Enhancing MapReduce Fault Recovery Through Binocular Speculation

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Abstract—MapReduce speculation plays an important role in finding potential task stragglers and failures. But a tacit dichotomy exists in MapReduce due to its inherent two-phase (map and reduce) management scheme in which map tasks and reduce tasks have distinctly different execution behaviors, yet reduce tasks are dependent on the results of map tasks. We reveal that speculation policies for fault handling in MapReduce do not recognize this dichotomy between map and reduce tasks, which leads to an issue of speculation myopia for MapReduce fault recovery. These issues cause significant performance degradation upon network and node failures. To address the speculation myopia caused by MapReduce dichotomy, we introduce a new scheme called binocular speculation to help MapReduce increase its assessment scope for speculation. As part of the scheme, we also design three component techniques including neighborhood glance, collective speculation and speculative rollback. Our evaluation shows that, with these techniques, binocular speculation can increase the coordination of map and reduce phases, and enhance the efficiency of MapReduce fault recovery.

Index Terms—MapReduce, Fault Recovery, Speculation.

I. INTRODUCTION

MapReduce has gained widespread popularity since Google introduced it [9] in 2004. Specifically, Hadoop and its successor YARN [1] are popular open-source implementations of MapReduce. Many previous works have focused on improving the performance and scalability of MapReduce [9], [25], task and job scheduling [26], [24], data redundancy and availability etc [17]. However, given the growing scale of hardware, firmware, and system components leveraged in computer systems, the mean time between failures or interruptions (MTBF/I) will be around 6.5-40 hours [22], [15]. It is expected that the resilience challenges will be further compounded by the advances in system technologies. Therefore, besides the paramount interest on efficient analytics, it is important to investigate the fault resilience of MapReduce and its impact on data analytics.

MapReduce adopts a two-phase (map and reduce) scheme to support many user applications (large batch jobs and small interactive queries), and schedule their tasks. To maximize the use of system capacity and ensure fairness among different jobs, existing task scheduling policies have focused on fair distribution of resources among tasks [26], [12]. The execution behaviors of these two phases in MapReduce are distinctly different. In the map phase, tasks are typically short-lived and are launched repetitively to balance the use of available map resources. Tasks in the reduce phase are typically longer in duration and start after the completion of the first map task. To compound the situation, there is a dependence between the two phases, i.e., reduce tasks must fetch intermediate data generated by map tasks. These two distinct system execution behaviors lead to a fundamental dichotomy between the two phases of MapReduce.

For fault resilience, MapReduce adopts a simple speculative task re-execution mechanism to launch redundant tasks. All tasks are treated in a similar manner for resource allocation, process speculation, synchronization and re-execution. We have revealed that the fundamental dichotomy of MapReduce can cause a number of efficiency and resilience issues. Particularly, it causes different requirements from map and reduce tasks in terms of resource allocation, speculation policies, and task temporal relationships. Such distinct requirements on resources can lead to the idleness of reduce tasks in big jobs and delay the completion of small jobs [20], [24], [26].

In addition, the dichotomy can lead to shortsighted decisions for speculative execution in MapReduce, a phenomenon we refer to as Speculation Myopia. It prevents a newly launched task, e.g., a reduce task from recognizing its data dependence on the intermediate data, which might have been damaged or lost on another node. Myopic speculation can only detect the need for launching additional tasks until multiple attempts fail. Furthermore, the dichotomy leads to serious fault handling issues such as wasteful redundant execution and degradation of system efficiency (See further details in Section II).

To this end, we have conducted an analysis on MapReduce speculation and characterized the impact of Speculation Myopia on MapReduce fault recovery. We have characterized two main symptoms of speculation myopia: dependency-oblivious speculation and scope-limited speculation. Accordingly, we have designed a new scheme called binocular speculation to increase the scope of MapReduce speculation with three component techniques: neighborhood glance, collective speculation and speculative roll-back. Our experimental results show that binocular speculation not only heals the speculation myopia while handling the failure-related stragglers, but also improves performance and scalability under heavy workloads. To the best of our knowledge, binocular speculation is the first to examine the failure-related stragglers in MapReduce with an effective mitigation method.

In summary, our paper makes the following contributions:

- We have analyzed MapReduce speculation, revealed the
existence of speculation myopia, and further characterized its causes and effects.

- We have introduced a new scheme called *Binocular Speculation* to heal the impact of speculation myopia, along with three techniques: neighborhood glance, collective speculation, and speculative roll-back.
- We have conducted an extensive set of experiments to evaluate binocular speculation. The results demonstrate that our new speculation scheme can heal all symptoms of speculation myopia for MapReduce fault recovery.

