

Design and Evaluation of Hierarchical Merge with RDT Algorithm for Hadoop Acceleration

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ABSTRACT: Map Reduce is programming model and it processes large scale data in distributed applications due to its efficiency, simplicity and ease of use. Hadoop is an open source implementation of the Map Reduce programming model for cloud computing. Though Hadoop is giving best performance but still it tackle number of issues to gain that performance . The issues faces by Hadoop are (1) A serialization barrier that delays the reduce phase, repetitive merges, and disk accesses (2) The lack of portability to different interconnects. In this paper, propose a distributed implementation of Hierarchical Merge using RDT algorithm using Map Reduce computing model, and deploy it on a Hadoop cluster. It resolve memory scalability problem and increases performance of Map reduce. It also speed up the delivery of data from MapTasks to Reduce Tasks. While their work reduces job completion time and improves system utilization.

KEYWORDS: Hadoop; MapReduce; virtual shuffling; hierarchical merge; Hadoop acceleration.

I. INTRODUCTION

Map-Reduce [1] has emerged as a popular and easy-to-use programming model for cloud computing . It has been used by numerous organizations to process explosive quantity of data, perform large number of computation, and fetch critical knowledge for business intelligence. Hadoop [2] is an open source implementation of MapReduce, currently maintained by the Apache Foundation, and supported by leading Information technology companies such as Facebook and Yahoo!.Hadoop is a implementation of MapReduce framework with two types of components: a Job Tracker and many Task-Trackers. The Job Tracker commands Task Trackers (a.k.a.slaves) to process data in parallel through two main functions: map and reduce. In this process, the JobTracker is in charge of scheduling map tasks (MapTasks) and reduce tasks (ReduceTasks) to Task Trackers.

It also monitors their growth, collects runtime execution result, and handles possible errors and faults through task reexecution. Between the two phases, the intermediate output from all finished MapTasks need to be fetch by reduce task. Globally, this leads to the shuffling of intermediate data (in segments) from all MapTasks to all ReduceTasks. For many data intensive MapReduce programs, data shuffling can cause to a significant number of operations on disk, contending for the limited I/O bandwidth. This severe problem of disk I/O contention in MapReduce programs, which entails further research on efficient data shuffling and merging algorithms.Fig. 1 shows overview of data processing in Hadoop.

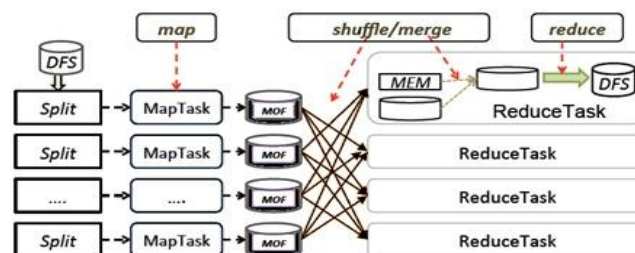


Fig.4. Data Processing In Hadoop MapReduce Framework

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Improving the performance of MapReduce recently. Originally, the Hadoop scheduler assumed that all nodes in a cluster were homogeneous and made progress with the same speed. Focuses on fast data output from MapTasks and changes Hadoop fault handling mechanism. The major issues faces by hadoop are Serialization barrier and continuous merging of data and disk access.

A. Serialization barrier in Hadoop :

Hadoop is easy to use data processing framework. When large number of task is given for processing a pool of concurrent MapTasks starts the map function on the first set of data splits. When Map Output Files (MOFs) are generated from these splits, a pool of ReduceTasks starts to fetch partitions from these MOFs. At each ReduceTask, when the number of segments is larger than a threshold, or when their total data size is more than a memory threshold, the smallest segments are merged. For the correctness of the MapReduce programming model, it is necessary to ensure that the reduce phase does not start until the map phase is done for all data splits. However, the pipeline, as shown in Fig.2, contains an implicit serialization. At each ReduceTask, only until all its segments are available and merged, will the reduce phase start to process data segments via the reduce function. This essentially enforce a serialization between the shuffle/ merge phase and the reduce phase. When there are many segments to process (which is often the case), it takes a significant amount of time for a ReduceTask to shuffle and merge them. As a result, the reduce phase will be significantly delayed and this can increase the total execution time.

