Adaptive Information Passing For Early State Pruning in MapReduce Data Processing Workflows

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ABSTRACT
MapReduce data processing workflows often consist of multiple cycles where each cycle hosts the execution of some data processing operators e.g., join, defined in a program. A common situation is that many data items that are propagated along in a workflow, end up being “fruitless” i.e. they do not contribute to the final output. Given that the dominant costs associated with MapReduce processing (I/O, sorting and network transfer) are very sensitive to the size of intermediate states, such fruitless data items contribute unnecessarily to workflow costs. Consequently, it may be possible to improve the performance of MapReduce data processing workflows by eliminating fruitless data items as early as possible. Achieving this will require maintaining extra information about the state (output) of each operator, and then passing this information to descendant operators in the workflow. The descendant operators can use this state information to prune fruitless data items from their other inputs. However, this process is not without any overhead and in some cases, its costs may outweigh its benefits. Consequently, a technique for adaptively selecting Information Passing as part of an execution plan is needed. This adaptivity will need to be determined by a cost model that accounts for MapReduce’s partitioned execution model as well as its restricted model of communication between operators. These nuances of MapReduce impose limitations on the applicability of information passing techniques developed for traditional database systems.

In this paper, we propose an approach for implementing Adaptive Information Passing for MapReduce platforms. Our proposal includes a benefit estimation model, and an approach for collecting data statistics needed for benefit estimation, which piggybacks on operator execution. Our approach has been integrated into Apache Hive and a comprehensive empirical evaluation is presented.

1. INTRODUCTION
A dominant trend for large scale data intensive processing is to use parallel processing over a cluster of commodity grade machines. The MapReduce [13] parallel processing model that was made popular a few years ago by Google has emerged as the de facto standard for processing data-intensive workloads. Data intensive tasks are captured in the MapReduce model as workflows made up of sequences of MapReduce cycles/jobs. Each MapReduce cycle consists of 2 phases - a Map and a Reduce phase. The Map phase executes the map function which takes a set of key-value pairs as input, and maps each pair to an intermediate key-value pair. Each phase can have multiple instances (mappers and reducers respectively) running concurrently on assigned data partitions i.e., partition parallelism. A popular open-source implementation of Google's MapReduce proposal is Apache Hadoop [1]. In order to implement a data processing task in this model, programmers have to figure out the best translation of their tasks into the MapReduce model. This process has been simplified with the introduction of extended MapReduce platforms such as Hive [22] and Pig [21], that provide high-level declarative languages with querying constructs ala SQL, and compilers for automatically compiling high-level programs into MapReduce execution workflows. The compilation process assigns query operators or constructs to specific MapReduce cycles. Fig.1 shows an abstract data processing MapReduce model which captures the structure of what each cycle with data processing operators looks like using Hive as an example. Primary operators ($P_m$, $P_r$) are operators that take input data from the Hadoop framework, process them, and feed them into other operators. Once the operators in each phase complete their processing, a terminal operator ($T_m$, $T_r$) collects the resulting output. Further, for non-trivial data processing tasks that require multiple MapReduce cycles, control and data dependencies are implied by the high-level program and represented as a workflow.

An important thing to note about MapReduce data processing workflows is that they can be very costly. Table 1 shows the dominant costs (CPU costs of map and reduce function are ignored) in a MapReduce cycle. The scheduler schedules a set of slave nodes (mappers) to execute the Map phase, and assigns a split or partition of the input file to each mapper. The input data loading cost is represented as $C_{Load}$ in Table 1. (Note that multiple splits can be assigned to a mapper, in which case multiple map function instances are executed on the node). Once all mappers are complete, the intermediate key-value pairs are materialized on the mappers’ local disk (cost $C_{MapStore}$) in preparation for the Reduce phase. The scheduler then assigns nodes (reducers) to reduce a partition of map output values in a

![Figure 1: An Abstract MapReduce Job](image-url)
process that consists of three phases: *copy* — copying the sorted map output from mappers’ disks to reducers nodes, resulting in a data transfer cost $C_{\text{Shuffle}}$; *merge* — merging the sorted output lists from different mappers based on the intermediate key with cost $C_{\text{Merge}}$, and *reduce* — reduce() is invoked once for each intermediate key, and applied to the associated group of values. The output key-value pairs generated by all reducer instances are merged and materialized into the underlying distributed file system e.g., Hadoop Distributed File System (HDFS) contributing to cost $C_{\text{RedStore}}$. The cost of a workflow is the aggregate cost of all cycles in the workflow. As can be observed, these costs are all sensitive to the size of data. Therefore, developing ways to keep the footprints of intermediate states small is crucial to performance of MapReduce workflows.