II. BACKGROUND AND MOTIVATION

A. Overview of YARN MapReduce

As a resource management infrastructure, YARN aims to simultaneously support various programming models, such as MapReduce [9]. We focus on the YARN MapReduce programs in this project. The execution of MapReduce programs includes two major phases: map and reduce. YARN supports such execution through a ResourceManager and several NodeManagers. The ResourceManager manages all resources and allocates containers to running applications. Each NodeManager abstracts the resources on the node as multiple *containers* to serve the need of different applications.

Each YARN job starts with one ApplicationMaster a.k.a. MRAppMaster, which negotiates with the ResourceManager for containers. When granted, it launches map tasks. Each map task applies the map function to an input split of many \(<k,v>\) pairs and generates intermediate data that are organized as a Map Output File (MOF). When MOFs are available, the MRAppMaster launches reduce tasks, overlapping the reduce phase with the map phase of remaining map tasks. A reduce task is a combination of two stages: shuffle/merge and reduce. In the former stage, it fetches and merges its partitions from all MOFs. It then enters into the reduce stage, where the reduce function is applied to the intermediate data. The final results are stored to the Hadoop Distributed File System (HDFS).

B. The Dichotomy of MapReduce

MapReduce offers a simple programming model for large scale analytics applications. Its map and reduce phases have very distinct execution behaviors, causing a variety of disparities in task management, resource allocation and fault handling. We refer to these disparities as the *Dichotomy of MapReduce*. This dichotomy leads to a disparity in the scheduling and resource management of map and reduce tasks [20], [24], [21]. The phases of Map tasks are typically short-lived. Their execution model can be represented as a typical processor sharing queue. Reduce tasks shuffle and process the intermediate data generated by more map tasks. Their execution model is a typical multi-server queue. To compound the situation, these two queues are dependent through a constraint that the reduce tasks in the multi-server queue must fetch intermediate data generated by the map tasks from the processor sharing queue. For Short-lived map tasks, it is easy to balance among available containers for processing data splits, but long-running reduce tasks can retain their containers while waiting on map tasks for intermediate data.

Such distinct requirements on resources can lead to the idleness of reduce tasks in big jobs and delay the completion of small jobs [20], [24], [26].

In addition, the dichotomy can lead to shortsighted decisions for speculative execution in MapReduce, a phenomenon we refer to as *Speculation Myopia*. Speculative execution is an essential mechanism for MapReduce to deal with stragglers and task failures [28], [2], [4], [5]. It monitors the progress of tasks and launches a redundant copy of slow or failed tasks. The dichotomy of MapReduce prevents a newly launched task, e.g., a reduce task from recognizing its dependence on the intermediate data, which might have been damaged or lost on another node. Such myopic speculation can only detect the need of launching additional tasks until multiple attempts fail. Finally, for task resilience, MapReduce recovers the work of any delayed or faulty task using a redundant or re-executed task, but the dichotomy leads to a disparity in the fault recovery of tasks. We have revealed serious fault handling issues such as wasteful redundant execution, asymmetric task recovery and failure amplifications, degrading system efficiency. The impact of these issues will be discussed in detail in the rest of this section.

C. MapReduce Speculation and Its Myopia

Many previous studies [19], [16] of failure characteristics have revealed that a large portion of failures are transient, ranging from 31% [16] to 65.2% [11]. MapReduce adopts a simple strategy via task and data regeneration to handle transient failures. Once a task is detected as failed, it re-launches another attempt of the same task, repeating the work achieved previously. This works very well for short-lived map tasks whose amount of work is generally much smaller compared to the reduce tasks, but it is not as effective for reduce tasks because of their long-running behaviors [26], [24]. In addition, MapReduce employs a global speculative for speculatively launching tasks to guard against stragglers or failures.

A global speculative proactively makes another attempt for a task that is lagging behind (a.k.a, stragglers) so that any attempt that finishes sooner will help the job to progress further. Similar speculation is adopted by other representative parallel computing paradigms such as Dryad [14].

**Speculation Myopia**: the existing speculation scheme in MapReduce is unable to peek through the dichotomy of its map and reduce phases, resulting in the shortsightedness of speculative tasks, i.e., Speculation Myopia. For example, a redundant reduce task cannot help when the failure was caused by the loss of intermediate data from prior map tasks. As a result, the redundant task will fail again. Myopic speculation also manifests itself in a number of other ways. The global speculative adopts a serial scheme to analyze the progress of tasks and launches speculative tasks in a sequential manner with a fixed delay interval. This is intended for an important
cause, i.e., limiting additional resource consumption. Nonetheless, such serial speculation with fixed delays is unable to meet the need of many speculative tasks when a MapReduce platform is affected by network congestion or resource contention. In addition, speculation relies on the significant variation of progress among tasks. When tasks from a job are located on a single node or a few nodes which are equally affected by a system condition, the global speculator is unable to launch any speculative task for the job because there is not enough progress variation among its tasks.

