Hold 'em or Fold 'em? Aggregation Queries under Performance Variations

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Abstract

Systems are increasingly required to provide responses to queries, even if not exact, within stringent time deadlines. These systems parallelize computations over many *processes* and *aggregate* them hierarchically to get the final response (*e.g.,* search engines and data analytics). Due to large performance variations in clusters, some processes are slower. Therefore, aggregators are faced with the question of how long to wait for outputs from processes before combining and sending them upstream. Longer waits increase the *response quality* as it would include outputs from more processes. However, it also increases the risk of the aggregator failing to provide its result by the deadline. This leads to all its results being ignored, degrading response quality. Our algorithm, Cedar, proposes a solution to this quandary of deciding wait durations at aggregators. It uses an online algorithm to learn distributions of durations at each level in the hierarchy and collectively optimizes the wait duration. Cedar's solution is theoretically sound, fully distributed, and generically applicable across systems that use aggregation trees since it is agnostic to the causes of performance variations. Evaluation using production latency distributions from Google, Microsoft and Facebook using deployment and simulation shows that Cedar improves average response quality by over 100%.

Categories and Subject Descriptors [*Networks*]: Cloud computing; [*Computer Systems Organization*]: Distributed Architectures

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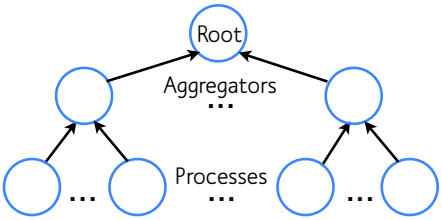


Figure 1: **Aggregation Trees. On arrival of a *query*, computations are spawned across multiple parallel *processes* whose outputs are combined using *aggregators* to produce the final *response*.**

Keywords Stragglers, Partition-aggregate, quality, deadline, order-statistics

1. Introduction

Systems using *aggregation trees* in their computation are increasingly pervasive (*e.g.,* web search engines and approximate querying frameworks [2]). These computations have many parallel *processes* with *aggregators* arranged hierarchically to combine their outputs. Figure 1 shows a simple abstract illustration. Modern systems that use aggregation trees run on large clusters and are required to provide responses to queries, *even if inexact*, within stringent time deadlines [2, 9, 18, 30].

Endemic to large clusters are broad performance variations, resulting in some processes being much slower than others. These variations can arise because of network congestion [3, 30, 34] as well as systemic contentions [6, 8, 13, 32]. For instance, production traces show that RTT values in Bing's search cluster can vary by a factor of nearly $50\times$ [3].

Due to slow processes, every aggregator faces the decision of how long to *wait* for outputs from processes before aggregating and sending the results upstream. The wait du-

ration has direct implication on the *quality* of the response. We define *response quality* as the *fraction of process outputs that are included in the response*; similar definitions of quality (or application throughput) have been used in many recent proposals [17, 30]. The longer the aggregator waits, the higher the quality of the overall response. However, longer wait durations also increase the risk of the aggregator failing to provide its results to the root by the deadline. If it misses its deadline, all its results are ignored by the root, thus lowering quality of the final response.[1]

Systems typically avoid aggregators periodically updating the root with intermediate results because, (i) it increases network traffic by a factor as much as the number of updates, and (ii) it complicates the root and aggregator executions along with their failure semantics. Production systems, to the best of our best knowledge, do not involve such periodic updates.

In this paper, we ask the question: *How long should every aggregator wait to maximize overall response quality within the deadline?*

The main observation behind our solution is that durations of queries follow a certain distribution type, and that it is possible to quite accurately compute the parameters of this distribution by observing a few process outputs. In particular, we use the durations of the processes that finish first to predict the durations' distribution, and use this distribution to optimize response quality by appropriately setting the wait-time for the aggregator.

However any approach to learn the distribution parameters must overcome the following challenges. First, learning must be done in an online fashion on a per-query basis given that different queries can vary substantially owing to the different amount of work they might need to perform. Second, given that we need to learn the distribution parameters online, the approach must be based on only the earliest completed processes. Naturally, this introduces a bias as the learning will not see the tail of the distribution, *i.e.,* the outputs of the processes that take longest to complete. Third, since we also target systems with short deadlines ($\sim 100 - 200$ms), the learning must be distributed, *i.e.,* not require aggregators to combine their samples, to avoid communication overheads.

To address the above challenges, we propose Cedar, an online algorithm to pick the wait duration for each aggregator. Cedar learns the distribution of process durations *during a query's execution* using statistically grounded techniques. It avoids the measurement bias because of observing only the earliest available process outputs by using the properties of *order statistics* [12]. Once it learns the distribution of process durations, Cedar picks a wait duration based on the query's end-to-end deadline, as well as the time taken by aggregators themselves to combine and send the results to the root.

Since Cedar learns the distribution parameters with high accuracy even using a small number of samples, each aggregator can estimate the parameters standalone without pooling their samples. Thus, Cedar can be implemented in a *fully distributed* manner.

Cedar's solution has the following key advantages.

- It considers the problem of deadline-aware scheduling *end-to-end*, *i.e.,* aiming to improve application performance instead of just individual processes.
- It makes no assumptions about the source of performance variations among processes nor does it attempt to mitigate such variations. This generality differentiates our solution from many prior efforts that assume specific causes like network congestion [6, 17, 30]. Such generality is critical for any solution to work well in practice because there is no single cause for performance variations and accurate modeling of these complex systems has proven challenging so far [8, 13, 21, 22]. In this way, Cedar's performance benefits are agnostic to the cause of these variations, whether they occur because of CPU, memory, network or disk contention.
- Unlike many prior solutions that require changes at the network layer [17, 30, 34], Cedar can be implemented entirely at the endhosts. This leads to a simpler and easily deployable solution. Furthermore, Cedar is robust across different workloads.

To the best of our knowledge, prior work on dealing with performance variations has not explored optimizing the wait duration at aggregators. Optimizing along this simple design dimension leads to remarkably good results in our experiments. We evaluate Cedar using a prototype implementation over the Spark framework [33] deployed on 80 machines on EC2, as well as through extensive simulations. Cedar improves the quality of results by up to 100% in simulations and deployment replaying production traces from Facebook and Cosmos's analytics clusters as well as Google and Bing's search clusters. The near-optimal performance is due to accurate learning of distribution parameters using order statistics leading to as little as 5% estimation error as well as a theoretically sound algorithm to select the correct wait duration given the distributions.

2. Aggregation Queries

Aggregation queries are widely prevalent in modern systems. We describe two such systems—web services and data analytics frameworks—that strive to provide results of the best quality (but not necessarily exact) within a deadline. We then quantify performance variations in production clusters that run these systems.

[1] Response times are critical for user engagement in interactive services. Therefore, the logical alternative of fixing a desired response quality and optimizing for response time is not a preferred option.

