Location-aware MapReduce in Virtual Cloud

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Abstract—**MapReduce is an important programming model for processing and generating large data sets in parallel. It is commonly applied in applications such as web indexing, data mining, machine learning, etc. As an open-source implementation of MapReduce, Hadoop is now widely used in industry. Virtualization, which is easy to configure and economical to use, shows great potential for cloud computing. With the increasing core number in a CPU and involving of virtualization technique, one physical machine can hosts more and more virtual machines, but I/O devices normally do not increase so rapidly. As MapReduce system is often used to running I/O intensive applications, decreasing of data redundancy and load unbalance, which increase I/O interference in virtual cloud, come to be serious problems. This paper builds a model and defines metrics to analyze the data allocation problem in virtual environment theoretically. And we design a location-aware file block allocation strategy that retains compatibility with the native Hadoop. Our model simulation and experiment in real system shows our new strategy can achieve better data redundancy and load balance to reduce I/O interference. Execution time of applications such as RandomWriter, TextSort and WordCount are reduced by up to 33% and 10% on average.**

Keywords-MapReduce, Virtualization, Data allocation, I/O interference, Load balance

I. INTRODUCTION

MapReduce is first proposed by Google, as a programming model for processing and generating large data sets. Hundreds of MapReduce programs on its clusters every day[1]. As one of the open-source implementation of MapReduce, Hadoop is now widely used in Yahoo, Facebook, IBM, etc.[2]

Nowadays, virtualization is getting more and more popular in cloud computing, as it helps to utilize and deploy computing resources. One good example is Amazon Elastic MapReduce[3], which utilizes Hadoop technology to enable MapReduce computing and is based on virtual machines. A computer with a multi-core CPU supporting virtualization technology can run two or more virtual machines (VMs) simultaneously, which share the I/O resources and appear the same as physical machines to users.

MapReduce is usually set up on a distributed file system. Goolge uses GFS and Hadoop uses HDFS. Normally, one file block has one or two copies in a distributed file system in case of data corruption. When MapReduce runs in a virtual environment, three major problems emerge.

- Disk sharing results in unbalanced data distribution and therefore leads to unbalanced workload. Data distribution in virtual environment has two aspects in physical view. One is the number distribution of file blocks that physical machines hold. The other is the number of file block collisions that exists in the system. File block collision occurs when two replicas of a file block are in the same physical machine though in different virtual machines. When running MapTask in MapReduce, it prefers to choose the local machine containing the file block [1], or the file block must be transferred from other machine. So one physical machine contains more file blocks or more replicas of a file block, it is likely to be allocated more workload.
- I/O interference caused by data unbalance and load unbalance is more serious in a virtual environment because of I/O virtualization implementation. I/O interference decreases the average I/O bandwidth and increases response time. I/O performance of virtual cloud like EC2 suffers from such interference [15]. Some researchers claim that I/O virtualization is the bottleneck in cloud computing [17].
- Disk sharing reduces the data redundancy. As distributed file system treats all virtual machines as physical machines, the replicas of a file block are allocated in different virtual disks, but actually they maybe are in the same physical disk. If the physical machine breaks down, file blocks whose replicas are all in that disk become unavailable.

MapReduce is often used for I/O intensive applications, so it's beneficial to design deliberate strategy to achieve more balanced data and workload in virtual environment. Optimization of MapReduce system is a hot issue. Most of existing work focused on resource provision and task scheduling by static application analysis or dynamic prediction in physical environment. We have the insight on the importance of data locality in virtual MapReduce system. Our method uses data locality to balance the workload and improve the data redundancy to reduce the degree of I/O interference natively.

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In this paper, we abstract a model and define evaluation metrics to analyze the data pattern and task pattern of MapReduce in virtual cloud. Moreover, we propose a location-aware file block allocation strategy for Hadoop. In the new strategy, HDFS is aware of the locations of the virtual machines. Our strategy allocates file blocks across all physical machines evenly and the replicas of a block are located in different physical machines. In sampling simulation, metrics of our strategy is better. Our experiment in real system also verifies that the following three main benefits can be achieved by using our strategy.

- MapReduce's workload is more balanced. MapTask workload is related to data distribution. Our strategy can balance data distribution so balance MapTask's workload as well
- Our strategy reduces I/O interference and improves HDFS's performance, especially the writing performance. When writing a file block to HDFS, all the replicas of the block have to be written. If these replicas exist in the same physical disk, the I/O interference is intensive. Our new strategy can eliminate this situation by allocating all file blocks locate across all physical disks on average. By doing so, the writing load is balanced and the total throughput increases.
- Our strategy retains data's redundancy as in physical environment. As replicas of each block are allocated in different physical machines, the data are still recoverable in case that one physical machine is down.

The rest of the paper is organized as follows. Section II gives a background introduction of I/O interference and I/O virtualization. Section III describes virtualized Hadoop. In Section IV we build a model and evaluation metrics to analyze the Hadoop's problem in virtual environment. Then we propose our new allocation strategy. Section V describes the implementation of our strategy in Hadoop. We evaluate our implementation both in a sampling simulation and real experiments in Section VI. Section VII discusses detailed results of our evaluation and some related issues.

II. Back ground

A. I/O interference

There are two traditional kinds of I/O interference, disk interference and network interference.

Disk interference occurs when multiple processes try to access the same disk simultaneously. Disk has limits on both accesses and the amount of data they can transfer per second. People often consider disk performance under two situations, sequence read/write (SR/SW) and random read/write (RR/RW). Traditional magnetic disk uses the mechanical heads for reading and writing. Its throughput of random read/write is much smaller than that of sequence read/write. The reason is that the heads have to frequently change positions in RR/RW while in SR/SW the heads are more stable. Recent years Flash based solid state device has emerged as a good candidate for the next generation of storage. It provides low access latency, low energy consumption, shock resistance and lightweight. Detailed analysis on it performance shows that Flash are excellent sequential stores while problematic for random access. The Flash's throughput of RW is even worse than that of mechanical disk [4]. So the gap between the sequence access and random access are still big. Parallel accessing with a high degree makes multiple sequential accessing patterns degenerate to random accessing patterns, which causes performance degeneration [4].