Impact to Fault Handling: We have found that the Speculation Myopia approach has some major issues for handling stragglers caused by various forms of system failures. Stragglers due to failures are not mitigated by the speculation mechanism, especially those from small size jobs. Fig. 1 shows the job slowdown caused by a single node failure, which is extremely common in real-world MapReduce systems. When the job size is large, the slowdown is not obvious. But when it comes to small jobs (1 GB to 10 GB), the slowdown can be as much as 4.6x to 9.2x to the normal job running time. To make things worse, the majority of jobs on production systems are actually small size jobs. It has been widely reported that the size of MapReduce jobs in production clusters follows the power-law distribution, with a vast majority of them (e.g., more than 80% for Facebook workloads) containing less than 10 GB input.

Fig. 1: Job Slowdown Caused by Node Failures

**D. Analysis of Speculation Myopia**

Failure is identified as one of the major causes of stragglers. We have closely examined the MapReduce speculation mechanism, and found that, in many common failure scenarios, it can seriously impede the efficiency of straggler mitigation. As mentioned before, this can lead to the shortsightedness of MapReduce speculation, i.e., Speculation Myopia, resulting in unsuccessful speculative decisions and wasteful system resources. For succinctness, we focus on two main symptoms for further elaboration.

1) Dependency-Oblivious Specification: The existing speculation scheme in MapReduce is not very effective for reduce tasks because of their long-running behaviors. It is unable to peek through the dependency between its map and reduce phases, resulting in a symptom called Dependency-Oblivious Specification. The speculative decision is made based on the progress of all running tasks. If a task is finished, it will be excluded from the candidates for further speculative execution.

Intuitively, it is reasonable to consider only running tasks since completed tasks should have no way of delaying a job. However, MapReduce typically requires the use of intermediate data that is produced by the completed map tasks. If this intermediate data was lost, the job would be held up until it finally found out that the intermediate data was permanently lost. Furthermore, when a new attempt for the failed reduce task is launched, the required intermediate data can still be missing. Because of this, a redundant reduce task cannot help but wait and encounter several fetch failures again. Thus, completed tasks could also become stragglers, which the current speculation mechanism is unable to address. To mitigate this issue, MapReduce needs to gain an awareness of task dependencies.

2) Scope-Limited Specification: MapReduce speculation relies on the variation of progress among individual tasks. Based on the progress reports from heartbeat messages, the global speculator of MapReduce measures the progress variation among all tasks and selects one of the tasks that falls behind for speculative execution. This works well when there is a sufficient number of tasks, for example, when a big job is running on multiple nodes. But when tasks from a job are located on a single node or a few nodes equally affected by a system condition, the global speculator is unable to launch any speculative task for the job because there is not enough progress variation among its tasks.

For example, for small jobs such as those with 1 GB of input data, their tasks are very likely to be all situated on the same node. The failure or slowdown of that node will lead to the lack of progress reports from all of them. Hence, the global speculator has no way of launching speculative tasks until the timeout. Clearly, the long delay should be avoided by early speculative tasks as soon as MapReduce recognizes that the tasks on one node are all slow. Thus the existing speculation mechanism has a limited scope in measuring the variation of progresses. For early speculation decision, it needs to expand the scope of progress assessment from the cross-node comparison of a limited few tasks. This way, MapReduce can analyze task progresses in a global manner and guard against stragglers from an unhealthy segment of the system.

III. BINOCULAR SPECULATION FOR FAILURE RECOVERY

We have explored the implementation of YARN speculator with simple walk-around options. For example, we have used a shorter timeout value before the speculator decides to launch a copy for a straggler task. Our unsuccessful attempts suggest that the symptoms of speculation myopia occur due to fundamental limitations of YARN speculation, and require an algorithmic renovation. A complete solution requires a new speculation scheme.

In this paper, we propose a new speculation scheme that can heal the vision of speculation with better awareness of task dependencies and wider scope for measuring progress variations. We refer to the new scheme as Binocular Speculation.
As shown in Fig. 2 the current speculation in YARN MapReduce focuses entirely on the present state of task execution, without an awareness on task dependence with past and present tasks. In contrast, we introduce a new scheme that can expand the scope of speculative decisions, taking into account the relationship of a task with other tasks in both directions of time: past and present, hence the name.