<table>
<thead>
<tr>
<th>Cost Factor</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{\text{Load}}$</td>
<td>Input data loading cost</td>
</tr>
<tr>
<td>$C_{\text{Sort}}$</td>
<td>Map-side sorting cost</td>
</tr>
<tr>
<td>$C_{\text{Shuffle}}$</td>
<td>Data transfer cost</td>
</tr>
<tr>
<td>$C_{\text{Merge}}$</td>
<td>Reduce-side partition merging cost</td>
</tr>
<tr>
<td>$C_{\text{MapStore}}$</td>
<td>Map output data materialization cost</td>
</tr>
<tr>
<td>$C_{\text{RedStore}}$</td>
<td>Reduce output data materialization cost</td>
</tr>
</tbody>
</table>

### 1.1 The Problem

Due to the significant overhead associated with each MapReduce cycle, a key objective when optimizing MapReduce data processing workflows is minimizing the length of the workflow i.e., the number of MapReduce cycles in the workflow. Another very important objective (similar to relational databases) is minimizing the overall size of intermediate results or states produced during a data processing workflow (query). This is particularly crucial because of the multiple I/O, sorting, and network data transfer phases of intermediate results during a MapReduce data processing workflow. State-producing operators such as the JOIN operator, whose outputs may be larger than their inputs are an important consideration when thinking about minimizing the size of intermediate states produced. Indeed, in relational query optimization, the JOIN operator is a very fundamental operator for combining datasets, and its optimization is the focus of a lot of research. Typically, this is achieved by ordering operators in a way that minimizes inputs to each join. Cost models based on heuristics are used to estimate outputs of each operation so as to determine the best ordering of operations. In order to achieve this during compile-time, the parameters to such cost models will have to be precomputed, requiring preprocessing of data. This is natural for relational databases where data structures like indexes and statistical profiles of data are maintained as data is ingested into the system. However, MapReduce data processing platforms are typically not used to manage or host data in the long term but rather just for processing data-intensive workloads. Thus, features like statistics and indexing are immature or absent in MapReduce-based platforms like Hive and Pig. Further, any cost models used for relational optimization are not adequate for MapReduce data processing, because they do not capture key MapReduce-specific costs. Consequently, it is very important to consider runtime optimization techniques that can be applied as data is being ingested. Further, since these platforms are often used in batch processing mode, information gathered during earlier tasks in the batch workload can be used to inform the execution of latter tasks within the same batch workload.

A useful group of runtime optimization techniques in relational query optimization is called *Information Passing (IP)*. Such techniques support passing information from earlier phases of data processing to later execution steps, particularly join operations, to help them prune their states more aggressively. If this is done early enough, we could avoid fruitless data from traveling along in the workflow only to be eventually pruned. As an example, Fig. 2 shows an example job plan consisting of three MapReduce jobs executing equi-join (joining relations on equality condition on particular fields). The execution sequence is $\text{Job}_1$, $\text{Job}_2$, and $\text{Job}_3$. $\text{Job}_3$ joins the two intermediate tables on $\text{ps_suppkey}$ and $\text{l_suppkey}$ after $\text{Job}_1$ and $\text{Job}_2$ complete. In this case, it is obvious that only records with suppkey 61025 will be joined and emitted to the final output (output of $\text{Job}_3$) while remaining records will be discarded. The other records are essentially fruitless or irrelevant to final result. Unfortunately, these fruitless records affect $C_{\text{Load}}$, $C_{\text{Sort}}$, $C_{\text{MapSort}}$, $C_{\text{Shuffle}}$, and $C_{\text{Merge}}$ costs for $\text{Job}_3$. Further, they contribute to the costs of $\text{Job}_1$ and $\text{Job}_2$. If on the other hand, it is possible to pass information about the output context of $\text{Job}_1$ to $\text{Job}_3$, then it is possible to have $\text{Job}_3$ prune its inputs (output of $\text{Job}_2$ and $\text{Job}_1$) while loading them, so that some savings in its $C_{\text{Sort}}$, $C_{\text{MapSort}}$, $C_{\text{Shuffle}}$, and $C_{\text{Merge}}$ can be achieved. Better still, we may be able to pass this information to $\text{Job}_2$ so that while it writes its output, it can prune records that are irrelevant to final results e.g., records 30114, 132210. In addition to savings in $\text{Job}_3$’s costs, we can get additional savings with respect to $\text{Job}_2$’s $C_{\text{RedStore}}$ and $\text{Job}_3$’s $C_{\text{Load}}$. Such savings can be significant if pruning irrelevant tuples can be done much earlier in the workflow. For example, assume an execution plan such that these records are eventually pruned in $\text{Job}_k$ and not in $\text{Job}_3$. Then, pruning these records from $\text{Job}_2$’s output will avoid carrying them along and processing them in some of jobs in $\text{Job}_3$ to $\text{Job}_k − 1$, before being eventually pruned out in $\text{Job}_k$.

In shared-memory or distributed environments where relational information passing techniques have been investigated, IP is usually achieved through some centralized shared memory structure which can be accessed by all operators. Shared nothing cluster environments and rigid communication models allowed by MapReduce make such an implementation strategy difficult. These issues will be elaborated in...
Section 2.1. More significant is that the overhead of information passing may surpass its benefits. Therefore, techniques for runtime, adaptive selection of an information passing strategy as part of workflow execution need to be developed. Further, the decision for information passing selection has to be based on a cost model that is MapReduce-aware and informed by characteristics of data as determined during processing. The latter also suggests the need for a light-weight technique for collecting information about data at runtime by piggybacking on data processing.