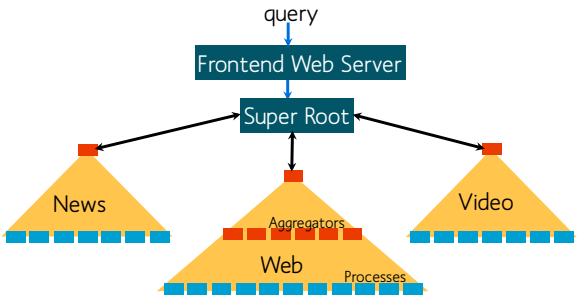


Figure 2: **A typical web search computation that aggregates results across many functional silos [13]. The small rectangles at the leaves denote processes of the computation.**

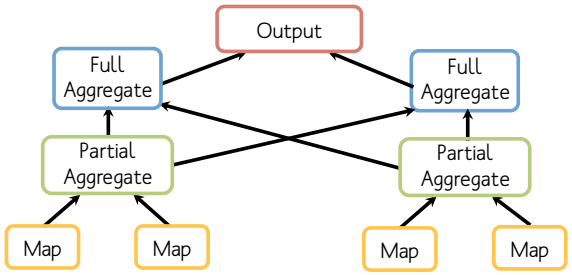


Figure 3: **A query to an interactive data analytics system compiled into a DAG of hierarchical parallel processes.**

2.1 Production Systems

Search Queries: Web search engines store indexes of crawled web content on large distributed clusters. The indexes are often divided into functional silos. To respond to a search query, lookups are performed on different machines within every relevant silo, effectively resulting in a computation of many parallel *processes* whose outputs are aggregated hierarchically (as shown in Figure 2). Every aggregator ranks results from nodes downstream and sends the top few of them upstream. The eventual response is based on results that arrive at the root by the deadline. The higher the number of processes whose outputs are included in the response, the better its quality and relevance [30], which in turn has significant competitive and financial implications [23]. Similar hierarchical computations are also invoked in the creation of a user's "wall" page in Facebook [34].

Typically, process durations are primarily influenced by contentions for multiple local resources as they read and compute on indexes from the underlying storage. Aggregator durations, on the other hand, are influenced more by networking and scheduling aspects.

Approximate Analytics: Interactive data analytics frameworks (*e.g.,* Dremel [25], BlinkDB [2]) are projected to be crucial in exploiting the ever growing data. These frameworks allow users to specify deadlines in the query syntax, and they strive to provide the best quality response within that deadline [9, 30]. Queries are compiled to a DAG of phases (or hierarchies) where each phase consists of multiple parallel processes. Figure 3 shows a DAG of a sample query. While the communication pattern between hierarchies can be either many-to-one or all-to-all, every aggregator aggregates results from nodes downstream and sends them upstream. The quality of responses is, again, dictated by the number of processes whose outputs are included in the response.

2.2 Performance Variations

The nature of large clusters is that processes exhibit significant and unpredictable variations in their completion. These variations arise because of network congestion or contention for resources on individual machines. We present variations (in increasing order of magnitude) from three production deployments—RTT variations in Microsoft Bing's search cluster [3], process durations in Google's search cluster [13], and task completion times in Facebook's and Microsoft Cosmos's production analytics cluster [7]. These clusters already have a variety of mitigation strategies to prevent processes from straggling [3, 6, 8, 32, 34].

The objective of describing these variations is two fold. First, is to show the prevalence and magnitude of performance variations, and also that they occur because of multiple reasons. Second, is to present building blocks for constructing a workload for aggregation queries in the absence of access to an end-to-end trace from systems as described in §2.1.

Figure 4 plots the distribution of RTT values in Bing's search cluster. The RTT values show a long-tailed distribution (median, 90^{th} percentile and 99^{th} percentile values of 330μs, 1.1ms and 14ms) caused due to sporadic network congestion. Variations among processes in Google's search cluster are primarily borne out of scheduling delays and network congestion on highly utilized machines/links [13]. While the distribution is relatively narrow, the magnitude of the variation is significantly higher. The median value is 19ms while the 99^{th} percentile is over 65ms.

The task durations in Facebook's and Cosmos's analytics clusters vary considerably more (factor of $1600\times$) and are caused by a combination of systemic contention for local resources (memory, CPU and disk IO). Note that these clusters already have speculation strategies [6, 32] for stragglers. When the earlier of the original or speculative copies finish, the unfinished task is killed; we exclude durations of such killed tasks. Further, task durations have recently fallen by a factor of two to three orders of magnitude with the advent of in-memory cluster frameworks (*e.g.,* Spark [33], Dremel [25]). At small task durations, effectiveness of existing straggler mitigation strategies are diminished owing to

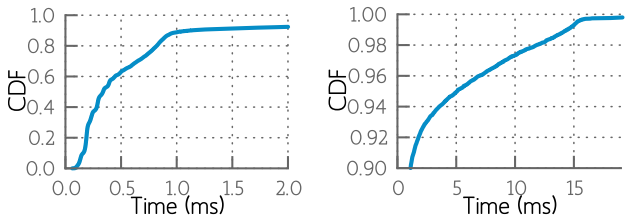


Figure 4: **Distribution of RTTs in Bing's search cluster. The median value is 330μs while the 90^{th} and 99^{th} percentile values are 1.1ms and 14ms, respectively.**

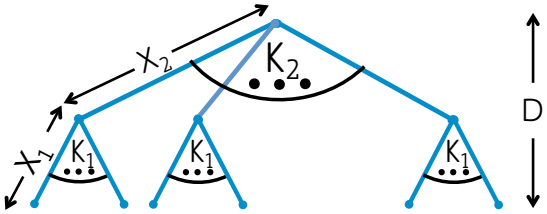


Figure 5: **A simple two level hierarchy. Let X_1 and X_2 be distribution of times taken in the first and the second levels of the hierarchy, respectively.**

their reactive nature of observing a straggler before scheduling speculative copies [8].

The upshot from these production traces is that performance variations are large and occur for many reasons. Ideally, algorithms to decide wait durations at aggregators should take a holistic end-to-end view of the variations and automatically adapt to any changes in the distributions, without being tied to the underlying specifics. Before proceeding to our solution, Cedar, in §4, we quantify the criticality of picking the right wait-duration in §3 using an idealized scheme.

3. The Case for Optimizing Wait Duration

We illustrate the value of picking the optimal wait duration at aggregators by comparing the difference in response quality between an ideal scheme and intuitive straw-man solutions. We focus on the traces from Facebook's Analytics (MapReduce) cluster in this section, though our evaluations (§5) are based on a number of production and synthetic workloads.

We assume a two level (or stage) hierarchy as shown in Figure 5, where X_1 and X_2 denote the distribution of times taken by nodes in the first and the second levels of the hierarchy, respectively, with k_1 and k_2 being the "fan out" at these levels.[2] There is an end-to-end deadline, D, imposed on the query which is common knowledge to workers and aggregators alike. However, while the aggregators know the top-level deadline, they can't exactly determine how long it will take to ship the aggregated result upstream. As mentioned in §1, one of the strengths of our model is that since X_1 and X_2 represent the duration of the entire stage *subsuming all types of variations*, the performance improvement doesn't depend on their exact cause, be it network, CPU, memory or disk.

Our model makes two assumptions. First is that the durations at the aggregators do *not* depend on the number of downstream processes that respond, which generally holds because the number of downstream straggler processes is small. Second is that the performance variations are purely caused by resource contentions and not inherent hardware heterogeneity.

[2] Two or three levels are common in the systems we focus on. However, we will show later that our model works with any number of levels.

