origin one, the re-shuffle will be triggered to transfer data to new scheduled host for further computing. This re-shuffle can be rare since the previous shuffled data in one reduce contributes a huge composition while doing the accumulate updating. It means in the schedule phase, the $swap - task$ can help revise the scheduling to match the previous mapping in $shuffles$ as much as possible while maintaining the good performance.

4 Implementation

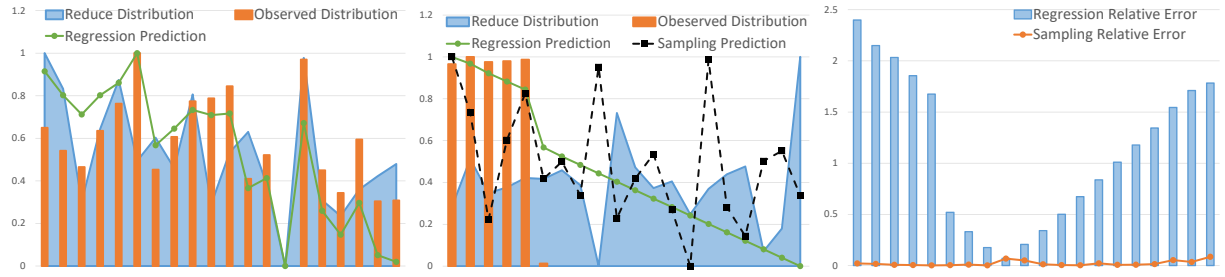
This section overviews the implementation of SCache – a distributed in-memory storage system that caches shuffle data of DAG framework. Here we use Spark as example of DAG framework to illustrate working process of shuffle optimization. We will first present system architecture in Subsection 4.1 while the following two subsections focus on the two constraints on memory management.

4.1 System Architecture

SCache consists mainly two components: A distributed in-memory shuffle data storage system and the daemon inside Spark. As shown in Figure 7, for the in-memory storage system, SCache employs the legacy master-slaves architecture like GFS[17]. The master node of SCache coordinates the shuffle blocks globally with application context from Spark. The coordination provides two guarantees: (a)store data in memory before tasks start and (b)schedule data on-off memory with all-or-nothing property and context-aware-priority constraints to benefit all jobs.

When a Spark job starts, the DAG will be first generated by Spark DAGScheduler[3]. The process starts on the last result stage, and recursively find the dependent stages until the beginning of the DAG. While going forward to the beginning, the DAG computing pipeline will be cut off if a RDD in the stage has one or more shuffle dependencies. These shuffle dependencies among RDDs will then be submitted through RPC call to SCache master by a daemon process in Spark driver. For each shuffle dependency, the shuffle ID(an integer generated by Spark), the type of partitioner, the number of map tasks and the number of reduce tasks are included in the RPC call. The SCache master will store the metadata of one RPC call as a set of multiple shuffles scheduling unit. If there is a specialized partitioner, such as Range Partitioner or a customized partitioiner, in the shuffle dependencies, the daemon will insert a sampling program in the host RDD that generates shuffle output using specialized partitioner. The sampling application will be scheduled ahead of that host RDD. We will illustrate the sampling procedure in the Section 4.1.1.

For the hash partitioner, when the map tasks in a stage finish computing on the work nodes, the SCache Worker Daemon process will hijack the shuffle map output in the JVM of each executor of Spark (see Figure 7). Then the data will be transferred into the reserved memory of SCache Worker on each node through memory copy. In the same time, the Spark tasks will end after the memory copy without the disk shuffle output writing, which leads to a reduction of the whole tasks completion time. When the shuffle map output block of a task is stored in