Network interference mainly considers the latency and throughput. All network resources are limited, including link bandwidth, switch and router processing time, etc. Implementations of connection-based protocol, such as TCP, have congestion avoidance algorithms to watch for packet losses and latency to adjust the transfer speed of connections. Research on parallel TCP [5] shows, as the number of simultaneous TCP connections increases, the total throughput will increase until the network becomes congested. The packet loss rate begins to increase depending on the number of connections and the congestion degree. Then the congestion mechanism reduces the congestion window, which decrease the transfer rate. As the number of parallel TCP connections increases, the effects of higher packet loss rates decreases the impact of multiple sockets, the TCP throughput will stop increasing or begin to decrease. Another interesting work on parallel TCP [6] indicates 90% utilization would already be achieved by as few as 3 TCP sockets.

B. I/O virtualization

There are two basic kinds of virtualization: full virtualization (e.g.,KVM [7] and paravirtualization (e.g., Xen[8]). Full virtualization is a complete simulation of the underlying hardware while paravirtualization provides a software interface to virtual machines and the interface is similar but not identical to that of the underlying hardware. In either case, virtualization is enabled by a layer called virtual machine monitor (VMM) or hypervisor. Virtual machines share CPUs and memory well, but not I/O.

When sending or receiving a network packet, the VMM domain and the virtual machine domain must be scheduled correctly before a network packet can be sent or received[10].The total overhead is much higher than that of CPU or memory virtualization. For example, Linux is only able to achieve only about 30% of the network throughput with Xen that it can achieve running natively [11]. Moreover, network I/O virtualization increases overheads in the utilization of device such as CPU. So it can cause loss of bandwidth utilization from a virtual machine because of CPU's limitation [11].

Compared with network I/O, virtualization for disk is simpler. In network virtualization, the system must be prepared to receive and respond to request for its virtual machines at any time. Disk access occurs only when requested by the virtual machine. But the overhead of disk virtualization is not negligible. Xen shows about 15% degradation of disk performance and KVM shows about 7% degradation of write performance and almost no degradation of read performance [12].

As one physical machine can host more and more virtual machines, the isolation must be considered. Different virtualization shows different characteristics. For example, Xen shows good isolation for disk I/O and poor isolation for network I/O, while KVM shows good isolation for network I/O and poor isolation for disk I/O [12].

III. Hadoop In Virtual Cloud

A. *Virtualized Hadoop*

The basic MapReduce's architecture [1] consists of one master and many workers. Hadoop is one of the most commonly-applied implementation of MapReduce. Figure 1 shows virtualized Hadoop architecture. NameNode is the master of a collection of DataNodes and it is responsible for their management and file maintenance. JobTracker is the master of a collection of TaskTraker and in charge of their management and task maintenance. A DataNode process and a TaskTracker process run on the same machine to utilize data locality. The TaskTracker should copy the data that it's needed from other machines through network if the data is not local. NameNode and JobTracker can be separated in different machines to achieve better performance. When the machine number is huge, this separation is necessary.

In virtual environment, virtual machines in a physical machine share the hardware resources such as CPU, memory, disk and network. Due to the isolation of virtualization, virtual machines appear to each other like physical machines. NameNode and JobTracker can also run in virtual machines though less efficient. In Hadoop's architecture view, there is no big difference between virtual environment and physical environment. But in Hadoop's performance view, differences emerge. Virtualization introduces extra overhead and interference, especially on I/O. And lack of virtual machines' locality brings other problems. When allocating three replicas of a file block, the three replicas are allocate in difference machines in Hadoop's view. But if these machines are virtualized, actually two or three replicas of a file block may in the same physical machine. So it causes imbalanced workload. And if one physical machine fails, the data may not be recoverable.

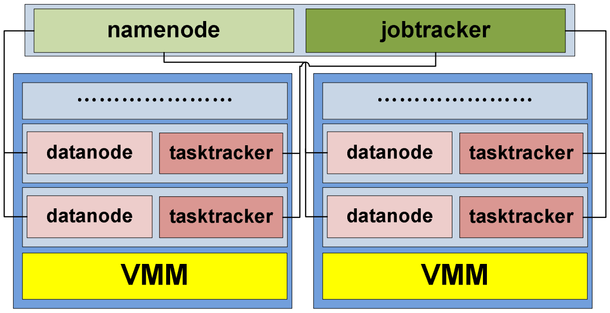


Figure 1 Virtualized Hadoop architecture

B. *Hadoop's Allocation Strategy*

HDFS is used as Hadoop's distributed file system, which commonly uses replica mechanism. Here we set 3 as the replica numbers, which is common in Hadoop cluster. A cluster may be consisted of many racks of computers. HDFS is rack-aware, which can support tree hierarchical network topology. "In most cases, network bandwidth between machines in the same rack is greater than network bandwidth between machines in different racks"[13]. If there is no rack, all the computers are in one rack called default-rack.

In Hadoop's allocation strategy, when a block is created, the first replica is placed on the local node that contains the source data. If the node containing the source data is not the DataNode of HDFS, HDFS will randomly choose a DataNode for the first replica. Next, if there are many racks, the second replica is placed on a DataNode in remote-rack compared to the first DataNode. Then HDFS chooses another different DataNode for the third replica in the same rack with the second DataNode. It ensures that no more than one replica is placed at one DataNode and no more than two replicas are placed in the same rack when the number of replicas is less than twice of its rack number. But if there is only one rack, the second and the third replicas are placed randomly in different DataNodes.

IV. MODELING AND NEW STRATEGY

A. *Modeling*

We build a generation model of data and task pattern to analyze different allocation strategies. To simply the problem for analyzing, we make the following assumptions.

- Each physical machine hosts the same number of virtual machines, which using the same I/O devices. Here we use a physical disk to present the I/O devices, as it determines the data's locality and number of network devices is no more than that of disks in common case.

