

# MRShare: Sharing Across Multiple Queries in MapReduce

Tomasz Nykiel  
University of Toronto  
tnykiel@cs.toronto.edu

Michalis Potamias \*  
Boston University  
mp@cs.bu.edu

Chaitanya Mishra †  
Facebook  
cmishra@facebook.com

George Kollios \*  
Boston University  
gkollios@cs.bu.edu

Nick Koudas  
University of Toronto  
koudas@cs.toronto.edu

## ABSTRACT

Large-scale data analysis lies in the core of modern enterprises and scientific research. With the emergence of cloud computing, the use of an analytical query processing infrastructure (e.g., Amazon EC2) can be directly mapped to monetary value. MapReduce has been a popular framework in the context of cloud computing, designed to serve long running queries (jobs) which can be processed in batch mode. Taking into account that different jobs often perform similar work, there are many opportunities for sharing. In principle, sharing similar work reduces the overall amount of work, which can lead to reducing monetary charges incurred while utilizing the processing infrastructure. In this paper we propose a sharing framework tailored to MapReduce.

Our framework, **MRShare**, transforms a batch of queries into a new batch that will be executed more efficiently, by merging jobs into groups and evaluating each group as a single query. Based on our cost model for MapReduce, we define an optimization problem and we provide a solution that derives the optimal grouping of queries. Experiments in our prototype, built on top of Hadoop, demonstrate the overall effectiveness of our approach and substantial savings.

## 1. INTRODUCTION

Present-day enterprise success often relies on analyzing expansive volumes of data. Even small companies invest effort and money in collecting and analyzing terabytes of data, in order to gain a competitive edge. Recently, Amazon Webservices deployed the Elastic Compute Cloud (EC2) [1], which is offered as a commodity, in exchange for money. EC2 enables third-parties to perform their analytical queries on massive datasets, abstracting the complexity entailed in building and maintaining computer clusters.

Analytical queries are usually long running tasks, suitable

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†C. Mishra conducted this work at University of Toronto.

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for batch execution. In batch execution mode, we can avoid redundant computations by *sharing work* among queries and save on total execution time. Therefore, as has been argued recently [16], it is imperative to apply ideas from *multiple query optimization* (MQO) [12, 21, 25] to analytical queries in the cloud. For EC2 users, reducing the execution time is directly translated to monetary savings. Furthermore, reducing energy consumption in data centers is a problem that has recently attracted increased interest [4]. Therefore, in this paper, we apply MQO ideas to MapReduce, the prevalent computational paradigm in the cloud.

MapReduce [11] serves as a platform for a considerable amount of massive data analysis. Besides, cloud computing has already turned MapReduce computation into commodity, e.g., with EC2's Elastic MapReduce. The MapReduce paradigm has been widely adopted, mainly because it abstracts away parallelism concerns and is very scalable. The wide scale of MapReduce's adoption for specific analytical tasks, can also be credited to Hadoop [3], a popular open source implementation. Yet, MapReduce does not readily provide the high level primitives that have led SQL and relational database systems to their success.

MapReduce logic is incorporated in several novel data analysis systems [5, 8, 10, 13, 14, 19, 22, 24]. Beyond doubt, high level language abstractions enable the underlying system to perform automatic optimization [16]. Along these lines, recently developed systems on top of Hadoop, such as Hive [22] and Pig [14], speak HiveQL [22], an SQL-like language, and Pig Latin [17], a dataflow language, respectively. They allow programmers to code using high level language abstractions, so that their programs can afterwards be compiled into MapReduce jobs. Already, standard optimizations, such as filter pushdown, are implemented in Pig [14, 16]. Pig also implements a number of work sharing optimizations using MQO ideas. However, these optimizations are usually not automatic; the programmer needs to specify the details of sharing among multiple jobs [14].

We present **MRShare**, a novel sharing framework, which enables *automatic* and principled work-sharing in MapReduce. In particular, we describe a module, which merges MapReduce jobs coming from different queries, in order to avoid performing redundant work and, ultimately, save processing time and money. To that end, we propose a cost model for MapReduce, independent of the MapReduce platform. Using the cost model, we define an optimization problem to find the optimal grouping of a set of queries and solve it, using dynamic programming. We demonstrate that significant savings are possible using our Hadoop based prototype

on representative MapReduce jobs.

We summarize our contributions:

1. We discuss sharing opportunities (Section 2), define *formally* the problem of *work-sharing* in MapReduce, and propose MRShare, a platform independent sharing framework.
2. We propose a simple MapReduce cost-model (Section 3) and we validate it experimentally.
3. We show that finding the optimal groups of queries (merged into single queries) according to our cost model is NP-hard. Thus, we relax the optimization problem and solve it efficiently (Section 4).
4. We implement MRShare on top of Hadoop (Section 5) and present an extensive experimental analysis demonstrating the effectiveness of our techniques (Section 6).

## 2. BACKGROUND

In this section, we review MapReduce and discuss sharing opportunities in the MapReduce pipeline.

### 2.1 MapReduce Preliminaries

A MapReduce *job* consists of two stages. The *map* stage processes input key/value pairs (tuples), and produces a new list of key/value pairs for each pair. The *reduce* stage performs group-by according to the intermediate key, and produces a final key/value pair per group. In brief, the stages perform the following transformation to their input (see Appendix A for examples):

$$\begin{aligned} \text{map}(K_1, V_1) &\rightarrow \text{list}(K_2, V_2) \\ \text{reduce}(K_2, \text{list}(V_2)) &\rightarrow (K_3, V_3) \end{aligned}$$

The computation is distributed across a cluster of hosts, with a designated *coordinator*, and the remaining *slave* machines. Map-Reduce engines utilize a *distributed file system* (DFS), instantiated at the nodes of the cluster, for storing the input and the output. The coordinator partitions the input data  $I_i$  of job  $J_i$  into  $m$  physical *input splits*, where  $m$  depends on the user-defined split size. Every input split is processed as a *map task* by a slave machine.

**Map tasks:** A slave assigned a map task processes its corresponding input split by reading and parsing the data into a set of input key/value pairs  $(K_1, V_1)$ . Then, it applies the user-defined *map* function to produce a new set of key/value pairs  $(K_2, V_2)$ . Next, the set of keys produced by map tasks is partitioned into a user-defined number of  $r$  partitions.

**Reduce tasks:** A slave assigned a reduce task copies the parts of the map output that refer to its partition. Once all outputs are copied, sorting is conducted to co-locate occurrences of each key  $K_2$ . Then, the user-defined *reduce* function is invoked for each group  $(K_2, \text{list}(V_2))$ , and the resulting output pairs  $(K_3, V_3)$  are stored in the DFS.

For ease of presentation, we will encode map and reduce functions of job  $J_i$  in the form of map and reduce *pipelines*:

$$\text{mapping}_i : I_i \rightarrow (K_{i1}, V_{i1}) \rightarrow \text{map}_i \rightarrow (K_{i2}, V_{i2}) \quad (1)$$

$$\text{reducing}_i : (K_{i2}, \text{list}(V_{i2})) \rightarrow \text{reduce}_i \rightarrow (K_{i3}, V_{i3}) \quad (2)$$

Note also that there are interesting MapReduce jobs, such as joins, that read multiple inputs and/or have multiple map pipelines. In this paper, we consider only single-input MapReduce jobs. We do not consider reducing locally with *combiners*. However, our techniques can be modified to handle scenarios with combiners.

## 2.2 Sharing Opportunities

We can now describe how several jobs can be processed as a single job in the MRShare framework, by merging their map and reduce tasks. We identify several non-trivial *sharing opportunities*. These opportunities have also been exploited in Pig [14]. For simplicity, we will use two jobs,  $J_i$  and  $J_j$ , for our presentation. Further details, together with examples can be found in Appendix B. We consider the following sharing opportunities:

**Sharing Scans.** To share scans, the input to both mapping pipelines for  $J_i$  and  $J_j$  must be the same. In addition, we assume that the key/value pairs are of the same type. This is a typical assumption in MapReduce settings [14]. Given that, we can merge the two pipelines into a single pipeline and scan the input data only once. Thus, the map tasks invoke the user-defined map functions for both merged jobs:

$$\text{mapping}_{ij} : I \rightarrow (K_{ij1}, V_{ij1}) \rightarrow \frac{\text{map}_i \rightarrow \text{tag}(i) + (K_{i2}, V_{i2})}{\text{map}_j \rightarrow \text{tag}(j) + (K_{j2}, V_{j2})}$$

Note that the combined pipeline  $\text{mapping}_{ij}$ , produces two streams of output tuples. In order to distinguish the streams at the reducer stage, each tuple is tagged with a  $\text{tag}()$  part, indicating its origin. So at the reducer side, the original pipelines are no longer of the form of Equation 2. Instead, they are merged into one pipeline.

$$\text{reducing}_{ij} : \frac{\text{tag}(i) + (K_{i2}, \text{list}(V_{i2})) \rightarrow \text{reduce}_i \rightarrow (K_{i3}, V_{i3})}{\text{tag}(j) + (K_{j2}, \text{list}(V_{j2})) \rightarrow \text{reduce}_j \rightarrow (K_{j3}, V_{j3})}$$

To distinguish between the tuples originating from two different jobs, we use a *tagging* technique, which enables evaluating multiple jobs within a single job. The details are deferred to Section 5.