(a) Linear Regression Prediction of Hash Partitioner

(b) Linear Regression and Sampling Prediction of Range Partitioner

(c) Prediction Relative Error of Range Partitioner

Figure 6: Reduction Distribution Prediction

the reserved memory, the SCache worker will then notify the master of the block belonging information with the reduce size distribution in this block (see Map Output in Figure 5). When the collected map output data reach the observed ratio of map output, the SCache master will then run the scheduling algorithm 2 (for multiple shuffle dependencies) and 1 (for single shuffle dependency) to get the reduce tasks – nodes mapping. When the scheduling resulted is made, the master will then notify each worker to prepare the memory space for the shuffle data for reduce tasks. The pre-fetch of shuffle data as soon as each worker receives the scheduling results. More specifically, each worker will check the ID of reduce tasks that will be scheduled on itself in the future. When a map task finishes, each node will receive a broadcast message. It will then trigger the pre-fetch process to start fetching shuffle data from the memory of remote SCache worker that just has the map task finished. After all blocks of shuffle map output is transferred, the SCache worker will flush these blocks to disks for saving memory space and maintaining fault tolerance of Spark.

Before the reduce stage starts, Spark DAG Scheduler will first generate a task set for this stage with different locality levels – ***PROCESS_LOCAL, NODE_LOCAL, NO_PREF, RACK_LOCAL, ANY***. The locality levels are set by finding a cached location of a RDD. For the RDDs that have narrow dependency(opposite of shuffle dependency), the prefered location can also be the same as the dependent RDDs. For those RDDs that have shuffle dependecies, the locality will be set as ***NO_PREF*** by default. To enforce SCache pre-allocated the reduce tasks, we insert some lines of codes in Spark DAG Scheduler to consult SCache Master to get the preferred node for each tasks. By doing this, the tasks with shuffle dependencies can be set as ***NODE_LOCAL***. Then the Task Scheduler will schedule tasks according to the task – node mapping from SCache.

When the scheduled reduce tasks start, the shuffle input data is requested. The SCache worker will then pass the requested data through memory copy from the reserved

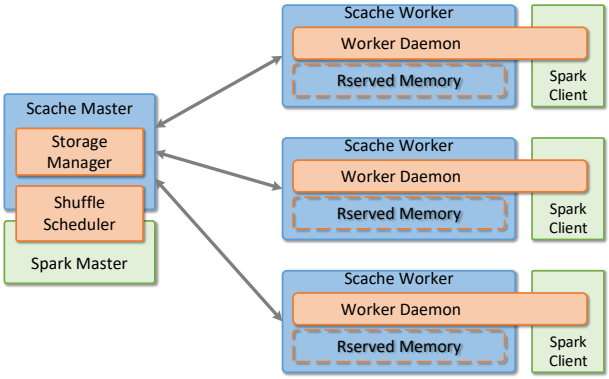


Figure 7: SCache Architecture

memory to Spark executor JVM memory. As soon as the memory copy finishes, the data in reserved memory will then be flushed to the disk.

4.1.1 Reservior Sampling

If the submitted shuffle dependencies contain a Range Partitioner or a customized partitioner, the SCache master will send a sampling request to the daemon process in Spark driver. The daemon process will then submit a job on Spark for the current RDD. This sampling job will use a reservoir sampling algorithm[29] on each partition of RDD since the items size of each partition is unknown before sampling. For the sample number, we set the size equals to $3 \times number\ of\ partitions$ for balancing overhead and accuracy (it can be tuned by configuration). The sampling job will then perform a local shuffle with the selected items and partitioner (see Figure 8). At the same time, the size of items is counted as the weight of each partition.These sampling data will be aggregated by $reduce\ ID$on SCache master. The size for each reduce partition can be easily computed by equation 1. After the prediction, master will call algorithm 2 and 1 to do the scheduling.