Three new techniques are introduced in our proposed scheme. We first design a neighborhood glance mechanism to help the global speculator to increase the assessment scope of task progresses to the neighboring nodes and tasks, as well as glancing over data and task dependencies across different phases. Then we introduce a technique called collective speculation to allow a flexible frequency of task speculation so that speculative tasks can be launched dynamically, and collectively, if permitted by available resources. Finally, we develop speculative rollback to periodically log the progress of tasks so that a speculative task can be launched by rolling back to a previous log and progress further, instead of starting from scratch.

A. Neighborhood Glance

A MapReduce job involves many concurrent tasks across computer nodes. In the temporal dimension, the progress of tasks and nodes can vary from time to time, and in the spatial dimension, the progress of some tasks/nodes can also differ from that of other tasks/nodes. To better assess the progress variations in a MapReduce job, we introduce the neighborhood glance mechanism to measure the progress variations and identify underperforming tasks/nodes around a spatial neighborhood for the local task/node, or a time range from the current time point.

In addition to progress assessment, we consider the responsiveness history of a node to assess a node failure as well for more swift recovery upon the node failure. To find a slow or failed node, we take on three independent assessment policies. Specifically, spatial progress assessment aims to find a slow node that is significantly slower than its neighbors. Temporal progress assessment is intended to identify a straggler that may happen to slow down compared to its progress history. Finally, faulty node monitoring is used to discover a disconnected node. Next, we describe each type of assessment in more detail.

1) Progress Assessment in the Spatial Neighborhood: By default, YARN speculation measures the accumulative task progress score \( \text{ProgressScore} \) to determine the stragglers. This metric can be easily affected by imbalanced task assignment or nonuniform workloads among jobs. The notations in YARN denote node \( N \) for job \( J \) as \( (N^J) \) and \( \rho(t_i) \) as the task progress rate of task \( i \) that belongs to job \( J \) on node \( N \). Furthermore, the progress is represented as \( p \), where \( p(t) = \frac{\zeta(t) + 1}{\tau} \), and \( \zeta(t) \) is the \( \text{ProgressScore} \) of task \( t \) and \( \tau \) is the running time for task \( t \).

In neighborhood glance, we introduce a metric called \( \text{NodeProgressChangeRate}(P) \) to quantify the average task progress rate on a compute node. For example, \( P \) of \( (N^J) \) is defined as

\[
P(N^J) = \text{Avg}(\rho(t_i)_{i\in J}).
\]

To decide a slow node, we compare its \( P \) with other nodes inside its neighborhood. We denote \( \sigma(P) \) as the standard deviation of \( P \) within a neighborhood, and \( NH(N_i) \) as the collection of all nodes in \( N_i \)’s neighborhood. So if

\[
P(N^J) < \text{Avg}(P(N^J)_{N_i\in NH(N_i)}) - \sigma(P(N^J)_{N_i\in NH(N_i)})
\]

we then mark node \( N \) as a slow node for job \( J \) in our speculation scheme.

2) Progress Assessment in the Temporal Neighborhood: To expand our assessment of progress into the historical temporal dimension, we introduce a metric called \( \text{NodeProgressChangeRate}(\Delta) \) to keep track of the acceleration of \( \text{NodeProgress} \) \( \zeta \):

\[
\Delta(N^J)|_{T_i} = \frac{\zeta(N^J)|_{T_i} - \zeta(N^J)|_{T_{i-1}}}{T_i - T_{i-1}},
\]

where \( \Delta(N^J)|_{T_i} \) is the \( \text{NodeProgressChangeRate} \) of \( (N^J) \) at time \( T_i \) and \( \zeta(N^J)|_{T_i} \) is the summation of \( \text{ProgressScore} \) of all the tasks on \( (N^J) \) at time \( T_i \).

Note that we only consider the on-going tasks for the calculation of \( \zeta \). Hence, we can avoid aggressive speculation when many tasks have completed and exited near the end, and the accumulative \( \text{ProgressScore} \) declines suddenly. To deduce that \( (N^J) \) is slow for job \( J \) at time \( T_i \), the following condition needs to be met:

\[
\Delta(N^J)|_{T_i} < \text{Threshold}_{\text{slowdown}} \times \Delta(N^J)|_{T_{i-1}}
\]

where \( \text{Threshold}_{\text{slowdown}} \) is the slowdown threshold for \( \delta \) that will determine a computer node as a straggler. This is a configurable parameter, by default 0.1.