**Sharing Map Output.** Assume now, that in addition to sharing scans, the map output key and value types are the same for both jobs  $J_i$  and  $J_j$  (i.e.  $(K_{i2}, V_{i2}) \equiv (K_{j2}, V_{j2})$ ). In that case, the map output streams for  $J_i$  and  $J_j$  can also be shared. The shared map pipeline is described as follows:

$$\text{mapping}_{ij} : I \rightarrow (K_{ij1}, V_{ij1}) \rightarrow \frac{\text{map}_i}{\text{map}_j} \rightarrow \text{tag}(i) + \text{tag}(j) + (K_{ij2}, V_{ij2})$$

Here,  $\text{map}_i$  and  $\text{map}_j$  are applied to each input tuple. Then, the map output tuples coming only from  $\text{map}_i$  are tagged with  $\text{tag}(i)$  only. If a map output tuple was produced from an input tuple by both  $\text{map}_i$  and  $\text{map}_j$ , it is tagged by  $\text{tag}(i) + \text{tag}(j)$ . Hence, any overlapping parts of the map output will be shared. Producing a smaller map output results to savings on sorting and copying intermediate data over the network.

At the reduce side, the grouping is based on  $K_{ij2}$ . Each group contains tuples belonging to both jobs, with each tuple possibly belonging to one or both jobs. The reduce stage needs to dispatch the tuples and push them to the appropriate reduce function, based on  $\text{tag}$ .

$$\text{reducing}_{ij} : \text{tag}(i) + \text{tag}(j) + (K_{ij2}, \text{list}(V_{ij2})) \rightarrow \frac{\text{reduce}_i \rightarrow (K_{i3}, V_{i3})}{\text{reduce}_j \rightarrow (K_{j3}, V_{j3})}$$

**Sharing Map Functions.** Sometimes the map functions are identical and thus they can be executed once. At the end of the map stage two streams are produced, each tagged with its job  $\text{tag}$ . If the map output is shared, then only one stream needs to be generated. Even if only some filters are common

in both jobs, it is possible to share parts of map functions. Details and examples can be found in the appendix.

**Discussion.** Among the identified sharing opportunities, sharing scans and sharing map-output yield I/O savings. On the other hand, sharing map functions, and parts of map functions additionally yield CPU savings. The I/O costs, which are due to reading, sorting, copying, etc., are usually dominant, and thus, in the remainder of this paper, we concentrate on the I/O sharing opportunities. Nevertheless, we believe that sharing expensive predicates (i.e., parts of map functions) is a promising direction for future work.

### 3. A COST MODEL FOR MapReduce

In this section, we introduce a simple cost model for MapReduce, based on the assumption that the execution time is dominated by I/O operations. We emphasize that our cost model is based on Hadoop but it can be easily adjusted to the original MapReduce [11].

#### 3.1 Cost without Grouping

Assume that we have a batch of  $n$  MapReduce jobs,  $\mathbb{J} = \{J_1, \dots, J_n\}$ , that read from the same input file  $F$ . Recall that a MapReduce job is processed as  $m$  map tasks and  $r$  reduce tasks<sup>1</sup>. For a given job  $J_i$ , let  $|M_i|$  be the average output size of a map task, measured in pages, and  $|R_i|$  be the average input size of a reduce task. The size of the intermediate data  $D_i$  of job  $J_i$  is  $|D_i| = |M_i| \cdot m = |R_i| \cdot r$ .

We also define some system parameters. Let  $C_r$  be the cost of reading/writing data remotely,  $C_l$  be the cost of reading/writing data locally, and  $C_t$  be the cost of transferring data from one node to another. All costs are measured in seconds per page. The sort buffer size is  $B + 1$  pages.

The total cost of executing the set of the  $n$  individual jobs is the sum of the cost  $T_{read}$  to read the data, the cost  $T_{sort}$  to do the sorting and copying at the map and reduce nodes, and the cost  $T_{tr}$  of transferring data between nodes<sup>2</sup>. Thus, the cost in Hadoop is:

$$T(\mathbb{J}) = T_{read}(\mathbb{J}) + T_{sort}(\mathbb{J}) + T_{tr}(\mathbb{J}) \quad (3)$$

where:

$$T_{read}(\mathbb{J}) = C_r \cdot n \cdot |F| \quad (4)$$

$$T_{sort}(\mathbb{J}) = C_l \cdot \sum_{i=1}^n (|D_i| \cdot 2 \cdot (\lceil \log_B |D_i| \rceil - \log_B m) + \lceil \log_B m \rceil) \quad (5)$$

$$T_{tr}(\mathbb{J}) = \sum_{i=1}^n C_t \cdot |D_i| \quad (6)$$

In the case that no sorting is performed at the map tasks [11], we consider a slightly different cost function for sorting:

$$T_{sort}(\mathbb{J}) = C_l \cdot \sum_{i=1}^n |D_i| \cdot 2 \cdot (\lceil \log_B |D_i| \rceil + \log_B m - \log_B r) \quad (7)$$

Since we implemented MRShare in Hadoop, for the remainder of this paper, we use Equation 6 to calculate the sorting cost. However, all our algorithms can be adjusted to handle the sorting cost (Equation 7) of the original MapReduce [11]. See Appendix C for further details of the cost model.

#### 3.2 Cost with Grouping

Another way to execute  $\mathbb{J}$  is to create a single group  $G$  that contains all  $n$  jobs and execute it as a single job  $J_G$ . However, as we show next, this may not be always beneficial.

<sup>1</sup>We assume that all jobs use the same  $m, r$  parameters, since  $m$  depends on the input size, and  $r$  is usually set based on the cluster size.

<sup>2</sup>We omit the cost of writing the final output, since it is the same for grouping and non-grouping scenarios.

Let  $|X_m|$  be the average size of the combined output of map tasks, and  $|X_r|$  be the average input size of the combined reduce tasks of job  $J_G$ . The size of the intermediate data is  $|X_G| = |X_m| \cdot m = |X_r| \cdot r$ . Reasoning as previously:

$$\begin{aligned} T_{read}(J_G) &= C_r \cdot |F| \\ T_{sort}(J_G) &= C_l \cdot |X_G| \cdot 2 \cdot (\lceil \log_B |X_G| \rceil - \log_B m) + \lceil \log_B m \rceil \\ T_{tr}(J_G) &= C_t \cdot |X_G| \\ T(J_G) &= T_{read}(J_G) + T_{sort}(J_G) + T_{tr}(J_G) \end{aligned} \quad (8)$$

We can determine if sharing is beneficial by comparing Equation 3 with 8. Let  $p_i = \lceil \log_B |D_i| \rceil - \log_B m + \lceil \log_B m \rceil$  be the original number of sorting passes for job  $J_i$ . Let  $p_G = \lceil \log_B |X_G| \rceil - \log_B m + \lceil \log_B m \rceil$  be the number of passes for job  $J_G$ . Let  $J_j$  be the constituent job with the largest intermediate data size  $|D_j|$ . Then,  $p_j$  is the number of passes it takes to sort  $D_j$ . No other original job takes more than  $p_j$  passes. We know that  $\lceil \frac{|X_G|}{|D_j|} \rceil \leq n$ . Then  $p_G$  is bounded from above by  $\lceil \log_B (n \cdot |D_j|) \rceil - \log_B m + \lceil \log_B m \rceil$ . Now, if  $n \leq B$ ,  $\lceil \log_B |D_j| \rceil - \log_B m + \log_B n + \lceil \log_B m \rceil$  is at most  $p_j + 1$ .  $p_G$  is clearly bounded from below by  $p_j$ . Hence, after merging all  $n$  jobs, the number of sorting passes is either equal to  $p_j$  or increases by 1.

We write  $p_G = p_j + \delta_G$ , where  $\delta_G = \{0, 1\}$ . Let  $d_i = |D_i|/|F|$ ,  $d_i$  be the *map-output-ratio* of the map stage of job  $J_i$ , and  $x_G = |X_G|/|F|$  be the map-output-ratio of the merged map stage. The map-output-ratio is the ratio between the average map output size and the input size. Unlike selectivity in relational operators, this ratio can be greater than one since in MapReduce the map stage can perform arbitrary operations on the input and produce even larger output.

Let  $g = C_l/C_l$  and  $f = C_r/C_l$ . Then, sharing is beneficial *only if*  $T(J_G) \leq T(\mathbb{J})$ . From Equations 3 and 8 we have:

$$f(n-1) + g \sum_{i=1}^n d_i + 2 \sum_{i=1}^n (d_i \cdot p_i) - x_G(g + 2 \cdot p_G) \geq 0 \quad (9)$$

We remark that greedily grouping all jobs (the GreedyShare algorithm) is not always the optimal choice. If for some job  $J_i$  it holds that  $p_G > p_i$ , Inequality 9 may not be satisfied. The reason is that the benefits of saving scans can be canceled or even surpassed by the added costs during sorting [14]. This is also verified by our experiments.

## 4. GROUPING ALGORITHMS

The core component of MRShare is the *grouping* layer. In particular, given a batch of queries, we seek to group them so that the overall execution time is minimized.

### 4.1 Sharing Scans only

Here, we consider the scenario in which we share only scans. We first formulate the optimization problem and show that it is NP-hard. In Section 4.1.2 we relax our original problem. In Section 4.1.3 we describe SplitJobs, an exact dynamic programming solution for the relaxed version, and finally in Section 4.1.4 we present the final algorithm MultiSplitJobs. For details about the formulas see Appendix G.

