

Title

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Abstract

Shuffle is the term used to describe the cross-network read and aggregation of partitioned ancestor data before invoking reduce operation. As DAG computing frameworks keep evolving, calculation and scheduling of each task are well optimized. However shuffle cuts off the data processing pipeline, introduce significant latency to successors. To remove shuffle overhead, we present XXX, a plugin system to decouple shuffle from DAG computing framework. XXX captures shuffle data in the memory and uses heuristic-MinHeap scheduling to balance data blocks to eliminate the explicit barrier. We implement XXX and change Spark to use XXX as external shuffle service and scheduler. We evaluate XXX performance both on simulation and 50-machine Amazon EC2 cluster. Results show that, by incorporating XXX in Spark, the shuffle overhead can be reduced XXX.

1 Introduction

2 Motivation

In this section, we first study the shuffle pattern (2.1). Then we show the observations of the opportunities to optimize shuffle in 2.2

2.1 Characteristic of Shuffle

In large scale data parallel computing, enormous datasets are partitioned into pieces to fit the memory of each node since the very beginning of MapReduce[11]. Meanwhile, complicated application procedures are divided into steps. The successor steps take the output of ancestors as input to do the computation. Shuffle occurs when each successor needs part of data from all ancestors' output. In order to provide a clear illustration, we define those computing each partition of data in one step as task. For tasks that generate shuffle output, we call them map task. For tasks that consume shuffle output, we call them reduce tasks. Note that one task may have both shuffle data generation and consumption in modern DAG framework. These tasks contain characteristics of both map task and reduce

task. But these tasks won't change the behavior of shuffle. To avoid ambiguity, in the following paper, we will only use term of map task to represent those who produce shuffle output, and reduce task to represent those who consume shuffle output.

Shuffle is designed to achieve an all-to-all data blocks transfer among nodes in cluster. It exists in both MapReduce models and DAG computation models.

The overview process of shuffle is presented 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 buckets number equals 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 [11, 20]. **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 will fetch the data that belongs to their corresponding partitions from both remote nodes and local storage.

In short, shuffle is loosely coupled with application context and it's I/O intensive.

Since intensive I/O operation will be triggered during a shuffle, this can introduce a significant latency to the application. Reports show that, 60% of MapReduce jobs at Yahoo and 20% at Facebook are shuffle intensive workloads[6]. For those shuffle intensive jobs, the shuffle latency may even dominate Job Completion Time. For instance, a MapReduce trace analysis from Facebook shows that shuffle accounts for 33% JCT on average, up to 70% in shuffle intensive jobs[9]. Meanwhile, the completion time of shuffle correlates with the performance of storage devices, network and even applications. This variation may bring a huge challenge for operators to find the correct configuration of the DAG framework.

2.2 Observations

Of course, shuffle is unavoidable in a DAG computing process. But *can we mitigate or even remove the overhead*

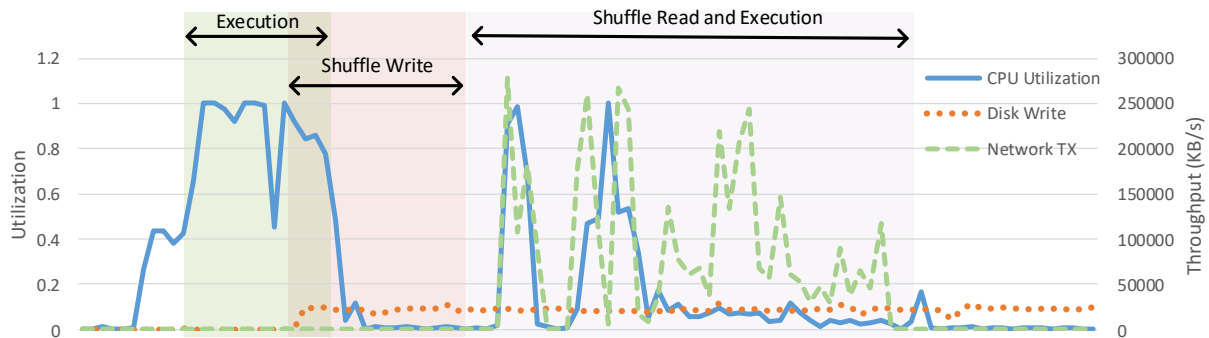


Figure 2: CPU utilization and I/O throughput of a node during a Spark single shuffle application