3) Node Failure Assessment: Although a failed node can be detected by our task progress assessment, the speculator can take a while to detect its progress slowdown. There are additional indicators of a node failure other than the execution progress, e.g., the loss of NodeManager heartbeat. YARN’s ResourceManager receives a heartbeat of each NodeManager in every second. A continuous stretch of lost heartbeats can affirm the node failure. But transient faults can cause lost heartbeats as well.

We use a heuristic algorithm to detect a node failure. First of all, a node \( N_i \) is marked as failed when the duration since its last response exceeds a \( \text{Threshold}_{\text{fail}} \). If a node is responsive in a heartbeat report, we check if it is a resuming heartbeat from a previously lost node. If that is the case, we measure the time duration that the node remains lost. This time duration is used later for updating \( \text{Threshold}_{\text{fail}} \).
To determine $\text{Threshold}_{i}^{\text{fail}}$, we use a window-based mechanism that can take the historical loss of responsiveness into account, where the earlier loss of responsiveness has less impact on the threshold. For instance, in order to capture the temporal locality between the last $L$ failures and the next failure at a node, we define the length of our window as $L$. We use $R_i$ to represent the duration of the node’s lost responsiveness during the $n$-th window in $L$. We hope to estimate the duration of lost responsiveness for the next failure ($P_{n+1}$) based on previous measurements. Given any node $i$ and a window of $L$, $P_{n+1}$ can be estimated as follows:

$$P_{n+1} = \frac{\sum_{k=1}^{L}(2^{L+1-k} \times R_{n+1-k})}{\sum_{k=1}^{L}(2^{k})} \quad (4)$$

The parameter $L$ is tuned based on the trade-off between the estimation accuracy and the computing overhead.

B. Collective Speculation

Once faults or failures are identified through neighborhood glance, we use a collective speculation mechanism to maximize the number of speculative tasks and minimize the progress delays caused by these faults or failures. Such mechanism needs to balance the recovery speed and resource consumption. Thus, instead of spawning speculative task attempts on all available compute nodes, we start with the neighboring nodes. If there are enough containers in the neighborhood, all speculative tasks are launched. If not, we use the available containers for those tasks. After that, we need to gradually add speculative tasks. To that purpose, we start with a small number of speculative tasks that equals to $\text{COLL\_INIT\_NUM}$ on compute nodes beyond the local neighborhood. We monitor the progress of both the speculative copy of a task and the original one. If either task is completed, we terminate the other one. If the speculative task has shown faster progress rate than the original copy, we continue to launch more speculative tasks (with a multiplication factor $\text{COLL\_MULTIPLY}$) until all stragglers have had an speculative attempt. In the $i$'s times of speculation, the number of speculative tasks to launch equals to $\text{COLL\_INIT\_NUM} \times \text{COLL\_MULTIPLY}^i$.

The process of collective speculation is shown by an example in Figure 3. Here we set $\text{COLL\_INIT\_NUM}$ to 1 and $\text{COLL\_MULTIPLY}$ to 2. At time $T_a$, through a progress assessment, the node that contains Task $t_1$, $t_2$ and $t_3$ is found to be slow and a speculative copy of $t_3$ is launched. Then we employ a very small duration for periodic progress checking. If we find that $t_3$ has higher progress rate than $t_1$, we then re-attempt $t_2$ and $t_3$ with a speculative copy. At $T_b$, $t_3$ finishes and kills the original attempt $t_1$. At $T_c$, the node that contains speculative tasks $t_2$ and $t_3$ fails, and is detected promptly by our failure assessment. Two further speculative copies are launched for $t_2$ and $t_3$, and the execution completes at $T_d$.

To facilitate the dependency-aware speculation, we also make speculative copies for completed tasks. Upon positive result of failure assessment or two consecutive intermediate data fetch failures, we launch a speculative copy for completed tasks. Our speculation for completed tasks works in the same way as the speculation for incomplete tasks, included to leverage the collective speculation scheme. However, when the speculative task completes, we do not discard its output. Instead we keep both the original and the speculative outputs until successful completion of the job.

C. Speculative Rollback

In the existing YARN’s speculation, the speculator launches a speculative task from scratch, the same as YARN’s fail-over mechanism where a failed task is rescheduled with a new attempt. We find that this is not efficient if the original task is delayed because of transient faults, such as disk I/O exception or packet loss, and the compute node for the task is still available. It can be more efficient to launch a task attempt on the original node and start from a previous execution point. Thus, we design a speculative rollback mechanism within binocular speculation. It leverages both YARN’s task failure report and our neighborhood assessment. When a task is reported as slow or failed, two attempts of the task are placed on its original node and a new node. The speculative copy on the original node will pick up the reserved task progress and start from there. The other copy will work as ordinary speculative task on another node. We do not use a heavyweight remote checkpointing mechanism because it incurs a lot of additional I/O overheads and would be too costly for short-lived map tasks.