- All the virtual machines are in local area network and the network topology is flat which can be easily achieved by running Hadoop by default without providing any rack information. We do not consider a physical machine as a rack because network bandwidth between virtual machines in the same physical machine is not greater than network bandwidth between virtual machines in different physical machines, which is measured in real cluster.

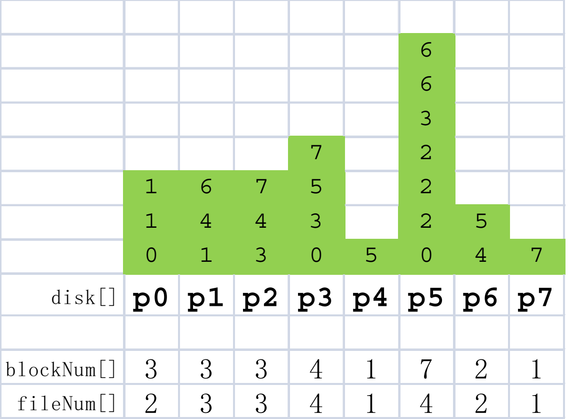
- There is no limitation for workload to be randomly assigned to each virtual machine. There is no mechanism such as taking into account the average load or limitation of task slots when running MapReduce.

- The total file size has linear relationship with total block number. One simple example is that all file blocks have the same size.

Now suppose we have a cluster containing p physical machines, each has a hard disk and the replica number is 3. Then n file blocks are put into the cluster from another computer out of the cluster or generated randomly in the cluster. So the model is about the data pattern generation and task pattern generation with a certain data pattern. A block has the same probability to be placed on physical machines that host the same number of virtual machine.

Take *p=8 (p0~p7), n=8(0~7)* for example, a data pattern may occurs as Figure 2 using Hadoop's strategy. It can be seen that replicas of *file 2* are all on *p5* and the distribution is not well balanced.

Next we consider the task pattern when reading these files. If all the file blocks are accessed by MapTasks, MapReduce tries to choose local node to run the MapTask. In the example above, physical machines' MapTask task pattern may be *assignedNum[8] =[1,2,1,1,0,2,0,1]*, means *p0* has 1 task ,*p1* has 2 tasks ,etc. The ideal pattern is *[1,1,1,1,1,1,1,1]*, but is less possible to happen.



						6		
						6		
						3		
				7		2		
	1	6	7	5		2		
	1	4	4	3		2	5	
	0	1	3	0	5	0	4	7
disk[]	p0	p1	p2	p3	p4	p5	p6	p7
blockNum[]	3	3	3	4	1	7	2	1
fileNum[]	2	3	3	4	1	4	2	1

Figure 2 An example data pattern may be generated using Hadoop's strategy, *blockNum[]* shows number of file blocks in each disk. *fileNum[]* shows number of different file blocks in each disk, it is smaller than *blockNum[]* if two replicas of a file block are in the same physical disk .

B. Evaluation Metrics

How to evaluate the data pattern and task pattern? Here we consider three metrics as follows for data pattern:

$$actualReplicaNum = \frac{1}{n}\sum_{i=0}^{p-1} fileNum[i] \quad \text{(a)}$$

$$maxBlockNum = \max(blockNum[0],\cdots,blockNum[\text{p-1}]) \quad \text{(b)}$$

$$blockNumSigma = \sqrt{\frac{1}{p}\sum_{i=0}^{p-1}(blockNum[i] - \frac{replicaNum*n}{p})^2} \quad \text{(c)}$$

$$maxAssignedNum = \max(assignedNum[0],\cdots,assignedNum[\text{p-1}]) \quad \text{(d)}$$

$$assignedNumSigma = \sqrt{\frac{1}{p}\sum_{i=0}^{p-1}(assignedNum[i] - \frac{n}{p})^2} \quad \text{(e)}$$

actualReplicaNum (a) is the average number of unique file blocks in a physical machine. The ideal value is *3* when the replica number is 3. If the file number is much larger than the disk number, the difference between *actualReplicaNum* and the ideal value becomes significant. Take *n=1000*, *p=8* for example, the *actualReplicaNum* is small, but considering *n* actualReplicaNum*, there are many file blocks that having two or three replicas in the same disk. It is very possible that each disk contains all replicas of the same file block. If one disk is down, the data on the disk will not be recoverable.

maxBlockNum (b) shows the maximum number of blocks in a physical machine, which is the bottleneck in parallel writing. The disk with *maxBlockNum* generally takes the longest time to finish the write operations in a distributed file system.

blockNumSigma (c) shows the variation of the pattern. The idea value is 0, which means that all blocks are evenly allocated. This parameter reveals the load balance of the distribution when writing files.

In the example of Figure 2, *actualReplicaNum=2.5 maxBlockNum=7 blockNumSigma=1.343*

We also can use the similar method as above to evaluate the task pattern. Since only one replica of each file block are needed when reading file, the *taskNumAvg* is useless. There are two metrics as follows.

maxAssignedNum (d) shows the max number of task that a physical machine is assigned. Similar with *maxBlockNum*, *maxAssignedNum* will be the longest tail in parallel executing.

assignedNumSigma (e) reveals the load balance of the task pattern. Because of the locality, the load includes not only reading but also processing the data which may generate great load.

For*[1,2,1,1,0,2,0,1]*,*maxAssignedNum=2*,*assignedNumSigma=0.707*. The data pattern and task pattern above occurs with a probability. Considering the full permutation, there are p^{3n} permutations for the data pattern and 3^n permutations for the task pattern. If *n* is small, we can enumerate the full permutation. If *n* is big, we can only use sampling simulation to evaluate the strategy. For the data pattern in Figure 2, the enumeration average results for task pattern are as follows: *maxAssignedNumAvg=2.6452,assignedNumSigmaAvg=0.9220.*

C. NEW STRATEGY

We design a new allocation strategy to allocate replicas of a file block to different physical machines and keeps balance of the block number of each physical machine. There are many ways to achieve the new strategy. Here we present two intuitive ways. One is round-robin allocation and the other is "serpentine allocation" used in this paper.

