Reining in the Outliers in Map-Reduce Clusters using Mantri

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Experience from an operational map-reduce cluster reveals that outliers significantly prolong job completion. The causes for outliers include (i) machine characteristics - both hardware reliability (e.g., disk failures) as well as run-time contention for processor, memory and other resources, (ii) network characteristics with varying bandwidths and congestion along paths, and (iii) imbalance in workload among tasks. We present Mantri, a system that monitors tasks and culls outliers using *cause-* and *resource-aware* techniques. Mantri's strategies include smart restart of outliers, network-aware placement of tasks and protecting outputs of valuable tasks. Mantri's principled strategy of dealing with outliers is a significant advancement over prior work that concentrate only on duplicating tasks. Using real-time progress reports, Mantri detects outliers early in their lifetime, and takes appropriate action based on their causes. Early action frees up resources that can be used by subsequent tasks and expedites the job overall. Deployment in Bing's production cluster and extensive trace-driven simulation indicate that Mantri is 3.1x more effective than the existing state-of-the-art in improving job completion times.

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1 Introduction

In a very short time, MapReduce has become the dominant paradigm for large data processing on compute clusters. Software frameworks based on MapReduce [1, 10, 12] have been deployed on tens of thousands of machines to implement a variety of applications, such as building search indices, recommendation engines, optimizing advertisements, and mining social networks.

While highly successful, MapReduce clusters come with their own set of challenges. One such challenge is the often unpredictable performance of the MapReduce jobs. A job consists of a set of tasks which are organized in phases. Tasks in a phase depend on the results computed by the tasks in the previous phase and can run in parallel. When a task takes longer to finish than other similar tasks, the tasks in the subsequent phase are delayed. At key points in the job, a few such *outlier* tasks can prevent the rest of the job from making progress (Table 1 defines the terms). As the size of the cluster and the size of the jobs grow, the impact of outliers increases dramatically. Addressing the outlier problem is critical to speed up job completion and improve cluster efficiency.

Even a few percent of improvement in the efficiency of a cluster consisting of tens of thousands of nodes can save millions of dollars a year. In addition, finishing production jobs quickly is a competitive advantage. Doing so predictably allows SLAs to be met. In iterative modify/ debug/ analyze development cycles, the ability to iterate faster improves programmer productivity.

In this paper, we characterize the impact and causes of outliers by measuring a large MapReduce production cluster. This cluster is up to two orders of magnitude larger than those in previous publications [1, 12, 20] and exhibits a high level of concurrency due to many jobs simultaneously running on the cluster and many tasks on a machine. We find that variation in completion times among functionally similar tasks is large and that outliers inflate the completion time of jobs by 34% at median.

We identify three categories of root causes for outliers that are induced by the interplay between storage, network and structure of map-reduce jobs. First, *machine characteristics* dictate the performance of tasks. These include static aspects such hardware reliability (e.g., disk failures) and dynamic aspects such as contention for processor, memory and other resources. Second, *network characteristics* affect the data transfer rates of tasks. Datacenter networks are over-subscribed leading to variance in congestion among different paths. Finally, the specifics of MapReduce leads to *imbalance* in work among tasks. For example, a partitioning of data over a key space with low entropy leads to skews among tasks in input sizes.

We present Mantri, [1] a system that monitors tasks and culls outliers based on their causes. It uses the following algorithms: (i) Restarting outlier tasks cognizant to resource constraints and work imbalances, (ii) Network-aware placement of tasks, and (iii) Protecting output of tasks based on a cost-benefit analysis.

The detailed analysis and decision process employed by Mantri is a key departure from the state-of-the-art for outlier mitigation in map-reduce implementations [10, 12, 20]; these focus only on duplicating tasks. To our knowledge, none of them protect against data loss induced recomputations or network congestion induced outliers. Mantri's placement of tasks is cognizant to the congestion in the network. On a task's completion, its output is replicated if the benefit of not having to recompute outweighs the cost of replicating.

Further, Mantri performs intelligent restarting of outliers. A task that runs for long because it has more work to do will not be restarted; if it lags due to reading data over a low-bandwidth path, it will be restarted only if a more advantageous network location becomes available. Unlike current approaches that duplicate tasks only at the end of a phase, Mantri uses real-time progress reports to act early. While early action on outliers frees up resources that could be used for pending tasks, doing so is nontrivial. A duplicate may finish faster than the original task but has the opportunity cost of using up an extra unit of resource that other pending work could have used.

[1] From Sanskrit, a minister who keeps the king's court in order

Term	**Description**
Task	Atomic unit of computation with a fixed input
Phase	A collection of tasks that can run in parallel, e.g., map, reduce
Outlier	A task that takes longer to finish compared to other tasks in the phase
Workflow	A directed acyclic graph denoting how data flows between phases
Job	An execution of the workflow

Table 1: Definitions of terms used in this paper.

Some of these outlier causes are known in the high performance and parallel computing community [2, 5]. However, the comprehensive formulation, relative break-down of contribution from each cause and a unified solution in the context of map-reduce is novel.

In summary we make the following contributions. First, we provide an analysis of the causes of outliers in a large production MapReduce cluster. Second, we develop Mantri, that takes early actions based on understanding the causes and the opportunity cost of actions. Finally, we perform an extensive evaluation of Mantri and compare it to existing solutions.

By deploying a Mantri prototype on a production cluster, of thousands of servers, that supports Bing and replaying several thousand jobs collected on this cluster in a simulator, we show that:

- Mantri reduces the completion time of jobs by 20% on average on the production clusters. Extensive simulations show that job phases are quicker by 21% and 42% at the 50th and 75th percentiles. Its median reduction in completion time improves on the next best scheme by $3.1\times$ while using fewer resources.
- By placing *reduce* tasks to avoid network hotspots, Mantri improves the completion times of the reduce phases by 60%.
- By preferentially replicating the output of tasks that are more likely to be lost or expensive to recompute, Mantri speeds up half of the jobs by at least 20% each, with only 1% increase in network traffic.

2 Background

We monitored the cluster and software systems that support the Bing search engine for over twelve months. This is a cluster of tens of thousands of commodity servers managed by Cosmos, a proprietary upgraded form of Dryad [12]. Despite some differences, implementations of map-reduce [1, 10, 12] are broadly similar.

While programmers can write native code, most of the jobs in the examined cluster are written in Scope [7], a mash-up language that mixes SQL-like declarative statements with user code. The Scope compiler transforms a job into a workflow– a directed acyclic graph where each node is a phase and each edge joins a phase that produces data to another that uses it. A phase is a set of one or more tasks that run in parallel and perform the same computation on different parts of the input stream. Typical phases are map, reduce and join. Compiler optimizations can merge different functionality into one phase or divide functionality across phases. The number of tasks in a phase is chosen at compile time. A task will read its input over the network if it is not available on the local disk but outputs are written to the local disk. The eventual outputs of a job (as well as raw data) are stored in a reliable block storage system implemented on the same servers that do computation. Blocks are replicated n-way's for reliability. A run-time scheduler assigns tasks to machines, based on data locations, dependence patterns and cluster-wide resource availability. The network layout is such that there is more bandwidth within a rack than across racks.

We obtain detailed logs from the Scope compiler and the Cosmos scheduler. At each of the job, phase and task levels, we record the execution behavior as represented by begin and end times, the machines(s) involved, the sizes

Dates	**Phases x 10^3**	**Jobs**	**Compute (years)**	**Data (PB)**	**Network (PB)**
May 25,26	19.0	938	49.1	12.6	.66
Jun 16,17	16.5	991	88.0	22.7	1.22
Jul 20,21	22.0	1183	51.6	14.3	.67
Aug 20,21	29.2	1873	60.6	18.7	.76
Sep 15,16	27.4	1653	73.0	22.8	.73
Oct 15,16	20.4	1362	84.1	25.3	.86
Nov 16,17	37.8	1834	88.4	25.0	.68
Dec 10,11	18.7	1777	96.2	18.6	.72
Jan 11,12	24.4	1842	79.5	21.5	1.99

Table 2: Details of the logs from a production cluster consisting of thousands of servers.

of input and output data, the fraction of data that was read across racks and a code denoting the success or type of failure. We also record the workflow of jobs. Table 2 depicts the random subset of logs that we analyze here. Spanning eighteen days, this dataset is at least one order of magnitude larger than prior published data along many dimensions, e.g., number of jobs, cluster size.

3 The Outlier Problem

We begin with a first principles approach to the outlier problem, then analyze data from the production cluster to quantify the problem and obtain a breakdown of the causes of outliers (§4). Beginning at the first principles motivates a distinct approach (§5), which as we show in §6 significantly improves on prior art.

3.1 Outliers in a Phase

Assume a phase consists of n tasks and has s slots. [2] On our cluster, the median ratio of $\frac{n}{s}$ is 2.11 with a stdev of 12.37. The goal is to minimize the phase completion time, *i.e.*, the time when the last task finishes.

