Cello: Efficient Computer Systems Optimization with Predictive Early Termination and Censored Regression

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ABSTRACT

Sample-efficient machine learning (SEML) has been widely applied to find optimal latency and power tradeoffs for configurable computer systems. Instead of randomly sampling from the configuration space, SEML reduces the search cost by dramatically reducing the number of configurations that must be sampled to optimize system goals (e.g., low latency or energy). Nevertheless, SEML only reduces one component of cost—the total number of samples collected—but does not decrease the cost of collecting each sample. Critically, not all samples are equal; some take much longer to collect because they correspond to slow system configurations. This paper presents Cello, a computer systems optimization framework that reduces sample collection costs—especially those that come from the slowest configurations. The key insight is to predict ahead of time whether samples will have poor system behavior (e.g., long latency or high energy) and terminate these samples early before their measured system behavior surpasses the termination threshold, which we call it *predictive early termination*. To predict the future system behavior accurately before it manifests as high runtime or energy, Cello uses censored regression to produce accurate predictions for running samples. We evaluate Cello by optimizing latency and energy for Apache Spark workloads. We give Cello a fixed amount of time to search a combined space of hardware and software configuration parameters. Our evaluation shows that compared to the state-of-the-art SEML approach in computer systems optimization, Cello improves latency by 1.19× for minimizing latency under a power constraint, and improves energy by 1.18× for minimizing energy under a latency constraint.

1 INTRODUCTION

Optimizing latency and power tradeoffs (e.g., minimizing latency while meeting a power constraint) is crucial to modern computer systems. To achieve these goals, hardware and software configuration parameters—e.g., number of cores, core frequency, memory management, etc.—are exposed to users such that both the underlying system and application can be configured to operate at an optimal point in the latency-power tradeoff space [1–3]. Selecting an optimal configuration, however, is a challenging problem as the size and complexity of the configuration space require intelligent methods to avoid local optima [4, 5].

Sample Efficiency. Machine learning techniques have proven effective solutions to optimizing computer system configurations [6–8]. While a variety of such methods have been applied, they require a large sampling effort; i.e., generating a candidate configuration, running it to measure its high-level system behavior (e.g., latency and energy), and then building a model to predict the system behavior of unsampled configurations. Among these techniques, an appealing direction is sample-efficient machine learning (SEML), which reduces the number of samples required to find the optimal configuration [9–13]. A powerful example of SEML is Bayesian optimization [10, 12, 13]. Bayesian optimization intelligently selects samples that provide the most information for the model updates, and this intelligence reduces the number of samples required to find the configuration that produces optimal systems behavior. Besides Bayesian optimization, other sample-efficient optimizers have been proposed for specific systems problems [9, 11, 14, 15].

Cost of Samples. SEML reduces the cost for computer systems optimization by reducing the number of samples to find the optimal configuration. There is, however, a significant additional cost: the time to collect each sample. Critically in computer systems optimization, the samples corresponding to the worst configurations take a much longer time to collect than others. For instance, a slow configuration can take 10x the execution time of the optimal configuration on the same Apache Spark workload [16]. Thus, there is a need for reducing the cost of individual sample collection and not just the total number of samples.

Compute Efficiency. We note that achieving compute efficiency for SEML should reduce both the number of samples and the cost of collecting each sample. To reduce the cost of collecting each sample, prior work relies on measured early termination that terminates samples when the measured system behavior surpasses a given termination threshold (e.g., a target latency) [17, 18]; and this threshold typically distinguishes between good and poor system behavior. For instance, if the termination threshold is 40 seconds and the true latency of the workload running at a particular configuration is 60 seconds, measured early termination techniques will terminate samples when their runtime surpasses 40 seconds. However, this approach still pays the cost of waiting for the sample to hit the termination threshold, which is compute-inefficient.
1.1 Compute Efficiency with Cello
In contrast to prior work based on measured early termination, we introduce predictive early termination. This approach monitors running samples, predicts whether the sample will surpass the threshold, and terminates such unpromising samples before they are measured to be poor (e.g., long latency or high energy).