3.1 Setting Wait Durations

Recall that wait duration at aggregators directly impacts *overall response quality*; we measure quality by the fraction of processes whose outputs are included in the final result. (Note that our model is easily extensible to weighted process outputs; Appendix A of [24]). If the wait duration is too short, outputs that would have arrived before the deadline are missed thereby degrading overall response quality. If the wait duration is too large, the aggregator misses its deadline which leads to outputs of all its processes (including the completed ones) being ignored upstream, again degrading overall response quality. Therefore, our problem is to *calculate the right wait duration at aggregators that maximizes overall response quality given a deadline D.*

Proportional-split: A natural straw-man solution to pick the wait duration is to continuously learn statistics about the underlying distributions X_1 and X_2 from completed queries, and split the deadline proportionally between the different levels based on the learned parameters. In fact, such a technique of estimating parameters from recent query behavior is in deployment in Google's clusters [18]. For a two-level tree (Figure 5), the wait duration is set as $D \times \left(\frac{\mu(X_1)}{\mu(X_1)+\mu(X_2)}\right)$, where $\mu(X_1)$ is the mean of the stage duration distribution X_1. We refer to such a scheme as "Proportional-split". [3]

Ideal Solution: We compare the Proportional-split baseline with an idealized scheme that has *a priori* information about the distribution of process as well as aggregator durations of every query. It uses that information to pick the wait duration that maximizes overall response quality. We measure the *percentage improvement in response quality of the idealized scheme over the straw-man solutions*. The ideal scheme serves as a ceiling to estimate the maximum achievable improvement; the higher the improvement, the more the potential for Cedar.

[3] Other statistics like median and (mean + stdev) exhibit similar results. Futher, we also considered other baselines like equally dividing the deadline between the stages or subtracting the mean of X_2 from the deadline, but they fare much worse.

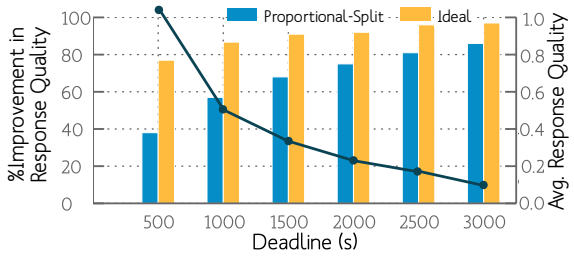


Figure 6: **Ideal solution's improvement in response quality over straw-man solutions for varying deadlines. Distribution X_1 is from the map tasks and X_2 is from the reduce tasks in the Facebook cluster. The fanout is kept constant at 50 (both k_1 and k_2) giving a total of 2500 processes.**

3.2 Potential Gains

Recall from §2.2 that the clusters from which we obtain our traces already have a variety of straggler mitigation strategies deployed. Despite that, we see substantial scope for improvement in quality of the overall response between the Proportional-split and the Ideal scheme. In Figure 6, the deadline for the query is varied from $500s$ to a really high value of $3000s$ while the fanout factors k_1 and k_2 are kept constant at 50 (based on [3]). Picking the right wait duration can improve average response quality by over 100% compared to Proportional-split, *i.e.,* the response includes outputs of 100% more processes. Also, while it is *ideally* possible to achieve high response quality (say 90%) at deadline values of $> 1000s$, the baseline fails to achieve such response quality even at an extremely large deadline of $3000s$.

The main drawback with Proportional-split is that it uses a single distribution (from the recent set of queries) thus missing query-specific variations which hold rich information regarding spatial and temporal performance characteristics. The potential for such high gains, despite the presence of straggler mitigation strategies, shows the criticality of setting the right wait duration by learning the distributions of durations online per-query.

Summary: Our analysis shows that setting the right wait duration for aggregators (i) can substantially improve response quality (by over 100%), and (ii) is non-trivial and simple straw-man solutions fall significantly short.

4. Cedar: Algorithm Description

The aggregator estimates the optimal wait time by learning the distribution parameters of process durations during a query's execution. The two main steps in doing so are, (i) learning the distribution based on the completion times of only the early processes in the query, and (ii) collectively optimizing for the wait duration taking into account the time taken by aggregators themselves to combine and send the results to the root. We describe these steps after presenting an overview.

```
⟨ProcessOutput⟩ outputSet ← φ        ▷ Response Initialization
numOutputs ← 0

procedure ParallelHierarchicalComp(D)
    SetTimer(D, TimerExpire)
    ListenResponse(ProcessHandler)

procedure ProcessHandler(ProcessOutput t_o)
                                  ▷ On arrival of a process's output
    outputSet +← t_o                    ▷ t_o added to outputSet
    numOutputs +← 1
    if numOutputs == k_1 then
        SetTimer(0, TimerExpire); return

    Distribution X_1 ← FitDistribution(outputSet)
    double wait ← CalculateWait(D, k_1, X_1)
     ▷ Also uses Distributions X_i's and k_i's for higher levels
    (global)

    double remWait ← wait − elapsedTime
                                  ▷ Subtract time elapsed so far.
    SetTimer(remWait, TimerExpire)
    ListenResponse(ProcessHandler)

procedure TimerExpire
    return outputSet
```

Pseudocode 1: Cedar**'s algorithm for executing aggregation queries with deadline of D. The algorithm describes the functioning of an aggregator at the lowest layer with k_1 processes whose durations are modeled as X_1, aggregators up the hierarchy work similarly.** FitDistribution **is described in §4.2 to estimate X_1 and** CalculateWait **is described in §4.3.**

4.1 Overview

Pseudocode 1 outlines Cedar's end-to-end functioning. The aggregator begins by setting a timer for the deadline, D (ParallelHierarchicalComp). On arrival of every process's output (ProcessHandler), Cedar improves its estimation of the distribution (FitDistribution) and updates its wait duration (CalculateWait). The aggregator returns with the available outputs when no process finishes in its current wait duration (TimerExpire).

Typically, higher levels in the hierarchy, *i.e.,* aggregators, have little variation in the distribution of their durations *across* queries (X_2 for the two-stage tree demonstrated in Figure 5). This is because aggregation operations are mostly similar across different queries (for example, sum and mean, which have similar complexities). These trends are observed in our analysis of traces from Google and Bing. These two traces are primarily from higher level aggregator operations and exhibit little variation across queries. Thus, Cedar learns the above stage distributions offline based on completed queries.

FitDistribution concerns itself with learning the distributions of process durations, X_1. As evidenced in the

Facebook distributions, process durations exhibit significant variation across queries. Processes execute custom code that involve a wide variety of compute and IO operations (across disk, network) leaving them susceptible to many resource contentions. As an illustration, the computation involved for a search query like "Britney Spears" may take considerably lesser time compared to a more sophisticated query like "Britney Spears Grammy Toxic" because the latter involves a combination of index lookups. Therefore, it becomes imperative to determine the distribution of process durations *per query*.

CALCULATEWAIT, then, uses both X_1 and higher level distributions, $X_2, \ldots, X_n$, to calculate the optimal wait duration for every aggregator.

We explain the learning of distribution of process durations (FITDISTRIBUTION) in §4.2. §4.3 explains the calculation of the optimal wait duration for aggregators (CALCULATEWAIT). Table 1 lists the relevant notations.

4.2 Learning the Distribution

Cedar estimates the parameters of the distribution of process durations *online* during the query's execution. The estimation involves two aspects—distribution *type* (*e.g.,* log-normal, exponential), and relevant distribution *parameters* (*e.g.,* mean and standard deviation).

4.2.1 Distribution Type

Inspection of process durations from our traces show that the distribution *type* across different queries remains unchanged, even though the parameters of the distribution vary. Therefore, estimating the distribution type is an offline process that is repeated periodically across many completed queries. We periodically fit percentile values using rriskDistributions [1] package to find the best fit of distribution type.

In our traces, log-normal distribution gave the best fit for each of the traces. The fit for the Facebook traces resulted in less than 1% error in mean and median; even at high percentiles the error was low. Google's percentile values for process durations fit with $< 5\%$ error even at the 99^{th} percentile. Log-normal distribution gave the best fit for the Bing traces as well with 1% error in median and 2% error in mean. More details about the goodness of our fit can be found in Appendix B of [24].