Take *p=8* and *n=8* for example, Figure 3 shows the round–robin allocation which is easy to understand. Figure 4 shows the serpentine allocation. The third replica of *file 2* is supposed to be placed in *p7* but *p7* has *file 2*, also *p6* has *file 2*. So at last the third block of *file 2* is placed on *p5*.

The evaluation metrics for data pattern in Figure 3 and Figure 4 are the same and the best (*actualReplicaNum=3*, *maxBlockNum=3*, *blockNumSigma=0*)

The enumeration average results for task patterns of Figure 3 are as follows:

maxAssignedNum=2.2724,assignedNumSigma=0.7943

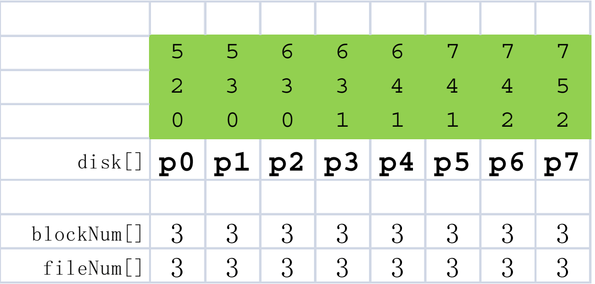
The enumeration average results for task patterns of Figure 4 are as follows:

maxAssignedNum=2.2705 assignedNumSigma=0.79323

So the difference between round-robin and serpentine allocation is little. It should be pointed out that the enumeration average result of task patterns of the new strategy is not always better than those of Hadoop's strategy. See an extreme example showed in Figure 5, the average evaluation results are as follows:

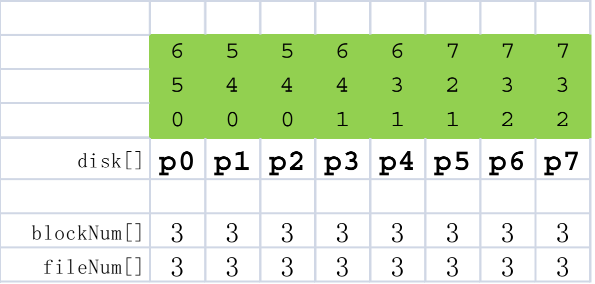
maxAssignedNum=1 assignedNumSigma=0.

But the *actualReplicaNum* of this pattern is only 1. The reason is that all replicas of each file block are located in the same disk. So there is only one pattern that the task with this block can choose. So we must consider all the metrics of data pattern and task pattern and also the probability that a pattern occurs. Our model reveals basic characteristics of the allocation strategy though it has some limitations that are discussed in Section VII.



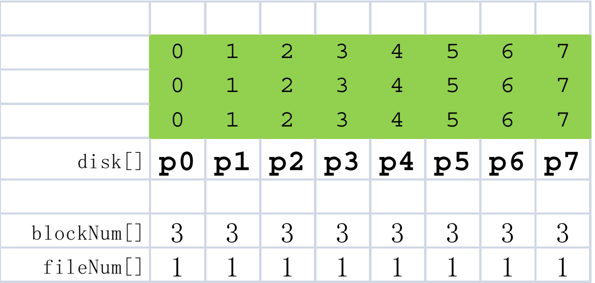
	5	5	6	6	6	7	7	7
	2	3	3	3	4	4	4	5
	0	0	0	1	1	1	2	2
disk[]	p0	p1	p2	p3	p4	p5	p6	p7
blockNum[]	3	3	3	3	3	3	3	3
fileNum[]	3	3	3	3	3	3	3	3

Figure 3 An example of round-robin allocation



	6	5	5	6	6	7	7	7
	5	4	4	4	3	2	3	3
	0	0	0	1	1	1	2	2
disk[]	p0	p1	p2	p3	p4	p5	p6	p7
blockNum[]	3	3	3	3	3	3	3	3
fileNum[]	3	3	3	3	3	3	3	3

Figure 4 An example of serpentine allocation



	0	1	2	3	4	5	6	7
	0	1	2	3	4	5	6	7
	0	1	2	3	4	5	6	7
disk[]	p0	p1	p2	p3	p4	p5	p6	p7
blockNum[]	3	3	3	3	3	3	3	3
fileNum[]	1	1	1	1	1	1	1	1

Figure 5 A extreme data pattern that may occur with Hadoop's strategy

V. IMPLEMENTATION

In the real implementation for Hadoop, we choose serpentine allocation because it can slightly reduce the cost of scheduling in our implementation.

The location of virtual machine and the number of file blocks are needed for the new strategy. Since Hadoop supported tree hierarchical network topology, we add the location information of virtual node into the network topology. For example, if there is only one rack among the physical machines, the network location of a virtual node may be changed from /default-rack to /Phy0, means that the virtual node is on Physical machine 0; if there are some racks among the physical machines, the network location of a virtual node may be changed from /rack1 to /rack1/Phy0, means that it is on the Physical machine 0 of rack1.The main idea is to add a layer beneath the network location of the physical node. This mechanism makes it easy to keep compatibility with the native Hadoop. We can make special label starting with "Phy" to identify locations of virtual machines. Our strategy works only when locations of virtual machines are provided in configuration file.

To maintain the block information for each virtual node, we add a sorted list by the number of blocks in NameNode of Hadoop. For each allocation for a replica, the list will be updated and the update is exclusive in case of concurrent access. When the block is removed or corrupted, the list will also be updated. In the update, we first update the block number of the virtual node, and then update its position in the sorted list. When adding blocks, round-robin allocation moves its position to where next position's block number is bigger, while serpentine allocation moves its position to where next position's block number is not smaller.

Data structure like heap may be better for maintaining the information of block number. The block information scales just with the number of virtual machines, and the operation is done in NameNode's memory. The real problem may be the synchronization cost when the system is busy with manipulating large number of files concurrently. But usually the I/O hit the peak first and NameNode's scheduling time is much smaller than that of I/O transfer time. In our experiment, choosing of three replicas is finished in several milliseconds. The linear data structure is good enough though not the best.