To apply this insight, we present Cello, an efficient computer systems optimization framework that augments Bayesian optimization with predictive early termination. To enable predictive early termination, Cello must predict, both early and accurately, whether a running sample will perform poorly; i.e., eventually exceed the termination threshold, which Cello sets as the best measured behavior. To do so, Cello applies censored regression, a prediction approach that is designed to model missing data (i.e., samples that are measured but not finish running) more accurately than techniques that do not account for the missing data [20, 21]. Formally, censoring is a condition where a measurement is only partially observable due to a given censoring threshold [19]. Instead of observing the true measurement, in censored regression we only know that it exceeded the censoring threshold. For example, if the censoring threshold is 30 seconds, the true latency of a sample that keeps running after 30 seconds is not observed at this moment because it is censored. Although its true latency is unknown at this moment, we know that it must be at least 30 seconds. The intuition behind censored regression is to model the censored and uncensored data (in our case, the samples that are still running and finished running before the termination threshold) differently, and then combine these models in a way that produces more accurate predictions than standard regression that does not account for censoring (§5.3).

1.2 Summary of Results
We implement Cello and test it on twelve Apache Spark workloads from HiBench [22]. We compare Cello to state-of-the-art Bayesian optimization techniques and different variants of early termination (including both measured and predictive). We give each method a fixed time to search a combined space of hardware and software configuration parameters and find solutions for two systems optimization problems: (1) minimizing latency under a power constraint (Latency-Under-Power) and (2) minimizing energy under a latency constraint (Energy-Under-Latency). Our evaluation shows a complete breakdown of results for different constraints and workloads for Cello and prior approaches to SEML. Compared to the prior work, we find that on average Cello (§5.1):
• improves latency by 1.19× for Latency-Under-Power and energy by 1.18× for Energy-Under-Latency compared to Bliss [29], the state of the art SEML approach for computer systems optimizations;
• improves latency by 1.24–1.61× for Latency-Under-Power and energy by 1.24–1.34× for Energy-Under-Latency compared to other SEML approaches that use measured early termination;
• improves latency by 1.90× for Latency-Under-Power and energy by 2.35× for Energy-Under-Latency compared to the SEML approach that uses predictive early termination based on standard regression, rather than Cello’s censored regression.

1.3 Contributions
This paper presents the following contributions:
• Introducing predictive early termination, based on predicted—rather than measured—behavior which allows SEML to terminate samples much earlier than prior work.
• Introducing censored regression to predict the system behavior of samples and enable predictive early termination. To the best of our knowledge this is the first demonstration of the benefits of censored regression for computer systems optimization.
• Presenting Cello, an efficient computer system optimization framework that combines predictive early termination and censored regression to reduce the cost of applying machine learning methods for systems optimization while still improving systems outcomes. Incomplete data are often prevalent in computer systems optimization. To the best of our knowledge, Cello is the first framework that reduces the time cost per sample by intelligently taking advantages of incomplete data via censored regression and predictive early termination. Our work provides a foundation on which the computer systems community can build new efficient frameworks that process incomplete data in computer systems research.

2 BACKGROUND AND RELATED WORK
This section discusses related work on machine learning for configuration optimization (§2.1), early termination (§2.2), and machine learning for prediction (§2.3).

2.1 Computer Systems Configuration Optimization
Modern computer systems are increasingly configurable [1, 23]. These configuration parameters have a large effect on high-level systems behavior including throughput [24], latency [25], and energy [4, 11]. Furthermore, the number of parameters and their complex interactions create a large search space with many local optima [5, 26], which present challenges for heuristics [4, 5]. To optimize systems behavior, machine learning techniques have been applied to search this configuration space for high-performing configurations.

Sample-efficient machine learning (SEML) represents a class of machine learning techniques that reduce the number of samples required to find the optimal configuration [27]. SEML approaches work iteratively, using their current predictions to determine which new configuration to sample and then update their model based on the observed behavior of that sample. Bayesian optimization is a typical SEML approach that has been applied in various domains [28]. For example, CherryPick uses Bayesian optimization to find optimal cloud configurations [10]. CLITE uses Bayesian optimization to schedule workloads for datacenters [13]. HyperMapper applies Bayesian optimization to tune compilers [12]. Bliss uses Bayesian optimization to tune parallel applications on large-scale systems [29]. Additional works propose problem-specific SEML approaches, including multi-phase sampling [11], optimal experiment design in Ernest [15], and fractional factorial design in Flicker [14].