Based on data from the production cluster, we model t_i, the completion time of task i, as a function of the size of the data it processes, the code it runs, the resources available on the machine it executes and the bandwidth available on the network paths involved:

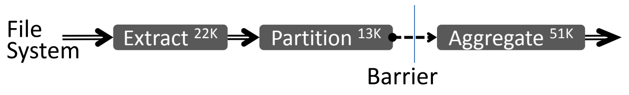
$$t_i = f\left(\text{datasize}, \text{code}, \text{machine}, \text{network}\right). \tag{1}$$

Large variation exists along each of the four variables leading to considerable difference in task completion times. The amount of data processed by tasks in the same phase varies, sometimes widely, due to limitations in dividing work evenly. The code is the same for tasks in a phase, but differs significantly across phases (*e.g.*, map and reduce). Placing a task on a machine that has other resource hungry tasks inflates completion time, as does reading data across congested links.

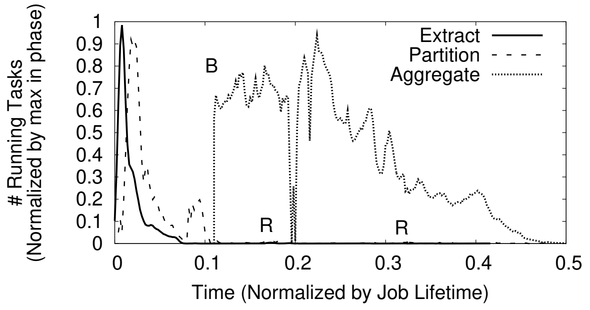
In the ideal scenario, where every task takes the same amount of time, say T, scheduling is simple. Any work-conserving schedule would complete the phase in $\left(\lceil \frac{n}{s} \rceil \times T\right)$. When the task completion time varies, however, a naive work-conserving scheduler can take up to $\left(\frac{\sum_n t_i}{s} + \max t_i\right)$. A large variation in t_i increases the term $\max t_i$ and manifests as outliers.

The goal of a scheduler is to minimize the phase completion time and make it closer to $\frac{\sum_n t_i}{s}$. Sometimes, it can do even better. By placing tasks at less congested machines or network locations, the t_i's themselves can be lowered. The challenge lies in recognizing the aspects that can be changed and scheduling accordingly.

[2]Slot is a virtual token, akin to a quota, for sharing cluster resources among multiple jobs. One task can run per slot at a time.



(a) Partial workflow with the number of tasks in each phase



(b) Time lapse of task execution (R=Recomputes, B=Barrier).

Figure 1: An example job from the production cluster

3.2 Extending from a phase to a job

The phase structure of map-reduce jobs adds to the variability. An outlier in an early phase, by delaying when tasks that use its output may start, has cumulative effects on the job. At *barriers* in the workflow, where none of the tasks in successive phase(s) can begin until all of the tasks in the preceding phase(s) finish, even one outlier can bring the job to a standstill [3]. Barriers occur primarily due to reduce operations that are neither commutative nor associative [30], for instance, a reduce that computes the median of records that have the same key. In our cluster, the median job workflow has eight phases and eleven edges, 47% are barriers (number of edges exceeds the number of phases due to table joins).

Dependency across phases also leads to outliers when task output is lost and needs to be *recomputed*. Data loss happens due to a combination of disk errors, software errors (*e.g.*, bugs in garbage collectors) and timeouts due to machines going unresponsive at times of high load. In fact, recomputes cause some of the longest waiting times observed on the production cluster. A recompute can cascade into earlier phases if the inputs for the recomputed task are no longer available and need to be regenerated.

3.3 Illustration of Outliers

Figure 1(a) shows the workflow for *Log_Merge*, a job whose structure is typical of those in the cluster. The job reads a dataset of search usage and derives an index. It consists of two map-reduce operations and a join, but for clarity we only show the first map-reduce here. Phase names follow the Dryad [12] convention– *extract* reads raw blocks, *partition* divides data on the key and *aggregate* reduces items that share a key.

Figure 1(b) depicts a timeline of an execution of this workflow. It plots the number of tasks of each phase that are active, normalized by the maximum tasks active at any time in that phase, over the lifetime of the job. Tasks in the first two phases start in quick succession to each other at $\sim$.05, whereas the third starts after a barrier.

Some of the outliers are evident in the long lulls before a phase ends when only a few of its tasks are active. In particular, note the regions before x$\sim$.1 and x$\sim$.5. The spike in phase #2 here is due to the outliers in phase #1 holding

[3]There is a variant in implementation where a slot is reserved for a task before all its inputs are ready. This is either to amortize the latency of network transfer by moving data over the network as soon as it is generated [1, 10], or compute partial results and present answers *online* even before the job is complete [8]. Regardless, pre-allocation of slots can hog more resources for longer periods if the input task(s) straggle.

on to the job's slots. At the barrier, x∼.1, just a few outliers hold back the job from making forward progress. Though most aggregate tasks finish at x∼.3, the phase persists for another 20%.

The worst cases of waiting immediately follow recomputations of lost intermediate data marked by R. Recomputations manifest as tiny blips near the x axes for phases that had finished earlier, *e.g.*, phase #2 sees recomputes at x∼.2 though it finished at x∼.1. At x∼.2, note that aggregate almost stops due to a few recomputations.

We now quantify the magnitude of the outlier problem, before presenting our solution in detail.

4 Quantifying the Outlier Problem

We characterize the prevalence and causes of outliers and their impact on job completion times and cluster resource usage. We will argue that three factors – dynamics, concurrency and scale, that are somewhat unique to large map-reduce clusters for efficient and economic operation, lie at the core of the outlier problem. To our knowledge, we are the first to report detailed experiences from a large production map-reduce cluster.

4.1 Prevalence of Outliers

Figure 2 plots the fraction of high runtime outliers and recomputes in a phase. For exposition, we arbitrarily say that a task has high runtime if its time to finish is longer than 1.5x the median task duration in its phase. By recomputes, we mean instances where a task output is lost and dependent tasks wait until the output is regenerated.

We see in Figure 2 that 25% of phases have more than 15% of their tasks as outliers. The figure also shows that 99% of the phases see no recomputes. Though rare, recomputes have a widespread impact (§4.3). Two out of a thousand phases have over 50% of their tasks waiting for data to be recomputed.

How much longer do outliers run for? Figure 3 shows that 80% of the runtime outliers last less than 2.5 times the median task duration in the phase, with a uniform probability of being delayed by between 1.5x to 2.5x.

The tail is heavy and long– 10% take more than 10x the median duration. Ignoring these if they happen early in a phase, as current approaches do, appears wasteful.

Figure 3 shows that most recomputations behave normally, 90% of them are clustered about the median task, but 3% take over 10x longer.

4.2 Causes of Outliers

To tease apart the contributions of each cause, we first determine whether a task's runtime can be explained by the amount of data it processes or reads across the network [4]. If not, then the outlier is likely due to workload imbalance or poor placement. Otherwise, the outlier is likely due to resource contention or problematic machines.

Figure 4(a) shows that in 40% of the phases (top right), all the tasks with high runtimes (i.e., over 1.5X the median task) are well explained by the amount of data they process or move on the network. Duplicating these tasks would not make them run faster and will waste resources. At the other extreme, in 18% of the phases (bottom left), none of the high runtime tasks are explained by the data they process. Figure 4(b) shows tasks that take longer than they should, as predicted by the model, but do not take over 1.5X the median task in their phase. Such tasks present an opportunity for improvement. They may finish faster if run elsewhere, yet current schemes do nothing for them. 20% of the phases (on the top right) have over 55% of such improvable tasks.

[4]For each phase, we fit a linear regression model for task lifetime given the size of input and the volume of traffic moved across low bandwidth links. When the residual error for a task is less than 20%, i.e., its run time is within [.8, 1.2]X of the time predicted by this model, we call it explainable.

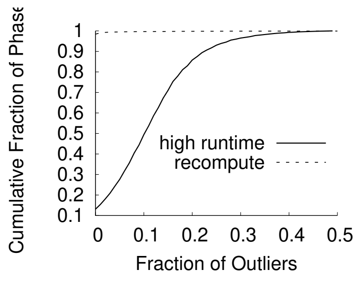


Figure 2: What fraction of tasks in a phase are outliers?

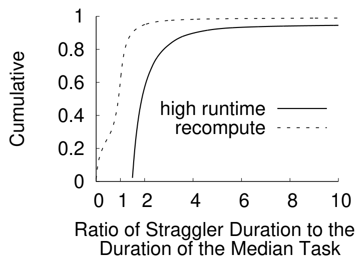


Figure 3: How much longer do outliers take to finish?