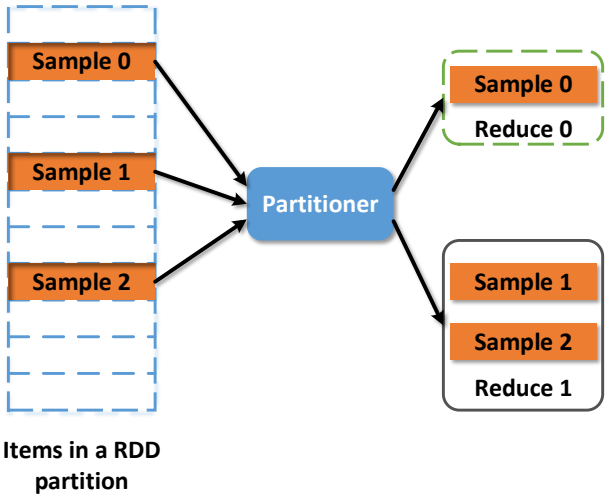


Figure 8: Reservoir Sampling of One Partition

4.2 Memory Management

As mentioned in section 2.2.4, the shuffle size is small enough that can be easily fit in memory. In order to minimize the reserved memory of SCache worker on each node or configure the wrong size by user, the probability of memory exceeded is still exist, especially for multiple existing applications scenarios. When the cached data meet the limitation of reserved memory, SCache flushes some of them to the disk temporarily. And re-fetch them as soon as some cached shuffle blocks is consumed by tasks. To achieve maximum improvement in overall, SCache leverages two constraints to manage the in-memory data – all-or-nothing and context-aware-priority property.

4.2.1 All-or-Nothing Property

Achieving memory cached shuffle data for a reduce task will shorten the task execution time. But this acceleration of single task doesn't speed up the whole stage. Base on the observation that in most cases one single stage contains multi-rounds of tasks from section 2.2.1, the shuffle cache should at least benefit all tasks in one round. If one of the task misses a memory cache and exceeds the original bottleneck of this round, that task will become the new bottleneck of that round and can further slow down the whole stage. PACMan[9] has proved that for multi-round stage/job, the completion times improves in steps when $n \times number\ of\ tasks\ in\ one\ round$ tasks have data cached in local memory. Therefore, the memory cache of shuffle data need to match at least every round of tasks in a stage. We refer to this as the all-or-noting property.

According to all-or-nothing property, SCache master leverages the scheduled results to determine the bound of each round of tasks, and then use this as the minimum unit of storage to manage the reserved memory globally. That is, there is one or more storage units for a shuffle schedule unit add figure. For those incomplete unit, SCache will mark them as the lowest priority. Following the all-or-noting constraint can maximum the improvement in stage completion time by using reserved memory efficiently.

4.2.2 Context-Aware-Priority Property

When the size of cached shuffle data exceeds the reserved memory, SCache should decide which of these should be flushed to disk according to the priorities of each storage unit. SCache master first searches if there is an incomplete unit and flush all blocks belonging to the unit to disk cluster-widely.

But what if all the units are completed in the cluster? Traditional cache replacement schemes, such as MIN[11], that only maximize cache hit ratio do not consider the application context in DAG computing thus will easily violate all-or-nothing constrain. In addition, since the cached shuffle blocks will be only read exactly once (without failure), the hit ratio is actually meaningless in this scenario. To decide the priorities among units, SCache makes decision in two dimensions – *inter shuffle units* and *intra shuffle unit*.

- Inter shuffle units: SCache master follows the scheduling scheme of the task scheduling schemes of Spark. For a FAIR scheduler, Spark will try to balance the resource of among task sets, which leads to a higher scheduled probability for those has more remaining tasks. The more remaining tasks a stage has, the more storage units exist in the corresponding shuffle unit. Based on this observation, SCache sets priorities from high to low to each shuffle units in descending order of storage units. For a FIFO scheduler, Spark will schedule the task set that is submitted first. So SCache can set the priorities according to the submit time of each shuffle unit and evict the recent ones.
- Intra shuffle unit: When a shuffle unit has been marked as the lowest priority, SCache should decide the order of eviciton among storage units in it. Refer to the task scheduling inside a task set of Spark, the tasks with smaller ID will be scheduled at first under one locality level. Recall that SCache sets all reduce tasks to ***NODE_LOCAL***, it can easily select the storage unit with larger tasks ID and flush them to disk.

5 Evaluation

In this section, we present the evaluation result of Spark with SCache comparing with the original Spark. We first

run simple DAG computing jobs with two stages to analyze the impact of shuffle pre-fetch in the Spark cluster. The shuffle dependency between two stages contains one shuffle and two shuffles respectively. In order to prove the performance gain of SCache with a real production workload, we run a benchmark named Spark Terasort[6] and TPC-DS[7] and evaluate the improvement of SCache for each stage and the overall performance. At last, we prsent the overhead of sampling. Because a complex Spark application consists of multiple stages. The completion time of each stage varies under different input data and configurations, as well as different number of stages. This uncertainty leads to the dilemma that dramatic fluctuation in overall performance comparing. To present a straightforward illustration, we limit the scope of most evalutions in single stages.