An example of cost per sample. The SEML approaches above reduce the cost of computer systems optimization by reducing the number of samples. However, there is also the opportunity to reduce the cost of each sample itself. To demonstrate this, we compare the
number of samples and cost per sample between random sampling (not a SEML approach), Bayesian optimization, and Cello. We run the Apache Spark workload on a cloud computing system (details in §4.2) with the goal of finding the configuration with the lowest latency. Figure 1 compares the time cost per sample between random sampling, Bayesian optimization, and Cello. We observe that the time cost per sample from random sampling and Bayesian optimization approaches are roughly the same, which validates that Bayesian optimization does not reduce the time cost of collecting samples Cello, however, focuses on reducing the cost of each sample. For achieving the same optimal latency, Cello only needs 7.12s per sample, which is a 44% reduction in the time cost per sample compared to Bayesian optimization.

Figure 1: Comparing cost per sample between random sampling (RS), Bayesian optimization (BO), and Cello on the al1s workload.

2.2 Early Termination

Early termination aborts poor performing configurations before they finish, leaving time and resources to sample more promising configurations. This approach has been applied to speed up hyperparameter optimization and deep neural network (DNN) training. For hyperparameter optimization, HyperBand [30] and HyperDrive [31] randomly generate a large number of configurations at one time rather than intelligently sampling a small number of configurations iteratively, which is much more compute-intensive than SEML approaches. For DNN training, prior work predicts future behavior using learning curves—i.e., the learning accuracy of an algorithm as a function of its training time [32–34]. However, Bayesian optimization does not have an analogous structure to learning curves, so we need a different mechanism for predicting future behavior and in this work we demonstrate the use of censored regression for this prediction problem.

For Bayesian optimization, Hutter et al. [17] and Eggensperger et al. [18] apply measured early termination to terminate samples when their measured behavior reaches the termination threshold. Cello, however, uses predictive early termination to terminate samples when their predicted behavior—obtained from censored regression—reaches the termination threshold. This prediction step enables much earlier termination and thus saves more time for Cello to explore more samples compared to prior work (§5.1, §5.4).

2.3 Machine Learning for Behavior Prediction

A large body of machine learning techniques have been applied to predict high-level system behavior for resource management [4, 5, 11, 14, 35–48] and scheduling [49–51, 56, 57]. The general strategy is to use low-level, readily-available metrics (e.g., branch miss rates, IPC) to predict high-level behavior (e.g., throughput or latency) [11, 40, 45, 52–55, 58–63]. For example, Lee and Brooks [52, 64] apply linear regression to predict performance and power. Delimitrou and Kozyrakis [56, 57] use collaborative filtering to predict job performance for datacenter workloads. Mishra et al. [4, 5] use hierarchical Bayesian models to predict latency and energy. Garza et al. [61] and Bhatia et al. [60] use perceptrons to predict branch and prefetcher behavior.

Most prior work achieves high prediction accuracy relying on a training set that includes samples in a wide range of behavior. Bayesian optimization, however, accumulates samples as more iterations finish. Thus, there are insufficient samples as training data in the early stage of Bayesian optimization, and these samples are likely to lie in the range of poor values [31]. Directly training models on these samples will predict running samples to be poor, which leads to an increasing number of predictions of poor values and thus inaccurate sample selection for the next round [29]. To overcome this inaccuracy, Cello utilizes knowledge of the current elapsed latency and energy at each time interval to generate more accurate predictions through censored regression.

An example of prediction accuracy. To demonstrate the benefits of censored regression, we run Bayesian optimization on the al1s workload and predict each new configuration’s latency with different predictors: standard and censored regression. We use gradient boosting trees as our standard regression model due to its high predictive accuracy [65]. We monitor the workload execution and predict its latency at each time interval (see §4.4). The censoring threshold for censored regression is the elapsed latency observed at each time interval. We compute the mean squared error (MSE) between predicted latency and true latency. Figure 2 shows the results, where the y-axis represents the average MSE over all time intervals, lower is better. Censored regression has 2.84× lower MSE than standard regression. This example illustrates that censored regression is effective at improving prediction accuracy when training on samples collected from Bayesian optimization. The accurate prediction from censored regression is fundamental to predictive early termination in Cello, as we describe next.