B. Continuous Merging and disk access:

Hadoop ReduceTasks merge data segments when the number of segments or their total size goes over a threshold. A newly merged segment has to be spilled to local disks due to memory pressure. However, the current merge algorithm in Hadoop often leads to repetitive merges, thus extra disk accesses. Fig. 3 shows a common sequence of merge operations in Hadoop. When more segments arrive, the threshold is reached again. It is then necessary to merge another set of segments. This again causes additional disk access, let alone the need to read segments back if they have been stored on local disks. As even more segments arrive, a previously merged segment will be grouped into another set and merged again. Furthermore, any segment merged from a subset of segments eventually needs to be merged for final results. Altogether, this means repetitive merges and disk access, causing degraded performance for Hadoop. Therefore, an alternative merge algorithm is critical for Hadoop to mitigate the impact of repetitive merges and extra disk accesses.

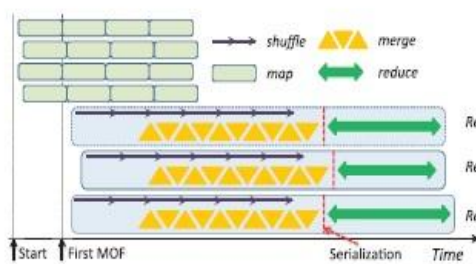


Fig.2. Serialization barrier in Hadoop

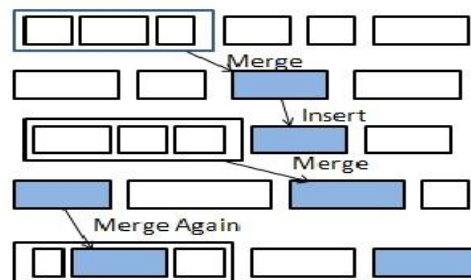


fig.3. Continuous Merging and disk access

II. RELATED WORK

The MapReduce[1] programming model has been successfully used. This model is very easily used by the programmers not having experience with parallelization and distributed systems, since it handles issues in distributed system such as parallelization, fault-tolerance, locality optimization, and load balancing. Hadoop Mapreduce[12] is the best tool available for processing data and its distributed, column-oriented database, HBase which uses HDFS for its underlying storage, and support provides more efficiency to the system. But still hadoop having some data shuffling problem and data shuffling can lead to a significant number of disk operations, contending for the limited I/O bandwidth. In network-levitated merging algorithm [3] the idea is to leave data on remote disks until it is time to merge the intended data records. In network levitated algorithm, number of remote segments S_1, S_2, \dots, S_n are to be fetched from local disks and then merged. the alternative way of accessing them to local disks, network levitated algorithm only fetches a small header from each segment. Each header is made up of partition length, offset, and the first pair of < key;



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val >. These < key; val > pairs are enough to build a priority queue (PQ) to manage these segments. After the first < key; val > pair, many records can be fetched as according to the available memory. Because it access only a tiny amount of data per segment, this algorithm does not store or merge segments onto local disks. When the number of segments is over a threshold without merging them, we keep building up the Priority Queue until all headers arrive and are merge. When the building of PQ has been completed, the merge phase starts its execution. The leading < key; val > pair will be the beginning point of merge operations for individual segments, i.e., the merge point. The design and architecture of Hadoops MapReduce framework propose by author Mrigank mridual, Kumar N[4]. In hadoop analysis is based on data processing. So bigdata is the new buzz word and Hadoop Mapreduce is the best tool available for processing data and its distributed, column-oriented database, HBase which uses HDFS for its underlying storage, and support provides more efficiency to the system. But still hadoop having some data shuffling problem and data shuffling can lead to a significant number of disk operations, contending for the limited I/O bandwidth.