5.1 Setup

We run our experiments on a 50 m4.xlarge nodes cluster on Amazon EC2[1]. Each node has 16GB memory and 4 CPUs. The network bandwidth is not specifically provided by Amazon. Our evaluation reveals the bandwidth is about 300 Mbps(see Figure 2).

5.2 Simple DAG Analysis

5.2.1 Differential Runtime Hardware Utilization

We first run the same single shuffle test (GroupByTest from Spark example[3]) as we mentioned in Figure 2. As shown in Figure, we can observe a huge overlap between CPU, disk and network. By running Spark with SCache, the overall utilization of the cluster stays in a high level. The decouple of shuffle write from map tasks free the CPU earlier, which leads to a faster task computation. The shuffle pre-fetch starts the shuffle data transfer in the early stage of map phase shift the network transfer completion time, so that the computaion of reduce can start immediately afther scheduled. And this is the main performance gain we achieved on the scope of hardware utilization by SCache.

5.2.2 Performace Gain in Both Stages

5.3 Performance Gain in Production Workload

5.4 Overhead of Sampling

6 Related Work

We summarize the shuffle optimization scheduling schemes in this Section. Basically, we categorize related works in two parts, pre-scheduling and delay scheduling.

Pre-scheduling: Starfish[19] is a self-tuning system in Hadoop. The basic idea is to get sampled data statics for tuning system parameters (e.g. slowstart, map and reduce slot ratio, etc). However, these parameters cannot be changed once the jobs begin. DynMR[27] dynamically starts reduce tasks in late map stage when there is enough data to be fetched. Thus it reduces the time for reducer to wait for mapper producing outputs. Those two works still left the explicit I/O time wait in both map and reduce phases. iShuffle[12] decouples shuffle from reducers and designs a centralized shuffle controller. The goal is also to find the right time, but it can neither handle multiple shuffles multiple nor schedule multiple rounds of reduce tasks. iHadoop[16] aggressively pre-schedules tasks in multiple successive stages, in order to start fetching data from previous stage earlier. 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 reduce tasks without consuming new task slots, whereas all these schemes do.

Delay-scheduling: Delay Scheduling[31] delays tasks assignment to get better data locality, which can reduce the network traffic. ShuffleWatcher[8] delays shuffle fetching when network is saturated. At the same time, it achieves better data locality. Both Quincy[22] and Fair Scheduling[30] can reduce shuffle data by optimizing data locality of map tasks.Even though these kind of schemes can achieve higher data locality, they cannot breach the shuffle cut off between map and reduce stages, whereas SCache does.

6.1 Limitation and Future Work

SCache aims to breach the shuffle cut off between DAG computing stages. And the evaluation results show a promising improvement. But we realize some limitations of SCache.

Fault tolerence of SCache: When a failure happened on the SCache master, the whole system will stop working. To prevent the machine failure leading to inconsistency SCache, the master node will log the meta data of shuffle register and scheduling on the disk. Master can reads logs during recovery. Since we remove the shuffle transfer from the critical path of DAG computing, the disk log will not introduce extra overhead to the DAG frameworks. Note that the master can be implemented with Apache ZooKeeper[21] to provide constantly service to DAG framework. If a failure happens on a worker, the optimization of tasks on that node will fail. It also violates the constraints of all-or-nothing, which means the gain of shuffle data cache maybe negligible. A promising way to solve the failure on worker is to reschedule reduce tasks and retransmit the data. Another solution is selecting some backup nodes to store repcliations of shuf-

fle data during scheduling to prevent the worker failure. We believe combing the high speed of network and memory is a better choice for fault tolerance. Since the mean time to failure(MTTF) for a server is counted in the scale of year[24]. As for now, fault tolerance is not a crucial goal of SCache, we leave it to the future work.