1.2 Contributions
Specifically, we make the following contributions:

- We propose an architecture that supports adaptively enabling information passing (IP) in Hadoop-based data processing platforms based on its cost-benefits trade-offs. The architecture provides support for IP-aware operators, IP-plan compilation and execution. We present a strategy for integrating these components into Apache Hive.

- We propose a MapReduce-based benefit estimation cost model for estimating the benefits of an IP-enabled execution plan. In addition, we present a light-weight data statistics collection technique that piggybacks on workflow execution, and collects necessary parameter values for the IP benefit estimation cost model.

- Finally, we present a comprehensive evaluation of the proposed framework using two datasets including a benchmark.

2. RELATED WORK

2.1 Sideways Information Passing

Relational database research has proposed a few variants of Sideways Information Passing (SIP) techniques [19, 17, 8, 9, 20] where information is passed between operators in an execution plan. Magic-set rewriting [19] ships summary information on examined values from a parent query to its sub-queries or views so that they can discard unmatched records. Semi-join [9] processes join over remote sites. It projects and sends join columns from one site to another, and joins the projection with a remote relation. The resulting records are transferred to the original site and joined. In a sense, the task of passing information is integrated into the semantics of the operator itself rather than being an augmentation. In [8], an operator named Eddy routes records among relational operators based on dynamic runtime properties so as to maximize performance. [17, 20] produce filters from operators to other co-related operators to prune unnecessary records. Compile-time plans are augmented by run-time benefit estimation to reduce the information passing overhead. [17, 8, 20] introduced adaptive SIP approaches. Adaptivity can selectively add IP to an execution plan based on a cost model that relies on statistics of the underlying database system.

Discussion. While these SIP techniques have similar goals with our proposal, their implementations make assumptions that do not carry over to MapReduce execution platforms, making their adoption infeasible. Specifically, [19, 20] is designed for a centralized shared-memory environment where summaries can be exchanged using buffers or other message passing techniques [17, 8] that assume the existence of a centralized repository for exchanging tuples or summaries at will. On the other hand, MapReduce executes in a shared-nothing environment with a very restricted communication model between nodes. Further, operator execution in existing techniques is holistic i.e, one instance of operator processes all the input for that operator. This is in contrast to partitioned execution in MapReduce where multiple instances of an operation are executed, each processing one partition of the operator’s input. The consequence is that information about the state of a MapReduce operator is fragmented across the different instances whereas in the traditional case, all summary information can be found in a single location. Finally, the adaptivity model proposed in [17] assumes the availability of data statistics. However, as was mentioned before, such features are lacking in existing MapReduce data processing platforms or require significant overhead [15] to compute. These assumptions by existing approaches make for a much simpler information passing problem than would be required in the MapReduce setting.

2.2 Information Passing Other Join Optimizations for MapReduce Platforms

Some recent efforts [10, 16] have focused on enabling information passing in MapReduce. A series of semi-join techniques in [10] resemble the traditional 2-way semi-join. However, each join operation is implemented using three MapReduce cycles which can be very expensive. In some earlier work [16], we proposed a basic information passing technique Hadoop Information Passing (HIP) that enables summary exchanges between multiple MapReduce jobs in a workflow. In this approach, fragmented summaries about the state of an operator are generated at the end of the cycle in which its executes. The summaries are stored into the Hadoop Distributed File System as compressed files of summary lists. If the total size of those summary fragments do not exceed a user-defined threshold, they are broadcast to nodes at the initiation of a subsequent job that takes as input, the earlier job’s output. Other relevant work include efforts to reduce the length of a MapReduce workflow by clustering operations into few cycles as possible using multi-way join algorithms [18, 7, 23]. If the length of a workflow is reduced to just one cycle, then information passing becomes unnecessary. However, this is not always feasible for non-trivial data processing tasks because invariably, different operators will have conflicting key partitioning requirements forcing their execution to be assigned to different cycles. Also, some of the algorithms result in a large amount of replication which impedes performance. In the case of [23], a cost-based query optimization approach is proposed, where the multiplicity of
replicated-join is decided by cost estimation. However, this approach requires additional MapReduce cycles per input table to calculate the necessary statistics.

3. ADAPTIVE INFORMATION PASSING IN HADOOP WORKFLOWS

In this section, we discuss our proposal for enabling information passing on Hadoop-based processing systems. Fig.4 shows our extended Hive framework with dotted lines denoting the new or extended components. Our system consists of three major components, (i) an information passing framework that enables IP-aware plans to generate and utilize summaries across jobs, (ii) a benefit estimator that estimates the costs for summary generation and propagation for each job, and (iii) a statistics collector that piggybacks on the MapReduce execution process to collect statistics required by the benefit estimator.

3.1 Information Passing Framework

At compile-time, this framework decides whether information passing or statistics generation should be enabled by contacting several components. The default Hive job executor was modified to enable and execute IP-related decisions.