MapReduce is a programming model for large-scale arbitrary data processing. To fully take advantage of the multicore and multiprocessor systems, Ranger et al. [4] designed Phoenix, a MapReduce implementation for shared-memory systems. In Phoenix, users only need to write simple parallel code without considering the complexity of thread creation, dynamic task scheduling, data partitioning, and fault tolerance across processor nodes. Kaashoek et al. [5] then designed a new MapReduce library with a compromise data structure, which outperforms its simpler peers, including Phoenix. Tiled-MapReduce designed by Chen et al. [6] further improves the Phoenix by leveraging the tiling strategy that is commonly used in compiler community. It divides a large MapReduce job into multiple discrete subjobs and extends the Reduce phase to process partial map output. By meticulously reusing memory and threads, Tiled-MapReduce achieves considerable speedup over Phoenix. But our work is completely different from these works in three aspects.

III. PROPOSED SYSTEM

A. System Architecture of Hadoop:

Figure 4. shows architecture of proposed system. The group of Task is given to the system, this group is splitting and given for the mapping. Map phase take the task and generate intermediate file this is based on RDT. The intermediate file get shuffle and merged and reducer reduces the result. All this phases generate tree so that performance of system get increases and because we create tree for each phase memory require is less.

B. Algorithm For Random decision tree:

C4.5 is a standard algorithm for inducing classification rules in the form of decision tree. As an extension of ID3, Fig.4. System Architecture of System the default criteria of choosing splitting attributes in C4.5 is information gain ratio. Instead of using information gain as that in ID3, information gain ratio avoids the bias of selecting attributes with many values.

Input: Dataset T, Attribute S;

Output: Decision Tree tree;

```
If T is Null then
    return Fail
end If
If s=1 then
    return Tree as a single Node
end If
set Tree=Empty
for a subset S do
    setInfo(a; T) = 0 and SplitInfo(a; T) = 0
    Compute Entropy(a);
    for v belongs values(a; T) do
        Set Ta;v as a subset of T as attribute a=v
        Info(a,T)+=Ta;v=TaEntropy(av)
        splitInfo(a,T)= -(Ta;v=Ta)Log(Ta;v=Ta)
    end for
```

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Gain(a,T)=Entropy(a)-Info(a,T)
GainRatio(a,T)=Gain(a,T)/SplitInfo(a,T)
end for
set a_best = argmaxGainRatio(a; T) attach a_best into Tree
for v values(a_best,T) do
    call again
end For
Return Tree
    