#### 4.1.1 Problem Formulation

Consider a group  $G$  of  $n$  merged jobs. Since no map output data is shared, the overall map-output-ratio of  $G$  is the sum of the original map-output-ratios of each job:

$$x_G = d_1 + \dots + d_n \quad (10)$$

Recall that  $J_j$  is the constituent job of the group, hence  $p_j = \max\{p_1, \dots, p_n\}$ . Furthermore,  $p_G = p_j + \delta_G$ . Based on our previous analysis, we derive the savings from merging the jobs into a group  $G$  and evaluating  $G$  as a single job  $J_G$ :

$$SS(G) = \sum_{i=1}^n (f - 2 \cdot d_i \cdot (p_j - p_i + \delta_G)) - f \quad (11)$$

We define the Scan-Shared Optimal Grouping problem of obtaining the optimal grouping sharing just the scans as:

**PROBLEM 1 (SCAN-SHARED OPTIMAL GROUPING).** *Given a set of jobs  $\mathbb{J} = \{J_1, \dots, J_n\}$ , group the jobs into  $S$  non-overlapping groups  $G_1, G_2, \dots, G_S$ , such that the overall sum of savings  $\sum_s SS(G_s)$ , is maximized.*

#### 4.1.2 A Relaxation of the Problem

In its original form, Problem 1 is **NP-hard** (see Appendix D). Thus we consider a relaxation.

Among all possible groups where  $J_j$  is the constituent job, the highest number of sorting passes occurs when  $J_j$  is merged with *all* the jobs  $J_i$  of  $\mathbb{J}$  that have map-output-ratios lower than  $J_j$  (i.e.,  $d_i < d_j$ ). We define  $\delta_j = \{0, 1\}$  based on this worst case scenario. Hence, for any group  $G$  with  $J_j$  as the constituent job we assign  $\delta_G$  to be equal to  $\delta_j$ . Then,  $\delta_G$  depends only on  $J_j$ .

Thus, we define the gain of merging job  $J_i$  with a group where  $J_j$  is the constituent job:

$$gain(i, j) = f - 2 \cdot d_i \cdot (p_j - p_i + \delta_j) \quad (12)$$

The total savings of executing  $G$  versus executing each job separately is  $\sum_{i=1}^n gain(i, j) - f$ . In other words, each merged job  $J_i$  saves one scan of the input, and incurs the cost of additional sorting if the number of passes  $p_j + \delta_j$  is greater than the original number of passes  $p_i$ . Also, the cost of an extra pass for job  $J_j$  must be paid if  $\delta_j = 1$ . Finally, we need to account for one input scan per group.

#### 4.1.3 SplitJobs - DP for Sharing Scans

In this part, we present an exact, dynamic programming algorithm for solving the relaxed version of Problem 1. Without loss of generality, assume that the jobs are sorted according to the map-output-ratios ( $d_i$ ), that is  $d_1 \leq d_2 \leq \dots \leq d_n$ . Obviously, they are also sorted on  $p_i$ .

Our main observation is that the optimal grouping for the relaxed version of Problem 1 will consist of consecutive jobs in the list (see Appendix E for details.) Thus, the problem now is to split the sorted list of jobs into sublists, so that the overall savings are maximized. To do that, we can use a dynamic programming algorithm that we call **SplitJobs**.

Define  $GAIN(t, u) = \sum_{t \leq i \leq u} gain(i, u)$ , to be the total gain of merging a sequence of jobs  $J_t, \dots, J_u$  into a single group. Clearly,  $p_u = \max\{p_t, \dots, p_u\}$ . The overall group savings from merging jobs  $J_t, \dots, J_u$  become  $GS(t, u) = GAIN(t, u) - f$ . Clearly,  $GS(t, t) = 0$ . Recall that our problem is to maximize the sum of  $GS()$  of all groups.

Consider an optimal arrangement of jobs  $J_1, \dots, J_l$ . Suppose we know that the last group, which ends in job  $J_l$ , begins with job  $J_i$ . Hence, the preceding groups, contain the jobs  $J_1, \dots, J_{i-1}$  in the optimal arrangement. Let  $c(l)$  be the savings of the optimal grouping of jobs  $J_1, \dots, J_l$ . Then, we have:  $c(l) = c(i-1) + GS(i, l)$ . In general,  $c(l)$  is:

$$c(l) = \max_{1 \leq i \leq l} \{c(i-1) + GS(i, l)\} \quad (13)$$

Now, we need to determine the first job of the last group for the subproblem of jobs  $J_1, \dots, J_l$ . We try all possible cases for job  $J_l$ , and we pick the one that gives the greatest overall savings ( $i$  ranges from 1 to  $l$ ). We can compute a table of  $c(i)$  values from left to right, since each value depends only on earlier values. To keep track of the split points, we maintain a table *source*( $l$ ). The pseudocode of the algorithm is:

**SplitJobs**( $J_1, \dots, J_n$ )

1. Compute  $GAIN(i, l)$  for  $1 \leq i \leq l \leq n$ .
2. Compute  $GS(i, l)$  for  $1 \leq i \leq l \leq n$ .
3. Compute  $c(l)$  and *source*( $l$ ) for  $1 \leq l \leq n$ .
4. Return  $c$  and *source*

**SplitJobs** has  $O(n^2)$  time and space complexity.

#### 4.1.4 Improving SplitJobs

Consider the following example: Assume  $J_1, J_2, \dots, J_{10}$  are sorted according to their map-output-ratio. Assume we compute the worst case  $\delta_j$  value for each job. Also, assume the **SplitJobs** algorithm returns the following groups:  $J_1, J_2, (J_3 J_4 J_5), (J_6 J_7), J_8, J_9, J_{10}$ . We observe that for the jobs that are left as singletons, we may run the **SplitJobs** program again. Before that, we *recompute*  $\delta_j$ 's, omitting the jobs that have been already merged into groups. Notice that  $\delta_j$ 's will change. If  $J_j$  is merged with all jobs with smaller output, we may not need to increase the number of sorting passes, even if we had to in the first iteration. For example, it is possible that  $\delta_{10} = 1$  in the first iteration, and  $\delta_{10} = 0$  in the second iteration.

In each iteration we have the following two cases:

- The iteration returns some new groups (e.g.,  $(J_1 J_2 J_8)$ ). Then, we remove all jobs that were merged in this iteration, and we iterate again (e.g., the input for next iteration is  $J_9$  and  $J_{10}$  only).
- The iteration returns all input singleton groups (e.g.,  $J_1, J_2, J_8, J_9, J_{10}$ ). Then we can safely remove the smallest job, since it does not give any savings when merged into any possible group. We iterate again with the remaining jobs (e.g.,  $J_2, J_8, J_9$ , and  $J_{10}$ ).

In brief, in each iteration we recompute  $\delta_j$  for each job and we remove at least one job. Thus, we have at most  $n$  iterations. The final **MultiSplitJobs** algorithm is the following:

**MultiSplitJobs**( $J_1, \dots, J_n$ )

$\mathbb{J} \leftarrow \{J_1, \dots, J_n\}$  (input jobs)

$\mathbb{G} \leftarrow \emptyset$  (output groups)

**while**  $\mathbb{J} \neq \emptyset$  **do**

  compute  $\delta_j$  for each  $J_j \in \mathbb{J}$

$ALL = \text{SplitJobs}(\mathbb{J})$

$\mathbb{G} \leftarrow \mathbb{G} \cup ALL.\text{getNonSingletonGroups}()$

$SINGLES \leftarrow ALL.\text{getSingletonGroups}()$

**if**  $|SINGLES| < |\mathbb{J}|$  **then**

$\mathbb{J} \leftarrow SINGLES$

**else**

$J_x = SINGLES.\text{theSmallest}()$

$\mathbb{G} \leftarrow \mathbb{G} \cup \{J_x\}$

$\mathbb{J} \leftarrow SINGLES \setminus J_x$

**end if**

**end while**

**return**  $\mathbb{G}$  as the final set of groups.

**MultiSplitJobs** yields a grouping which is at least as good as **SplitJobs** and runs in  $O(n^3)$ .

## 4.2 Sharing Map Output

We move on to consider the problem of optimal grouping when jobs share not only scans, but also their map output. For further details about some of the formulas see Appendix G.

### 4.2.1 Problem Formulation

The map-output-ratios,  $d_i$ s of the original jobs and  $x_G$  of the merged jobs no longer satisfy Equation 10. Instead, we have:

$$x_G = \frac{|D_1 \cup \dots \cup D_n|}{|F|}$$

where the union operator takes into account lineage of map output tuples. By Equation 9, the total savings from executing  $n$  jobs together are:

$$SM(G) = (f(n-1) - x_G(g + 2p_G)) + (g \sum_{i=1}^n d_i + 2 \sum_{i=1}^n (d_i p_i))$$

Our problem is to maximize the sum of savings over groups:

**PROBLEM 2** (**SCAN+MAP-SHARED OPTIMAL GROUPING**).  
*Given a set of jobs  $\mathbb{J} = \{J_1, \dots, J_n\}$ , group the jobs into  $S$  non-overlapping groups  $G_1, G_2, \dots, G_S$ , such that the overall sum of savings  $\sum_s SM(G_s)$  is maximized.*

First, observe that the second parenthesis of  $SM(G)$  is constant among all possible groupings and thus can be omitted for the optimization problem. Let  $n_{G_s}$  denote the number of jobs in  $G_s$ , and  $p_{G_s}$  the final number of sorting passes for  $G_s$ . We search for a grouping into  $S$  groups, (where  $S$  is not fixed) that maximizes:

$$\sum_{s=1}^S (f \cdot (n_{G_s} - 1) - x_{G_s}(g + 2(p_{G_s}))), \quad (14)$$

which depends on  $x_{G_s}$ , and  $p_{G_s}$ . However, any algorithm maximizing the savings now needs explicit knowledge of the size of the intermediate data of all subsets of  $\mathbb{J}$ . The cost of collecting this information is exponential to the number of jobs and thus this approach is unrealistic. However, the following holds (see Appendix F for the proof):

**THEOREM 1.** *Given a set of jobs  $\mathbb{J} = \{J_1, \dots, J_n\}$ , for any two jobs  $J_k$  and  $J_l$ , if the map output of  $J_k$  is entirely contained in the map output of  $J_l$ , then there is some optimal grouping that contains a group with both  $J_k$  and  $J_l$ .*

Hence, we can greedily group jobs  $J_k$  and  $J_l$ , and treat them cost-wise as a single job  $J_l$ , which can be further merged with other jobs. We emphasize that the containment can often be determined by syntactical analysis. For example, consider two jobs  $J_k$ , and  $J_l$  which read the input  $T(a, b, c)$ . The map stage of  $J_k$  filters tuples by  $T.a > 3$ , and  $J_l$  by  $T.a > 2$ ; both jobs perform aggregation on  $T.a$ . We are able to determine syntactically that the map output of  $J_k$  is entirely contained in the map output of  $J_l$ . For the remainder of the paper, we assume that all such containments have been identified.