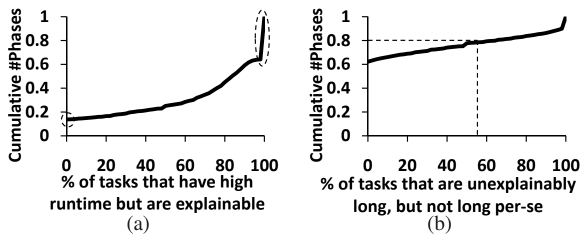


Figure 4: Contribution of data size to task runtime (see §4.2)

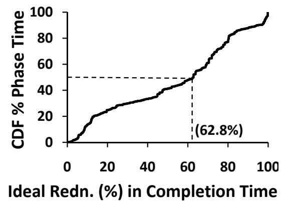


Figure 5: For reduce phases, the reduction in completion time over the current placement by placing tasks in a network-aware fashion.

Data Skew: It is natural to ask why data size varies across tasks in a phase. Across phases, the coefficient of variation ($\frac{stdev}{mean}$) in data size is .34 and 3.1 at the 50th and 90th percentiles. From experience, dividing work evenly is non-trivial for a few reasons. First, scheduling each additional task has overhead at the job manager. Network bandwidth is another reason. There might be too much data on a machine for a task to process, but it may be worse to split the work into multiple tasks and move data over the network. A third reason is poor coding practice. If the data is partitioned on a key space that has too little entropy, i.e., a few keys correspond to a lot of data, then the partitions will differ in size. Some reduce tasks are not amenable to splitting (neither commutative nor associative [31]), and hence each partition has to be processed by one task. Some joins and sorts are similarly constrained. Duplicating tasks that run for long because they have a lot of work to do is counter productive.

Crossrack Traffic: We find that reduce phases contribute over 70% of the cross rack traffic in the cluster, while most of the rest is due to joins. We focus on cross rack traffic because the network links upstream of the racks have less bandwidth than the cumulative capacity of servers in the rack.

We find that crossrack traffic leads to outliers in two ways. First, in phases where moving data across racks is avoidable (through locality constraints), a task that ends up in a disadvantageous network location runs slower than others. Second, in phases where moving data across racks is unavoidable, not accounting for the competition among tasks within the phase (self-interference) leads to outliers. In a reduce phase, for example, each task reads from every map task. Since the maps are spread across the cluster, regardless of where a reduce task is placed, it will read a lot of data from other racks. Current implementations place reduce tasks on any machine with spare slots. A rack that has too many reduce tasks will be congested on its downlink leading to outliers.

Figure 5 compares the current placement with an ideal one that minimizes the cost of network transfer. When possible it avoids reading data across racks, and if not, places tasks such that their competition for bandwidth does not result in hotspots. In over 50% of the jobs, reduce phases account for 17% of the job's lifetime. For the reduce phases, the figure shows that the median phase takes 62% longer under the current placement.

Bad and Busy Machines: We rarely find machines that persistently inflate runtimes. Recomputations, however,

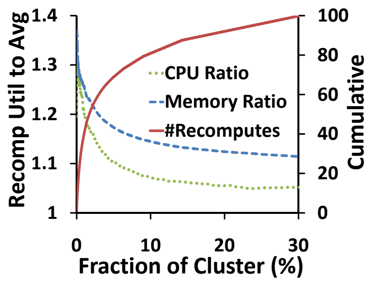


Figure 6: The ratio of processor and memory usage when recomputations happen to the average at that machine (y1). Also, the cumulative percentage of recomputations across machines (y2).

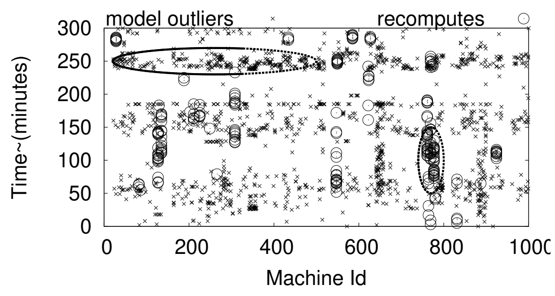


Figure 7: Clustering recomputations and outliers across time

are more localized. Half of them happen on 5% of the machines in the cluster. Figure 6 plots the cumulative share of recomputes across machines on the axes on the right. The figure also plots the ratio of processor and memory utilization during recomputes to the overall average on that machine. The occurrence of recomputes is correlated with increased use of resources by at least 20%. The subset of machines that triggers most of the recomputes is steady over days but varies over weeks, likely indicative of changing hotspots in data popularity or corruption in disks [6].

Figure 7 investigates the occurrence of "spikes" in outliers. We find that runtime outliers (shown as stars) cluster by time. If outliers were happening at random, there should not be any horizontal bands. Rather it appears that jobs contend for resources at some times. Even at these busy times, other lightly loaded machines exist. Recomputations (shown as circles) cluster by machine. When a machine loses the output of a task, it has a higher chance of losing the output of other tasks.

Rarely does an entire rack of servers experience the same anomaly. When an anomaly happens, the fraction of other machines within the rack that see the same anomaly is less than $\frac{1}{20}$ for recomputes, and $\frac{4}{20}$ for runtime with high probability. So, it is possible to restart a task, or replicate output to protect against loss on another machine within the same rack as the original machine.

4.3 Impact of Outliers

We now examine the impact of outliers on job completion times and cluster usage. Figure 8 plots the CDF for the ratio of job completion times, with different types of outliers included, to an ideal execution that neither has skewed run times nor loses intermediate data. The y-axes weighs each job by the total cluster time its tasks take to run. The hypothetical scenarios, with some combination of outliers present but not the others, do not exist in practice. So we replayed the logs in a trace driven simulator that retains the structure of the job, the observed task durations and the probabilities of the various anomalies (details in §6). The figure shows that at median, the job completion time would be lower by 15% if runtime outliers did not happen, and by more than 34% when none of the outliers happen. Recomputations impact fewer jobs than runtime outliers, but when they do, they delay completion time by a larger amount.

By inducing high variability in repeat runs of the same job, outliers make it hard to meet SLAs. At median, the ratio of $\frac{stdev}{mean}$ in job completion time is 0.8, i.e., jobs have a non-trivial probability of taking twice as long or finishing half as quickly.

To summarize, we take the following lessons from our experience.

- High running times of tasks do not necessarily indicate slow execution - there are multiple reasons for legitimate variation in durations of tasks.

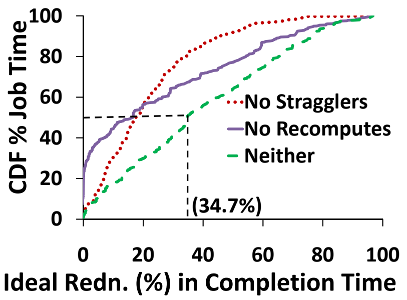


Figure 8: Percentage speed-up of job completion time in the ideal case when (some combination of) outliers do not happen

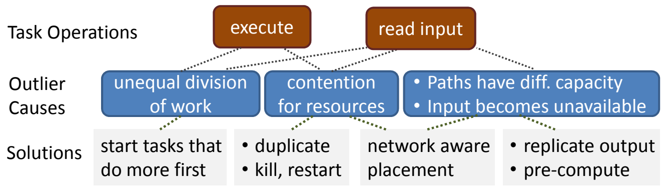


Figure 9: The Outlier Problem: Causes and Solutions

- Every job is guaranteed some slots, as determined by cluster policy, but can use idle slots of other jobs. Hence, judicious usage of resources while mitigating outliers has collateral benefit.
- Recomputations affect jobs disproportionately. They manifest in select faulty machines and during times of heavy resource usage. Nonetheless, there are no indications of faulty racks.

5 Mantri Design

Mantri identifies points at which tasks are unable to make progress at the normal rate and implements targeted solutions. The guiding principles that distinguish Mantri from prior outlier mitigation schemes are *cause awareness* and *resource cognizance*.

Distinct actions are required for different causes. Figure 9 specifies the actions Mantri takes for each cause. If a task straggles due to contention for resources on the machine, restarting or duplicating it elsewhere can speed it up (§5.1). If a task takes too long because it has a lot of work to do, there are two options: split it into smaller tasks or schedule large tasks before the others to avoid being stuck with the large ones near completion (§5.1, §5.4). However, not moving data over the low bandwidth links between racks, and if unavoidable, doing so while avoiding hotspots requires systematic placement (§5.2). To speed up tasks that wait for lost input to be recomputed, we find ways to protect task output (§5.3).

There is a subtle point with outlier mitigation: reducing the completion time of a task may in fact increase the job completion time. For example, replicating the output of every task will drastically avoid recomputations, both copies are unlikely to be lost at the same time, but can slow down the job because more time and bandwidth are used up for this task denying resources to other tasks that are waiting to run. Similarly, addressing outliers early in a phase vacates slots for outstanding tasks and can speed up completion. But, potentially uses twice as many resources per task. Unlike Mantri, none of the existing approaches act early or replicate output. Further, naively extending current schemes to act early without being cognizant of the cost of resources, as we show in §6, leads to worse performance.