Compile-time preparation. A Plan analyzer analyzes a MapReduce job plan to produce plan information. Plan information contains job-specific information and relationships among the multiple jobs in a job plan. Information for each job is stored in a data structure called JobDescriptor, which maintains the job ID, a pointer to the Hive job descriptor, the type of reduce-side primitive operator Pr (e.g., join or group-by), paths for summary input and output, and so on. The relationships among jobs are represented in a dataflow graph and a dependency graph. A dataflow graph describes the input/output dataflow of jobs, and a dependency graph (reverse of the dataflow graph) describes their execution order. A job executor that submits each job in a MapReduce job plan to the Hadoop framework, references the plan information to make a decision on information passing. A cost estimator retrieves statistics about the job’s input tables from the statistics repository, and calculates job costs. Job descriptors are augmented with such job cost information. Before submitting the current job JC, the job executor invokes the IP planner to check whether the job should generate summary information (SUMMARY_CREATION) for any subsequent jobs, and/or load any summaries created by previous jobs (SUMMARY_USAGE).

Algorithm 1 corresponds to the decision-making process for summary generation, which consists of two steps. First, the IP planner probes the plan information and checks whether any subsequent job processing a join operation can leverage the summary information that JC may produce (lines 3-4). For example, job JN−1 in Fig.5a is eligible for summary generation since job JN can use the summary to prune unnecessary data while loading TableA. Next, the IP planner calls the benefit estimator to estimate the benefit that the summary can bring about (line 5). If there is considerable benefit (configurable via parameter β > 0), the planner makes a decision to enable SUMMARY_CREATION (line 6) so that JC generates summary information during its execution.

Algorithm 1: Decision-making for State Creation

```
1 SUMMARY_CREATION ← false;
2 if IP is enabled in configuration file then
3   if JC linked to any job JN in dataflow graph then
4     if descriptor(JN).ReducerType == JOIN then
5       if BenefitEstimator.estimate(JC) > β then
6         SUMMARY_CREATION ← true;
7       end if
8     end if
9   end if
10 end if
```

![Figure 5: Possible IP Plans (a) Map-side pruning using child-to-parent IP, (b) Reduce-side pruning using sibling-to-sibling IP, (c) another example of child-to-parent IP using intermediate tables](image)

The IP planner also examines JC to determine usability of available summaries from a previously executed job JP. Algorithm 2 shows the corresponding decision-making algorithm for summary utilization which considers two possible cases of information passing: child-to-parent and sibling-to-sibling. Fig.5 shows three job plans illustrating the two scenarios (the execution sequence is JN−2, JN−1, JN, JN+1, and current job JC = JN). First is the case of child-to-parent IP between a parent job JC and a child job JP (lines 3-7). If job JC has a join operator in its reduce-phase (line 3), the planner looks up the dependency graph to find any jobs whose output is fed into JC i.e., child jobs which have generated summaries that have not yet been used (lines 4-5). There are two possible cases of child-to-parent IP: a job may either join an intermediate table and a base table (Fig.5a), or it may join two intermediate tables (Fig.5c) such that the summary generated by the child was not used by its sibling. In both cases, the planner determines whether the size of the summary files Pi (1 ≤ i ≤ r, for r reducers) generated by the child job is less than a user-defined threshold α. This is done to avoid heap memory leakage issues caused by loading large summary information. If the summary size is less than the threshold, the planner invokes the benefit estimator to determine the benefit in summary usage. Based on the estimated benefit, the summary from the child job is used by JC to prevent irrelevant data from being shuffled between
map and reduce phases. This map-side pruning helps to reduce $C_{\text{Sort}}, C_{\text{Shuffle}},$ and $C_{\text{Merge}}$ costs in $J_C$. The second case is that of *sibling-to-sibling* IP where the summary information generated by a previously-executed sibling job $J_S$ in the dataflow graph, can be used to prune the output of $J_C$ (line 8). For example, $J_y$ in Fig.5b has a sibling job ($J_{y+1}$) which generated a summary. $J_y$ uses the summary to curtail $C_{\text{Store}}$ costs in $J_N$, and $C_{\text{Load}}, C_{\text{Sort}}, C_{\text{Shuffle}},$ and $C_{\text{Merge}}$ in $J_{N+1}$. Before the job executor submits each job to Hadoop, all decisions are encoded in the job so that corresponding operators generate and / or load summaries.

Algorithm 2: Decision-making for State Utilization

```plaintext
1 SUMMARY_USAGE ← false;
2 if IP is enabled in configuration file then
3   //Child-to-Parent IP
4   if descriptor(Jc).ReducerType == JOIN then
5     if $J_C$ has a neighbor $J_P$ in dependency graph then
6       // If $J_P$ generated summaries $P_1$ ($1 \leq i \leq r$) such that $\sum|P_i| \leq \alpha$ then
7         SUMMARY_USAGE ← true;
8 if Jc has a sibling job J_S in dataflow graph then
9   //Sibling-to-Sibling IP
10   if Jc generated summaries $P_i$ ($1 \leq i \leq r$) such that $\sum|P_i| \leq \alpha$ then
11     SUMMARY_USAGE ← true;
//End of decision-making
```

Run-time operation. In order to generate summary information and utilize it, operators in a job should be aware of decisions and operate accordingly. Hence, we designed *IP-aware* reduce-side $T_r$ and map-side $P_m$ operators. As described earlier, $T_r$ is the final logical operator in the reduce phase that stores the reduce output to HDFS. If a job should generate summary information ($SUMMARY\_CREATION$ is true), decision-aware $T_r$ operator generates bloom filters on the target column that is a join key in a subsequent job. Algorithm 3 describes the pseudo code for the IP-Aware *map* and *reduce* function skeletons.