### 4.2.2 A Single Parameter Problem

We consider a simpler version of Problem 2 by introducing a global parameter  $\gamma$  ( $0 \leq \gamma \leq 1$ ), which quantifies the amount of sharing among all jobs. For a group  $G$  of  $n$  merged jobs, where  $J_j$  is the constituent job,  $\gamma$  satisfies:

$$x_G = d_j + \gamma \sum_{i=1, i \neq j}^n d_i \quad (15)$$

We remark that if  $\gamma = 1$ , then no map output is shared. In other words, this is the case considered previously, where only scans may be shared. If  $\gamma = 0$  then the map output of each “smaller” job is fully contained in the map output of the job with the largest map-output. Our relaxed problem is the following:

**PROBLEM 3** ( **$\gamma$  SCAN+MAP-SHARED OPTIMAL GROUPING**).  
*Given a set of jobs  $\mathbb{J} = \{J_1, \dots, J_n\}$ , and parameter  $\gamma$ , group the jobs into  $S$  non-overlapping groups  $G_1, G_2, \dots, G_S$ , such that the overall sum of savings is maximized.*

By Equation 9 the total savings from executing  $n$  jobs together are:

$$savings(G) = fn - f -$$

$$\left( g(\gamma - 1) \sum_{i=1, i \neq j}^n d_i + 2d_j \delta_j + 2 \sum_{i=1, i \neq j}^n (d_i(\gamma(p_j + \delta_j) - p_i)) \right)$$

As before, we define the gain:

$$\begin{aligned} gain(i, j) &= f - (g(\gamma - 1)d_i + 2 \cdot d_i \cdot (\gamma(p_j + \delta_j) - p_i)) \\ gain(j, j) &= f - 2 \cdot d_j \cdot \delta_j \end{aligned} \quad (16)$$

The total savings of executing group  $G$  together versus executing each job separately are:

$$savings(G) = \sum_{i=1}^n gain(i, j) - f \quad (17)$$

Due to the monotonicity of the  $gain()$  function, we can show that Problem 3 reduces to the problem of optimal partitioning of the sequence of jobs sorted according to  $d_i$ 's. We devise algorithm **MultiSplitJobs $^\gamma$**  based on algorithm **MultiSplitJobs** from Section 4.1.3.  $GAIN$ ,  $GS$ , and  $c$  are defined as in Section 4.1.3, but this time, using Equation 16 for the  $gain$ . We just need to modify the computation of the increase in the number of sorting passes ( $\delta_j$ ) for each job (i.e., we consider the number of sorting passes when job  $J_j$  is merged with all jobs with map-output-ratios smaller than  $d_j$ , but we add only the  $\gamma$  part of the map output of the smaller jobs).

## 5. IMPLEMENTING MRSHARE

We implemented our framework, **MRShare**, on top of Hadoop. However, it can be easily plugged in any MapReduce system. First, we get a batch of MapReduce jobs from queries collected in a short time interval  $T$ . The choice of  $T$  depends on the query characteristics and arrival times [6]. Then, **MultiSplitJobs** is called to compute the optimal grouping of the jobs. Afterwards, the groups are *rewritten*, using a *meta-map* and a *meta-reduce* function. These are **MRShare** specific containers, for merged map and reduce functions of multiple jobs, which are implemented as regular map and reduce functions, and their functionality relies on *tagging* (explained below). The new jobs are then submitted for execution. We remark that a simple change in the infrastructure, which in our case is Hadoop, is necessary. It involves adding the capability of writing into multiple output files on the reduce side, since now a single MapReduce job processes multiple jobs and each reduce task produces multiple outputs.

Next, we focus on the tagging technique, which enables evaluating multiple jobs within a single job.

## 5.1 Tagging for Sharing Only Scans

Recall from Section 2.2 that each map output tuple contains a  $tag()$ , which refers to exactly one original job. We include  $tag()$  in the key of each map output tuple. It consists of  $b$  bits,  $B_{b-1}, \dots, B_0$ . The MSB is reserved, and the remaining  $b - 1$  bits are mapped to jobs<sup>3</sup>. If the tuple belongs to job  $J_j$ , the  $j - 1^{th}$  bit is set. Then, the sorting is performed on the  $(key + tag())$ . However, the grouping is based on the  $key$  only. This implies that each group at the reduce side, will contain tuples belonging to different jobs. Given  $n$  merged MapReduce jobs  $J_1, \dots, J_n$ , where  $n \leq b - 1$ , each reduce-group contains tuples to be processed by up to  $n$  different original reduce functions (see also Appendix H).

## 5.2 Tagging for Sharing Map Output

We now consider sharing map output, in addition to scans. If a map output tuple originates from two jobs  $J_i$  and  $J_j$ , the  $tag()$  field, after merging, has both the  $i - 1^{th}$  and the  $j - 1^{th}$  bits set. The most significant bit is set to 0, meaning that the tuple belongs to more than one job. At the reduce stage, if a tuple belongs to multiple jobs, it needs to be pushed to all respective reduce functions.

## 6. EMPIRICAL EVALUATION

In this section, we present an experimental evaluation of the MRShare framework. We ran all experiments on a cluster of 40 virtual machines, using Amazon EC2 [1]. Our real-world 30GB text dataset, consists of blog posts [2]. We present our experimental setting and the measurements of the system parameters in Appendix I. In 6.1 we validate experimentally our cost model for MapReduce. Then, in 6.2, we establish that the GreedyShare policy is not always beneficial. Subsequently, in 6.3 we evaluate our MultiSplitJobs algorithm for sharing scans. In 6.4 we demonstrate that sharing intermediate data can introduce tremendous savings. Finally, in 6.5 we evaluate our heuristic algorithm MultiSplitJobs<sup>7</sup> for sharing scans and intermediate data. We show scale independence of our approach in Appendix I.

### 6.1 Validation of the Cost Model

First, we validate the cost model that we presented in Section 3. In order to estimate the system parameters, we used a text dataset of 10GBs and a set of MapReduce jobs based on random *grep-wordcount* queries (see Appendix I) with map-output-ratio of 0.35. Recall that the map-output-ratio of a job is the ratio of the map stage output size to the map stage input size. We run the queries using Hadoop on a small cluster of 10 machines. We measured the running times and we derived the values for the system parameters.

Then, we used new datasets of various sizes between 10 and 50 GBs and a new set of queries with map-output-ratio of 0.7. We run queries on the same cluster and we measured the running times in seconds. In addition, we used the cost model from Section 3 to derive the estimated running times. The results are shown in Figure 1(a). As we can see, the prediction of the model is very close to the actual values.

### 6.2 The GreedyShare Approach

Here, we demonstrate that the GreedyShare approach for sharing scans is not always beneficial. We created three ran-

<sup>3</sup>We decided to reserve a bit for future use of sharing among jobs processing multiple inputs

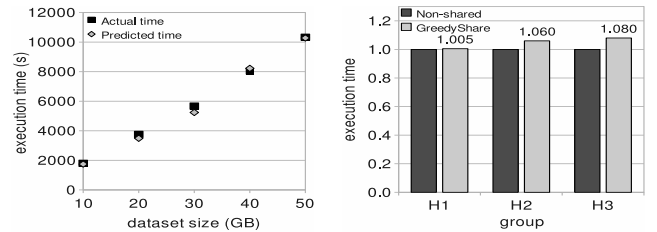


Figure 1: (a) Cost Model (b) Non-shared vs GreedyShare. Sharing is not always beneficial.

Table 1: GreedyShare setting

Series	Size	map-output-ratio $d_i$
H1	16	$0.3 \leq d_i \leq 0.7$
H2	16	$0.7 \leq d_i$
H3	16	$0.9 \leq d_i$

dom series of 16 *grep-wordcount* jobs ( $H1, H2, H3$ ), which we describe in Table 1, with constraints on the average map-output-ratios ( $d_i$ ). The maximum  $d_i$  was equal to 1.35.

For each of the series we compare running all the jobs separately versus merging them in a single group. Figure 1(b) illustrates our results. For each group, the execution times when no grouping was performed, is normalized to 1.00. The measurements were taken for multiple randomly generated groups. Even for  $H1$ , where the map output sizes were, on average, half size of the input, sharing was not beneficial. For  $H2$  and  $H3$ , the performance decreased despite savings introduced by scan-sharing, e.g., for  $H2$ , the 6% increase incurs an overhead of more than 30 minutes.

Obviously, the GreedyShare yields poorer performance as we increase the size of the intermediate data. This confirms our claim, that sharing in MapReduce has associated costs, which depend on the size of the intermediate data.

### 6.3 MultiSplitJobs Evaluation

Here, we study the effectiveness of the MultiSplitJobs algorithm for sharing scans. As discussed in Section 3, the savings depend strongly on the intermediate data sizes. We created five series of jobs varying the map-output-ratios ( $d_i$ ), as described in Table 2. Series  $G1, G2, G3$  contained jobs with increasing sizes of the intermediate data, while  $G4$  and  $G5$  consisted of random jobs. We performed the experiment for multiple random series  $G1, \dots, G5$  of *grep-wordcount* jobs.