3 CELLO DESIGN

Cello is an efficient computer systems optimization framework that reduces the cost of samples by predictive early termination which we enable with censored regression. Figure 3 illustrates the Cello design. After a configuration is selected from Bayesian optimization
(A)), Cello starts monitoring it (B), and records the current latency and energy at regular time intervals. At each interval, Cello checks if the configuration has finished running (Branch 1). If so, Cello goes back to Bayesian Optimization (A) for the next round. Otherwise, Cello predicts the final latency or energy using the Censored Regressor (C). Then, Cello sends the predictions to Predictive Early Termination (D) to determine whether the configuration should be terminated based on its prediction (Branch 2). If the prediction is worse than the existing best from the collected samples, Cello terminates this sample collection and goes to the next round. Otherwise, the configuration continues running until the next time interval. When the configuration finishes, Cello records the data for this sample and goes to the next Bayesian optimization round (A).

The remainder of this section provides a brief set of definitions to establish the core concepts, and then describe Cello’s design, and concludes with the Cello’s application to computer systems optimization problems.

### 3.1 Definitions

Cello’s input includes a workload and a list of configuration parameters over which to optimize. The goal is to find a configuration that meets the goal of systems optimization—e.g., the configuration that minimizes latency under a power constraint. We assume that Cello can measure high-level systems behavior including latency, power, and energy at different time intervals, which is reasonable since many software frameworks (e.g., Apache Spark [66], MapReduce [67], Cassandra [68], HBase [69], etc) already have this capability as they log systems behavior at regular time intervals.

**Workload.** A program that runs on a computer system.

**Configuration.** A configuration $\mathbf{x}_i$ is a $p$-dimensional vector where $p$ is the number of configuration parameters:

$$\mathbf{x}_i = [x_{i1}, x_{i2}, \cdots, x_{ip}], \quad (1)$$

As SEML sequentially explores configurations, we use index $i$ to refer to the sequence of configurations explored; $x_{ij}$ refers to an individual parameter setting, the $j$-th parameter, $j \in [p]$. A configuration parameter can either be a hardware feature such as the number of cores, core frequency, etc. or a software feature such as execution behavior, networking, scheduling, etc. A complete list of configuration parameters studied in this paper is in Table 1.

**System behavior.** The high-level system behavior that Cello monitors and optimizes. In this paper, we use latency (i.e., execution time of a workload), power, and energy consumption as system behavior, depending on the specific problem.

**Sample.** Given the above, a sample is the pair of a configuration along with its system behavior.

**Termination threshold.** The termination threshold is a latency or energy value that is used to determine whether to terminate a sample early or not. Unlike prior approaches [17, 18], Cello dynamically updates this threshold based on the best latency or energy seen so far.

Next, we will describe each labeled box in Figure 3.

### 3.2 Bayesian Optimization

Cello uses Bayesian optimization (A) to select the configuration at each round [27]. Formally,

$$\mathbf{x}^* = \arg \min_{\mathbf{x} \in \mathbb{R}^p} f(\mathbf{x}), \quad (2)$$

where $f(\cdot)$ is the unknown underlying function which is being optimized. There are two main components in Bayesian optimization: the surrogate model and the acquisition function. The surrogate model learns the unknown underlying function $f(\cdot)$. The acquisition function selects the most informative configuration at each round. We describe these two components as follows.

#### 3.2.1 Surrogate Model

Bayesian optimization requires a surrogate model that produces uncertainty estimates, and Cello requires the surrogate model that can handle different variable modalities (continuous, discrete, etc.) that exist in configuration space. In this paper, we use random forest as our surrogate model as it satisfies both of these requirements [12, 70]. As an ensemble learning method, random forest constructs a multitude of decision trees, where its predictions are the average of the output from its component trees. The uncertainty, therefore, can be obtained by taking the standard deviation from the predictions of each tree [71]. For configuration $\mathbf{x}_i$, we denote $\mu_i(\cdot)$ and $\sigma_i(\cdot)$ as its predictive mean and uncertainty from the surrogate model.

#### 3.2.2 Acquisition Function

After the surrogate model outputs predictive mean and uncertainty for the unseen configurations, Cello needs an acquisition function to select the best configuration to sample. A good acquisition function should balance the tradeoffs between exploration and exploitation. For Cello, we chose the expected improvement (EI) acquisition function, which has been demonstrated to perform well in configuration search [10, 13, 29]. EI selects the configuration that would have the highest expected improvement. The uncertainty, therefore, can be obtained by taking the standard deviation from the predictions of each tree [71].
improvement over the best observed system behavior so far. Assuming \( m_i \) is the best observed system behavior at the \( i \)-th round, we have
\[
x_i = \arg \max_{x \in \mathbb{R}^p} \left\{ (\mu_i(x) - m_i) \Phi(Z) + \sigma_i(x) \phi(Z), \quad \text{if } \sigma_i(x) > 0 \right\}
\[
0, \quad \text{if } \sigma_i(x) = 0
\]
where \( Z = \frac{\mu_i(x) - m_i}{\sigma_i(x)} \). \( \Phi(\cdot) \) is the cumulative distribution function and \( \phi(\cdot) \) is the probability density function, both assuming normal distributions. In particular, \( (\mu_i(x) - m_i) \Phi(Z) \) indicates the improvement in favor of exploitation, and \( \sigma_i(x) \phi(Z) \) indicates the uncertainty in favor of exploration. The unseen configuration with the highest expected improvement will be selected.