Closed-loop action allows Mantri to act optimistically by bounding the cost when probabilistic predictions go awry. For example, even when Mantri cannot ascertain the cause of an outlier, it experimentally starts copies. If the cause does

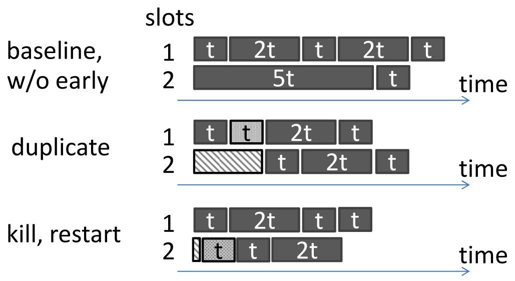


Figure 10: A stylized example to illustrate our main ideas. Tasks that are eventually killed are filled with stripes, repeat instances of a task are filled with a mesh.

not repeatedly impact the task, the copy can finish faster. To handle the contrary case, Mantri continuously monitors running copies and kills those whose cost exceeds the benefit.

Based on task progress reports, Mantri estimates for each task the remaining time to finish, t_{rem}, and the predicted completion time of a new copy of the task, t_{new}. Tasks report progress once every 10s or ten times in their lifetime, whichever is smaller. We use Δ to refer to this period. We defer details of the estimation to §5.5 and proceed to describe the algorithms for mitigating each of the main causes of outliers. All that matters is that t_{rem} be an accurate estimate and that the predicted distribution t_{new} account for the underlying work that the task has to do, the appropriateness of the network location and any persistent slowness of the new machine.

5.1 Resource-aware Restart

We begin with a simple example to help exposition. Figure 10 shows a phase that has seven tasks and two slots. Normal tasks run for times t and $2t$. One outlier has a runtime of $5t$. Time increases along the x axes.

The timeline at the top shows a baseline which ignores outliers and finishes at $7t$. Prior approaches that only address outliers at the end of the phase also finish at $7t$.

Note that if this outlier has a large amount of data to process letting the straggling task be is better than killing or duplicating it, both of which waste resources.

If however, the outlier was slowed down by its location, the second and third timelines compare duplication to a restart that kills the original copy. After a short time to identify the outlier, the scheduler can duplicate it at the next available slot (the middle time-line) or restart it in-place (the bottom timeline). If prediction is accurate, restarting is strictly better. However, if slots are going idle, it may be worthwhile to duplicate rather than incur the risk of losing work by killing.

Duplicating the outlier costs a total of $3t$ in resources ($2t$ before the original task is killed and t for the duplicate) which may be wasteful if the outlier were to finish in sooner than $3t$ by itself.

5.1.1 Restart Algorithm

Mantri uses two variants of restart, the first kills a running task and restarts it elsewhere, the second schedules a duplicate copy. In either method, Mantri restarts only when the probability of success, i.e., $\mathbb{P}(t_{new} < t_{rem})$ is high. Since t_{new} accounts for the systematic differences and the expected dynamic variation, Mantri does not restart tasks that are normal (e.g., runtime proportional to work). Pseudocode 1 summarizes the algorithm. Mantri kills and restarts a task if its remaining time is so large that there is a more than even chance that a restart would finish sooner. In

```
1: let $\Delta$ = period of progress reports
2: let $c$ = number of copies of a task
3: periodically, for each running task, kill all but the fastest $\alpha$ copies after $\Delta$ time has passed since begin
4: while slots are available do
5:     if tasks are waiting for slots then
6:         kill, restart task if $t_{rem} > \mathbb{E}(t_{new}) + \Delta$, stop at $\gamma$ restarts
7:         duplicate if $\mathbb{P}(t_{rem} > t_{new}\frac{c+1}{c}) > \delta$
8:         start the waiting task that has the largest data to read
9:     else                                                          ▷ all tasks have begun
10:        duplicate iff $\mathbb{E}(t_{new} - t_{rem}) > \rho\Delta$
11:    end if
12: end while
```

Pseudocode 1: Algorithm for Resource-aware restarts (simplified).

particular, Mantri does so when $t_{rem} > \mathbb{E}(t_{new}) + \Delta$.[5] To not thrash on inaccurate estimates, Mantri never kills a task more than $\gamma = 3$ times.

The "kill and restart" scheme drastically improves the job completion time without requiring extra slots as we show analytically (§A). However, the current job scheduler incurs a queueing delay before a task is restarted. This delay can be large and has a high variation. Hence, we consider scheduling duplicates.

Scheduling a duplicate results in the minimum completion time of the two copies and provides a safety net when estimates are noisy or the queueing delay is large. However, it requires an extra slot and if allowed to run to finish, consumes extra computation resource that will increase the job completion time if outstanding tasks are prevented from starting. Hence, when there are outstanding tasks and no spare slots, we schedule a duplicate only if the total amount of computation resource consumed decreases. In particular, if c copies of the task are currently running, a duplicate is scheduled only if $\mathbb{P}(t_{new} < \frac{c}{c+1} t_{rem}) > \delta$. By default, $\delta = .25$. For example, a task with one running copy is duplicated only if t_{new} is less than half of t_{rem}. For stability, Mantri does not re-duplicate a task for which it launched a copy recently. Any copy that has run for some time and is slower than the second fastest copy of the task will be killed to conserve resources. Hence, the number of running copies of a task is never larger than 3 [6]. On the other hand, when spare slots are available, a duplicate is scheduled if the reduction in the job completion time is larger than the extra resource consumed, $\mathbb{E}(t_{new} - t_{rem}) > \rho\Delta$. By default, $\rho = 3$.

Mantri's restart algorithm is independent of the values for its parameters. Setting γ to a larger and ρ, δ to a smaller value trades off the risk of wasteful restarts for the reward of a larger speed-up. The default values err on the side of caution.

By scheduling duplicates conservatively and pruning aggressively, Mantri has a high success rate of its restarts. As a result, it reduces completion time and conserves resources (§6.2).

5.2 Network-Aware Placement

Reduce tasks, as noted before (§4.2), have to read data across racks. A rack with too many reduce tasks is congested on its downlink and such tasks will straggle. Figure 11 illustrates such a scenario.

Mantri approximates the optimal placement that relieves congestion by the following greedy local algorithm. For a reduce phase with n tasks running on a cluster with r racks, it takes the input matrix $I_{n,r}$ that specifies the size of input available on a rack for each of the reduce tasks[7]. Note that the sizes of the map outputs in each rack are known to the scheduler prior to placing the tasks of the subsequent reduce phase. For every permutation of reduce tasks allocated

[5]Since the median of the heavy tailed task completion time distribution is smaller than the mean, this check implies that $\mathbb{P}(t_{new} < t_{rem}) > \mathbb{P}(t_{new} < \mathbb{E}(t_{new})) \geq .5$

[6]The fastest copy, the second fastest one and a copy that has recently been started.

[7]In I, the sum over rows in column i is the output of map phase output on the i^{th} rack, and the sum over columns in row j is the size of data to be read by the j^{th} reduce task.

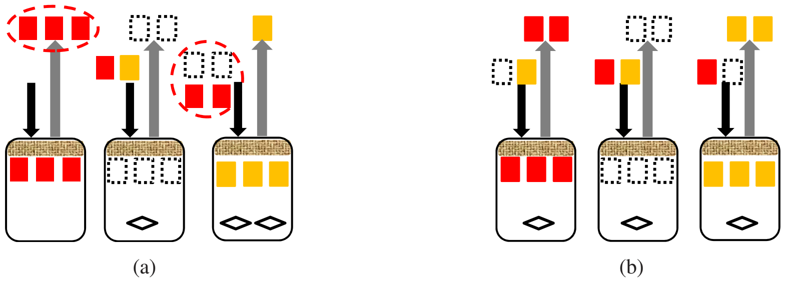


Figure 11: Three reduce tasks (rhombus boxes) are to be placed across three racks. The rectangles indicate map output, written out as three partitions, present in each of the racks. Each reduce task has to process one block of each type. An ad-hoc placement on the left creates network bottlenecks on the cross-rack links (highlighted) causing tasks in such racks to straggle. If the network were to have no other traffic, the even placement on the right avoids hotspots.