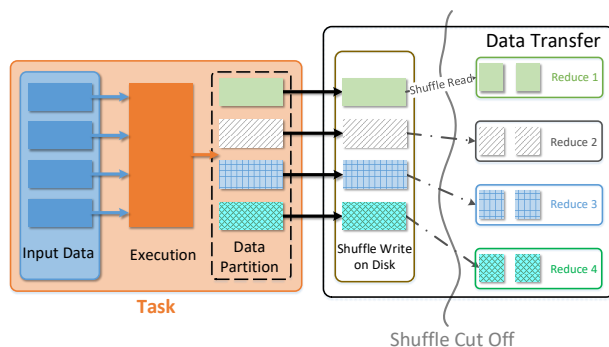


Figure 1: Shuffle Overview

of shuffle? To find the answers, we run some representative applications on a Spark in a 5 m4.xlarge Amazon EC2 cluster. We then capture and plot the CPU utilization, I/O throughput and tasks execution information on each node. Take the trace in Figure 2 as an example, which is captured during one Spark GroupByTest job. This job has 2 rounds of tasks for each node. We mark the 'Execution' phase in the figure from the launch time of the first task on 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 contains data including two stages connected by one shuffle. By analyzing the trace combining with Spark, we propose following observations.

2.2.1 Multi-rounds tasks in each stages

Both experience and DAG framework manuals recommend that multi-rounds execution of each stage will benefit the performance of whole application. For example, Hadoop MapReduce Tutorial [2] suggests that $10-100$ maps per node and 0.95 or $1.75 \times \text{no. of nodes} \times \text{no. of maximum container per node}$ 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 about 70GB data. 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. However, if the destination of the shuffle output of each task is aware, the property of multi-round 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 shuffle should be decoupled from task which is an execution unit in both Spark and Hadoop MapReduce. In general, CPU and memory are bound as a schedule slot in DAG resource scheduler. When a task is scheduled to a slot, it won't release until it reaches the end of task. 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 job. 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 I/O performance varies

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 disk is poor. At the same time, the exclusive bandwidth of each instance is 750 Mbps[1]. 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[10]. The un-

certainty of the I/O performance cause 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 mean time to failure(MTTF) for a server is counted in the scale of year[15]. In addition, we believe combining the high speed of network and memory is a better choice for fault tolerance. We will present more details in Section 4.

2.2.4 Shuffle size is small

In order to accelerate computation, Spark will put all the input data set for a task into memory. Comparing to the input dataset, size of shuffle data is relatively small. We present to typical application on Spark to show the relationship between shuffle data comparing with the input dataset in Figure 3. Although TeraSort[16] 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 nodes cluster, it only takes about 500MB memory (5% of input size for each node) to cache the shuffle data in memory. The data reported in [17] also shows that the amount of data shuffled is less than input data, 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 a optimization to use memory to store the shuffle data and overlap the I/O operations of shuffle by leveraging multi-rounds 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 framework. We choose Spark as the representative of DAG computing framework 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 then it calculates the partitioner number of a key-value pair 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[14, 7, 13] 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 whole stage, which make the performance even worse than those without shuffle-prefetch. In addi-

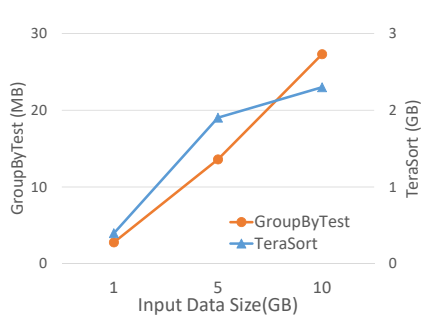
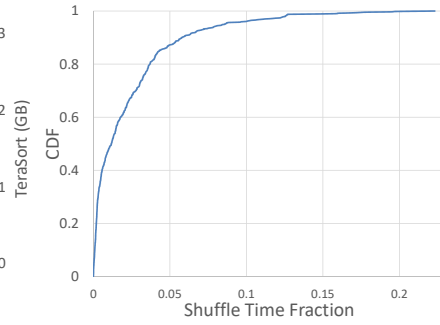
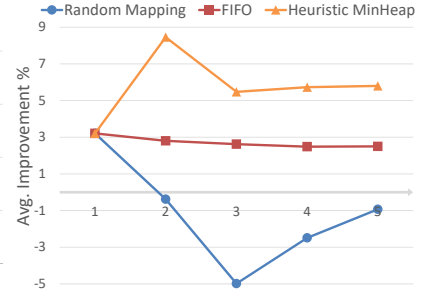