The merged summary is broadcasted to computing nodes via *JobConf* before the subsequent job executes. *JobConf* is a data transport facility provided by the Hadoop framework to propagate system-wide and job-specific configurations to nodes. The *JobConf* is copied once to each node’s local disk rather than to every mapper or reducer, and hence reduces the summary propagation costs. At the initialization phase of the subsequent job, the IP-aware map-side operator $P_m$ loads the merged summaries into an in-memory buffer (lines 12-13). Whenever a record is read, the operator calculates the hash value for the target column (join key), probes the in-memory buffer, and prunes out irrelevant records (lines 15-17). Note that in the case of sibling-to-sibling IP, the summary loading and pruning happens in the reduce phase using the IP-aware $T_r$ operator. If the $T_r$ operator also needs to generate summary, the pruning precedes the summary generation phase. The next section describes the benefit estimation model that guides decisions in the information passing framework.

### 3.2 Benefit Estimation Model

Our benefit estimation model does not consider the case of sending summaries to sibling jobs (e.g., Fig.5b). Instead, it estimates the benefit from consuming summaries in parent jobs (e.g., Fig.5a and 5c). If a given summary is beneficial for a parent job, it is expected that a sibling job can achieve more benefit by using the summary in terms of $C_{\text{STORE}}$ and $C_{\text{LOAD}}$. Hence, the proposed benefit estimation model aggregates partial benefits in $C_{\text{SORT}}, C_{\text{SHUFFLE}},$ and $C_{\text{MERGE}}$ ($B_{\text{sort}}, B_{\text{shuffle}},$ and $B_{\text{merge}}$ respectively), and differences the aggregated benefit and the cost for summary creation and propagation ($C_{\text{summary}}$):

$$B = B_{\text{sort}} + B_{\text{shuffle}} + B_{\text{merge}} - C_{\text{summary}} \quad (1)$$

Benefit in each step is estimated by subtracting the cost in the IP-enabled approach from the cost in the default approach. Hence, benefits in the three steps are:

$$B_{\text{sort}} = C_{\text{sort-orig}} - C_{\text{sort-ip}} \quad (2)$$

$$B_{\text{shuffle}} = C_{\text{shuffle-orig}} - C_{\text{shuffle-ip}} \quad (3)$$

$$B_{\text{merge}} = C_{\text{merge-orig}} - C_{\text{merge-ip}} \quad (4)$$

In sort-phase, MapReduce performs external merge sort.

Algorithm 3: IP-Aware map() / reduce() Skeletons

```plaintext
//Reduce() of current job $J_n$
Reduce (key: grpKey, val: Corresponding list of tuples T)
Init ()
reduce ()
1 foreach tu ∈ T do
2   out_tup ← Normal reduce processing;
3   nextJoin_key ← extract join key for next job;
4   hashVal ← nextJoin_key.hash();
5   Add distinct hashVal to in-memory sorted set;
6   emit <null, out_tup>;
7   Close ()
8   status ← close status of all reduce operators;
9   if status is Success then
10     Store summary to HDFS;
//Merge summary from $r$ reducers
11 mergedSummary ← merge(summary1, ..., summary$r$);
//Map() of a subsequent job $J_{n+1}$
Map (key: null, val: Tuple tup from Input)
Init ()
12 Load mergedSummary;
13 summarySet ← build in-memory sorted set from mergedSummary;
14 join_key ← extract the join column from tup;
15 if tup ∈ baseRelation then
16   if join_key.hash() does not exist in summarySet then
17     Prune out tup;
18 out_tup ← Normal map processing;
19 emit <join_key, out_tup> ;
Close ()
```

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and the cost can be estimated as follows:

\[ C_{\text{sort-orig}} = M(C_R + C_W)(\log_{B^{-1}} M_B^r + 1) \]  
when each mapper emits intermediate data of \( M \) pages on average, and the size of sorting buffer is \( B \). \( C_R \) (/\( C_W \)) is the unit cost to read (write) a page from (to) disk. Let \( \Delta \) be the average size of unnecessary data that is expected to be pruned by a given summary information, then the cost in the IP approach is:

\[ C_{\text{sort-ip}} = (M - \Delta)(C_R + C_W)(\log_{B^{-1}} M_B - \Delta B^r + 1) \]  

When the intermediate data is shuffled into \( r \) reducers, each reducer receives, on average, \((M \times m)/r \) pages from \( m \) mappers. Hence, the estimated data shuffle cost of the original approach is:

\[ C_{\text{shuffle-orig}} = \frac{M \times m}{r} C_T \]  
where \( C_T \) is the unit cost to transfer a page. The estimated data shuffle cost in the IP approach is:

\[ C_{\text{shuffle-ip}} = \frac{(M - \Delta)m}{r} C_T \]  

In reduce-phase, each reducer receives partitions from all \( m \) mappers and merges them into one block. Hence, we estimate the merge cost in the default approach as equation 9, and that of the IP approach as equation 10.