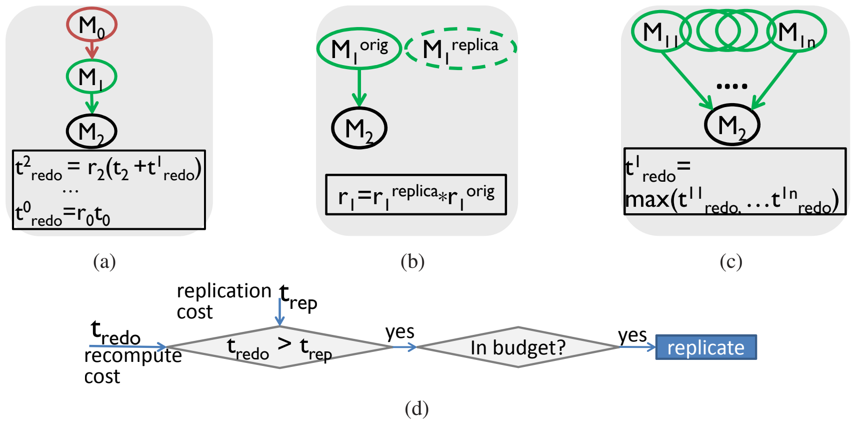


Figure 12: Avoiding costly recomputations: The cost to redo a task includes the recursive probability of predecessor tasks having to be re-done (a). Replicating output reduces the effective probability of loss (b). Tasks with many-to-one input patterns have high recomputation cost and are more valuable (c). The time to replicate, t_{rep} is calculated based on the available rack-local bandwidth and data is replicated only if $t_{redo} > t_{rep}$.

across racks, let the data to be moved out (on the uplink) and read in (on the downlink) on the i^{th} rack be d_u^i, d_v^i, and the corresponding available bandwidths be b_u^i and b_d^i respectively. For each rack, compute two terms $c_{2i-1} = \frac{d_u^i}{b_u^i}$ and $c_{2i} = \frac{d_v^i}{b_d^i}$. The first term is the ratio of outgoing traffic and available uplink bandwidth, and the second term is the ratio of incoming traffic and available downlink bandwidth. The algorithm computes the optimal value over all placement permutations that specifies the rack location for each task, as $\arg\min \max_j c_j,\ j = 1, \cdots, 2n,$, by minimizing the maximum data transfer time.

The available bandwidths b_u^i and b_d^i change with time and as a function of other jobs in the cluster. Rather than track the changes as an oracle could [28], Mantri estimates the bandwidths as follows. Reduce phases with a small amount of data finish quickly, and the bandwidths can be assumed to be constant throughout the execution of the phase. Phases with a large amount of data take longer to finish, and the bandwidth averaged over their long lifetime can be assumed to be equal for all links. With these estimates, Mantri's placement comes close to the ideal in our experiments (see §6.4).

For phases other than reduce, Mantri complements the Cosmos policy of placing a task close to its data [14]. By accounting for the cost of moving data over low bandwidth links in t_{new}, Mantri ensures that no copy is started at a location where it has little chance of finishing earlier thereby not wasting resources.

5.3 Avoiding Recomputation

To mitigate costly recomputations that stall a job, Mantri protects against interim data loss by replicating task output. Mantri acts early by replicating those outputs whose cost to recompute exceeds the cost to replicate. Mantri estimates the cost to recompute as the product of the probability that the output will be lost and the time to repeat the task. The probability of loss is estimated for a machine over a long period of time. The time to repeat the task is t_{redo} with a recursive adjustment that accounts for the task's inputs also being lost. The cost to replicate is the time to move the data to another machine in the rack. Figure 12 illustrates the calculation of t_{redo} that tasks data loss probabilities (r_i's), time taken by the tasks (t_i's) and recursively looks at prior phases. Replicating output reduces the likelihood of recomputation to the case when all replicas are unavailable. If a task reads input from many tasks (e.g., a reduce), t_{redo} is higher since any of the inputs needing to be recomputed will stall the task's recomputation. In Fig. 12(c), we assume that if multiple inputs are lost, they can be recomputed in parallel and the task is only stalled by the longest input. Since the overall number of recomputes is small (Figure 2) this is a fair approximation of practice.

In effect, the algorithm above replicates tasks at key places in a job's workflow – when the cumulative cost of not replicating many successive tasks builds up or when some tasks ran on very flaky machines (high r_i) or when the output is so small that replicating it would cost little (low t_{rep}).

Further, to avoid excessive replication, Mantri limits the amount of data replicated to 10% of the data processed by the job. This limit is implemented by granting tokens proportional to the amount of data processed by each task. Task output that satisfies the above cost-benefit check is replicated only if an equal number of tokens are available. Tokens are deducted on replication.

Mantri proactively recomputes tasks whose output and replicas, if any, have been lost. From §4, we see that recomputations on a machine cluster by time, hence Mantri considers a recompute to be the onset of a temporal problem and that future requests for data on this machine will fail. Such *pre-computation* decreases the time that a dependent task will have to wait for lost input to be regenerated. As before, Mantri imposes a budget on the extra cluster cycles used for pre-computation. Together, probabilistic replication and pre-computation approximate the ideal scheme in our evaluation (§6.5).

5.4 Data-aware Task Ordering

Workload imbalance causes tasks to straggle. In particular, given a set of n tasks, s slots and data sizes $d[1 \cdots n]$, computing the optimal schedule that minimizes the job completion time is known to be NP-hard. Mantri improves job completion time by scheduling tasks in a phase in descending order of their data size. If the optimal completion time is T_O, we know:

Theorem 1 $\frac{T}{T_O} \leq \frac{4}{3} - \frac{1}{3s}$. *from [11]*

This means that scheduling tasks with the longest processing time first is at most 30% worse than the optimal.

5.5 Estimation of t_{rem} and t_{new}

Periodically, every running task informs the job scheduler of its status, including how many bytes it has read or written thus far. Combining progress reports with the size of the input data that each task has to process, d, Mantri predicts how much longer the task would take to finish as follows:

$$t_{rem} = t_{elapsed} * \frac{d}{d_{read}} + t_{wrapup}. \tag{2}$$

The first term captures the remaining time to process data. The second term is the time to compute after all the input has been read and is estimated from the behavior of earlier tasks in the phase. Tasks may speed up or slow down and hence, rather than extrapolating from each progress report, Mantri uses a moving average. To be robust against lost progress reports, when a task hasn't reported for a while, Mantri increases t_{rem} by assuming that the task has not progressed since its last report.

Mantri estimates t_{new}, the distribution over time that a new copy of the task will take to run, as follows:

$$t_{new} = \textit{processRate} * \textit{locationFactor} * d + \textit{schedLag}. \tag{3}$$

The first term is a distribution of the process rate, i.e., $\frac{\Delta time}{\Delta data}$, of all the tasks in this phase. The second term is a relative factor that accounts for whether the candidate machine for running this task is persistently slower (or faster) than other machines or has smaller (or larger) capacity on the network path to where the task's inputs are located. The third term, as before, is the amount of data the task has to process. The last term is the average delay between a task being scheduled and when it gets to run. We show in §6.2 that these estimates are sufficiently accurate for Mantri's algorithms to function.

6 Evaluation

We deployed and evaluated Mantri on two of Bing's clusters, a production cluster consisting of thousands of servers and a smaller pre-production cluster. To compare against a wide range of alternate techniques, we built a trace driven simulator that replays logs from production.

6.1 Setup

Clusters The production cluster consists of thousands of server-class multi-core machines with tens of GBs of RAM that are spread roughly 40 servers to a rack. This cluster is used by Bing product groups. The data we analyzed earlier is from this cluster, so the observations from §4 hold here. The pre-production cluster is a smaller bed with similar machines and network. It is used to bake new releases and debug production code.

Workload In the pre-production cluster, Mantri was deployed for nine days as the default build for all jobs on this cluster. An internal test harness, independent of us, stress tests this cluster by issuing replicas of production jobs. Here, we report Mantri's performance on 202 jobs, each of which repeated over three times. We compare with runs of these jobs that used the unmodified build.

In the production cluster, we evaluate Mantri on four applications that represent common building blocks. *Word Count* calculates the number of unique words in the input. *Table Join* inner joins two tables each with three columns of data on one of the columns. *Group By* counts the number of occurrences of each word in the file. Finally, *grep* searches for string patterns in the input. We vary input sizes from 53 GB to 500 GB.

Prototype Mantri builds on the Cosmos job scheduler and consists of about 1000 lines of C++ code. To compute t_{rem}, Mantri maintains an execution record for each of the running tasks that is updated when the task reports progress. A phase-wide data structure stores the necessary statistics to compute t_{new}. When slots become available, Mantri runs Pseudocode 1 and restarts or duplicates the task that would benefit the most or starts new tasks in descending order of data size. To place tasks appropriately, name builds on the per-task *affinity list*, a preferred set of machines and racks that the task can run on. At run-time the job manager attempts to place the task at its preferred locations in random order, and when none of them are available runs the task at the first available slot. The affinity list for map tasks has machines that have replicas of the input blocks. For reduce tasks, to obtain the desired proportional spread across racks (see §5.2), we populate the affinity list with a proportional number of machines in those racks.

Trace-driven Simulator The simulator replays the logs shown in Table 2. It faithfully repeats the observed distributions of task completion time, data read by each task, size and location of inputs, probability of failures and fairness based evictions. It mimics the job workflow, the numbers of tasks per phase, the input/output relationships, barriers and cluster characteristics like machine failures and availability of computation slots. For the network, it uses a fluid model rather than simulating individual packets. Doing the latter, at petabyte scale, is out of scope for this work. On a 12 node testbed where each node had 8 core 2.5 GHz Intel Xeon processors and 32GB of RAM the simulations reported here took several weeks to complete.