```

IV. SIMULATION RESULTS

The system conduct our experiment on 1 master node and 1 slave node having 5 GB RAM. This node run ubuntu operating system name centos cloudera having 1 processor and 1 TB hard disk. Weather forecasting dataset. we require hadoop framework and apache framework with eclipse. The forecasting dataset is given as a input to the system. The Figure 5. shows the final execution of system. fig 6. Shows memory require for the file system which include no. of bytes read ,written,operation on file system etc. fig 7 display final result in which number of map task ,reduce task, memory required ,number of nodes ,entropy is shown.

When total execution of system is completed the RDT is generated for final result based on dataset shown in fig.8. For intermediate files also RDT is generated shown in fig. 9. In this experiment 8 homogeneous clusters are generated from weather forecasting dataset. Number of Clusters are generated according to size of dataset at runtime. Fig. 10 shows the Fig. 7. Final Result cluster information ,intermediate file , Source file and output file.

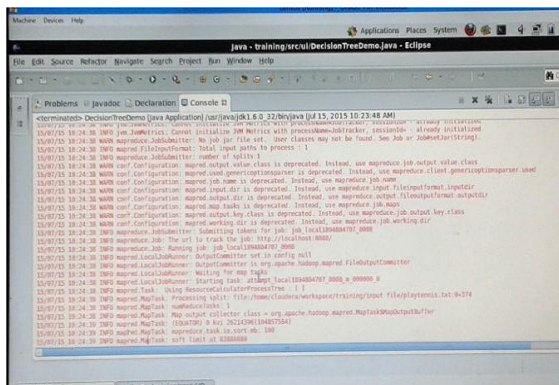


Fig.5. System Execution

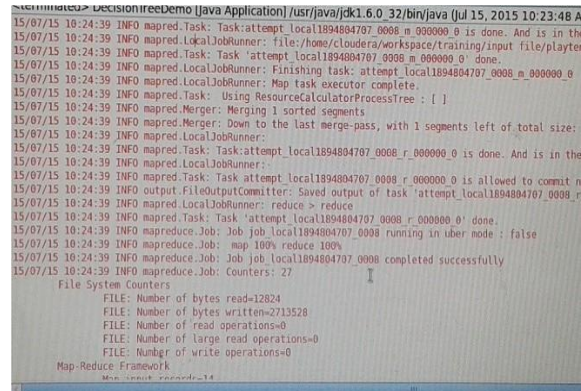


Fig.6. Memory Required For System

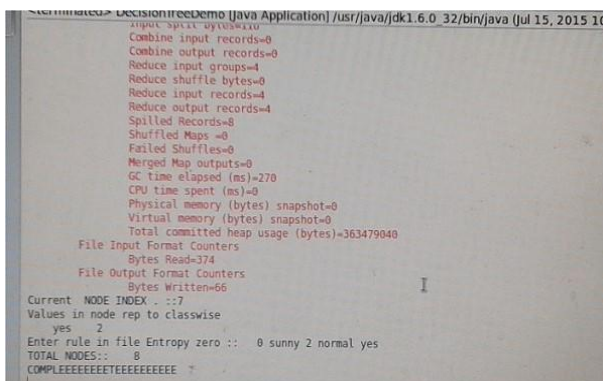


Fig.7. Final Result

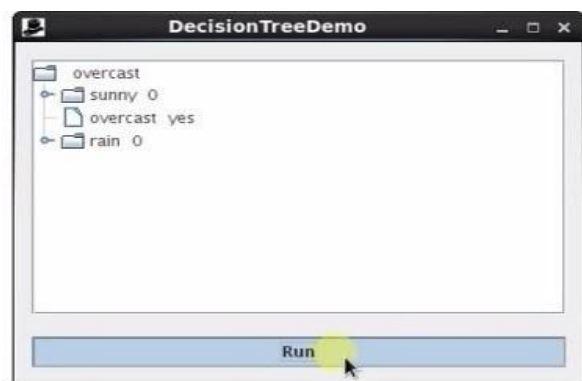


Fig.8. Final RDT of System

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Fig.9. Intermediate file RDT

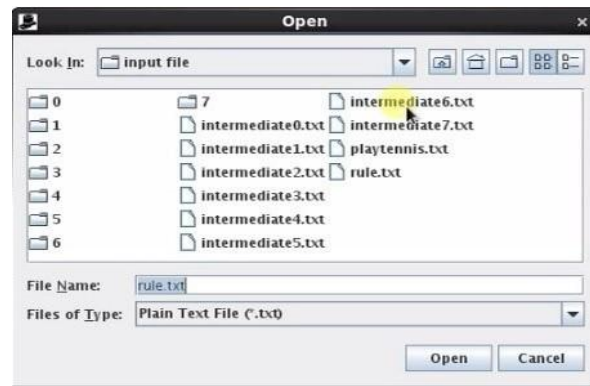


Fig.10. Clusters, Input, Intermediate, Output files

V. CONCLUSION AND FUTURE WORK

In this paper, we are describing Hierarchical merge with RDT algorithm to resolve Hadoop issues. The proposed hierarchical merge with RDT algorithm that merges data without touching disks and designing a full Queue of shuffle, merge, and reduce phases for Reduce Tasks. Direct network channels between MapTasks and Reduce Tasks and speed up the delivery of data from MapTasks to Reduce Tasks. While their work reduces job completion time and improves system utilization. The structure of a random tree is constructed completely independent of the training data. The training data is scanned exactly once to update the statistics in multiple random trees. The memory requirement is to store multiple random trees and one data item at any given time. With the necessary number of random trees to ensure optimality, the memory requirement of the random tree algorithm is significantly less even if the very large training data could have been held entirely in main memory to compute the single best tree.

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