Figure 2(a) illustrates the comparison between the performance of individual-query execution, and the execution of merged groups obtained by the MultiSplitJobs algorithm. The left bar for each series is 1.00, and it represents the time to execute the jobs individually. The left bar is split into two parts: the upper part represents the percentage of the execution time spent for scanning, and the lower part represents the rest of the execution time. Obviously, the savings cannot exceed the time spent for scanning for all the queries. The right bar represents the time to execute the jobs according to the grouping obtained from MultiSplitJobs.

We observe that even for jobs with large map output sizes ( $G1$ ), MultiSplitJobs yields savings (contrary to the GreedyShare approach). For  $G2$  and  $G3$ , which exhibit smaller map-output sizes, our approach yielded higher savings. For jobs with map-output sizes lower than 0.2 ( $G3$ ) we achieved up to 25% improvement.

In every case, MultiSplitJobs yields substantial savings

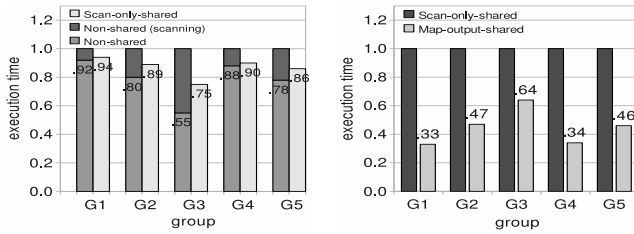


Figure 2: MultiSplitJobs (a) scans (b) map-output.

Table 2: MultiSplitJobs setup and grouping example

Series	Size	map-output-ratio $d_i$	#groups	Group-size
G1	16	$0.7 \leq d_i$	4	5,4,4,3
G2	16	$0.2 \leq d_i \leq 0.7$	3	8,5,3
G3	16	$0 \leq d_i \leq 0.2$	2	8,8
G4	16	$0 \leq d_i \leq max$	3	7,5,4
G5	64	$0 \leq d_i \leq max$	5	16,15,14,9,5,4

with respect to the original time spent for scanning. For example, for  $G4$  the original time spent for scanning was 12%. MultiSplitJobs reduced the overall time by 10%, which is very close to the ideal case. We do not report results for SplitJobs since MultiSplitJobs is provably better.

In addition, Table 2 presents example groupings obtained for each series  $G1, \dots, G5$ . Observe that in every case, the optimal grouping consisted of groups of variable size. With increasing intermediate data sizes, the number of groups increases, and the groups become smaller. Indeed, merging many jobs with high map-output-ratios is likely to increase the number of sorting passes, and degrade the performance.

## 6.4 Map Output Sharing Utility

Here, we demonstrate that sharing intermediate data (i.e., map output) introduces additional savings. For the purpose of this experiment we used the same series of jobs as in the previous Section (Table 2). We used the same groupings obtained by MultiSplitJobs. We enable the sharing-map-outputs feature and we compare it to sharing scans only.

Our results are illustrated in Figure 2(b). For  $G1$ , where map output sizes were large, the jobs shared large portions of intermediate data. The execution time dropped by 67%. Recall, that sharing intermediate data, introduces savings on copying data over the network and sorting.  $G2$  and  $G3$  had smaller intermediate map output sizes and the savings were lower, but still significant. For  $G4$  (fully random jobs) we achieved savings up to 65%. Clearly, the greater the redundancy among queries, the more the savings. We emphasize that the degree of sharing of the intermediate data is query dependent. Note also that MultiSplitJobs does not provide the optimal solution in this case (i.e., some other grouping could yield even higher savings), since it has no information on the degree of sharing among map outputs. Even so, our experiments show significant savings.

## 6.5 MultiSplitJobs $^\gamma$ Evaluation

Finally, we study the performance of the MultiSplitJobs $^\gamma$  algorithm, where  $\gamma$  is the global parameter indicating the desired aggressiveness of sharing. We ran the series of jobs  $G1, \dots, G3$  described before, and set  $\gamma = 0.5$ . Our objective, is to study the possible outcomes when using MultiSplitJobs $^\gamma$ .

With respect to the value for  $\gamma$  we remark the following. In some cases, we are able to determine  $\gamma$  syntactically, e.g., when the aggregation key is different for each job, then no

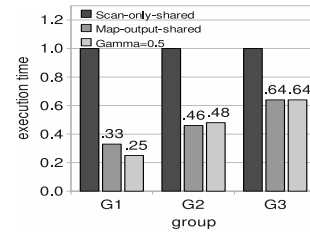


Figure 3: MultiSplitJobs $^\gamma$  behaviour

map output sharing is possible and  $\gamma = 1.00$ . On the other hand, if filters in the map stage for different jobs have hierarchical structure (each job’s map stage produces a superset of map output of all jobs with smaller map output), we can set  $\gamma = 0.00$ . By tuning  $\gamma$ , we can be more pessimistic or more optimistic. In principle, a *good*  $\gamma$  can be learned from the data (e.g., sampling of the current workload, statistics from previous runs), but this issue is out of the scope of this paper. However, we note that when gamma is set to 1 the scheme performs at least as well as MultiSplitJobs.

Figure 3 illustrates the results. We compare MultiSplitJobs with the map-output-sharing feature disabled (left bar) and enabled (center), with MultiSplitJobs $^\gamma$  for  $\gamma = 0.5$  (right), which allows for more aggressive merging.

For  $G1$  we achieved further savings. For  $G2$  the average execution time increased with respect to the original solution with map-output-sharing enabled;  $\gamma = 0.5$  was too optimistic, since the jobs shared less on average. It caused more aggressive merging, and, in effect, degraded the performance. For  $G3$  setting  $\gamma = 0.5$  did not cause any changes.

We conclude that MultiSplitJobs $^\gamma$  can introduce additional savings, if the choice of  $\gamma$  is appropriate. If the choice is too pessimistic, the additional savings may be moderate. If it is too optimistic, the savings might decrease with respect to MultiSplitJobs.

## 6.6 Discussion

Overall, our evaluation demonstrated that substantial savings are possible in MapReduce. Our experimental evaluation on EC2 utilized 8000 machine hours, with a cost of \$800. Introducing even 20% savings in the execution time, translates into \$160. Our experiments confirm our initial claim, that work-sharing in the MapReduce setting, may yield significant monetary savings.

## 7. RELATED WORK

**MapReduce.** Since its original publication [11], MapReduce style computation has become the norm for certain analytical tasks. Furthermore, it is now offered as a cloud service from Amazon EC2 [1]. Moreover, MapReduce logic has been integrated as a core component in various projects towards novel, alternative data analysis systems [5, 8, 10, 14, 13, 19, 22, 24]. Hadoop [3] is the most popular open source implementation of MapReduce and serves as the platform for many projects [5, 10, 14, 22], including ours.

**MapReduce systems.** There has been an increased interest in combining MapReduce and traditional database systems in an effort to maintain the benefits of both. Projects such as Pig [17], Hive [22], and Scope [8] focus on providing high-level SQL-like abstractions on top of MapReduce engines, to enable programmers to specify more complex queries in an easier way. SQL/MapReduce [13] in-

tegrates MapReduce functionality for UDF processing in Asterdata's nCluster, a shared nothing parallel database. Greenplum's [10] approach is similar. HadoopDB [5] is an architectural hybrid of MapReduce and relational databases, that is based on the findings of an experimental comparison between Hadoop and parallel database systems [18] and tries to combine the advantages of both approaches. MapReduce-Merge extends MapReduce by adding a *merger* step which combines multiple reducers' outputs [23]. Our framework, MRShare, enables work-sharing within MapReduce, and relies only on the core MapReduce functionality. Thus, it is complementary to all aforementioned systems.

**Work sharing.** Cooperative scans have been studied in traditional database systems [20, 26]. Among the MapReduce systems, Hive [22] supports user-defined scan-sharing. Given two jobs reading from the same file, Hive adds a new, preprocessing MapReduce job. This job reads and parses the data in order to create two temporary files, which the original jobs will eventually read. No automatic optimization is supported, and the execution time can be worse than without sharing, due to the newly added job. Contrary to Hive, MRShare shares scans by creating a single job for multiple jobs, with no use of temporary files. Besides both our cost model and our experimental analysis confirm that greedily sharing scans is not always beneficial. Pig [14] supports a large number of sharing mechanisms among multiple queries, including shared scans, partial sharing of map pipelines, and even partial sharing of the reduce pipeline, by executing multiple queries in a single group. However no cost-based optimization takes place. In this paper, we provide novel algorithms that provably perform automatic *beneficial* sharing. We perform cost-based optimization without the user's interference, for a set of ad-hoc queries. On another perspective, scheduling scans for MapReduce has been considered by Agrawal et al. [6] for a dynamic environment. Their objective is to schedule jobs, so that more scans will get to be shared eventually, while making sure that jobs will not suffer from starvation. Finally, in dynamic settings, work-sharing can be performed at runtime [15, 7].

## 8. CONCLUSION AND FUTURE WORK

This paper described MRShare - the first principled analysis for automatic work-sharing across multiple MapReduce jobs. Based on specific sharing opportunities that we identified and our cost model for MapReduce we defined and solved several optimization problems. Moreover, we described a system that implements the MRShare functionality on top of Hadoop. Our experiments on Amazon EC2 demonstrated that our approach yields vast savings.

There are plenty of directions for future work - this work is a first step towards automatic optimization for MapReduce. We have not yet considered scenarios where the jobs operate on multiple inputs (e.g., joins). Also, sharing parts of map functions was identified as a sharing opportunity, but not addressed. Finally, we aim to handle sequences of jobs, which are common in systems like Hive [22] or Pig [17].