### 3.3 System Monitor

When a configuration is selected, Cello runs the workload in this configuration and monitors its status. The System Monitor (\( \mathbb{B} \)) records behavior (i.e., latency and energy) at regular time intervals to check if the configuration has finished running (\( \mathbb{D} \)). If the configuration finishes, Cello reports the latency and energy back to Bayesian Optimization (\( \mathbb{A} \)) for the next round. If the configuration is still running, the System Monitor reports the current latency and energy to the next module.

### 3.4 Censored Regressor

Cello’s Censored Regressor (\( \mathbb{C} \)) takes the information from the System Monitor (\( \mathbb{B} \)) and predicts the current configuration’s final latency and energy. The key idea of censored regression is to use the system behavior at the current time interval to accurately predict whether the current configuration will exceed the termination threshold. In particular, censored regression categorizes the training samples as follows:

- Samples that finish running; i.e., those which have terminated normally and thus have known latency and energy.
- Samples that do not finish running; i.e., those which are terminated early and their latency and energy are censored at the current elapsed latency and energy.

Next, we describe how censored regression models these two categories of training data. We will use the problem of minimizing latency under a power constraint as an example, in which we will predict latency.

Let \( z_i \) be the observed latency associated with \( x_i \) at the \( i \)-th round, and \( g(\cdot) \) be the output from censored regression. Then the formal definition of censored regression model [72] is:
\[
\log z_i = g(x_i) + \varsigma \varepsilon_i, \tag{3}
\]
where \( \varsigma \) is a constant and \( \varepsilon_i \) is the measurement noise. The log-scale of the response simplifies modeling different types of exponential distributions. The goal of censored regression is to estimate \( g(\cdot) \). When \( x_i \) is running and the System Monitor returns the current latency at the \( t \)-th time interval, the current latency \( y_{it} \) is a censored value of \( z_i \) such that
\[
y_{it} = \begin{cases} z_i, & z_i < t_{it} \quad (\mathbb{I}) \\ t_{it}, & z_i \geq t_{it} \quad (\mathbb{II}) \end{cases}
\tag{4}
\]
where \( t_{it} \) is the current latency at the \( t \)-th time interval (i.e., the amount of time that has elapsed during the execution of the sample). In eq. (4):

- If the observed latency is less than the current latency \( z_i < t_{it} \), Cello observes the latency when the configuration finishes running; i.e., \( y_{it} = z_i \), where \( y_{it} \) is the observed latency of a sample that terminated normally. Cello treats these uncensored (finished) samples by fitting them with regression, corresponding to \( \mathbb{I} \).
- If the observed latency is greater than or equal to the current latency \( z_i \geq t_{it} \), Cello observes the current latency censored at the \( t \)-th time interval, and \( t_{it} \) is the current elapsed latency. Cello treats this censored (running) sample by estimating its probability of \( z_i \) exceeding \( t_{it} \) given the configuration, corresponding to \( \mathbb{II} \).

Censored regression treats the uncensored (finished) samples and the censored (running) sample differently, and solves them together by minimizing the total negative log-likelihood (NLL) loss function. The NLL loss function at the \( t \)-th time interval in the \( i \)-th round is:
\[
r \left( g; (x_j; y_j); j=1, \ldots, (x_i; t_{it}) \right) = -\sum_{j=1}^{i-1} \mathbb{I} [z_j=y_j] \log \frac{1}{y_j} \phi \left( \frac{\log y_j - g(x_j)}{\sigma} \right) - \log \left( 1 - \Phi \left( \frac{\log t_{it} - g(x_j)}{\sigma} \right) \right), \tag{5}
\]
where \( \phi(\cdot) \) and \( \Phi(\cdot) \) are the probability density and cumulative distribution functions of the noise \( \varepsilon_i \) in eq. (3), respectively. The first term is the log-likelihood function for the uncensored (finished) samples that measures the discrepancy between \( \log y_j \) and \( g(x_j) \) where \( j \in \{1, i-1\} \), corresponding to \( \mathbb{I} \). The second term is the log-likelihood function for the censored (running) sample of the current \( i \)-th round that encourages \( g(x_i) > \log t_{it} \) when \( y_{it} = t_{it} \), corresponding to \( \mathbb{II} \). To fit this loss function, Cello uses gradient boosting trees due to its high fitting power in various predictive tasks [65]. Because, all else equal, the loss function in eq. (5) is lower when \( g(x_j) \) is higher, we regularize the predictor by training with early stopping [74, Chapter 5.5.2].