One concern is that log-normal fit does seem to falter near the extreme tail (say upwards of 99.5 percentile); the tail being generally better modeled by distributions like Pareto [14]. Such high percentiles, however, would consist of processes whose outputs will *not* be aggregated irrespective of any optimization of wait-duration given the heavy-tail behavior of such systems. Thus Cedar's performance doesn't suffer due to this and remains near-optimal (§5).

Regardless of the distribution type, its parameters exhibit considerable variation on a query to query basis. We estimate them online, during the query's execution.

Table 1: **Table of Notation**

D	$\triangleq$	Deadline at the top-level aggregator
n	$\triangleq$	Number of stages in the aggregation tree
X_i	$\triangleq$	Stage duration distribution for the i^{th} stage (1 being bottom-most)
k_i	$\triangleq$	Fan-out at the i^{th} stage
X, k	$\triangleq$	Stage duration distribution and fan-out when a single stage is considered
$X_{(i)}$	$\triangleq$	i^{th}-order statistic of X
q_n	$\triangleq$	Maximum achievable quality for an n-level tree (under given D, $X_i's$ and $k_i's$).

4.2.2 Estimating Parameters of Distribution

We consider a single level in which an aggregator observes process duration distribution given by X with a fan-out of k (omitting the subscript that denotes the level since we are concerned with a single stage in this section). The objective is to estimate the parameters of the distribution X based on the durations of only the completed processes thus far. Denote the number of processes that have completed at this point to be r, where $r < k$. A naive attempt at estimating the parameters of the distribution would be to simply calculate the mean and standard deviation using the r samples. Such an empirical calculation would, however, be sub-optimal because the r samples are *biased*, *i.e.,* these are not uniformly sampled r values from the distribution but rather the smallest r values out of k samples from the distribution. The key challenge in learning the parameters of the distribution is, therefore, eradicating this bias. As we show in §5, this bias can affect the accuracy of learnt parameters considerably.

We alleviate the sampling bias using *order statistics* [12]. Given a distribution, X in our case, and k random samples drawn from the distribution, the r^{th} order statistic denotes the distribution of the random variable corresponding to the r^{th}-minimum of the k samples. The key insight that Cedar uses is that the time taken for the r^{th} process output received is not a random sample obtained from the distribution X, but instead, is a random sample obtained from the r^{th} order-statistic of the k samples drawn from X.[4] In this way, Cedar models *each* process duration as per a different distribution which are given by the *order statistics* for the given distribution.

Formally, denote the random variables corresponding to the first r order statistics (or process durations in our case) by $X_{(1)}, X_{(2)}, \ldots X_{(r)}$ (the subscript denotes the order they arrive in),[5] and let $x_{(1)}, x_{(2)}, \ldots, x_{(r)}$ be the observed values of process durations for the received outputs. The maximum likelihood estimate, θ, of the distribution parameters (*e.g.,* λ for exponential distributions, or μ, σ for normal/log-normal

[4] Order statistics are dependent on the sample size (or k in our case).

[5] $X_{(i)}$ is not to be confused with X_i that signifies the stage duration distribution for the i^{th} stage.

distributions), is written as: $\theta_{MLE} = \arg\max_\theta P(X_{(1)} = x_{(1)}, X_{(2)} = x_{(2)}, \ldots, X_{(r)} = x_{(r)}; \theta)$.

Unfortunately, it is computationally expensive to maximize the above likelihood expression in an online setting. Instead, we compute the maximum likelihood estimates of the parameters θ independently from each random variable $X_{(i)}$ and average the estimates together. While some internals of the estimation algorithm vary depending on the distribution type, the general idea remains the same. We present the details for log-normal and normal distributions. The maximum likelihood estimates for the order-statistics for the standard log-normal distribution are known, denoted by $o_1, o_2, \ldots, o_k$ henceforth. These are values that are available online or can be computed quite accurately using a simple simulation.

Since there are two parameters to estimate, μ, and σ, at least two outputs are required. Let t_1 and t_2 denote the arrival times for the first two responses. Then, we have $ln\ t_1 = \hat{\mu} + \hat{\sigma} ln\ o_1$, and $ln\ t_2 = \hat{\mu} + \hat{\sigma} ln\ o_2$. This gives us the first estimate of μ and σ. The i^{th} estimate comes from t_i and t_{i+1} and the final estimates are obtained by averaging individual estimates, a practical approach that is computationally efficient in practice. The method for normal distribution is similar; the equations do not have a logarithm on either side.

4.3 Optimal Wait Duration

Once the underlying distribution is estimated, the next step is selection of the optimal value of the wait duration to maximize the quality (CALCULATEWAIT in Pseudocode 1, and Pseudocode 2). As before, we focus our attention only on the quality contributed by a single aggregator, since the contribution of different aggregators to the overall quality is independent of each other.

At a high level, the intuition is to model the expected gain and loss in qualities due to a small additional wait. We next formalize the gain and loss in quality. For ease of understanding, we present the analysis for a two-level tree (§4.3.1), before generalizing it to a n-level tree (§4.3.2).

4.3.1 Two-level tree

Consider an aggregator that has waited for t units of time and has not received all the outputs. A small additional wait of Δt can result in additional responses being collected by the aggregator.

Improvement in Quality: The probability that a process's output is received by the aggregator in time $(t, t+\Delta t]$ is given by $a = \big(\phi_{X_1}(t+\Delta t) - \phi_{X_1}(t)\big)$, where ϕ_{X_1} is the CDF of X_1. The number of additional outputs from processes received in the Δt interval, then, is a binomial random variable with success probability a. The expected number of additional outputs received (given that the random variable is binomial) is then $k_1 a$, where k_1 is the maximum number of outputs (fanout) that an aggregator can collect. These additional processes add to the quality of the final response only if they reach the top-level aggregator in time whose probability is $b = \phi_{X_2}(D - (t + \Delta t))$. The expected gain due to these additional outputs is given by multiplying a with b:

$$k_1(\phi_{X_1}(t+\Delta t) - \phi_{X_1}(t)) \cdot \phi_{X_2}(D - (t+\Delta t)) \quad (1)$$

Since quality is the fraction of process outputs, the expected gain in quality is obtained by dividing the above expression by k_1.

Reduction in quality: The additional wait of Δt, however, might lead to all the outputs of the aggregator (including the additional garnered ones) not being included in the final result. This happens if the aggregator itself misses its deadline and is ignored altogether. The expected number of outputs received till time t is $k_1 \frac{\left(\phi_{X_1}(t) - [\phi_{X_1}(t)]^{k_1}\right)}{1-[\phi_{X_1}(t)]^{k_1}}$ (Appendix C of [24]). The probability that the deadline is missed due to the additional waiting is $\phi_{X_2}(D-t) - \phi_{X_2}(D-(t+\Delta t))$. However, the above loss only occurs if all the outputs have not been collected by the aggregator, which happens with probability $\left(1-[\phi_{X_1}(t)]^{k_1}\right)$. Thus, the expected loss in process outputs is obtained by multiplying the above three expressions:

$$k_1(\phi_{X_1}(t) - [\phi_{X_1}(t)]^{k_1}) \cdot (\phi_{X_2}(D-t) - \phi_{X_2}(D-(t+\Delta t))) \quad (2)$$

Dividing the above expression by k_1 gives us the expected loss in quality.

4.3.2 Extension to n-level tree

Denote the number of levels in the aggregation tree to be n, the fanout of each level denoted by $k_1, k_2, \ldots, k_n$, and stage duration distributions by $X_1, X_2, \ldots, X_n$; X_1 being the lowermost stage. Denote $q_n(D, X_1, k_1, X_2, k_2, \ldots, X_n, k_n)$ (abbreviated as $q_n(D)$ whenever $X_1, k_1, \ldots, X_n, k_n$ can be treated implicit) to be the maximum quality (in expectation) of this aggregation tree. The previous section formulated the gain and loss in q_2.