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## APPENDIX

### A. EXAMPLES OF MapReduce JOBS

As an example, in a *wordcount* job, the map stage reads the input text, line by line, and emits a tuple (*word*, 1) for each *word*. The reduce stage counts all tuples corresponding to a particular *word*, and emits a final output tuple (*word*, *group\_cardinality*).

An aggregation on a relational table can be evaluated in a similar way [22]. Each input tuple represents a relational tuple with a specified schema. After parsing the input tuple, the map stage emits a key/value pair of the form (*aggr\_col*, *aggr\_value*). The reduce stage groups all tuples corresponding to a particular value in the aggregation column, and computes the final value of the aggregate function.

### B. EXAMPLES OF SHARING OPPORTUNITIES

In this section we provide several useful examples of sharing opportunities. For illustration purposes we use SQL notation. An SQL group-by query, over a table  $T(a, b, c)$ :

```
SELECT T.a, aggr(T.b)
FROM T
WHERE T.c > 10
GROUP BY T.a
```

can be translated into the following MapReduce job:

**Map tasks:** A slave assigned a map task reads the corresponding input split and parses the data according to  $T(a, b, c)$  schema. The input key/value pairs are of the form  $(\emptyset, (T.a, T.b, T.c))$ . Each tuple is checked against  $T.c > 10$ , and if it passes the filter, a map output tuple of the form  $(T.a, T.b)$  is produced. The output is partitioned into a user-defined number of  $r$  partitions.

**Reduce tasks:** A slave assigned a reduce task copies the parts of the map output corresponding to its partition. Once the copying is done, the outputs are sorted to co-locate occurrences of each key  $T.a$ . Then, the aggregate function *aggr()* is applied for each group, and the final output tuples are produced.

EXAMPLE 1 (SHARING SCANS - AGGREGATION). Consider an input table  $T(a, b, c)$ , and the following queries:

```
SELECT T.a, sum(T.b)      SELECT T.c, avg(T.b)
FROM T                    FROM T
WHERE T.c > 10            WHERE T.a = 100
GROUP BY T.a              GROUP BY T.c
```

The original map pipelines are:

```
mappingi : T → (∅, (T.a, T.b, T.c)) → filter(T.c > 10) → (T.a, T.b)
mappingj : T → (∅, (T.a, T.b, T.c)) → filter(T.a = 100) → (T.c, T.b)
```

The shared scan conditions are met. Thus, the merged pipeline is:

$$\text{mapping}_{ij} : T \rightarrow (\emptyset, (T.a, T.b, T.c)) \rightarrow \frac{\text{filter}(T.c > 10) \rightarrow \text{tag}(i) + (T.a, T.b)}{\text{filter}(T.a = 100) \rightarrow \text{tag}(j) + (T.c, T.b)}$$

The reduce stage groups tuples based on their key. If a tuple contains  $\text{tag}(i)$ , the reduce stage pushes the tuple to  $\text{reduce}_i$ , otherwise it pushes the tuple to  $\text{reduce}_j$ .

$$\text{reducing}_{ij} : \frac{\text{tag}(i) + (T.a, T.b) \rightarrow \text{sum}(T.b) \rightarrow (T.a, \text{sum})}{\text{tag}(j) + (T.c, T.b) \rightarrow \text{avg}(T.b) \rightarrow (T.c, \text{avg})}$$

In this scenario, the savings result from scanning and parsing the input only once. Clearly, this sharing scheme can be easily extended to multiple jobs. Note that there is no sharing at the reduce stage. After grouping at the reduce side, each tuple has either  $\text{tag}(i)$  or  $\text{tag}(j)$  attached, hence we can easily push each tuple to the appropriate reduce function. The size of the intermediate data processed is the same as in the case of two different jobs, with a minor overhead that comes from the tags.

EXAMPLE 2 (SHARING MAP OUTPUT - AGGREGATION). Consider an input table  $T(a, b, c)$ , and the following queries:

```
SELECT T.a, sum(T.b)      SELECT T.a, avg(T.b)
FROM T                    FROM T
WHERE T.a > 10 AND T.a < 20  WHERE T.b > 10 AND T.c < 100
GROUP BY T.a              GROUP BY T.a
```

The map pipelines are described as follows:

```
mappingi : T → (∅, (T.a, T.b, T.c)) →
→ filter(T.a > 10), filter(T.a < 20) → (T.a, T.b)
mappingj : T → (∅, (T.a, T.b, T.c)) →
→ filter(T.b > 10), filter(T.c < 100) → (T.a, T.b)
```

The map functions are not the same. However, the filtering can produce overlapping sets of tuples. The map output key ( $T.a$ ) and value ( $T.b$ ) types are the same. Hence, we can share the overlapping parts of map output.

$$\text{mapping}_{ij} : T \rightarrow (\emptyset, (T.a, T.b, T.c)) \rightarrow \frac{\text{filter}(T.a > 10, T.a < 20)}{\text{filter}(T.b > 10, T.c < 100)} \rightarrow \text{tag}(i) + \text{tag}(j) + (T.a, T.b)$$

The reduce stage applies the appropriate reduce function by dispatching the tuples based on  $\text{tag}()$ :

$$\text{reducing}_{ij} : \text{tag}(i) + \text{tag}(j) + (T.a, T.b) \rightarrow \frac{\text{sum}(T.b) \rightarrow (T.a, \text{sum})}{\text{avg}(T.b) \rightarrow (T.c, \text{avg})}$$

Producing a smaller map output results to savings on sorting and copying intermediate data over the network. This mechanism can be easily generalized to more than two jobs.

EXAMPLE 3 (SHARING MAP - AGGREGATION). Consider an input table  $T(a, b, c)$ , and the following queries:

```
SELECT T.c, sum(T.b)      SELECT T.a, avg(T.b)
FROM T                    FROM T
WHERE T.c > 10            WHERE T.c > 10
GROUP BY T.c              GROUP BY T.a
```

The map pipelines are described as follows:

```
mappingj : Ij → (∅, (T.a, T.b, T.c)) → filter(T.c > 10) → (T.c, T.b)
mappingi : Ii → (∅, (T.a, T.b, T.c)) → filter(T.c > 10) → (T.a, T.b)
```

The map pipelines are identical. Note that in this case, by identical map pipelines we mean the parsing and the set of filters/transformations in the map function - the map output key and value types are not necessarily the same. After merging we have:

$$\text{mapping}_{ij} : T \rightarrow (\emptyset, (T.a, T.b, T.c)) \rightarrow \text{filter}(T.c > 10) \rightarrow \frac{\text{tag}(i) + (T.c, T.b)}{\text{tag}(j) + (T.a, T.b)}$$

If, additionally, the map output key and value types are the same, we can apply map output sharing as well. In our

example, assuming that the second query groups by  $T.c$  instead of  $T.a$ , we would have:

$$\begin{aligned} \text{mapping}_{ij} : T &\rightarrow (\emptyset, (T.a, T.b, T.c)) \rightarrow \text{filter}(T.c > 10) \rightarrow \\ &\rightarrow \text{tag}(i) + \text{tag}(j) + (T.c, T.b) \end{aligned}$$

The reducing pipeline is similar to the previous examples.

EXAMPLE 4 (SHARING PARTS OF MAP - AGGREGATION). Consider an input table  $T(a, b, c)$ , and the following queries:

SELECT	$T.a, \text{sum}(T.b)$	SELECT	$T.a, \text{avg}(T.b)$
FROM	$T$	FROM	$T$
WHERE	$T.c > 10 \text{ AND } T.a < 20$	WHERE	$T.c > 10 \text{ AND } T.c < 100$
GROUP BY	$T.a$	GROUP BY	$T.a$

The map pipelines are described as follows:

$$\begin{aligned} \text{mapping}_i : & T \rightarrow (\emptyset, (T.a, T.b, T.c)) \rightarrow \\ & \rightarrow \text{filter}(T.c > 10), \text{filter}(T.a < 20) \rightarrow (T.a, T.b) \\ \text{mapping}_j : & T \rightarrow (\emptyset, (T.a, T.b, T.c)) \rightarrow \\ & \rightarrow \text{filter}(T.c > 10), \text{filter}(T.c < 100) \rightarrow (T.a, T.b) \end{aligned}$$

In this case, the map pipelines are not the same. However, some of their filters overlap:

$$\begin{aligned} \text{mapping}_{ij} : T &\rightarrow (\emptyset, (T.a, T.b, T.c)) \rightarrow \text{filter}(T.c > 10) \rightarrow \\ & \rightarrow \frac{\text{filter}(T.a < 20)}{\text{filter}(T.c < 100)} \rightarrow \frac{\text{tag}(i) + (T.a, T.b)}{\text{tag}(j) + (T.a, T.b)} \end{aligned}$$

Also in this case, the key and value types of map output tuples are the same, and we can apply map output sharing:

$$\begin{aligned} \text{mapping}_{ij} : T &\rightarrow (\emptyset, (T.a, T.b, T.c)) \rightarrow \text{filter}(T.c > 10) \rightarrow \\ & \rightarrow \frac{\text{filter}(T.a < 20)}{\text{filter}(T.c < 100)} \rightarrow \text{tag}(i) + \text{tag}(j) + (T.a, T.b) \end{aligned}$$

We remark that sharing parts of map functions has many implications. It involves identifying common subexpressions [12, 21] and filter reordering [9], which are hard problems.