Scheduling with different frameworks: A cluster for data parallel computing always contains more than one frameworks. Setting priority among jobs submitted from different framework is challenging and complex. However, combining the resource management facilities in data center such as Mesos[20] may be a good direction.

7 Conclusion

In this paper, we present SCache, a shuffle optimization scheme for DAG computing framework. SCache decouples the shuffle from computing pipeline and leverages shuffle data pre-fetch to mitigate I/O overhead of the whole system. By scheduling tasks with application context, SCache bridges the gap among computing stages. Our implementation on Spark and evaluations show that SCache can provide a promising speedup to the DAG framework. We believe that SCache is a simple and efficient plugin system to enhance the performance of most DAG computing frameworks.

References

[1] Amazon ec2. `https://aws.amazon.com/ec2/`.

[2] Apache hadoop tutorial. `http://hadoop.apache.org/docs/current/hadoop-mapreduce-client/hadoop-mapreduce-client-core/MapReduceTutorial.html`.

[3] Apache spark 1.6 source. `https://github.com/apache/spark/tree/branch-1.6`.

[4] Apache spark 1.6.2 configuration. `http://spark.apache.org/docs/1.6.2/configuration.html`.

[5] Opencloud hadoop cluster trace. `http://ftp.pdl.cmu.edu/pub/datasets/hla/dataset.html`.

[6] Spark terasort. `https://github.com/ehiggs/spark-terasort`.

[7] Tpc benchmark ds (tpc-ds): The benchmark standard for decision support solutions including big data. `http://www.tpc.org/tpcds/`.

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

[9] 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*, pages 20–20. USENIX Association, 2012.

[10] 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*, volume 10, page 24, 2010.

[11] L. A. Belady. A study of replacement algorithms for a virtual-storage computer. *IBM Systems journal*, 5(2):78–101, 1966.

[12] D. Cheng, J. Rao, Y. Guo, and X. Zhou. Improving mapreduce performance in heterogeneous environments with adaptive task tuning. In *Proceedings of the 15th International Middleware Conference*, pages 97–108. ACM, 2014.

[13] 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*, volume 41, pages 98–109. ACM, 2011.

[14] M. Chowdhury, Y. Zhong, and I. Stoica. Efficient coflow scheduling with varys. In *ACM SIGCOMM Computer Communication Review*, volume 44, pages 443–454. ACM, 2014.

[15] J. Dean and S. Ghemawat. Mapreduce: simplified data processing on large clusters. *Communications of the ACM*, 51(1):107–113, 2008.

[16] 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*, pages 81–90. IEEE, 2011.

[17] S. Ghemawat, H. Gobioff, and S.-T. Leung. The google file system. In *ACM SIGOPS operating systems review*, volume 37, pages 29–43. ACM, 2003.

[18] 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*, pages 522–533. IEEE, 2012.

[19] 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*, volume 11, pages 261–272, 2011.

[20] B. Hindman, A. Konwinski, M. Zaharia, A. Ghodsi, A. D. Joseph, R. H. Katz, S. Shenker, and I. Stoica. Mesos: A platform for fine-grained resource sharing in the data center. In *NSDI*, volume 11, pages 22–22, 2011.

[21] P. Hunt, M. Konar, F. P. Junqueira, and B. Reed. Zookeeper: Wait-free coordination for internet-scale systems. In *USENIX annual technical conference*, volume 8, page 9, 2010.

[22] 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*, pages 261–276. ACM, 2009.

[23] 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*, pages 25–36. ACM, 2012.

[24] 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*, pages 1–15. ACM, 2014.

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

[26] O. OMalley. Terabyte sort on apache hadoop. *Yahoo, available online at: http://sortbenchmark. org/Yahoo-Hadoop. pdf,(May)*, pages 1–3, 2008.

[27] 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*, page 2. ACM, 2014.

[28] 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*, pages 165–186. Springer, 2011.

[29] J. S. Vitter. Random sampling with a reservoir. *ACM Transactions on Mathematical Software (TOMS)*, 11(1):37–57, 1985.

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

[31] 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*, pages 265–278. ACM, 2010.

[32] 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*, pages 2–2. USENIX Association, 2012.