### 3.5 Predictive Early Termination

Cello’s Predictive Early Termination Module (\( \mathbb{D} \)) will terminate the current configuration based on the predictions from the Censored Regressor (\( \mathbb{C} \)). If the prediction is better than the existing best from the collected samples, Cello lets the configuration keep running until the next time interval, when Cello will make another prediction to check if the configuration should be terminated. If the prediction is worse than the existing best from the collected samples, Cello will terminate the running process, drop this configuration, and begin the next round of Bayesian Optimization (\( \mathbb{A} \)). In this case, the surrogate model does not change since no new samples are added to the training set. To avoid selecting the same configuration as the previous rounds, Cello only selects the configuration that maximizes the acquisition function from the unsampled configurations. With this module, Cello reduces the time cost of each sample by dynamically determining whether predictive early termination should happen and when it will happen.
Algorithm 1 Cello for systems optimization.

Require: $T_{\text{budget}}$ \quad \triangleright \text{Time budget.}
Require: $C$ \quad \triangleright \text{Target constraint in power or latency.}
1: Randomly sample a configuration $x_0$ to construct $X_{\text{train}}$ and obtain its system behavior $y_0$ to construct $Y_{\text{train}}$.
2: $i = 1$
3: while $T_{\text{budget}} > 0$ do
4: Train surrogate model using $X_{\text{train}}$ and $Y_{\text{train}}$.
5: Select configuration $x_i$ based on acquisition function.
6: Run experiment at $x_i$ and monitor its system behavior.
7: $y_i \leftarrow \min Y_{\text{train}}$. \quad \triangleright \text{Update the existing best.}
8: for each interval $t = 1, \ldots, \text{do}$
9: if sample not finished then
10: Get current system behavior $y_{it}$.
11: Build censored regressor on $X_{\text{train}}, Y_{\text{train}}, x_i, y_{it}$.
12: Get predicted latency $\hat{y}_{it}$ for $x_i$.
13: if $\hat{y}_{it} \geq y_i$ then
14: Early terminate experiment.
15: Get current running time $t_{it}$.
16: $T_{\text{budget}} \leftarrow T_{\text{budget}} - t_{it}$.
17: else
18: Get system behavior $y_i$ and constraint $c_i$ for $x_i$.
19: if $c_i \leq C$ then
20: $X_{\text{train}} \leftarrow X_{\text{train}} \cup x_i, Y_{\text{train}} \leftarrow Y_{\text{train}} \cup y_i$.
21: else
22: $X_{\text{train}} \leftarrow X_{\text{train}} \cup x_i, Y_{\text{train}} \leftarrow Y_{\text{train}} \cup \text{inf}$.
23: Get current running time $t_{it}$.
24: $T_{\text{budget}} \leftarrow T_{\text{budget}} - t_{it}$.
25: $i \leftarrow i + 1$.
26: return $x^*$ with the best system behavior from $X_{\text{train}}$ that meets the target constraint.

4.3 Points of Comparison

We compare a spectrum of approaches including random sampling (RS), Bayesian optimization (BO), Bayesian optimization with measured early termination (BO-ST, BO-TC, BO-IM, BO-NN) and predictive early termination (BO-GB), and ensemble Bayesian optimization (Bliss).