\[ C_{\text{merge-orig}} = R(C_R + C_W)(\log_{B^{-1}} m) \]  
\[ C_{\text{merge-ip}} = (R - \Delta \cdot \frac{m}{r})(C_R + C_W)(\log_{B^{-1}} m) \]  

where \( R \) is the average input size per reducer. Since \( M \cdot m = R \cdot r \), we substitute \((M \cdot m)/r \) for \( R \) producing the following equations:

\[ C_{\text{merge-orig}} = M \cdot \frac{m}{r} (C_R + C_W)(\log_{B^{-1}} m) \]  
\[ C_{\text{merge-ip}} = \frac{m}{r} (M - \Delta)(C_R + C_W)(\log_{B^{-1}} m) \]  

Cost \( C_{\text{summary}} \) is caused by summary generation and propagation and consists of four costs:

\[ C_{\text{summary}} = C_{\text{ip-store}} + C_{\text{ip-merge}} + C_{\text{ip-copy}} + C_{\text{ip-load}} \]  

(13)

Each \( T_i \) operator stores a partial summary information in a bloom filter of size \(|F|\) into HDFS. Hence, the cost to store a partial summary is:

\[ C_{\text{ip-store}} = (U_R + U_W)|F| \]  

where \( U_R, U_W \), and \( U_T \) are unit costs to read, write, and transfer a single byte, respectively. Since partial summaries generated by \( r \) reducers are combined into one bloom filter, the cost to merge partial summaries is:

\[ C_{\text{ip-merge}} = (U_T + U_R)|F|r^r + (U_T + U_W)|F| \]  

(15)

The cost to copy a merged summary to nodes is:

\[ C_{\text{ip-copy}} = N(U_R + U_W + U_T)|F| \]  

(16)

The summary loading cost of each operator from local disk is:

\[ C_{\text{ip-load}} = U_T|F| \]  

(17)

Parameters such as \( C_R, C_W, C_T, U_R, U_W \), and \( U_T \) are machine-specific and can be earned by performance measurement. \( B \) and \( N \) can be calculated with Hadoop configuration parameters, and \(|F| \) is set in the Hive configuration file. At the time that benefit estimation is performed, the number of reducers (\( r \)) in a current job has already been set by the Hive compiler. However, the number of mappers (\( m \)) and reducers (\( r \)) in its parent job are unknown since they depend on the input table sizes of the parent job and it is complicated to estimate those parameters without input statistics. For the same reason, the estimation of \( M \) and \( \Delta \) is complicated. In the next section, we describe our statistics collection approach that piggybacks on MapReduce job execution.

### 3.3 Piggybacking Statistics Collection on Operator Execution

Our approach for statistics collection piggybacks on the execution of MapReduce jobs. Generated statistics are used by the cost estimator to estimate statistics on intermediate data in a MapReduce job plan. These statistics are used by the benefit estimator to calculate necessary parameters such as \( m, r, M \), and \( \Delta \), which are supplied to the benefit estimation model to make decisions about information passing. Required statistics include the size of tables, the number of records, the average sizes of columns, and the value distributions within a column. The general idea is that rather than requiring a separate pre-processing step for computing statistics, we choose to exploit the fact there is a good likelihood that users will want to execute multiple queries on their datasets. Therefore, for each query, we compute and store statistics on selected columns of the tables being processed. Then, for future queries that refer those columns, we use the already computed statistics. Note that the statistics planner does not estimate statistics on all columns in input tables. For example, while evaluating TPC-H queries, columns for comments (e.g., ps_comment, l_comment, c_comment, and p_comment) and auxiliary information (e.g., c_address, s_address, and s_phone) are rarely positioned in filter or join conditions, and hence are not important for cost estimation. Such columns can be excluded to reduce the overhead of statistics generation and transmission costs. Users can manually specify additional columns into the column set by updating the Hive configuration file.

At compile-time, the statistics planner creates a list of input tables from a MapReduce job plan, and extracts a set of meaningful columns whose statistics are required for cost estimation. The statistics planner probes the statistics repository using Java Remote Method Invocation (Java RMI) to check the availability of statistics related to the listed tables and columns. If the statistics are unavailable, the statistics planner enables statistics collection and embeds the decision into the job plan. Additionally, the statistics planner registers the input table sizes in the statistics repository if such information is missing.

At run-time, the map-side primary operators \( (P_{\text{m}}) \) in each job generate the statistics on the required columns. Once the operators finish execution, the generated statistics are registered with the statistics repository. The generated statistics are partial since the \( P_{\text{m}} \) operators process records from different input portions. In this environment, it is straightforward to calculate the number of records and the average sizes of columns from fragmented statistics. However, re-
4. EXPERIMENTAL EVALUATION

The information passing approach has been implemented in Apache Hive 0.5 [2] on top of Apache Hadoop 0.20.0 [3]. This section presents an extensive study of the proposed approach by comparisons with original Hive, HIP [16], and semi-join [10]. For HIP, the threshold of total summary size was set to 512KB and 4MB. For the proposed IP approach, two sizes of bloom-filter were used for storing summary information (512KB and 4MB). First two steps of semi-join were implemented using vanilla MapReduce applications. However, the last step was implemented as a repartitioning join, instead of Hive’s fragment-replication join named map-side join. This is because the map-side join failed for experiments in which the size of intermediate data from the first two steps was not small enough to fit into memory.