There are some special files like job configure file that have many replicas when the job is running. So we randomly place replicas exceeding the configured replica number among all virtual nodes.

Now we can make sure that three replicas of a file block are allocated in three different physical machine and the blocks is almost well balanced across all virtual machines. If the number of virtual machine in each physical machine is the same, the blocks are also balanced across all physical machines. It is useful if some physical machine is less powerful and can host less number of virtual machines. We can adjust the load of a physical machine with the number of its virtual machine. Also our new strategy makes it possible to shut down nodes by the unit of a physical machine instead of a virtual machine, which achieves faster resource shrinking.

VI. EVALUATION

A. *Simulation Evaluation*

When *n* or *p* is large, it is impossible to calculate the five metrics with the full permutation. So we use sampling simulation to compare our new strategy (serpentine allocation) with Hadoop's original strategy. Each sampling unit consists of allocating a data pattern of 3n file blocks and generating a task pattern of reading 3n file blocks with such generated data pattern using corresponding strategy.

We have set the parameter *n=256*, and *p = [8,16,32,64,128,256]*, the sampling number is set to 1,000,000.

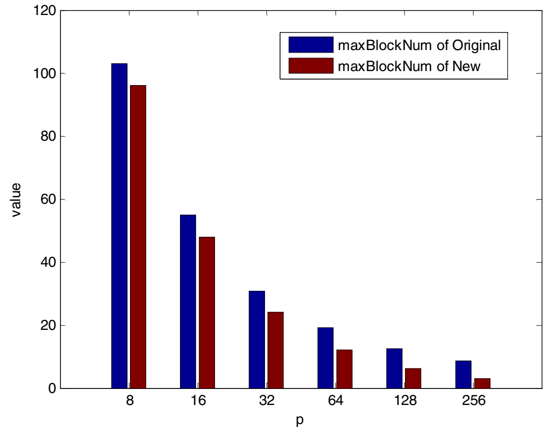


Figure 6 *maxBlockNum*'s comparison of Hadoop's original strategy and our new strategy using sampling

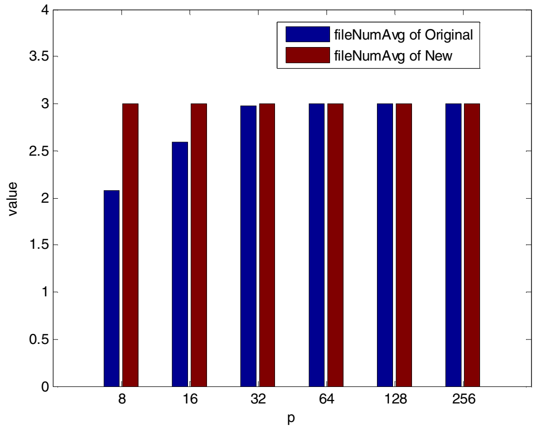


Figure 7 *actualReplicaNum*'s comparison of Hadoop's original strategy and our new strategy using sampling

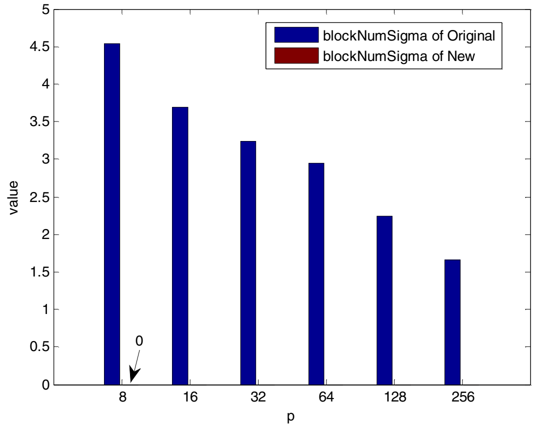


Figure 8 *blockNumSigma*'s Comparison of Hadoop's original strategy and our new strategy using sampling

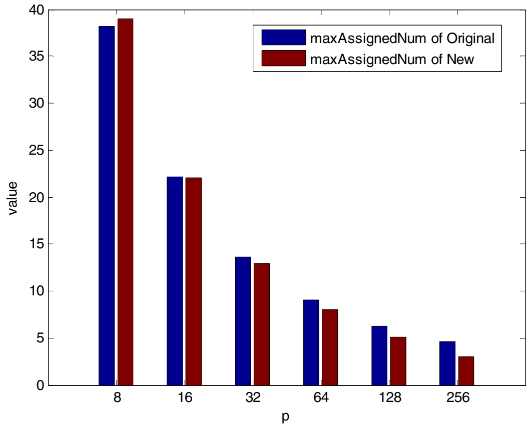


Figure 9 *maxAssignedNum*'s comparison of Hadoop's original strategy and our new strategy using sampling

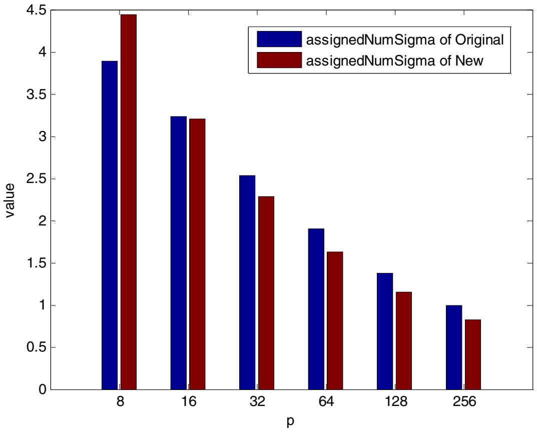


Figure 10 *assignedNumSigma*'s comparison of Hadoop's original strategy and our new strategy using sampling

TABLE I. COMPARISON OF HADOOP'S ORIGINAL STRATEGY AND OUR NEW STRATEGY WHEN (N=224 P=8 SAMPLING NUMBER=1,000,000)

	Original	New
Average of *actualReplicaNum*	*2.0657*	*3*
Average of *maxBlockNum*	*90.5798*	*84*
Average of *blockNumSigma*	*4.1722*	0
Average of *maxAssignedNum*	*33.7660*	*34.5946*
Average of *assignedNumSigma*	*3.6256*	*4.14939*

The average metrics' results of data pattern are showed in Figure 6(*maxBlockNum*), Figure 7(*actualReplicaNum*) and Figure 8(*blockNumSigma*). In data pattern evaluation, three metrics of our new strategy are all better than those of Hadoop's original one. And when *p* is getting smaller, *actualReplicaNum* drops dramatically. The average metrics' results of task pattern are showed in Figure 9(*maxAssignedNum*) and Figure 10 (*assignedNumSigma*), when p>=16 *maxAssignedNum* and *assignedNumSigma* of our strategy are better.