Figure 3: Shuffle Size Comparing with Input Size



(a) Shuffle Time Fraction CDF



(b) Stage Completion Time Improvement

Figure 4: Emulate Result of OpenCloud Trace

tion, 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) unawareness, which results in a heavier 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 dependency number with input size for each task. unfortunately these data is unavaliable when the pre-fetch starts. But the approximate size of each reduce task can be predicted using the prophase map output data 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[8]. They propose a liner regression model based on Verma et al.[18] 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 dif-

ferent 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 chossing k samples from n items, where n is either a very large or unknown number[19]. 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 shoven 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 = 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 vari-

ance 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 comparing 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:    $R \leftarrow$  sort  $p\_reduces$  by size
3:    $M \leftarrow$  mapping of host id in  $h$  to reduce id and size
4:    $rid \leftarrow \text{len}(R)$   $\triangleright$  Current scheduled reduce id
5:   while  $rid \geq 0$  do  $\triangleright$  Schedule reduces by MinHeap
6:     Update  $M[0].size$ 
7:     Assign  $rid$  to  $M[0]$ 
8:     sift_down( $M[0]$ )
9:      $\triangleright$  Use min-heap according to size in  $M$ 
10:     $rid \leftarrow rid - 1$ 
11:     $max \leftarrow$  maximum size in  $M$ 
12:     $rid \leftarrow \text{len}(R)$ 
13:    while  $rid \geq 0$  do  $\triangleright$  Heuristic swap by locality
14:       $prob \leftarrow$  max composition portion of  $rid$ 
15:       $nor \leftarrow (prob - 1/m) / (1 - 1/m) / 10$ 
16:       $\triangleright$  Use  $nor$  to limit the performance degradation in
      tasks swap
17:       $t\_h \leftarrow$  host that produces  $prob$  data of  $rid$ 
18:       $c\_h \leftarrow$  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:       $rid \leftarrow rid - 1$ 
24:    return  $M$ 
25: procedure SWAP_TASKS( $rid, c\_h, t\_h, max, nor$ )
26:    $num \leftarrow$  number of reduces
27:   selected from  $t\_h$  that  $total\_size$  won't
28:   make both  $c\_h$  and  $t\_h$  exceed  $(1 + nor) * max$ 
29:   after swapping
30:   if  $num == 0$  then
31:     return
32:   else
33:     # Swap  $num$ s of reduces with  $rid$  between  $c\_h$  and
      $t\_h$ 
     # 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. Combining 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 its 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 heuristically swapping tasks.