The rollback mechanism provides another advantage because multiple attempts of the same task compete for completion. To achieve lightweight logs, we keep only a limited set of task information that is sufficient for resuming the execution of a map task. The log includes the spill path and offset of the input split for a map task. When the recovered map task is launched, it reclaims the completed work done by the previous attempt and rolls directly back to the previous offset of input split to start processing from the offset. In order to avoid making wasteful speculative attempts, we also check the
status of the previous node. If the node is not slow or failed, the rollback speculative task will be scheduled. Otherwise, an additional speculation is not allowed. Like the original YARN, we will try the speculative attempt on a fast node. The rollback mechanism is integrated with the other two techniques of binocular speculation, validated through sample programs such as TeraValidate from Terasort.

IV. PERFORMANCE EVALUATION

A. Experimental Environment

All our experiments are conducted on a cluster of 21 server nodes that are connected through 1 Gigabit Ethernet. Each machine is equipped with four 2.67 GHZ hex-core Intel Xeon X5650 CPUs, 24 GB memory and one 500 GB hard disk. We use YARN 2.7.1 as the code base with JDK 1.7. One node of the cluster is dedicated to run the ResourceManager of YARN and the NameNode of HDFS.

BENCHMARKS: We have selected a representative set of MapReduce benchmarks, including Terasort, Wordcount, Secondarysort and Grep from YARN’s built-in suite and Aggregation, Join, Kmeans, Pagerank, Scan and Sort from the well-known HiBench suite [13]. Unless specified, we report the results as the average of the suite of the benchmarks.

Evaluation Metrics: To emulate temporary system faults, we introduce delays in the progress of MapReduce tasks. To emulate node failures, we disconnect the targeted compute nodes. To measure the efficiency of fault recovery, we compare the job execution time. In addition, we measure the average job slowdown as the ratio between the job execution time upon failures and that without failures. To evaluate the gracefulfulness of binocular speculation in handling stressful scenarios, we run jobs in a heavily loaded MapReduce cluster and report the distribution of job execution time as PDF (probability density function) and CDF (cumulative density function) distributions.

We compare our design of binocular speculation against the original YARN, which uses the LATE scheduler [28] as its default specifier. We denote the original speculation as YARN and binocular speculation as Bino.

B. Overall Benefits of Binocular Speculation

We conduct experiments to examine the overall benefits of binocular speculation. We first measure its job execution time with different speculation policies, then evaluate if binocular speculation can mitigate the symptoms of dependency-oblivious speculation and scope-limited speculation.

1) Job Execution Time: Fig. 4(a) shows the job execution time for the two speculation policies with and without node failures. For this experiment, we report the average result from 10 test runs. For each run, we introduce a node failure at various points of job execution, i.e., from 10% to 100% of map progress. On average, Bino achieves 7.3x improvement for 1 GB jobs and 1.9x for 10 GB jobs compared to the original YARN. Some applications, e.g., Aggregation, are very sensitive to node failures and can experience a job slowdown of more than 20x. Bino is especially beneficial to these applications due to its speculation coverage and short timeouts.

2) Dependency-oblivious speculation: To validate the mitigation of dependency-oblivious speculation, we measure the job execution time only when we observe the loss of intermediate data. These tests used 10 GB of input data, and the measurements were collected when there is at least one fetch failure of MOF but no map task failure in order to exclude the effect of scope-limited speculation. Fig. 4(b) shows both YARN and Bino’s increments of job execution time upon the task failure. YARN’s default speculation is unaware of the dependency of lost data and causes the jobs to run much longer, on average a performance slowdown of 4.0x compared to the case without failure.

In contrast, with dependency awareness, binocular speculation pinpoints the corresponding map task for the lost intermediate data and launches a speculative task for timely recomputation. Thus compared to the default YARN speculation, binocular speculation provides an improvement of 2.0x average to these benchmarks.

3) Scope-limited speculation: We also test scope-limited speculation with 1 GB of input data and only adopt the result that is affected solely by the scope-limited speculation, i.e., there are failed map tasks that are not timely speculated but no MOF is lost.

Fig. 4(c) shows Bino’s benefits in restoring the scope-limited speculation from inactivity and recover the tasks effectively. Since the jobs are relatively small here, a node failure can cause significant performance degradation to the benchmarks. Binocular speculation in this case provides a much bigger improvement (an average of 6.8x) because it can quickly detect the failure-related stragglers.