Compared Schemes Our simulator compares Mantri with the outlier mitigation strategies in Hadoop [1], Dryad [12], MapReduce [10] and LATE [20]. We further compare against a modified form of LATE that varies in one aspect; it acts on stragglers early in the phase.

We also compare Mantri against some ideal benchmarks. *NoSkew* mimics the case when all tasks in a phase take the same amount of time. *NoSkew + ChopTail* removes the worst quartile of durations, and sets every task to the average of remaining durations. *IdealReduce* assumes perfect up-to-date knowledge of available bandwidths and places reduce tasks accordingly and *IdealRecompute* uses future knowledge of which tasks will wait for their inputs to be recomputed and acts to ensure that they do not happen.

Metrics As our primary metrics, we use the reduction in completion time and resource usage, where

$$\text{Reduction} = \frac{\text{Current} - \text{Modified}}{\text{Current}}. \tag{4}$$

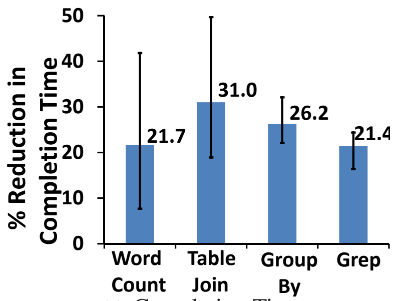
A reduction of 50% implies that the property in question, completion time or resources used, decreases by half. Negative values of reduction imply that the modification uses more resources or takes longer.

Our results are summarized as follows:

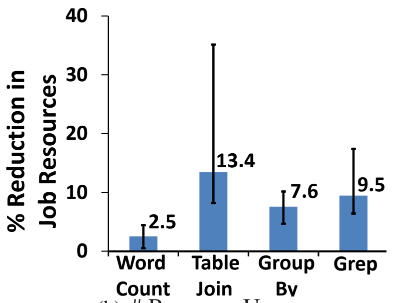
- Mantri's intelligent duplication and network-aware placement of reduce phases reduced the completion times of representative jobs/phases on the production cluster by an average of 25% and 28.4%.
- Simulations driven from production logs show that Mantri's duplication reduces the completion time of phases by 21% and 42% at 50^{th} and 75^{th} percentiles. Here, Mantri's reduction in completion time improves on Hadoop by 3.1x while using fewer resources than MapReduce, each of which are the current best on those respective metrics.
- Mantri's network-aware placement of tasks speeds up half of the reduce phases by at least 60% each.
- Mantri reduces the completion times due to recomputations of jobs that constitute 25% (or 50%) of the workload by at least 40% (or 20%) each, consuming negligible extra resources.

6.2 Deployment Results

Straggler Mitigation Figure 13 compares Mantri with the baseline Cosmos implementation for four jobs running on the larger cluster. Each job was repeated twenty times with and without Mantri. The histograms plot the average reduction, error bars are the 10th and 90th percentiles of samples. We see that Mantri improves job completion times by roughly 25%. Further, by terminating the largest stragglers early, resource usage *falls* by roughly 10%. As we show later in §6.3, this is because very few of the duplicates scheduled by the current mitigation scheme based on Dryad are useful.



(a) Completion Time



(b) # Resource Usage

Figure 13: Comparing Mantri's straggler mitigation with the baseline implementation on a production cluster of thousands of servers for the four representative jobs.

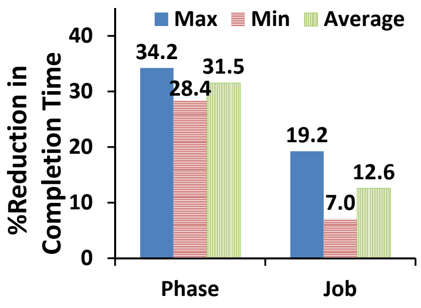
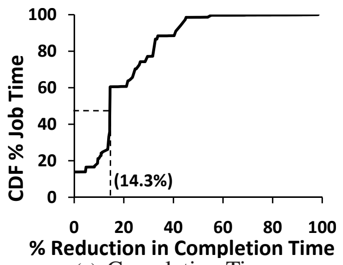
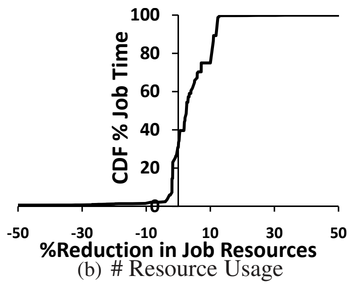


Figure 14: Comparing Mantri's network-aware spread of tasks with the baseline implementation on a production cluster of thousands of servers.



(a) Completion Time

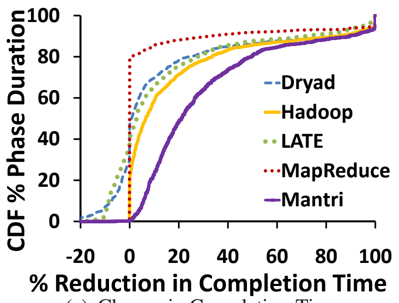


(b) # Resource Usage

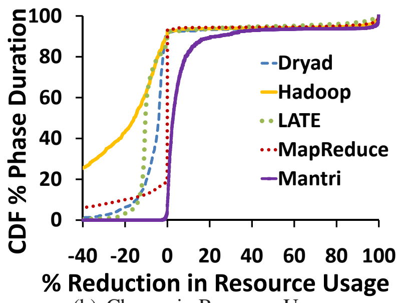
Figure 15: Evaluation of Mantri as the default build for all jobs on a pre-production cluster for nine days.

To micro-benchmark Mantri's estimators, we logged progress reports from these production runs. We find that Mantri's predictor, based on reports from the recent past, estimates t_{rem} to within a 2.9% error of the actual completion time. From the results above, we see that this accuracy suffices to see practical gains.

Placement of Tasks To evaluate Mantri's network-aware spreading of reduce tasks, we ran *Group By*, a job with a long-running reduce phase, ten times on the larger cluster. Figure 14 shows an average reduction in completion time of the reduce phase of 28.4% with a maximum of 34%. Overall, the job speeds-up by an average of 12.6%. To understand why, we measure the *spread* of tasks, i.e., the ratio of the number of concurrently running tasks to the number of racks they are running in. High spread value means some racks are congested, causing their tasks to straggle, while other racks are idle. The spread for Mantri is 1.5 compared to 5.5 for the default implementation.



(a) Change in Completion Time



(b) Change in Resource Usage

Figure 16: Comparing straggler mitigation strategies. Mantri provides a greater speed-up in completion time while using fewer resources than existing schemes.

Jobs in the Wild All the jobs submitted to the pre-production cluster ran with Mantri for a nine day period. We compare these job runs with earlier runs of the same jobs that ran with the unmodified build. Figure 15(a) plots the CDF of the net improvement in completion times of 202 jobs. Jobs that occupy the cluster for half the time sped up by at least 14.3%. We see larger gains on the benchmark jobs in the production cluster and in trace driven simulations. This is perhaps because, the pre-production being lightly loaded has fewer outliers and hence, less room for Mantri to improve. Figure 15(b) also shows that 60% of jobs see a *reduction* in resource consumption while the others use up a few extra resources.

To compare against alternative schemes and to piece apart gains from the various algorithms in Mantri, we present results from the trace-driven simulator.

6.3 Can Mantri mitigate stragglers?

Figure 16 compares straggler mitigation strategies in their impact on completion time and resource usage. The y-axes weighs phases by their lifetime since improving the longer phases improves cluster efficiency. The figures plots the cumulative reduction in these metrics over each of the 210K phases in Table 2 with each phase repeated 3 times.

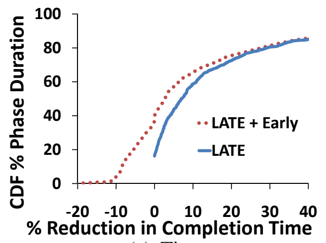
Figures 16(a) and 16(b) show that Mantri improves completion time by 21% and 42% at the 50th and 75th percentiles and reduces resource usage by 3% and 7% at these percentiles. Results from simulation are consistent with those from our production deployment (§6.2). We attribute these gains to the combination of *early action* and *cause-aware* restarts.

From Figure 16(a), at the 50th percentile, Mantri sped up phases by 21.1%, an additional 3.1X over the 6.9% improvement of Hadoop, the next best scheme. To achieve this Hadoop uses 15.9% more resources (Fig.16(b)).

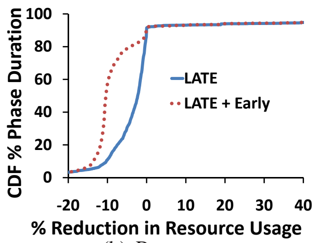
MapReduce and Dryad have no positive impact until the 80th and 50th percentile respectively. Up to the 30th percentile Dryad increases the completion time of phases. LATE is similar in its time improvement to Hadoop but does so using fewer resources.