4.1 Experiment Setup

Experiments were conducted on a cluster on NCSU VCL [6] which consists of 21 blade servers (one master node and 20 slave nodes). Each node has a 3.0GHz dual-core Xeon processor, 4GB memory, and a 28GB SCSI disk, and runs Red Hat Enterprise Linux 5. Hadoop framework was configured with 512MB of block size, replication factor 1, no speculative execution, and 1024MB of heap size for mappers and reducers.

4.2 Workloads and Analysis

Two kinds of synthetic datasets, including one benchmark were used. The first synthetic dataset is generated based on user-supplied parameters such as number of records, column sizes, and range of join column values. This benchmark was chosen since it is complicated to manually set reference ratios among generated tables with existing benchmarks. Three tables were generated using this benchmark: TableA, TableB, and TableC. Each table is 20GB and includes three columns (key: 25B, columnA: 75B, columnB: 100B). The key column in each table was used as a join key. The join key density of TableB and TableC is fixed to one while the join key density in TableA varies across experiments. Hence, records in TableA match different numbers of records in other tables. Records in TableB and TableC are exactly same. In order to evaluate the effects of passing summary information to different MapReduce jobs, two benchmark queries were used as shown in Fig.6. The query in Fig.6(a) compiles into two MapReduce jobs. The first job joins TableA and TableB, producing intermediate records of (TableB.key, TableA.columnA). The second job joins the intermediate output from the first job with TableC, and generates (TableB.key, TableA.columnA, TableC.columnA). For HIP and IP, the execution time of Job2 is summed up with any delay in execution time of Job1. Semi-join was computed on the intermediate records from Job1 and TableC, and the execution times of three steps were summed up. Next, the query in Fig.6(b) is translated into three MapReduce jobs. The first job joins TableB and TableC, and produces same number of records. The intermediate records are of (TableB.key and TableC.columnA). The last job joins the two intermediate tables and generates records of the form (TableB.key, TableA.columnA, TableC.columnA). Execution times for Job2 and Job3 for different approaches were also compared. However, semi-join was not performed for this query since the first two steps of semi-join cannot remove any records deriving no benefit. Second set of experiments used the TPC-H benchmark [5] dataset (40GB). The Hive version of TPC-H queries [4], which are written in HiveQL were used. Among the TPC-H benchmark queries, a set of relevant queries with multiple join operations were chosen. Different query plans were evaluated.

Figure 7: Execution times for Query1:Job2 with varying reference ratios (a) HIP: 512KB threshold, IP: 512KB bloom-filter, (b) HIP: 4MB threshold, IP: 4MB bloom-filter

4.3 Experimental Results

Performance improvement with varying reference ratios. The IP approach enhances query processing performance by pruning unnecessary records before joining. Hence, the effectiveness of the approach depends on the reference ratio between joined tables. To check the relationship between performance and reference ratio, TableA’s reference ratio was varied such that its records match different numbers of records in the other tables. Fig.7 shows...
the execution times of the query in Fig.6(a). First, semi-join failed for reference ratio 0.1 and 0.5 (denoted by broken lines on the y-axis to indicate that execution failed after a lengthy execution period) since the size of join key list exceeded available heap memory in its first step. For reference ratio 0.001 and 0.01, the semi-join approach did not show better performance than the original Hive approach. On the other hand, HIP and IP showed performance improvements as the reference ratio decreases. However, the IP approach was beneficial with relatively higher reference ratio than HIP (reference ratio = 0.01 in Fig.7(a) and reference ratio = 0.1 in Fig.7(b)). A problem with HIP approach is that it cannot calculate the size of summary information before partial summary fragments are merged and loaded into memory. Hence, the total size of summary fragments is compared with the user-defined threshold. As a consequence, even if the size of merged summary information is less than the threshold, it may disallow generated summary information to be loaded by jobs. On the other hand, IP approach decides about summary generation and utilization based on benefit estimation, and can maximize the benefit of information passing. In Fig.7(b), for example, HIP disabled the use of summary for reference ratio 0.1, while IP allowed summary to be used by Job2 deriving benefit.

When HIP processes Query2 in Fig.6(b), Job1 and Job2 generate summaries, and Job3 utilizes those summaries. Hence, as shown in Fig.8(a-b), Job2 execution times in HIP are longer than the original Hive approach due to summary generation overhead. On the other hand, the IP approach transports summary information from Job1 to Job2, and prunes unnecessary records at the end of Job2. Hence, it could derive benefits in materialization steps when its benefit estimation enables summary information (e.g., when reference ratio = 0.001 and 0.01 in Fig.8(a) and reference ratio = 0.001, 0.01, and 0.1 in Fig.8(b)). The benefits were less than 8% performance improvement. In case of Job3, IP achieved more performance improvement than HIP since reduced intermediate data from Job2 derived benefits in data loading phase in addition to shuffle-phase as shown in Fig.8(c-d).