## C. COST MODEL FOR MapReduce DETAILS

Recall that for a given job  $J_i$ ,  $|M_i|$  is the average output size of a map task, measured in pages, and  $|R_i|$  is the average input size of a reduce task. The size of the intermediate data  $D_i$  of job  $J_i$  is  $|D_i| = |M_i| \cdot m = |R_i| \cdot r$ . In the no-grouping scenario, the cost of reading the data is:

$$T_{read}(\mathbb{J}) = C_r \cdot n \cdot |F|$$

Hadoop buffers and sorts map outputs locally at the map task side. We recall that The cost of sorting and writing the data at the output of the map tasks for the  $n$  jobs is approximately:

$$\begin{aligned} T_{\text{sort-map}}(\mathbb{J}) &= C_l \cdot \sum_{i=1}^n (m \times |M_i| (2 + 2(\lceil \log_B \frac{|M_i|}{(B+1)} \rceil))) \\ &= C_l \cdot \sum_{i=1}^n (|D_i| (2 + 2(\lceil \log_B \frac{|D_i|}{(B+1) \times m} \rceil))) \\ &\approx C_l \cdot \sum_{i=1}^n (|D_i| \lceil 2(\log_B |D_i| - \log_B m) \rceil) \quad (18) \end{aligned}$$

At the reduce task side we start with  $m$  sorted runs. A merge step of the  $m$  runs involves  $\lceil \log_B m \rceil$  passes. Therefore the sorting cost at the reduce tasks is:

$$\begin{aligned} T_{\text{sort-red}}(\mathbb{J}) &= C_l \cdot \sum_{i=1}^n (r \times |R_i| \lceil 2 \log_B m \rceil) \\ &= C_l \cdot \sum_{i=1}^n (|D_i| \lceil 2 \log_B m \rceil) \end{aligned}$$

Thus the total cost of sorting is:

$$T_{\text{sort}}(\mathbb{J}) = C_l \cdot \sum_{i=1}^n (|D_i| \lceil 2(\log_B |D_i| - \log_B m) + \lceil \log_B m \rceil \rceil) \quad (19)$$

Finally, the cost of transferring intermediate data is:

$$T_{tr}(\mathbb{J}) = \sum_{i=1}^n C_t \cdot |D_i| \quad (20)$$

The overall cost is the sum of the above:

$$T(\mathbb{J}) = T_{read}(\mathbb{J}) + T_{\text{sort}}(\mathbb{J}) + T_{tr}(\mathbb{J}) \quad (21)$$

## D. HARDNESS OF PROBLEM 1

THEOREM 2. Scan-Shared Optimal Grouping (Problem 1) is NP-hard.

**Proof.** We reduce the Set-Partitioning (SP) problem to the Scan-Shared Optimal Grouping (SSOG) problem. The SP problem is to decide whether a given multiset of integers  $\{a_1, \dots, a_n\}$  can be partitioned into two ‘halves’ that have the same sum  $t = \frac{\sum_{i=1}^n a_i}{2}$ . Without loss of generality we can assume that  $\forall i a_i < t$ , otherwise the answer is immediate.

Every instance of the SP problem, can be transformed into a valid instance of the SSOG as follows. Let the size of the sort buffer  $B$  be equal to  $t$ , and the size of the input data be equal to  $2 \cdot t$ . We construct a job  $J_i$  for each of  $a_i$  in the set. Let the map output size for each job  $J_i$  be  $|D_i| = a_i$ , then the map-output-ratio of  $J_i$  is  $d_i = \frac{a_i}{2 \cdot t}$ . The number of sorting passes for each job  $J_i$  is  $p_i = \lceil \log_B |D_i| - \log_B m \rceil + \lceil \log_B m \rceil$ . Let  $m = 1$ , then  $p_i = \lceil \log_B |D_i| \rceil$ . Since  $\forall i a_i < t$ , hence  $\forall i a_i < B$ , then  $\forall i p_i = 0$  – the map output of each job  $J_i$  is sorted in memory. We also set  $f = 1.00$ . This is a valid instance of the SSOG problem.

An optimal solution for SSOG with two group exists, if and only if, there exists a partitioning of the original SP problem. For a group  $G_s$  of  $n_{G_s}$  jobs,  $p_{G_s} = \lceil \log_B |X_{G_s}| \rceil$ . Hence,  $p_{G_s} = 1$  for all  $G_s$  such that  $|X_{G_s}| > B$  (aka  $x_{G_s} > 0.5$ ) – if the size of the intermediate data exceeds the buffer size we need one additional sorting pass. By our assumption on  $f$ , for any such group  $G_s$ , the savings are  $\mathcal{SS}(G_s) = (n_{G_s} \cdot f - 2 \cdot x_{G_s} \cdot p_{G_s}) - f < 0$ . Hence, it is better to execute the jobs in  $G_s$  separately. We conclude that the final solution will have only groups  $G_s$  with  $p_{G_s} = 0$ , and for any group  $G_s$  in the solution  $\mathcal{SS}(G_s) = n_{G_s} \times f - f$ . We maximize  $\mathcal{SS}(G_s)$  over all  $S$  groups, but  $\sum_{s=1}^S n_{G_s} \cdot f$  is constant among all groupings, hence our problem is equivalent to minimizing the number of groups.

If the optimal solution consists of only two groups  $G_1$  and  $G_2$ , then there exists a partitioning of jobs  $J_i$  into two sets, such that  $\sum_{J_i \in G_1} D_i = \sum_{J_i \in G_2} D_i = B = t$ , which is a solution to the original SP problem. Since we are minimizing the number of groups (subject to constraints), then if there is a partitioning of the original SP problem, our algorithm will return two groups (as three groups would yield lower savings). We conclude that the exact SSOG problem is NP-hard.

## E. RELAXED PROBLEM 1 PROPERTY

THEOREM 3. Given a list of jobs  $\mathbb{J} = \{J_1, \dots, J_n\}$  and assuming that the jobs are sorted according to the map-output-ratios ( $d_i$ ), each group of the optimal grouping of the relaxed version of Problem 1 will consist of consecutive jobs as they appear in the list.

**Proof.** Assume the optimal solution contains the following group:  $G_s = (t, \dots, u-1, u+1, \dots, v)$ , which is sorted

by the indices (and thus  $d_i$ s, and  $p_i + \delta_i$ s). Observe that group  $G_s$  does not contain  $u$ .

i)  $\{u\}$  is a singleton group. If  $gain(u, v) > 0$  then putting  $u$  into this group would yield higher savings (as we will have one less group), hence the solution can not be optimal. If  $gain(u, v) < 0$ , then also  $gain(u-1, v) < 0$ . Hence executing  $\{u-1\}$  as a singleton would give higher savings. Same for all  $\{t, \dots, u-1\}$ . The given solution when  $\{u\}$  would be a singleton cannot be the optimal solution.

ii)  $\{u\}$  is not a singleton group.

- $\{u\}$  is in  $G_{s+1} = (u, w, \dots, z)$  where  $z > v$ . If  $p_v + \delta_v = p_z + \delta_z$  (the final number of sorting passes are equal) then  $G_{s+1}$  and  $G_s$  can be merged with no cost yielding higher savings (having one scan versus two). Hence this would not be the optimal solution. By our sorting criterion:  $p_z + \delta_z > p_v + \delta_v \geq p_u + \delta_u$ , hence  $gain(u, z) < gain(u, v)$ . Putting  $\{u\}$  to  $G_s$  yields higher savings, hence the partitioning is not optimal.
- $\{u\}$  is in  $G_{s-1} = (w, \dots, x, u, z)$  where  $z < v$ . Again we know that  $p_v + \delta_v > p_z + \delta_z \geq p_u + \delta_u$ . But then  $gain(u-1, z) > gain(u-1, v)$ . Putting  $\{u-1\}$  (all  $\{t, \dots, u-1\}$ ) to  $G_{s-1}$  yields higher savings. Similarly, if  $G_{s-1} = (w, \dots, x, u)$  ( $u$  is the constituent job), putting  $\{u-1\}$  to  $G_{s-1}$  yields higher savings.

## F. PROOF OF THEOREM 1

**Proof.** Assume that the optimal solution  $\mathcal{S}$  contains two groups  $G_1$  and  $G_2$ , such that  $J_k \in G_1$  and  $J_l \in G_2$ . Then  $\mathcal{SM}(G_1) = f \cdot (n_{G_1} - 1) - x_{G_1}(g + 2(p_{G_1}))$ , and same for  $G_2$ . By switching  $J_k$  to  $G_2$ , we obtain  $\mathcal{SM}(G_2 \cup \{J_k\}) = \mathcal{SM}(G_2) + f$ , since  $x_{G_2 \cup \{J_k\}} = x_{G_2}$ . However,  $\mathcal{SM}(G_1 \setminus \{J_k\}) \geq \mathcal{SM}(G_1) - f$ , since  $x_{G_1 \setminus \{J_k\}} \leq x_{G_1}$ . By switching  $J_k$  to  $G_2$  we obtain a solution at least as good as  $\mathcal{S}$  and thus still optimal.  $\square$

## G. DESCRIPTION OF THE FORMULAS

In this section, we describe in detail several formulas used in our algorithms.