To extend our formulation to more than two levels, we devise a recursive formulation by expressing the gain and loss in q_n in terms of q_{n-1}. The key observation that we make is that the *maximum quality achieved under a certain deadline, $q_n(D)$, is exactly the same as the maximum probability that a particular process' output reaches the root*. This happens only when each aggregator in the hierarchy selects the optimal wait-duration. For a single level tree, $q_1(D)$ is simply the probability of a process output reaching the (only) aggregator by the deadline D. Thus, $q_1(D, X_1, k_1) = \mathbb{P}[X_1 \leq D] = \phi_{X_1}(D)$.

Therefore, the changes to the expressions for gain and loss of quality are as follows.

Improvement in quality

The probability of additional outputs collected in Δt reachign the root is $q_{n-1}(D-(t+\Delta t), X_2, k_2, \ldots, X_n, k_n)$, *i.e.,* the maximum achievable quality for the $n-1$ level tree beginning at X_2 (abbreviated as $q_{n-1}(D-(t+\Delta t))$ below). For a two level tree, this is $q_1(D-(t+\Delta t), X_2, k_2) =$

```
procedure CALCULATEWAIT(D, k_1, Distribution X_1)
    ▷ Also uses Distributions X_i's and k_i's for higher levels (global)

    double wait ← 0                                   ▷ Wait Duration
    double q ← 0; bestQ ← 0                           ▷ Quality
    for double c = 0; c ≤ D; c += ε do
                                  ▷ Incremental search in steps of ε
        double G = QUALITYGAIN(c, X_1, k_1)           ▷ Eqn. 3
        double L = QUALITYLOSS(c, X_1, k_1)           ▷ Eqn. 4
        q+ ← G − L
        if q ≥ bestQ then
            bestQ ← q
            wait ← c
    return wait
```

Pseudocode 2: **Calculation of the optimal wait duration by balancing gain and loss. The optimal wait duration depends on the distributions $X_1, X_2, \ldots, X_n$, deadline D and the fanouts $k_1, k_2, \ldots, k_n$.**

$\phi_{X_2}\Big(D-(t+\Delta t)\Big)$. Thus, the expression for gain in quality for a two-level tree, or q_2, is $\Big(\phi_{X_1}(t+\Delta t)-\phi_{X_1}(t)\Big)\cdot q_1\Big(D-(t+\Delta t), X_2, k_2\Big) \triangleq$ Equation 1. Thus, the expected gain in quality for an n-level tree is:

$$\Big(\phi_{X_1}(t+\Delta t)-\phi_{X_1}(t)\Big)\cdot q_{n-1}\Big(D-(t+\Delta t)\Big) \quad (3)$$

Reduction in quality

To get the expression for n levels, we need to replace $\phi_{X_2}(.)$ by $q_{n-1}(.)$ in Equation 2 which gives:

$$\Big(\phi_{X_1}(t)-[\phi_{X_1}(t)]^{k_1}\Big)\cdot\Big(q_{n-1}\big(D-t\big)-q_{n-1}\big(D-(t+\Delta t)\big)\Big) \quad (4)$$

The loss in q_2 is $\Big(\phi_{X_1}(t)-[\phi_{X_1}(t)]^{k_1}\Big)\cdot\Big(q_1(D-t, X_2, k_2)-q_1(D-(t+\Delta t), X_2, k_2)\Big) \triangleq$ Equation 2.

This recursive nature enables us to simply extend our algorithm to any number of levels.

4.3.3 Picking Wait Duration

Pseudocode 2 describes the algorithm for picking the optimal wait duration. Note that since the closed form solution is not known, we compute the wait duration by searching the space in small increments of ϵ. The net change in quality is the difference between the expressions in Equation 3 and Equation 4. We pick the value of wait duration which maximizes the quality. By keeping the value of ϵ to be small, we can reduce the discretization error. Note that while Pseudocode 2 provides a serial exploration of the space for wait duration, the exploration is easily parallelizable, *i.e.,* we can perform the calculation for each value of ϵ independently. Further, one can simply precompute these wait-durations for recorded distributions.

5. Evaluation

We evaluate Cedar using an implementation over the Spark framework [33] and a simulator. We first explain the methodology of our evaluation before proceeding to present the results.

5.1 Methodology

Implementation: We implement Cedar's algorithm over Spark [33]. Spark caches data in-memory allowing for fast interactive querying. For this, we first implement an aggregator that can do partial aggregation, *i.e.,* send results upstream after some timeout even when a subset of the lower level tasks have completed. Along with minor changes in the scheduler, we are able to run an entire partition aggregate workflow. Finally, we implement the baseline and Cedar's algorithm in the aggregators to select appropriate wait-duration. The total code is $\sim$ 300 LOC in Scala; but Cedar's algorithm took $<$ 50 LOC. We deploy Cedar on an EC2 cluster of 80 quad-core machines (320 slots to run processes).

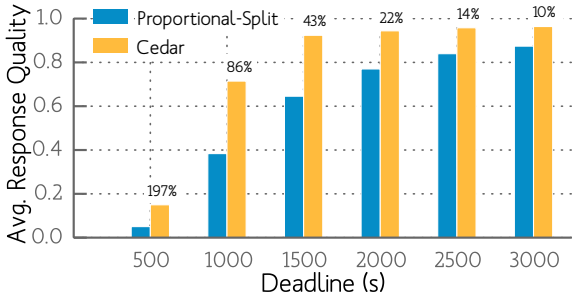
Simulator: Our simulator mimics aggregation queries and can take as its input different fanout factors, deadlines, as well as distributions (both real-world distributions as well as synthetic). We use the simulator to evaluate Cedar's sensitivity to fanout values (§5.4), and when there are multiple levels in the aggregation tree(§5.5).

Workloads: We simulate Cedar using production traces from Facebook's Hadoop cluster [7], RTT values in Bing's search values [3], task duration statistics from Microsoft Cosmos's production analytics cluster [7], and statistics from Google's search cluster [13]. We also evaluate the effect of variances in the distributions by synthetically injecting them to the original traces. For the latter, we change the parameters of a log-normal approximation learned from the traces.

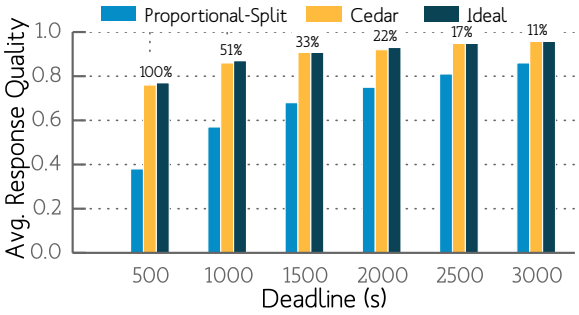
Primary Workload: We use the production traces from the Facebook cluster as our primary workload where we have exact durations of map and reduce tasks per job and naturally contains performance variations seen in practice. For a particular job, process durations are given by the map tasks and aggregator durations are given by the reduce tasks. In this way, we are able to replay individual jobs. Since, we have perfect information of task durations, we are also able to dissect Cedar's performance in detail (§5.3).

Data analytics frameworks are increasingly being used for interactive purposes, so we believe our workload is well-suited to test Cedar's functioning. Regardless, we also evaluate Cedar's robustness to different distributions based on both other production and synthetic traces and show that gains continue to be substantial (§5.6 and §5.7).