Here we also present the result of (n=224 p=8) in TABLE I, because it fits our experiments configuration in a real system. Notice that when (*n=256* or *224, p*=8), *maxAssignedNum* and *assignedNumSigma* of Hadoop's strategies are better than those of ours. The reason is similar to Figure 5 as we mentioned above, imbalanced data pattern may achieve balanced task pattern. When n=8, *actualReplicaNum* is close to 2, it means that each task with a file block has only about two physical locations to choose.

Now we get a clear understanding about the data allocation in virtual environment. However, how these metrics affect the real system's performance is more complicated than the numerical values we see here. For example, task pattern of our strategy is still better when *n=8* in real experiment, we explain this in Section VII.

B. *Experiment Evaluation*

1) *Testbed Description*

We build our cluster with 8 HP x2600 Workstations. Each physical machine hosts 7 virtual machines, so we have 56 virtual machines in the virtual cloud. TABLE II shows the hardware and software details in our experiment. What's more, Tashi [18] is used to manage the virtual machines. There is another machine with 4 CPU and 8G memory used as Hadoop's NameNode, JobTracker and ganglia server, which makes it simple to analyze the workload with ganglia. The network bandwidth between these machines is 1Gbps.

TABLE II. EXPERIMENT SETUP

SW	Hadoop	Hadoop 0.20.0
	Guest OS	Ubuntu 8.04 1CPU 1GB Memory 1Gbps Ethernet
	Host OS	Ubuntu 8.04
	Virtualization	KVM 1Gbps Ethernet
HW	CPU	2x4 2.83GHz
	Memory	16G
	Disk	250G 7200rmp
	Network	1Gbps Ethernet

2) *Applications*

The MapReduce applications we use for evaluation are RandomWriter TextSort and WordCount.

RandomWriter randomly chooses words from a small vocabulary (100 words), forms them into lines in MapTask. The map outputs are directly committed to distributed file system, so there is no ReduceTask in RandomWriter. TextSort sorts each line in existing text files by vocabulary order. The map and reduce functions in TextSort are both identity functions and the sort of the texts is realized by the inherent merge sort of MapReduce framework. WordCount counts the appearance frequency of words in the text. The input text of TextSort and WordCount are the RandomWriter's outputs.

3) *Profiling with Ganglia*

Ganglia[19] is a scalable distributed monitoring system for high-performance computing systems. We have deployed Ganglia to the physical cluster, so we can get information about the usage of CPU, memory, disk I/O and network in real-time. We modified Ganglia to display all metrics in ten minutes. The collection interval is set to 3s. Before each experiment, the previous data of Ganglia was cleared. So the metric pictures became more readable.

4) *Experiment Design*

We have done two groups of experiments use Hadoop's default configuration. The difference of the two groups is whether speculative execution of map and reduce turns on.

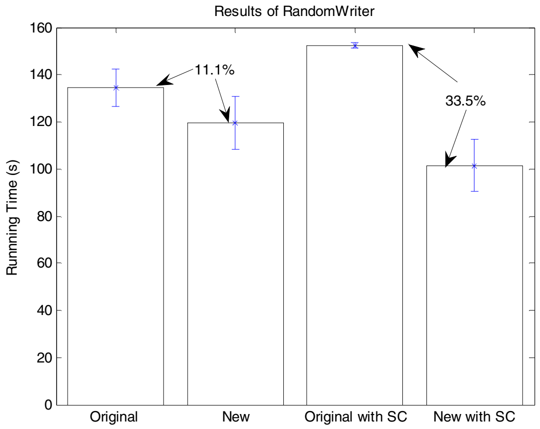


Figure 11 Experiment results of RandomWriter's execution time

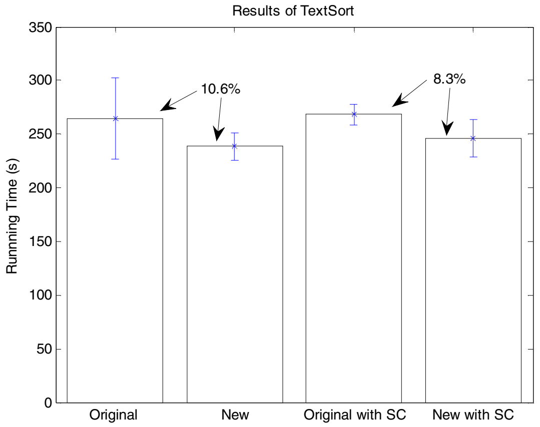


Figure 12 Experiment results of TextSort's execution time

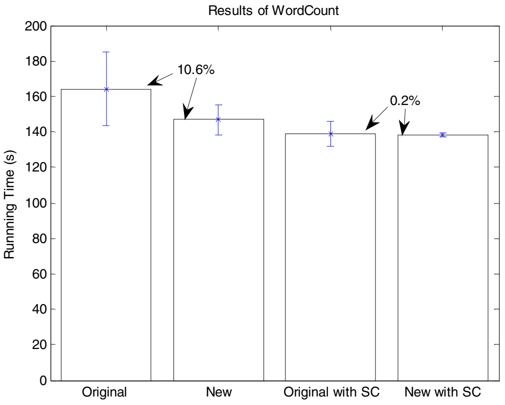


Figure 13 Experiment results of WordCount's execution time

Speculative execution (SC) is like backup task which is used to reduce the long tail of parallel execution. First we turn off the speculative execution to get a better understanding how our new strategy affects the system. Then we turn on speculative execution (Hadoop's default) which is often used in real systems to see whether our new strategy is better.