C. Impact to Task Skew and Job Slowdown

A task or node failure can have very different impact on different tasks in a job because of their proximity or dependency. A good speculation shall overcome the disruptive impact of system faults, and smoothen the execution times of different tasks. We compare the two speculation policies by measuring the distribution of task execution times and the overall job slowdown upon a node failure.

Fig. 5 shows the PDF distribution of the average job slowdown for the benchmarks under two different speculation policies, as well as their standard variations.

YARN default speculation leads to a much wider distribution of job slowdown with an average around 2.8. Binocular speculation significantly reduces the average slowdown and decreases the variance σ from 0.61 to 0.107.

D. System Efficiency Under Stress

We evaluate how binocular speculation performs when the system is under a heavy load of many concurrent jobs. Because many jobs are competing for shared resources, more tasks will experience significantly slower progress [26], [24]. We run Terasort, Wordcount, Secondarysort and Grep jobs with different input sizes. We have followed the PACMan work [3] to set the size of jobs. 85% of jobs have 1 GB input data, 8% with 10 GB, and 5% with 50 GB and the rest with
parameters. We describe our evaluation and analysis in the rest of this section. On average, it decreases the job execution time of all running jobs that are due to the long turnaround time of big jobs. Both YARN and Bino have tails of long jobs in our synthetic workload by 30%. Big jobs can still benefit from binocular speculation, but relatively less due to the bigger tasks. Both YARN and Bino have tails of long-running jobs that are due to the long turnaround time of big jobs. Our results suggest that binocular speculation can also provide comparable or even larger improvement than detecting temporal progress changes. Moreover, spatial assessment does not help node failures in small jobs but it can mitigate node failures in larger jobs better than temporal assessment, e.g. an average of 5.7x improvement for node failures. In addition, our experiments show that enabling failure assessment provides more accurate or even larger improvement than detecting temporal progress changes. We further evaluate the failure assessment by tuning a key parameter $L$ (window size) used in the temporal window-based assessment, which is the number of prior unresponsive scenarios that Bino takes into account. We examine the correctness of our node failure assessment in a heterogeneous environment where both node failures and network delays are common. Thus, in each test, we inject a number of node failures and/or network delays. The number of failures and delays are following a failure ratio, varying from 0% to 100%. The duration of delays is randomly generated according to a Poisson Distribution.

As shown in Fig. 7(b), there are two major trends. Firstly, the larger the failure ratio is, the more accurate our failure assessment is. Secondly, to set $L$ higher also leads to higher accuracy. Furthermore, we investigate the impact of $\text{SIZE}_{\text{NEIGHBOR}}$, i.e., the number of nodes in a neighborhood. We manually slow down a compute node during the job execution, and then measure the job slowdown and the number of speculative tasks for the job to complete.

As shown in Fig. 7(c) $\text{SIZE}_{\text{NEIGHBOR}}$ does not have a very large impact on job slowdown or the number of speculative tasks. However, a neighborhood with only two nodes has smaller performance improvement due to its limited capacity for spatial progress assessment.

This implies that we can keep $\text{SIZE}_{\text{NEIGHBOR}}$ small to minimize cross traffic I/O overheads so long as enough progress.

100 GB. We let the job arrive at random times following a Poisson distribution. We then inject task failures, node crashes and network delays. Fig. 6 measures the job execution times and plots their CDF distribution. Binocular speculation leads to significant improvement for MapReduce jobs. A greater improvement can be observed for small jobs. Big jobs can also show that node slowdown can cause smaller but notable performance degradation, and our neighborhood glance has similar effect on the recovery.

We manually slow down a compute node during the job execution, and then measure the job slowdown and the number of speculative tasks for the job to complete.

E. Analysis and Tuning of Component Techniques

We evaluate the performance of individual techniques in binocular speculation and tune some of the key configuration parameters. We describe our evaluation and analysis in the rest of this section.
variation can be detected within the neighborhood.

![Graph](image)

**Fig. 8: Tuning collective speculation**

(a) Performance dissection.
(b) Correctness of failure assessment.
(c) Tuning neighborhood size.

**Fig. 7: Understanding neighborhood glance**

2) **Collective Speculation**: COLL_INIT_NUM and COLL_MULTIPLY are two critical parameters in the collective speculation.