Topology: We use a two level hierarchy for all our experiments (except when experimenting with multiple levels). Unless otherwise specified, the fanout at the lower level is fixed at 50 (based on values in Bing's cluster [3]) and the upper layer fanout is also set to be 50. For Spark results, we



(a) Spark Implementation



(b) Simulation

Figure 7: **Improvement in Response Quality. X_1 is per Facebook's Map distribution and X_2 is per Facebook's Reduce distribution for different queries. The fanout at both levels is fixed at 50.**

set the lower layer fanout to be 20 and upper layer fanout to be 16 giving us a total of 320 processes. We also analyze the sensitivity of Cedar's gains to the fanout.

Metric: Our figure of merit is the increase in average response quality compared to the baseline of "Proportional-split" defined in §3. Proportional-split estimates the distribution in every level in the hierarchy from previous queries by fitting the best parameters. Therefore, if the quality of response achieved with our baseline and Cedar is $Quality_B$ and $Quality_C$ respectively, the improvement is defined as $100 \times \frac{Quality_C - Quality_B}{Quality_B}$.

We also report other percentile values, when appropriate, to show the spread in improvements. Further, we also compare Cedar's performance to the "ideal" scheme described in §3. The ideal scheme is aware of distribution of process durations of all queries, and represents the maximum achievable improvement.

We start with the highlights of our results.

- Response quality improves by over 100% with Cedar compared to straw-man solutions. The absolute value of the quality goes to over 0.9. (§5.2)
- Online estimation of distribution parameters using order statistics results in less than 5% error even with very few samples. (§5.3)
- Cedar's gains hold up for different fanouts and different distributions. (§5.4 and §5.7)

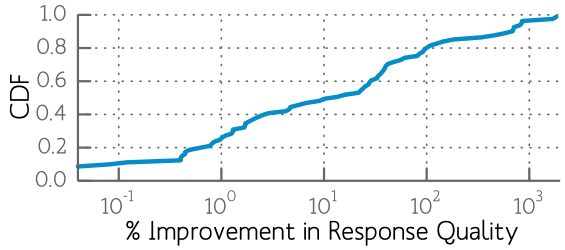


Figure 8: **CDF of Percentage improvement of individual queries. The deadline is set to 1000s. We only look at queries having $> 5\%$ quality in the baseline approach to prevent improvements from being unreasonably high.**

- Cedar's importance only increases with number of stages in aggregation trees. (§5.5)
- Cedar's algorithm is robust across different distributions. (§5.6 and §5.7)

5.2 Improvement in Response Quality

Figure 7 plots the average response quality achieved by Proportional-split as well as Cedar, along with the relative improvements for the Facebook workload.[6] Our results show three key points. First, Cedar significantly improves the quality of the response over Proportional-split (the improvements lie between $10 - 197\%$ in deployment and $11 - 100\%$ in simulation). These results reinforce the extent to which variations in the distribution can affect response quality and the importance of picking the right wait duration. Second, while Cedar consistently pushes the quality to over 0.9 at deadlines $> 1000s$, the baseline *cannot* achieve a similar quality even at a humongous deadline of $3000s$. Third, Cedar's performance closely matches that of the ideal system that is aware of process distribution of the query beforehand (Figure 7b).

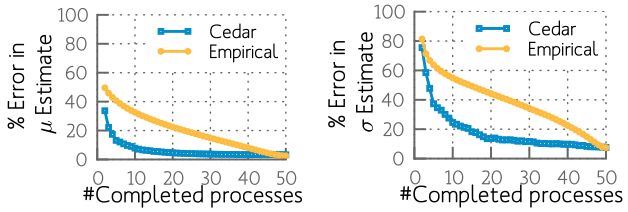
Figure 8 plots the distribution in improvements at the deadline of $1000s$. 40% of the queries see their quality improve by over 50%. However, the bottom one-fifth of queries see little gains. This is primarily due to the long tail in the distribution of process durations in these queries, leaving little scope for improvement in quality regardless of the wait duration. Improvement in quality of these queries will occur only by specific techniques that reduce systemic and network contentions. Efforts to that end are focus of many current research projects, and Cedar's algorithms will beneficially coexist with them.

Cedar's algorithm also completes within tens of milliseconds even without the parallelization proposed in §4.3.3.

5.3 Dissecting Cedar's Learning

We next turn to dissecting Cedar's performance to better understand the reasons behind the improvements. There are two factors in Cedar's learning mechanism contributing to

[6] We prune the trace to only consider jobs with > 2500 map tasks (for 2500 processes) and > 50 reduce tasks (for 50 aggregators).



(a) Estimate of μ (b) Estimate of σ

Figure 9: **Variation in % error in estimation of the μ and σ parameters of Facebook's distribution (log-normal with μ = 2.77 and σ = 0.84) with the number of responses that have arrived at the aggregator (maximum of 50). The baseline is the empirical estimates for μ and σ from the responses.**

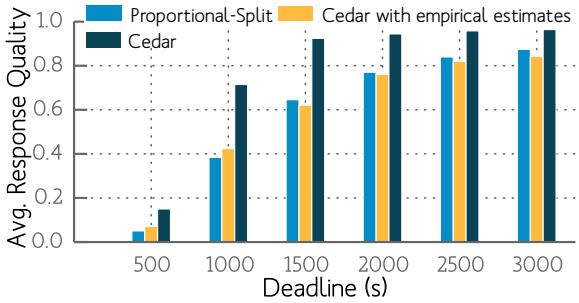


Figure 10: **Spark implementation results showing that Cedar's learning algorithm provides significant benefits over using empirical estimates for the parameters.**

its gains—eliminating bias in received samples using order statistics (§5.3.1); and a simple yet accurate online learning algorithm (§5.3.2).

5.3.1 Estimation using Order Statistics

Recall from §4.2 that Cedar uses order statistics to estimate the mean μ and standard deviation σ of the distribution. This helps us to eradicate the error in its estimates despite being provided a biased sample of durations from only the early processes. We compare it with an "empirical" technique that estimates the mean and standard deviation directly from the available responses, and is hence susceptible to biased samples.

Figure 9 compares the error in Cedar's estimation to the empirical technique, as the number of samples increases. Cedar's estimation of μ is not only more accurate, the error also drops off to less than 5% when at least ten processes have completed. Error in estimation of σ is relatively higher ($\sim$ 20%), however it has a lesser effect on the wait duration. This is also evidenced by Cedar's improvements closely matching an ideal scheme (Figure 7).

Regardless, Cedar's improvements in response quality are $30 - 70\%$ higher than the empirical technique (Figure 10), due to the use of order statistics in its learning.