The input data is 224*61.5MB, which is generated using RandomWriter. TextSort's reducer number is set to 56 and WordCount's reducer number is set to 1. 5 experiments have been done for each application in the group with speculative execution off and 3 experiments have been done for that with speculative execution on. Then we take the average execution time and standard deviation of each case. The results are showed in Figure 11, Figure 12 and Figure 13. We can see that our strategy is generally better in all three applications. With SC off, we reduce about 10% execution time of three applications with the new strategy. With SC turn on, RandomWriter reduces 33.5% execution time, TextSort reduces 8.3% execution time, but WordCount's improvement is little.

VII. Discussion

A. Model's limitation

Some of our model's assumptions break down in real system, but still shows the general characteristics.

Physical machines may host different number of virtual machines, but our strategy can still reduce block collisions and balance the workload according to the number of virtual machine in a physical machine.

When choosing DataNode for a replica, HDFS calculates an average load based on number of active connections. If the chosen DataNode's load is bigger than two times of average load, another selection will be performed. This can control the maximum load in a DataNode in real-time, but has limit effect on balancing the data pattern. Figure 14 shows a data pattern generated by RandomWriter with Hadoop's strategy. The data pattern is not well balanced and is close to our sampling simulation results.

Hadoop assigns MapTasks when the TaskTracker sends heartbeat to the JobTracker. We can take the procedure as a random selection. However, Each TaskTracker in Hadoop has task slots which can hold 2 tasks by default at the same time. New task will be accepted only when the TaskTracker has a free slot. This mechanism prevents too many tasks to be assigned to a node. And Hadoop schedules some MapTasks to run on DataNodes not containing the source file. However, this schedule balances MapTask load at the expense of extra network transfer .On Averagy about 85% of MapTasks are local and the rest 15% are non-local. So our model for task pattern is not fully consistent with the real system. But it tells us that the node that has more file blocks, are likely been assigned more workload.

B. Evaluation Analysis

1) Our strategy is better in sampling and experiment evaluation. But how it works in real system and where is the improvement comes from? So the experiment design and result need to be discussed.

The benefit of our new strategy with small workload size is not very impressive. We choose 224*61.5MB as the workload size, which stresses the whole cluster and leads to reasonable execution time. We also tried larger workload size, the improvement was a bit more obvious, but the experiment took much more time.

2) Effect of speculative execution

We can run exactly the number of MapTask and ReduceTask with SC off. It will eliminate unnecessary interference. With SC turning on, SC will run extra map and reduce tasks when it detects some slow tasks.

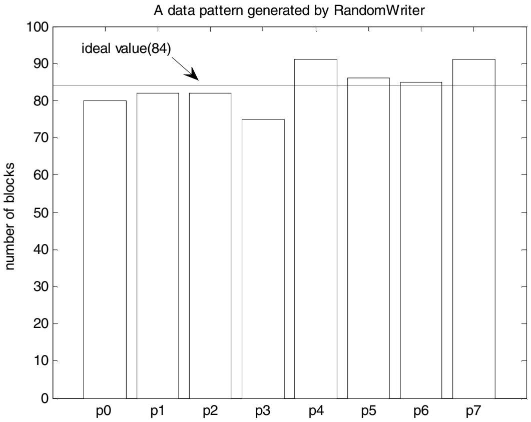


Figure 14 A data pattern generated by RandomWriter with Hadoop's strategy. Its execution time is 132s. The evaluation results of this data pattern are *maxBlockNum=91, blockNumSigma=5.099.* And the sampling average results are: *maxBlockNumAvg=90.58, blockNumSigmaAvg=4.172*

As showed in Figure 11, Figure 12 and Figure 13, SC generally reduces the variation not the execution time. But it increases the execution time of RandomWriter of original strategy and TextSort of both strategies. The reason is that RandomWriter and TextSort are I/O intensive while WordCount is CPU intensive. The CPU usage of the physical machine are up to 85% (7 of 8 CPUs are used for Virtual Machines) when WordCount running. SC runs extra map and reduce tasks consuming the resources. Considering I/O interference when the system is stressed, SC's extra load takes more negative effects than the benefit of long-tail cutting. The interesting one is the RandomWriter of new Strategy, its execution time significant decreases with SC on. The possible reason is that our new strategy reduces the I/O interference so SC's benefit overcomes its extra workload.

3) Ganglia's result

RandomWriter is I/O intensive, Figure 15 shows network throughput of the cluster when RandomWriter runs. The pillar's width shows the execution time. The pillar' area shows the total amount of network transfer. The throughput of our new strategy can reach more than 700MB/s while that of original one is about 600MB/s. So the total network throughput of the system has been improved, which benefit the total execution time. The total amount of network transfer increases with SC on. However, the throughput does not increase. It indicates that the system is stressed and the load is not well balance with original strategy. It's clear that our new strategy balances the write load and reduces the I/O interference to get higher I/O throughput.