The reason for poor performance is that they miss outliers that happen early in the phase and by not knowing the true causes of outliers, the duplicates they schedule are mostly not useful. Mantri and Dryad schedule .2 restarts per task for the average phase (.06 and .56 for LATE and Hadoop). But, Mantri's restarts have a success rate of 70% compared to the 15% for LATE. The other schemes have lower success rates.

While the insight of *early action* on stragglers is valuable, it is nonetheless non trivial. We evaluate this in Figures 17(a) and 17(b) that present a form of LATE that is identical in all ways except that it addresses stragglers early. We see that addressing stragglers early increases completion time up to the 40th percentile, uses more resources and is worse than vanilla LATE. Being resource aware is crucial to get the best out of early action (§5.1).

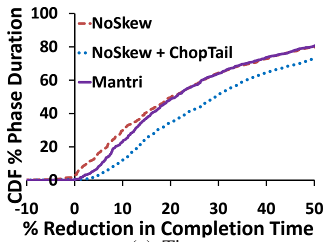


(a) Time

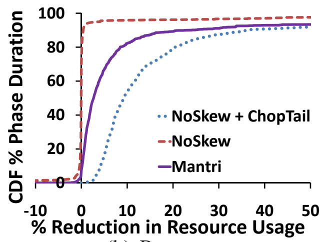


(b) Resources

Figure 17: Extending LATE to speculate early results in worse performance



(a) Time



(b) Resources

Figure 18: Mantri is on par with an ideal *NoSkew* benchmark and slightly worse than *NoSkew+ChopTail* (see end of §6.3)

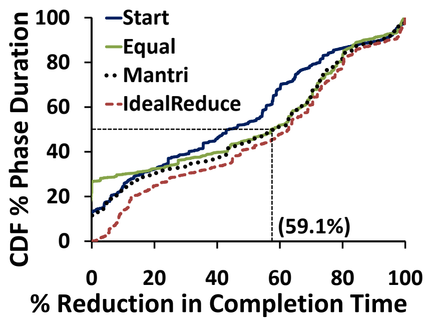


Figure 19: Compared to the current placement, Mantri's network aware placement speeds up the median reduce phase by 60%.

Finally, Fig. 18 shows that Mantri is on par with the ideal benchmark that has no variation in tasks, *NoSkew*, and is slightly worse than the variant that removes all durations in the top quartile, *NoSkew+ChopTail*. The reason is that Mantri's ability to substitute long running tasks with their faster copies makes up for its inability to act with perfect future knowledge of which tasks straggle.

6.4 Does Mantri improve placement?

Figure 19 plots the reduction in completion time due to Mantri's placement of reduce tasks as a CDF over all reduce phases in the dataset in Table 2. As before, the y-axes weighs phases by their lifetime. The figure shows that Mantri provides a median speed up of 60% or a 2.5X improvement over the current implementation, vindicating our choice of monitoring and judiciously using the available resources (network bandwidths).

The figure also compares Mantri against strategies that estimate available bandwidths differently. The *IdealReduce* strategy tracks perfectly the changes in available bandwidth of links due to the other jobs in the cluster. The *Equal*

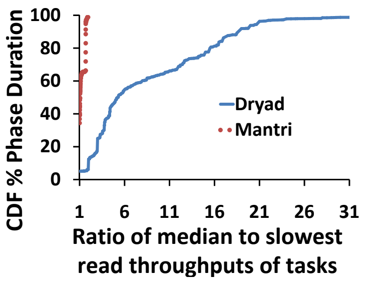


Figure 20: Ratio of median to the slowest throughput among tasks in every reduce phase, with placement policies of Mantri and Dryad.

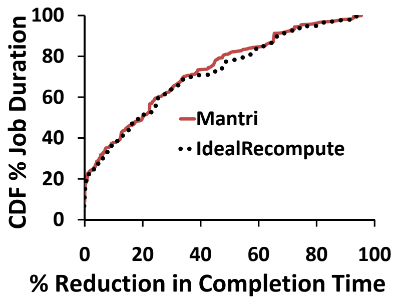


Figure 21: By probabilistically replicating task output and recomputing lost data before it is needed Mantri speeds up jobs by an amount equal to the ideal case of no data loss.

strategy assumes that the available bandwidths are equal across all links whereas *Start* assumes that the available bandwidths are the same as at the start of the phase. We see a partial order between *Start* and *Equal*. Short phases are impacted by transient differences in the available bandwidths and *Start* is a good choice for these phases. However, these differences even out over the lifetime of long phases for whom *Equal* works better. Mantri is a hybrid of *Start* and *Equal*. It achieves a good approximation of *IdealReduce* without re-sampling available bandwidths.

To capture how Mantri's placement differs from Dryad, Figure 20 plots the ratio of the throughput obtained by the median task in each reduce phase to that obtained by the slowest task. Mantri's network aware placement, based on the available bandwidths and data transfer patterns, ensures that in the median reduce phase, the slowest throughput experienced by a task is about 5% lower than the median. This ratio never exceeds 2. Dryad's policy of placing tasks at the first available slot causes outliers– the ratio of the median throughput to the slowest is 5.25 (or 14.33) at the 50^{th} (or 75^{th}) percentile. Duplicating the tasks that were delayed due to reading across congested links without considering available bandwidths would not have helped.

6.5 Does Mantri help with recomputations?

The best possible protection against loss of output would (a) eliminate all the increase in job completion time due to tasks waiting for their inputs to be recomputed and (b) do so with little additional cost. Mantri approximates both goals. Fig. 21 shows that by selectively replicating tasks that are more likely to have their inputs corrupted (by noting their cause - problematic machines) and early action to pre-compute data that has already been lost, Mantri achieves parity with *IdealRecompute*. Recall that IdealRecompute has perfect future knowledge of loss. The improvement in job completion time is 20% and 40% at the 50th and 75th percentiles.

As supporting evidence, Figure 22 shows that Mantri is successful in eliminating most of the recomputations. 78% of the median job's recomputations are eliminated. Though some jobs have only a small fraction of their recomputes eliminated (the bottom 5% of the phases), Mantri's policy to protect the output of tasks that are more expensive to recompute lets it reach parity with IdealRecompute. Figure 22 also shows the individual contributions from replication and pre-computation; they contribute roughly two-third and one-third towards the eliminated recomputations, complementing each other.

Fig. 23(a) shows that the extra network traffic due to replication is (overall negligible and) comparable to a scheme that has perfect future knowledge of which data is lost and replicates just that data. Mantri sometimes replicates more data than the ideal, and at other times misses some tasks that should be replicated. Fig. 23(b) shows that speculative recomputations take no more than a few percentage extra cluster resources.

The reason for improvements with low overhead is Mantri's accurate prediction of cause and resource cognizant decisions. The probability that task output that was replicated will be used, because the original data becomes un-

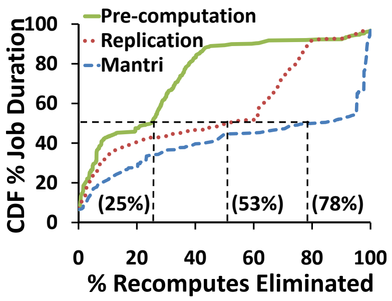
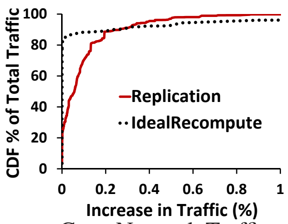
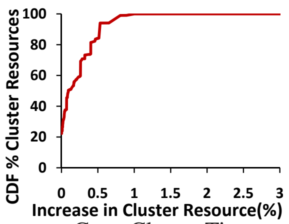


Figure 22: Fraction of recomputations that are eliminated due to Mantri's recomputation mitigation strategy, along with individual contributions from replication and pre-computation.



(a) Cost: Network Traffic



(b) Cost: Cluster Time

Figure 23: The cost to protect against recomputes is fewer than a few percentage points in both the extra traffic on the network and cluster time for speculative recomputation.

available, is 84%. Similarly, the probability that a task that was pre-computed becomes necessary, because the original data remains unavailable when it is needed for the subsequent task, is 76%. If pre-computations are triggered when two recomputations happen at a machine in quick succession, rather than one, this success rate increases to 93%. We consider the high success rate as a validation of our estimation of t_{redo} and the prediction of the onset of failure.

7 Related Work

Outliers inevitably occur in systems that compete for a share of resource pools [29], of which mapreduce is one example. OpenDHT [24] and MONET [4] reported outliers over planetlab and wide-area Internet respectively.

Much recent work focuses on large scale data parallel computing. Following on the map-reduce [10] paper, there has been work in improving workflows [1, 12], language design [7, 21, 31], fair schedulers [13, 32], and providing privacy [25]. Our work here takes the next step of understanding how such production clusters behave and can be improved.