**Performance improvement with varying block sizes.** This experiment evaluates the impact of varying HDFS block size on the different approaches. The reference ratio was fixed to 0.01, and HIP threshold and size of bloom-filter in IP were set to 4MB. Fig.9(a) shows the performance improvement rates of Job2 in Query1 relative to the original Hive approach. Semi-join was worse than Hive in all settings while the performance degradation rate decreased as block size increased since the execution time of semi-join increased slower than that of Hive. Both HIP and IP showed linear speedups with increasing block sizes. Each mapper that loads a block from TableC is assigned more data as the block size increases. Hence, given the summary information produced in the previous job, both approaches are able to prune out larger amount of “fruitless” data items before being shuffled, thus deriving higher cost saving in shuffle-phase.

Fig.9(b) shows the performance improvement rates of HIP and IP for processing Job2 in Query2. In HIP, summary information is always generated by children jobs (e.g., Job1 and Job2 in Fig.6(b)), and transported to parent jobs (e.g., Job3 in Fig.6(b)) in a dataflow graph. Hence, in the case of HIP, Job2 is accompanied with an overhead to generate summary information causing less than 1% slowdown. On the other hand, the IP approach can prune unnecessary data by using summary information transported from a sibling job (e.g., Job1 in Fig.6(b)) in a dataflow graph. Hence, IP derives benefit in the output materialization step of Job2 as shown in Fig.9(b). However, the benefit is relatively small (less than 1% speedups) for all block sizes.

Fig.9(c) compares the performance improvement rates of HIP and IP for Job3 in Query2. First of all, the IP approach outperforms HIP for all block sizes. HIP showed more than 20% performance improvement by preventing unnecessary data before data shuffle-phase. On the other hand, IP achieved relatively better performance enhancements than HIP since already reduced intermediate data could reduce the cost in data loading phase in addition to the data shuffle cost. In the second place, with 512MB to 1024MB block sizes, both approaches showed almost constant performance improvements. Hive and IP scheduled same numbers of mappers (86 mappers) and reducers (26 reducers) with those block sizes where the amounts of input data to each mapper and each reducer were not changed even if the block size increased. Hence, the effect of summary information in shuffle-phase was almost same with those block sizes. In case of IP, the same numbers of mappers (86 mappers) and reducers (14 reducers) were scheduled from 512MB to 1024MB block sizes. Therefore, the effect of reduced input data was almost same in data-loading and shuffling steps with different block sizes.

**Performance measurements with TPC-H benchmark.** Experiments with TPC-H benchmark were performed to measure the effectiveness of the IP approach. In these experiments, the bloom-filter size of IP and the
summarize information as long as they have subsequent jobs to benefit estimation. In HIP, jobs always generate summaries and transport them to next jobs. However, HIP does not improve the performance of $Q_3$, and degraded the performance of $Q_{10}$ a little due to overhead of generating and transporting summaries. With non-linear plans as shown in Fig.10(b), the IP approach showed 5-6% performance improvements when processing $Q_2$, $Q_5$, and $Q_{10}$, and improved the execution time of $Q_7$ by about 31%. In HIP, the execution times of $Q_2$ and $Q_7$ were improved 2% and 26%, respectively while that of $Q_{10}$ was degraded about 3% due to the overhead of summary generation. It is notable that HIP did not work for $Q_5$ because one of the jobs in the plan did not have enough heap memory space for storing its output summary information. HIP stores a list of hash values on a join column in memory. Hence, if the size of the in-memory list exceeds available memory space, it drives reducers to fail their execution. On the other hand, IP stores such data in a more compact bloom filter whose size is configurable, thus avoiding such problems.

**Benefit Estimation.** HIP and IP approaches without benefit estimation, may worsen query processing performance for cases where the overhead of generating and transporting summary information exceeds the benefit achieved by using the summary information. For example, with TPC-H $Q_9$, both approaches showed worse performance when they were enabled. Fig.10(c) shows the execution times of a $Q_9$ linear plan in different approaches. We compared the original Hive, HIP, IP without benefit estimation, and IP with benefit estimation. In HIP, jobs always generate summary information as long as they have subsequent jobs to which such summary information can be transferred. In addition, it transports summary information to the next job if its size is less than a user-defined threshold, even if the summary may not be beneficial. Because of such summary generation and transmission overheads, HIP brought about a 80 second delay in the execution time of the $Q_9$ linear plan. In IP without benefit estimation, all jobs in the query plan always generate summaries and transport them to next jobs. As a result, such imprudent use of summary information added a cost of about 125 seconds to the original execution time. On the other hand, the IP approach which leverages benefit estimation, could selectively allow summary generations and transmissions based on cost estimations. This allowed for maximizing the benefit of IP and preventing any large performance degradation in worst cases.

**Piggyback Statistics Collection.** Statistics collection which piggybacks query processing may impose penalties on its performance. This section evaluates the effect of piggybacking statistics collection in different approaches.
5. CONCLUSIONS

We present an adaptive information passing approach for early pruning of intermediate states in a MapReduce data processing workflow. The approach is based on a MapReduce-aware cost model for estimating potential benefits or loss of information passing in a particular workflow. We also present a light-weight approach for computing statistics by piggybacking on operator execution. Our approach for integrating the proposed information passing technique into a popular platform, Apache Hive, is presented. A comprehensive empirical evaluation using two datasets shows the benefits of our approach over existing techniques.

6. ACKNOWLEDGMENTS

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7. REFERENCES