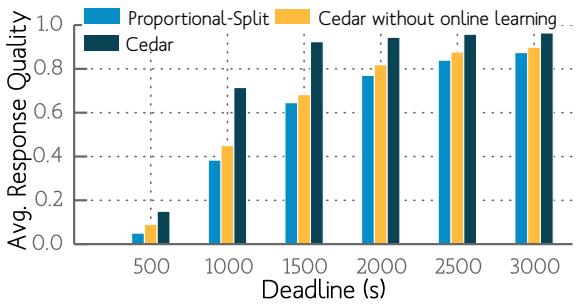


Figure 11: **Spark implementation results showing that Cedar copes well with load fluctuations that can increase (or decrease) mean process durations by learning the distributions in an online fashion.**

5.3.2 Importance of Online Learning

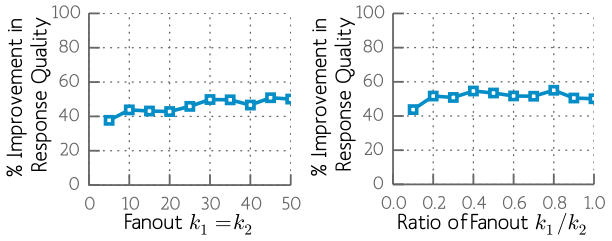
Cedar estimates the wait duration by learning the parameters of the distribution per query in an online fashion. Such learning has significant impact on performance. To illustrate this, we consider the processes in the aggregation tree to be first operating at a lower load than Facebook's map distribution, and use a *log-normal*$(2.77, 0.84)$ distribution to model X_1 (i.e., we keep σ to be as per the Facebook's distribution but with lower μ). Figure 11 shows what happens when the load increases, and the distribution becomes the same as Facebook's map distribution. If Cedar's optimal wait-duration computation algorithm is used when the load is low, then the quality of the responses was $> 90\%$. However, if the same wait-duration (that was ideal previously) is used when the load increases then the quality of responses drops. Since Cedar learns the distribution in an online fashion, it is able to cope with such load fluctuations.

5.4 Effect of Fanout

While our experiments so far have assumed a fanout of 50 at both levels based on values from Bing's cluster [3], we evaluate the performance of Cedar with differing fanout values using our trace-driven simulator.

Equal fanout at both levels. We vary the fan-out value of both the levels in the hierarchy and plot the results in Figure 12a. We observe that at lower values of fanout, Cedar's gains are slightly lower. This is because at lower values of fanout, there are quadratically fewer processes and hence reduced variation between process durations. Therefore, the potential gains achievable by Cedar are slightly less. However, beyond a fanout of 25, Cedar's estimation starts showing value with $\sim 50\%$ gain.

Different fanout across levels. We now compare the performance of Cedar for differing values of fanout in the two hierarchies. The fanout in the upper level of the hierarchy, k_2, is set to 50 while the lower level's fanout, k_1, is varied between 5 and 50. Figure 12b plots the improvement in response quality with the ratio of k_1 to k_2. Beyond a value of 0.2 for the ratio, the improvements stabilize and hover



(a) Same Fanout (b) Different Fanout

Figure 12: **Simulation results showing that Cedar's gains hold up when the structure of the aggregation tree changes. In (a), we keep the fanout at both the levels. In (b), we choose different fanout for the lower-level while keeping the upper-level fanout at 50. The deadline is set to 1000s.**

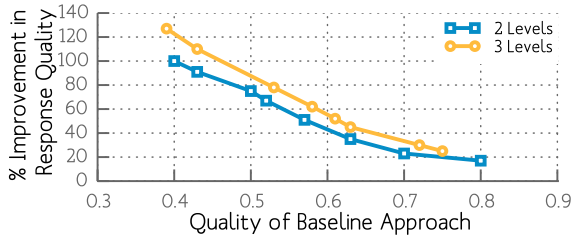


Figure 13: **Simulation results showing that Cedar performs even better when the number of levels in the aggregation tree increases.**

around 55%. Varying the ratio of k_1 over k_2 to over 1 does not change the trend in improvements.

5.5 Multiple Stages

Given that Cedar's formulation is recursive, it is directly applicable to aggregation trees with more than two stages in the hierarchy. To evaluate if Cedar's gains hold up when the number of levels in the hierarchy increase, we consider a 3-stage aggregation tree. We model the lowest level using Facebook's Map distribution and the upper two levels using Facebook's Reduce distribution. Figure 13 compares the percentage improvement in response quality over the baseline (proportional-split) for a two-level and a three-level aggregation tree. Since, the three-level would require higher deadline values to achieve the same quality, we instead plot quality of the baseline approach on the x-axis to make a fair comparison. We observe that not only Cedar's gains hold up, they provide greater improvements for higher number of stages. This is because Cedar near-optimally balances the deadline among the different stages which becomes more crucial as the number of stages increase.

5.6 Other Production Workloads

In this section, we consider a number of different setups based on other production workloads.

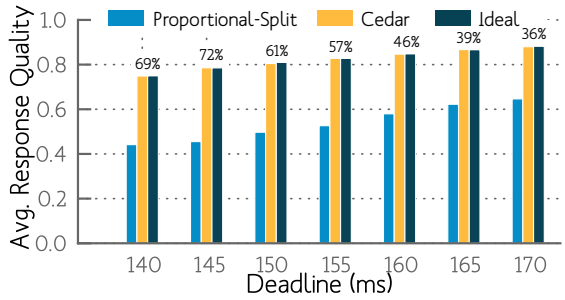


Figure 14: **Improvement in Response Quality. X_1 is per Facebook's map distribution and X_2 is per Google's distribution. The fanout at both layers is 50.**

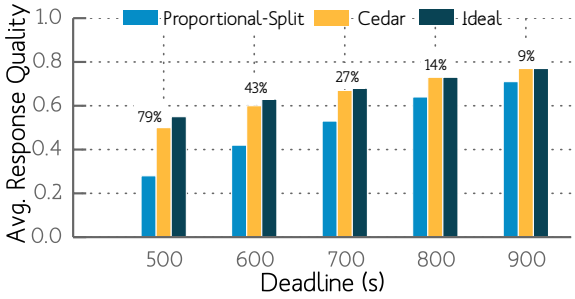


Figure 15: **Improvement in Response Quality. X_1 is per Cosmos's *extract* distribution and X_2 is per Cosmos's *full-aggregate* distribution. The fanout at both levels is fixed at 50.**

Interactive workload: The Hadoop workload at Facebook, while representative of performance variations encumbering large clusters, has really large process and aggregator durations. We consider a workload where the lower stage is modeled as per the Facebook's map distribution (albeit expressed in ms) and the upper stage is modeled by the Google's distribution (already in ms). Thus, this workload has higher variations in the lower stage compared to the upper stage. We believe this to be representative of partition-aggregate workflows for the following two reasons. First, processes at the lower levels perform arbitrary user-defined functions and hence are susceptible to multiple local systemic contentions (as in the Facebook traces), while aggregators perform relatively standard functions and are more influenced by networking and scheduling factors (as in the Google and Bing traces). Second, variation in process durations is statistically expected to be higher than among aggregators because there are far more of them in a query. Since the Facebook distribution has much higher variation than the Google trace, our assumption helps match the statistical expectation. The deadline is varied from $140 - 170ms$ (based on quoted deadlines values for production search queries [30, 34]). Figure 14 plots the results. Cedar provides significant improvements over the baseline algorithm and manages to nearly match ideal performance even in this scenario.

Analytics cluster at Microsoft Cosmos: We obtained statistics about the task duration values from an analytics cluster running in production at Microsoft. We run Cedar on this workload. The lower stage is modeled using the statistics from *extract* phase and the upper stage is modeled as per the *full-aggregate* phase. Despite the fact that Cedar's online learning algorithm is not in play here due to the lack of task durations *per job*, Cedar provides considerable improvements in response quality as shown in Figure 15 and comes close to the ideal scheme. We expect the improvements to only be higher if the per-job task durations were available.

Similar Distribution at both stages: We also used similar distribution for X_1 and X_2, that are derived from each of Bing, Google and Facebook distributions. We evaluate Cedar for varying values of σ of X_1, *i.e.,* the lower stage. The results for varying σ of X_2 look similar and we omit them in the interest of space. The upshot is that Cedar's performance continues to match the gains of an ideal scheme.