We tune those parameters when a node is delayed in progress or failed. The results are shown in Fig. 8. Overall, increasing COLL_MULTIPLY has a bigger impact to the job performance for both node delays and failures. Increasing COLL_INIT_NUM reduces the average job slowdown but has a smaller impact. However, launching more speculative tasks aggressively can consume resources very quickly. It can be tolerable when the system workload is light, but can be very disruptive to all users and jobs on a shared system that is heavily loaded.

3) **Speculative Rollback**: We conduct experiments to demonstrate the benefits of speculative rollback. We inject map task failures by incurring a disk write exception to a single map task. For each job we inject only one failure but at a different progress point. The progress point of a task is indicated by the number of spills it has generated before the failure. Fig. 9 shows the performance improvement from the speculative rollback to a new attempt of the failed task. We can see that the actual performance gain depends on the amount of task progress that has reached before failures. When there is more task progress, the speculative rollback recovery is faster. For instance, re-execution for a failure after 4 spills takes 73% shorter time than the one after 1 spill, effectively preserving map task progress and speeding up job recovery.

![Graph](image)

**Fig. 9: Benefits of speculative rollback**

V. RELATED WORK

**A. MapReduce Speculation**

Speculation mechanism had been actively studied with a variety of viewpoints [28], [5], [4], [2]. But compared to our work, they either overlooked the particular behaviors of failure-related stragglers and/or adopted a mitigation strategy that is inefficient. To describe a few, LATE [28] scheduler took node heterogeneity into account. But its speculator scope was limited and it used the suboptimal serial speculation. Mantri [5] searched for the causes of stragglers and identified in part the impact of failure-related stragglers. Moreover, it made many interesting observations. For example, the failure-related stragglers are very often localized on a few bad machines but those machines are usually scattered apart across the cluster. However, it also had a limited scope of speculation and only used the costly replication of intermediate data to avoid data recomputation during failures. GRASS [4] improved speculation only for the approximation jobs using two distinct scheduling strategies, a.k.a. Greedy Speculative and Resource Aware Speculative scheduling. But neither of the two strategies addressed failure recovery.

DOLLY [2] used undifferentiated task cloning to mitigate stragglers in small jobs. Although such design could be helpful for solving the performance breakdown of node failures, it had an obvious downside that cloning every task would incur a lot more computation and network I/O than making only necessary speculation for a few stragglers. This is especially true for a shared MapReduce cluster that is already heavily loaded as discussed in [20], [24]. Without handling failures respectively, relying on such exhaustive speculation for mitigating failure-related stragglers is not practical. To the best of
our knowledge, our work is the first one to examine the failure-related stragglers in MapReduce, and accordingly, presents an effective and efficient mitigation solution.

B. MapReduce Failure Recovery

Besides speculation, MapReduce failure resiliency has also gained much attention. Since failures are gradually becoming the norm in large-scale systems, the recovery efficiency is equally important. Many recent studies have been working towards efficient failure recovery for MapReduce systems [17, 10, 23]. RAFTing MapReduce [17] for preserving the computation of map tasks and replicating the MOFs to reduce side. This design avoided the re-computation of map tasks on the failed node, but it required the pre-assignment of reduce tasks and incurred much additional network overheads.

Dinu et al. [10] took an experimental analysis on the node failure in MapReduce. They revealed an issue called delayed speculative execution during node failure. Moreover, they found that the failure of the node containing reduce tasks can infect other healthy tasks and nodes, causing drastic performance degradation. Wang et al. [23] revealed a similar issue, which is referred to as failure amplification. But both works failed to recognize the inherent cause, i.e., the issue of dependency oblivious speculation so neither of them provided an efficient solution for this issue. Both works did not look into failures occurring at the map phase. Our work is orthogonal to these prior studies by addressing speculation myopia and its impact on fault recovery in MapReduce.

VI. CONCLUSION

In this paper, we have examined the dichotomy of MapReduce caused by its two-phase execution model and then used the next-generation Hadoop framework, i.e., YARN, to examine the role of MapReduce speculation for failure recovery. We reveal that MapReduce dichotomy leads to a problem called speculation myopia, which has impact on MapReduce fault recovery upon temporary system faults and/or node failures. Speculation myopia often manifests itself in two main symptoms: dependency-oblivious speculation and scope-limited speculation. We have designed and implemented a new speculation scheme called binocular speculation to address speculation myopia and its symptoms. Binocular speculation is designed with three constituent techniques including neighborhood glance, collective speculation and speculative rollback. We have conducted a substantial set of experiments to evaluate the benefits of binocular speculation for performance breakdown and variations on MapReduce systems. Our experimental results demonstrate that binocular speculation can heal all symptoms of speculation myopia and deliver fast fault recovery compared to the existing speculation mechanism in YARN MapReduce.

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