Run-time stragglers have been identified by past work [1, 10, 15, 20]. However, this paper is the first to characterize the prevalence of stragglers in production and their various causes. By understanding the causes, addressing stragglers early and scheduling duplicates only when there is a fair chance that the speculation saves both time and resources, our approach provides a greater reduction in job completion time while using fewer resources than prior strategies that duplicate tasks towards the end of a phase. Also, we uniquely avoid network hotspots and protect against loss of task output, two further causes of outliers.

By only acting at the end of a phase, current schemes [1, 10, 12] miss early outliers. They vary in the choice of which among the tasks that remain at the end of a phase to duplicate. After a threshold number of tasks have finished, MapReduce [10] duplicates all the tasks that remain. Dryad [12] duplicates those that have been running for longer than the 75th percentile of task durations. After all tasks have started, Hadoop [1] uses slots that free up to duplicate any task that has read less data than the others, while Late [20] duplicates only those reading at a slow rate.

Further, current approaches [1, 10, 12] only duplicate tasks except for Late [20] which also stops using persistently slow machines. Logs from the production cluster (§4) show that persistent slowness occurs rarely and duplicates do not counter most of the causes of outliers, e.g., those that do a lot of work.

Though some recent proposals do away with capacity over-subscription in data centers [3, 18], today's networks remain over-subscribed albeit with smaller ratios than those in the past. It is common to place tasks near their input (same machine, rack etc.) for map and at the first free slot for reduce [1, 10, 12]. Our approach to eliminate outliers by a network-aware placement is orthogonal to recent work that picks tasks requiring different resources on to a machine [27], or trades-off fairness with efficiency [13]. In particular, Quincy accounts for capacity but not for runtime variations in bandwidth due to competition from other tasks.

Addressing loss of intermediate data is of recent focus. ISS [16] protects intermediate data by replicating locally-consumed data, i.e., the output of reduce tasks. ISS's replication strategy runs the risk of being both wasteful (very few machines are error-prone) as well as insufficient (when map tasks are long). In contrast, we analyze the magnitude and origin of the problem with real traces and present a broader solution that replicates output of any task based on the probability of data loss and speculatively precompute outputs that are already lost.

The MapReduce paradigm is similar to parallel databases in its goal of analyzing large data [23] and to dedicated HPC clusters or parallel programs [17] by presenting similar optimization opportunities. In these contexts, task scheduling and duplication have been studied for multiple processors [5, 26]. Notably, Star-MPI [2] adapts placement of parallel MPI programs by observing performance over time. Research has also focused on modeling and optimizing the communication in parallel programs [9, 19, 22] that have one-to-all or all-to-all traffic, i.e., where every receiver cares for all of the input. The many-to-many traffic typical of mapreduce is different from these patterns and leads to different optimizations.

8 Conclusion

Mantri delivers effective mitigation of outliers in map-reduce networks. It is motivated by, what we believe is, the first study of a large production map-reduce cluster. The root of Mantri's advantage lies in integrating static knowledge of job structure and dynamically available progress reports into a unified framework that identifies outliers early, applies cause-specific mitigation and does so only if the benefit is higher than the cost. In our implementation on a cluster of thousands of servers, we find Mantri to be highly effective.

Outliers are an inevitable side-effect of parallelizing work. They hurt map-reduce networks more due to the structure of jobs as graphs of dependent phases that pass data from one to the other. Their many causes reflect the interplay between the network, storage and, computation in map-reduce. Current systems shirk this complexity and assume that a duplicate would speed things up. Mantri embraces it to mitigate a broad set of outliers.

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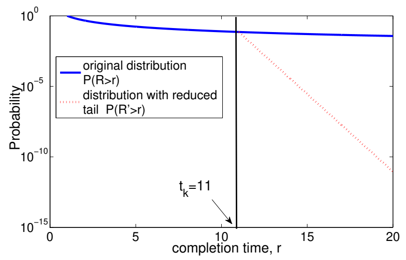

Figure 24: Comparing a heavy-tailed task completion time distribution ($\beta = 1.1$) with the eventual distribution after long tasks are killed and re-started ($t_k = 11$, $t_s = 10$), see §A.

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A Analysis: Chopping the heavy tail

Consider "kill and restart" §5.1. Suppose the task completion time distribution R is heavy tailed, such that

$$\mathbb{P}(R > r) = r^{-\beta},\ \beta > 1,\ r \geq 1.$$

Let $t_s = t_k - \Delta$. Given some technical conditions on t_k which is satisfied by setting $t_k = \mathbb{E}R + \Delta$, the task completion time after "kill and restart" R' satisfies this proposition:

Proposition 1

$$\mathbb{P}(R' > r) \leq \begin{cases} \mathbb{P}(R > r) = r^{-\beta}, \textit{ for } r < t_k \\ \mathbb{P}(R > t_s^{(\frac{r-t_s}{\Delta}-1)} t_k) = (t_s^{(\frac{r-t_s}{\Delta}-1)} t_k)^{-\beta}, \textit{ o/w.} \end{cases} \tag{5}$$

This means that the new distribution is dominated by the original distribution below the threshold to kill t_k, and has only an exponential tail above the threshold. The proof is in the Appendix. Fig. 24 compares the two distributions.

Due to the smaller variation, the job completion time decreases. Let the job completion time before and after be T, T'. Recall that n, s are the numbers of tasks and slots.

Proposition 2

$$\mathbb{E}(T - T') \geq \max\left(\mathbb{E}(\max_{1 \leq i \leq n} R_i), \frac{n}{s}\mathbb{E}R\right) - \mathbb{E}(\max_{1 \leq i \leq n} R'_i) - \frac{n}{s}\mathbb{E}R',$$

where each term is evaluated given the distribution R' specified in Proposition 1.

To understand what this means, suppose $\Delta = 1$, $t_s = \mathbb{E}R$ and $t_k = \mathbb{E}R + 1$. For different values of the number of tasks, slots and heavy-tail exponent (n, s, β), we empirically estimate the the percentage reduction in job completion time, $\frac{\mathbb{E}(T-T')}{\mathbb{E}T}$. Table 3 shows that when $\beta = 2$, which is a moderately heavy tail, chopping the tail via restarting leads to atleast a 59% speed up in job completion.

Proof for Proposition 1. For $r < t_k$, $\mathbb{P}(R < r) \leq \mathbb{P}(R' < r)$ since tasks less than r remain, and tasks greater than t_k can become less than r.

β	n	s	time reduction
1.1	200	100	99%
1.5	200	100	91%
1.5	100	50	86%
2	100	50	59%

Table 3: Reduction in job completion time.

For $r > t_k$, we need

$$\mathbb{P}(R' > r, R < r) < \mathbb{P}(R' < r, R > r)\ \forall r \geq t_k. \tag{6}$$

Observe that for $R > t_k$, if one of the $\lfloor \frac{r-t_s}{\Delta} \rfloor$ restarts succeeds, $R' \leq t_s + \Delta \cdot \frac{r-t_s}{\Delta} = r$. Hence $\mathbb{P}(R' > r | R < r) \leq t_s^{-\frac{\beta(r-t_s-\Delta)}{\Delta}}$. Similarly, $\mathbb{P}(R' < r | R > r) \geq 1 - t_s^{-\frac{\beta(r-t_s-\Delta)}{\Delta}}$.

We derive the condition for (6) to hold.

$$\begin{aligned} t_s^{-\frac{\beta(r-t_s-\Delta)}{\Delta}} \mathbb{P}(t_k < R < r) &\leq (1 - t_s^{-\frac{\beta(r-t_s-\Delta)}{\Delta}})\mathbb{P}(R > r) \\ t_s^{-\frac{\beta(r-t_s-\Delta)}{\Delta}} (t_k^{-\beta} - r^{-\beta}) &\leq (1 - t_s^{-\frac{\beta(r-t_s-\Delta)}{\Delta}}) r^{-\beta} \\ t_s^{(\frac{r-t_s}{\Delta}-1)} &\geq \frac{r}{t_k}\ \forall\ r \geq t_k \end{aligned} \tag{7}$$

Evaluating (7) and its gradient at $r = t_k$, we obtain that $t_r > 1$ and $t_k \geq \max(\Delta/\log t_r, t_r + \Delta)$ is sufficient.

Hence, for $r \geq t$,

$$\mathbb{P}(R' > r) = (t_s^{(\frac{r-t_s}{\Delta}-1)} t_k)^{-\beta} = \mathbb{P}(R > t_s^{(\frac{r-t_s}{\Delta}-1)} t_k). \quad \blacksquare$$

Proof for Proposition 2. We need the following lemmas regarding the job completion time, T. Assume there are s slots and a total of n tasks with sizes x_i, $i = 1, \cdots, n$.

Lemma 1 $T \geq \max_i x_i$.

Lemma 2 $T \geq \frac{1}{m} \sum_i x_i$.

With the policy that a task is assigned whenever a slot is idle,

Lemma 3 $T \leq \max_i x_i + \frac{1}{m} \sum_i x_i$

Proposition 2 follows from lower bounds for T and upper bound for T'. $\blacksquare$