- $\mathcal{SS}(G) = \sum_{i=1}^n (f - 2 \cdot d_i \cdot (p_j - p_i + \delta_G)) - f$  (Equation 11): recall that  $J_j$  is the constituent job of group  $G$ , i.e., it has the largest intermediate data size ( $d_j$ ), incurring the highest number of passes ( $p_j$ ).  $\delta_G$  indicates if the final number of sorting passes increases with respect to  $p_j$ . Each job  $J_i$  in  $G$  introduces savings of  $(f - 2 \cdot d_i \cdot (p_j - p_i + \delta_G))$ , where  $f$  accounts for the input scan, and  $-2 \cdot d_i \cdot (p_j - p_i + \delta_G)$  is subtracted to account for additional cost of sorting – if the original number of passes  $p_i$  of job  $J_i$  is lower than the final number of passes  $p_j + \delta_G$ . Overall savings  $\mathcal{SS}(G)$  for group  $G$  is a sum over all jobs minus  $f$  for performing a single input scan when executing  $G$ .
- $gain(i, j) = f - 2 \cdot d_i \cdot (p_j - p_i + \delta_j)$  (Equation 12): represents savings introduced by job  $J_i$  merged with a group where  $J_j$  is a constituent job in a sharing scans only scenario. Originally, job  $J_i$  sorts its intermediate data in  $p_i$  passes, and job  $J_j$  in  $p_j$  passes. Here,  $\delta_j$  is only dependent on  $J_j$ , and is either 0 or 1.  $gain(i, j)$  quantifies savings incurred by one input scan ( $f$ ) minus the cost of additional sorting of  $J_i$ 's map output – if the original number of passes  $p_i$  is lower than  $p_j + \delta_j$ .

- $GAIN(t, u) = \sum_{t \leq i \leq u} gain(i, u)$  (Section 4.1.3): quantifies savings of merging a sequence of jobs  $J_t, \dots, J_u$  into a single group, without accounting the single input scan that needs to be performed for this group.  $GS(t, u) = GAIN(t, u) - f$  accounts for one additional input scan per group.
- $c(l) = \max_{1 \leq i \leq l} \{c(i-1) + GS(i, l)\}$  (Equation 13): represents the maximal savings over all possible groupings of a sequence of jobs  $J_1, \dots, J_l$ . To obtain it in our dynamic program, we need to try all possible  $i$ s ranging from 1 to  $l$ , and pick the one that yields the highest  $c(l)$ .
- $gain(i, j) = f - (g(\gamma - 1)d_i + 2 \cdot d_i \cdot (\gamma(p_j + \delta_j) - p_i))$  (Equation 16): quantifies savings introduced by job  $J_i$  merged with a group where  $J_j$  is a constituent job in a sharing map output scenario, where we assume that  $(1 - \gamma)$  part of  $J_i$ 's map output is shared with  $J_j$ . Hence, merging  $J_j$  with the group introduces savings on scanning the input  $f$ , plus the savings on copying  $(1 - \gamma)$  part of the  $J_i$ 's map output, minus the cost of additional sorting (which can be negative in this case).  $-g(\gamma - 1)d_i$  quantifies the savings on copying the intermediate data.  $2 \cdot d_i \cdot (\gamma(p_j + \delta_j) - p_i)$  is the difference of sorting cost in the shared scenario, where we need to sort only the  $\gamma$  part of  $J_i$ 's map output in  $p_j + \delta_j$  passes, and the non-shared scenario, where we sort the entire map output of  $J_i$  in  $p_i$  passes.

## H. EXAMPLES OF TAGGING SCHEMES

There are two cases for which MRShare automatically combines the processing logic of two jobs: (i) If we know that the parsing of the input is identical then scan sharing is applied – the map output tuples are tagged as shown in Example 5. (ii) If, in addition, the two map functions produce identical tuples from the same input tuple, then we also share the common map output – Example 6 depicts how the map output tuples are tagged in this case. In both cases the original map functions are treated as black boxes and they are combined by the meta-map wrapper function.

In both cases, we do not consider separating the map output after the map stage. This would require substantial changes in the MapReduce architecture and counter our goal of developing a framework that minimally modifies the existing MapReduce architecture. Other side-effects of such an approach would be: more files would need to be managed which means more overhead and errors; running multiple reduce stages would cause network and resource contention.

**EXAMPLE 5 (TAGGING FOR SHARING SCANS).** *Table 3 is an example of tagging for sharing scans. The appropriate reduce function is indicated for each tuple, based on the tag() field. Each tuple within a group will be processed by exactly one of the original reduce functions. Since tuples are sorted according to the (key + tag()), the reduce functions will be executed sequentially. First, all tuples belonging to  $J_3$  will be processed, then  $J_2$ , etc. At any point in time, only the state of one reduce function must be maintained. In this example, tag() is one byte long. Also,  $B_7$  is always set to 1, meaning that a tuple belongs to exactly one job.  $B_6 \dots B_0$  determines the job, in which the tuple belongs.*

**EXAMPLE 6 (TAGGING FOR SHARING MAP OUTPUT).** *Table 4 describes tuples produced by  $n$  mapping pipelines*

**Table 3: Sharing-scans tagging**

key	$B_7$	$B_6 \dots B_0$	value	reduce function
key	1	0000100	$v_1$	$reduce_3$
key	1	0000100	$v_2$	$reduce_3$
key	1	0000100	$v_3$	$reduce_3$
key	1	0000010	$v_4$	$reduce_2$
key	1	0000010	$v_5$	$reduce_2$
key	1	0000001	$v_6$	$reduce_1$

from one input tuple, sorted according to key. The tag() field is byte long ( $B_7, \dots, B_0$ ), as before.

**Table 4: Map output of  $n$  pipelines**

job	key	$B_7$	$B_6 \dots B_0$	value
1	1	1	0000001	$v_1$
3	1	1	0000100	$v_1$
2	1	1	0000010	$v_1$
4	2	1	0001000	$v_2$
6	2	1	0100000	$v_2$
5	3	1	0010000	$v_3$

Going back to our example, the output produced by the mapping pipelines can be shared as shown in Table 5. Observe that the MSB of tag() is set according to the number of originating pipelines.

**Table 5: Merged map output**

job	key	$B_7$	$B_6 \dots B_0$	value
1,2,3	1	0	0000111	$v_1$
4,6	2	0	0101000	$v_2$
5	3	1	0010000	$v_3$

Table 6 depicts some groups’ examples, processed at the reduce side. The last column indicates the reduce functions to which each tuple needs to be pushed. We remark that we need to maintain the states of multiple reduce functions. However, since the group is sorted also on tag(), we are able to finalize some reduce functions as the tuples are processed.

## I. EXPERIMENTAL EVALUATION

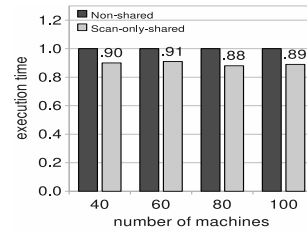
### I.1 Experimental Setting

We ran all experiments on a cluster of 40 virtual machines, using Amazon EC2 [1], unless stated otherwise. We used the small size instances (1 virtual core, 1.7 GB RAM, 160GB of disk space). All settings for Hadoop were set to defaults. Our real-world 30GB text dataset, consists of blog posts [2]. We utilized approximately 8000 machine hours to evaluate our framework. We ran each experiment three times and averaged the results.

We ran *wordcount* jobs, which were modified to count only words containing given regular expressions (aka *grep-wordcount*). Hence, we were able to run jobs with various intermediate data sizes, depending on the selectivity of the regular expression. We remark that *wordcount* is a commonly used benchmark for MapReduce systems. However, we cannot use it in our experiments because we cannot control the map-output sizes. Another reason for choosing *grep-wordcount* is that it is a generic MapReduce job. The map stage filters the input (by the given regular expression), while the reduce stage performs aggregation. In other words, any group-by-aggregate job in MapReduce is similar in its structure to *grep-wordcount*. We clarify that we produced random jobs with various intermediate data sizes. In real-world settings, however, the information about approximate intermediate data sizes would have been obtained

**Table 6: Processing a group at the reduce side**

key	$B_7$	$B_6 \dots B_0$	value	reduce function
$k$	1	0100000	$v_1$	$reduce_6$
$k$	1	0010000	$v_2$	$reduce_5$
$k$	0	0001001	$v_3$	$reduce_1; reduce_4$
$k$	0	0000111	$v_4$	$reduce_1; reduce_2; reduce_3$

**Figure 4: MRShare scale independence.**

either from historical data, or by sampling the input, or by syntactical analysis of the jobs.

### I.2 System Dependent Parameters

The first step of our evaluation was to measure the system dependent parameters,  $f$  and  $g$ , by running multiple *grep-wordcount* jobs. Our experiments revealed that the costs of reading from the DFS and the cost of reading/writing locally during sorting, were comparable, hence we set  $f = 1.00$ . This is not surprising, since Hadoop favors reading blocks of data from the DFS, which are placed locally. Hence, the vast majority of data scans are local.

The cost of copying the intermediate data of jobs over the network was approximately  $g = 2.3$  times the cost of reading/writing locally. This is expected, since copying intermediate data between map and reduce stages involves reading the data on one machine, copying over the network, and writing locally at the destination machine.

We remark that our experiments revealed that the cost of scanning the input is rarely dominant, unless the map output sizes are very small. For example, when we ran a series of random *grep-wordcount* jobs, the average cost of scanning was approximately 12% of the total execution time of a job. Thus, even if there is no scanning at all, the overall savings from sharing scans cannot exceed this threshold.

### I.3 MRShare Scale Independence

We demonstrate the scalability of MRShare with respect to the size of the MapReduce cluster. In particular, we show that the relative savings, using MultiSplitJobs for sharing scans, do not depend on the size of the cluster. We ran queries G4 with random map-output-ratio (see Table 2), and measured the resulting savings for 4 cluster sizes, 40,60,80, and 100. Figure 4 illustrates our results. In each case, the left bar represents the normalized execution time, when no sharing occurs. The relative saving from sharing scans were approximately the same in each case, independent of the size of the cluster. Indeed, our cost model does not depend on the number of machines and this is confirmed by our results. The overall cost is only distributed among the machines in the cluster. However, the relative savings from sharing e.g., scans do not depend on the cluster’s size.