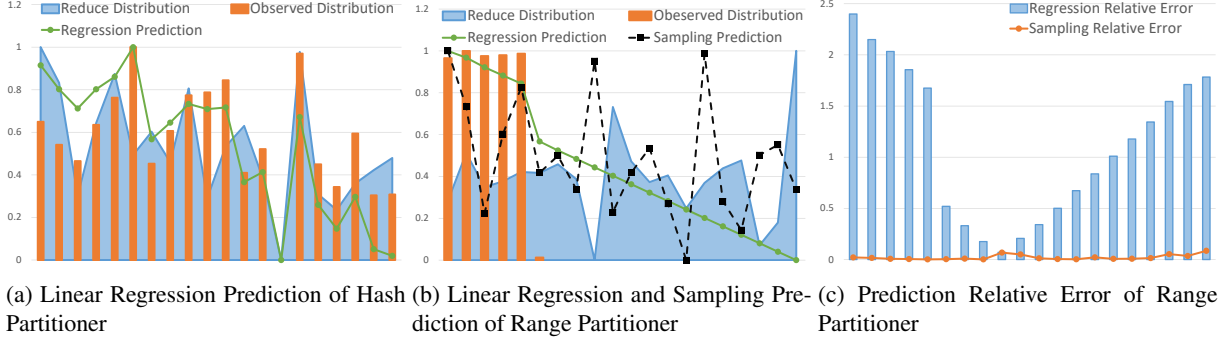


Figure 6: Reduction Distribution Prediction

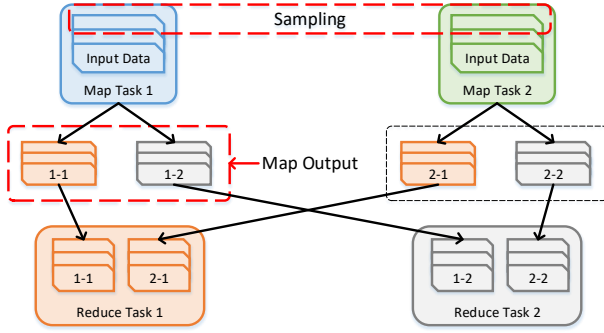


Figure 5: Shuffle Data Prediction

Algorithm 2 Accumulate Scheduling for Multi-Shuffles

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1: procedure MSCHEDULE( $m, h, p\_reduces, shuffles$ )
2:    $\triangleright shuffles$  is the previous array of reduce partition
   ID, host ID and size
3:   for all  $r\_id$  in  $p\_reduces$  do
4:      $p\_reduce[r\_id].size \leftarrow p\_reduce[r\_id].size +$ 
        $shuffles[r\_id].size$ 
5:     if  $shuffles[r\_id].size \geq p\_reduce[r\_id].size *$ 
        $p\_reduce[r\_id].prob$  then
6:       Update  $prob$  set  $host$  to  $shuffles[r\_id].host$ 
7:    $M \leftarrow schedule(m, h, p\_reduces)$ 
8:   for all  $host$  in  $M$  do
9:     for all  $r\_id$  in  $host$  do
10:      if  $host \neq shuffles[r\_id].host$  then
11:        Re-shuffle data to  $host$ 
12:         $shuffles[r\_id].host \leftarrow host$ 
   return  $M$ 

```

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 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.

When a new shuffle start, the *mSchedule* is called to schedule the current shuffle with previous *shuffles*. The size of reduce on each node of previous scheduled *shuffles* are counted. Combined with the predicted reduces size of current shuffle in *p_reduces*, the *size* of each reduce and its corresponding *prob* and *host* are updated accumulately. 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 equal 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 focuss on the two main challenges: memory manangement and fault tolerance.

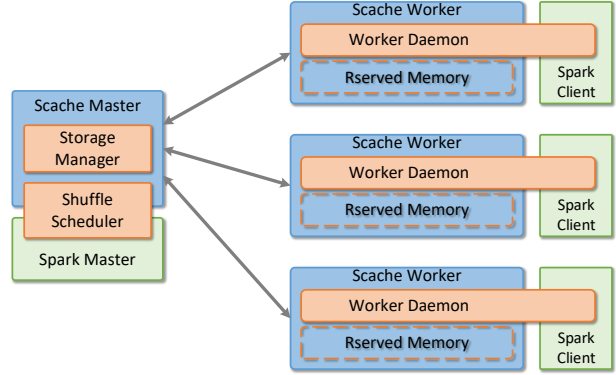


Figure 7: SCache Architecture

4.1.1 Reservoir Sampling

5 Evaluation

6 Conclusion

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[12]. 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 and strict priority constraints to benifit all jobs.

When a Spark job starts, the DAG will be first generated by Spark DAGScheduler. The process start on the last result stage, and recursively find the dependent stage to the beginning of the DAG. While going forward to the beginning, the DAG will be cut off if the RDD in one stage has one or more shuffle dependencies. These shuffle dependencies among stages 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 mutilpule shuffles scheduling unit. If there is a specialized partitioner, such as Range Partitioner or a customed partitioner, in the shuffle dependencies, the daemon will insert a sampling program in the 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.

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