Bing's Distribution: We consider the case where both the stages are distributed as per the Bing distribution (a log-normal fit with parameters, μ = 5.9 and σ = 1.25, in μs). We are interested in the case when both levels have different amount of variabilities and thus, vary the σ parameter of the process duration distribution. We plot the % improvement over Proportional-split and also compare against the improvement of the ideal scheme in Figure 16a.

Google Distribution: We perform a similar experiment as above when both stages are distributed as per Google's cluster (log-normal fit with parameters, μ = 2.94 and σ = 0.55 in ms). Figure 16b shows how the performance gains (compared to Proportional-split) varies as the variability increases among process durations.

Facebook Distribution: Finally, we use the distribution from Facebook's Hadoop cluster logs for X_2 and samples from a log-normal fit for these map-task durations for X_1, studying the performance gains as one induces more variance in the first stage in Figure 16c.

5.7 Other Distribution Types

Since all our traces fit the log-normal distribution, our results thus far, were based on that. To demonstrate that Cedar is agnostic to the type of distribution, we evaluate its performance with the Gaussian distribution. The experiment uses a two-level tree with process durations distributed normally with mean 40ms at both the levels; the standard deviation being 10ms and 80ms for the top and bottom levels respectively (keeping variance at bottom level higher than above levels). As Figure 17 shows, while the percentage improvements are smaller than the log-normal cases, Cedar achieves quite high absolute values of quality. This is expected given that normal distributions are not heavy tailed.

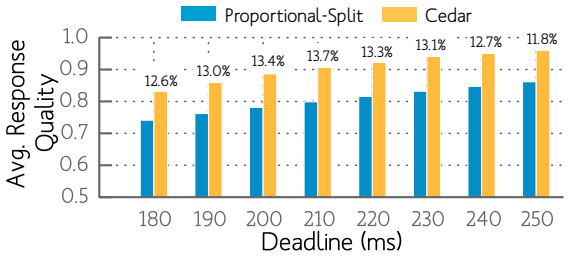


Figure 17: Cedar**'s performance with the Gaussian distribution. The percentages on the bars denote the improvement that** Cedar **provides over Proportional-Split.**

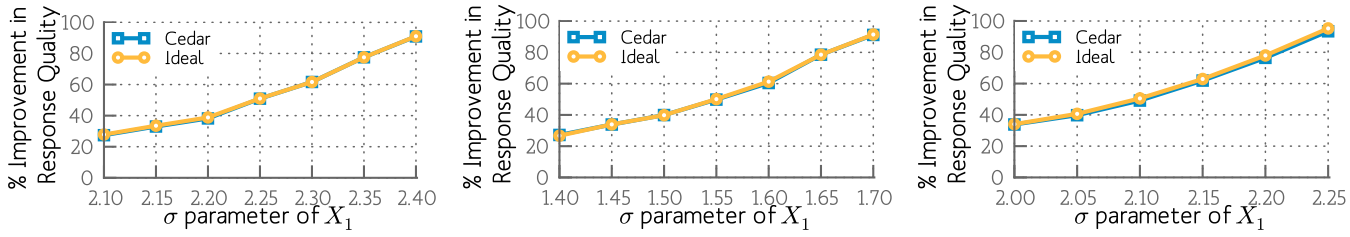
6. Discussion and Related Work

Aggregation trees is a classic topic, the optimization of which has been of significant interest in sensor systems [10, 16, 28], parallel computations [27] and Internet services [11]. All these systems focus on optimizing response quality of the aggregation queries under a variety of computation and communication (wide-area, wireless) constraints. We adopt the same problem statement in the context of datacenters running interactive services but uniquely employ order statistics to learn the distributions and set the wait durations, which results in a statistically grounded approach with significant benefits.

Straggler mitigation techniques work to reduce the variability in task durations [3, 4, 6, 8, 26, 31, 32, 34]. First, Cedar can complement these mitigation techniques, since stragglers still occur *despite* them (as seen in our traces). Second, by virtue of being *reactive*, straggler mitigation techniques fail to work effectively when process durations are sub-second, as for interactive queries [8], whereas Cedar still works well. Third, while straggler mitigation techniques attempt to remove variance from within a query (or a job), some queries are inherently more expensive (computationally or otherwise) than other. Cedar tailors a query-specific wait duration to improve application performance.

In **approximate analytics**, recent work, GRASS [9], has looked at mitigating stragglers in approximate-analytics. Unlike GRASS, Cedar's benefits hold whether or not a stage is single-wave (the common case for partition-aggregate style workloads, e.g., web-search) or multi-wave. This is because while GRASS primarily focusses on the question of which task to schedule when a slot frees up within one stage of a job, Cedar focuses on optimizing the wait time between stages. This leads to two important differences. First, GRASS considers each stage of a job independently; Cedar optimizes the stages jointly (by optimizing wait-durations at aggregators). Second, GRASS's scheduling benefits only "multi-wave" stages in a job – i.e., stages with more tasks than slots available. Cedar treats the question of when and how tasks should be scheduled as orthogonal. Thus, in summary, the two are complementary.

Deadline-aware scheduling has garnered significant attention recently, both in systems [15, 19, 20] and networking



(a) Bing-Bing (b) Google-Google (c) Facebook-Facebook

Figure 16: **Same Distributions: Percentage Improvement in Response Quality as the σ parameter of X_1 is varied. μ parameter of log-normal distributions X_1 and X_2 and σ parameter of X_2 are obtained from (a) Bing, (b) Google, and (c), Facebook distributions.**

[5, 17, 29, 30] communities. The networking community has focussed on meeting flow deadlines such that the *application throughput* (analogous to response quality) is maximized. However, such approaches aim to improve the performance of a single level. Cedar's approach is end-to-end, in that it aims to maximize the final response quality without worrying about individual stages. The systems community has also been looking at providing job SLOs [15], but the focus has been on jobs that require exact results which do not trade-off quality of the response with its latency. Kwiken [20] improves performance of request-response workflows using a variety of techniques including request reissues, catching-up on laggards, and trading off accuracy for responsiveness. Cedar's approach is closest to the last technique in that it solves the dual problem of maximizing accuracy under a desired responsiveness. Cedar differs as it considers the entire partition-aggregate workflow in a holistic way. Further, Cedar's online learning algorithm using order-statistics can aid in determining reissue budget across stages in a better way.

Consider the **alternate system model** of running an approximate-query system where the deadline is set such that $x\%$ of the process outputs are collected at the root. This imposes a threshold on response quality instead of its latency. Since Cedar's algorithm is solving the dual problem, it can be applied to such systems as well, *i.e.,* Cedar can provide the same quality threshold ($x\%$) at a lower deadline value thereby improving query's response time.

7. Conclusion and Future Work

We formalize the dilemma that an aggregator faces whilst deciding whether it should wait for additional time in the hope of getting new process outputs, or to stop in order to meet the upper-level deadline. We show that wait-time duration selection has great potential (over 100%) to improve the quality of responses within tight time budgets. Our solution Cedar, builds upon *(i)* an algorithm to perform online estimation of stage-duration distribution parameters; and *(ii)*, a theoretically optimal algorithm to maximize the expected quality given the distributions. We show that Cedar achieves near-optimal improvements in response qualities under a variety of distributions, most notably so when there is high variability in the system.

Going forward, we plan to extend Cedar's algorithm to work tightly with straggler mitigation techniques by leveraging and contributing to speculation of processes and blacklisting of problematic machines. We also intend to consider the relevance of outputs from the processes instead of just the fraction, a hugely significant factor as we test it out on real recommendation systems and sentiment analyses workloads. Finally, we will also relax our approach of being agnostic to the underlying resource and explore the value of designing algorithms specifically based on the dominant resource of the query (e.g., computationally intensive, network intensive).

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