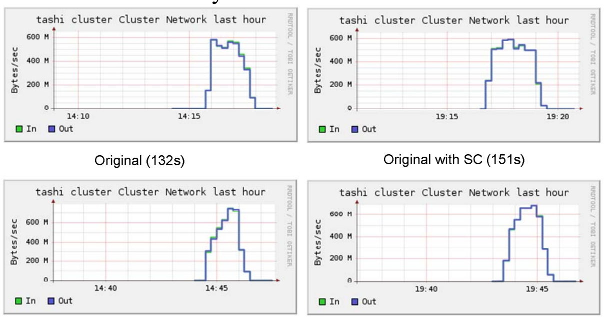
TextSort is also I/O intensive. MapReduce framework has three stages: Map, Shuffle and Reduce. Figure 16 shows network throughput of the cluster when TextSort runs. It has two main pillars. The first pillar shows the network transfer of Map and Shuffle. In Map stage, most of the files are read from local, so shuffle contributes most in the first pillar. The second pillar shows the network transfer of reduce stage. In reduce stage, the result are committed to HDFS. The total amount of second pillar is much larger than that of the first pillar because threes replicas of a block have to be written to HDFS in reduce stage. Though the first replica is preferred to written in the node which generates the result block, the amount of network transferring of reduce stage is at least twice large that of the Shuffle. In first pillar, our new strategy's improvement is not very obvious. Maybe the reason is that the I/O amount of shuffle doesn't stress the system yet. But for the second pillar, the improvement is significant, which pushes the throughput from 400MB/s to more than 500MB/s.

WordCount is CPU intensive. Here we don't present the result of CPU utilization of four cases because it's quite difficult to draw useful information by comparing those pictures at a glance. We still focus at the network throughput, which shows in Figure 17. Compared with RandomWriter and TextSort, both the throughput and amount of total network transfer is much smaller (not more than 70MB/s). It's "surprising" that the original strategy has larger throughput and total amount. However, it doesn't indicate our new strategy is worse but the opposite. WordCount' mid-output and reduce output is quite small, so the MapTasks contribute most of network transfer. As we mentioned above, about 85% of MapTasks are local. This percent varies according to the data distribution and real-time execution. Smaller amount of network transfer indicates that our strategy achieves more local MapTasks. It proves that our new strategy has good effect on task assignment. The reason of the little improvement of execution time with SC may be that the CPU is not fully stressed and the benefit of SC overcomes that of balanced task assignment.

C. Multi-user sharing

MapReduce system is usually shared by multi-users, our strategy can easily be applied in such sharing environment.

If the resources are strict partitioned, we can use our strategy in the partitioned resources. As a user occupies a certain amount of physical nodes, MapReduce can allocate its data in its nodes using our strategy. If the resources are relax partitioned, a little modification can be made to achieve better user response time and system utilization. MapReduce allocates the first two replicas of a user's file blocks to his physical nodes using our strategy. The third replicas are placed in other physical nodes randomly or on average. The modification's benefit is that a user has the possibility (about 2/3) to run his job in his nodes while he can still use other nodes if they are idle. It also provides optimizing chances for detailed task scheduler. In both cases, our strategy makes sure that no file block collision exists and the data and task distribution is reasonably balanced.



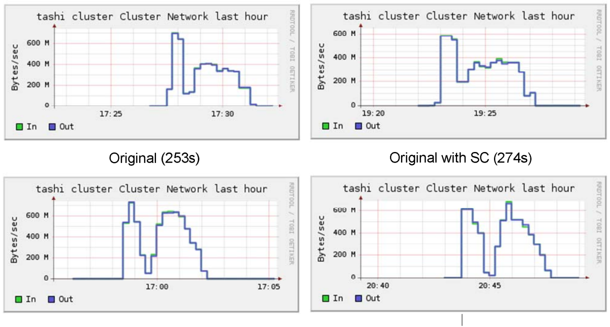
Original (132s)

Original with SC (151s)

New (111s)

New with SC (102s)

Figure 15 Network throughput of experiment cluster with Ganglia in RandomWriter.



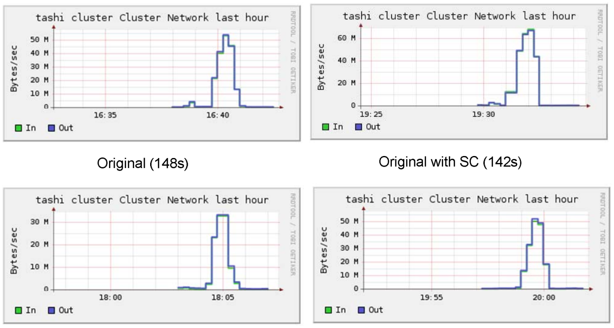
Original (253s)

Original with SC (274s)

New (231s)

New with SC (242s)

Figure 16 Network throughput of experiment cluster with Ganglia in TestSort.



Original (148s)

Original with SC (142s)

New (139s)

New with SC (139s)

Figure 17 Network throughput of experiment cluster with Ganglia in WordCount.

VIII. RELATED WORK

MapReduce was first described architecturally and evaluated in [1]. [1] describes the locality of data in brief, giving the general principle that the MapReduce master attempts to schedule a MapTask on a machine that contains a replica of the corresponding input data to reduce network cost. This principle is also used in Hadoop.

Much work has been done to improve the performance of MapReduce system. Most of it falls to two broad categories. The first focuses on applications characteristics. One way is to analyze and compare resource consumption of the application at hand, and then use this information to set optimized configurations for different applications [20]. Another is to monitoring the usage of system's resources to adjust resource allocations to fit the requirements of different job stages [21][22]. Virtual machine monitor can be modified to dynamic allocate resources to VMs according to resource usage of applications [23].

The second category focuses on MapReduce System itself. A new scheduling algorithm for speculative execution is designed for Hadoop in heterogeneous environments [24]. Cloudlet[25] is design is to overcome the overhead of VM by adding a local reducer for virtual machines in each physical machine. Differing from existing work, our work focuses on the data locality's influence on MapReduce in virtual environment. Our work is also related with job scheduler considering data locality [26], though it doesn't care about virtual environment.

IX. CONCLUSION

We address fundamental problems of data allocation and its impact on MapReduce system in a virtual environment. We build a theory model and define evaluation metrics to evaluate the data pattern and task pattern. Based on it, we propose a new strategy for file block allocation in Hadoop. It uses the locality of virtual machines to achieve new data distribution, which balances the workload and reduces I/O interference. Our simulation and real experiments results prove the good characteristics of our new allocation strategy both in theory and in practice.

As core number of CPU increases fast, our work indicates that it's beneficial to be aware of the virtual machines' locations when serving I/O intensive system like MapReduce in virtual cloud.

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