- **RS**: randomly sample configurations and select the best configuration that meets the constraint.
- **BO**: Bayesian optimization using random forest as the surrogate model and expected improvement as the acquisition function [10, 12, 13, 83]. We also use the same setting for the following approaches.
- **BO-ST**: Bayesian optimization with measured early termination using the static termination threshold; i.e., terminate the experiment when the measured latency or energy is observed to reach the static termination threshold, and then drop the sample. The static threshold is the latency or energy of the initial sample because it is the only prior knowledge we have to set this threshold.
- **BO-TC**: Bayesian optimization with measured early termination by truncation; i.e., terminate the experiment when the measured energy is observed to reach the static termination threshold.
Table 1: Hardware and software configuration parameters tuned in the experiments.

| Category | Configuration parameter | Range | Description |
|----------|-------------------------|-------|-------------|
| Hardware | cpu.freq                | 1.0–3.7 GHz | CPU frequency, in GHz. |
|          | uncore.freq             | 1.0–2.4 GHz | Uncore frequency, in GHz. |
|          | hyperthreading          | on, off | Hyperthreading. |
|          | nsockets                | 1, 2 | Number of sockets. |
|          | ncores                  | 1–12 | Number of cores per socket. |
| Software | spark.reducer.maxSizeInFlight | 24–128 MB | Max size of map outputs to fetch from each reduce task, in MB. |
|          | spark.shuffle.file.buffer | 24–128 KB | Size of the in-memory buffer for each shuffle file output stream, in KB. |
|          | spark.shuffle.sort.bypassMergeThreshold | 100–1000 MB | Avoid merge-sorting data if there is no map-side aggregation. |
|          | spark.speculation.interval | 100–1000 ms | How often Spark will check for tasks to speculate, in millisecond. |
|          | spark.speculation.multiplier | 1–5 | How many times slower a task is than median considered for speculation. |
|          | spark.speculation.quantile | 0–1 | Percentage of tasks to be complete before speculation is enabled. |
|          | spark.broadcast.blockSize | 2–128 MB | Size of each piece of a block for TorrentBroadcastFactory, in MB. |
|          | spark.io.compression.snappy.blockSize | 24–128 KB | Block size used in snappy, in KB. |
|          | spark.kryoserializer.buffer.max | 24–128 MB | Maximum allowable size of Kryo serialization buffer, in MB. |
|          | spark.kryoserializer.buffer | 24–128 MB | Initial size of Kryo’s serialization buffer, in KB. |
|          | spark.driver.memory | 6–12 GB | Amount of memory to use for the driver process, in GB. |
|          | spark.executor.memory | 6–16 GB | Amount of memory to use per executor process, in GB. |
|          | spark.network.timeout | 20–500 ms | Default timeout for all network interactions, in second. |
|          | spark.locality.wait | 1–10 | How long to launch a data-local task before giving up, in second. |
|          | spark.task.maxFailures | 1–8 | Number of task failures before giving up on the job. |
|          | spark.shuffle.compress | false, true | Whether to compress map output files. |
|          | spark.memory.fraction | 0–1 | Fraction of (heap space–300 MB) used for execution and storage. |
|          | spark.shuffle.spill.compress | false, true | Whether to compress data spilled during shuffles. |
|          | spark.broadcast.compress | false, true | Whether to compress broadcast variables before sending them. |
|          | spark.memory.storageFraction | 0.5–1 | Amount of storage memory immune to eviction. |

Table 2: HiBench workloads.

| Workload | Data size |
|----------|-----------|
| als      | 0.6 GB    |
| gbt      | 2 GB      |
| linear   | 48 GB     |
| nweight  | 0.9 GB    |
| pca      | 4 GB      |
| terasort | 3.2 GB    |
| bayes    | 19 GB     |
| kmeans   | 20 GB     |
| lr       | 8 GB      |
| pagerank | 1.5 GB    |
| rf       | 0.8 GB    |
| wordcount| 32 GB     |

- **BO-IM**: Bayesian optimization with measured early termination by imputation [17]; i.e., terminate the experiment when the measured latency or energy is observed to be worse than the existing best, and then impute—i.e., replace missing data with predicted values—the unfinished configuration.
- **BO-NN**: Neural model-based Bayesian optimization with measured early termination and censored observations [18]; i.e., train the neural network with the Tobit loss function for the censored training data. The same neural network architecture and hyperparameter settings are used in [18]. We use the same static threshold setting as the experiments in [18]. The threshold is the latency or energy of the initial sample because it is the only prior knowledge we have to set this threshold.

- **BO-GB**: Bayesian optimization with predictive early termination by predicting with standard regression; i.e., terminate the experiment when the predicted latency or energy is worse than the existing best, and drop the configuration. We use gradient boosting trees as the standard regressor due to its high accuracy [65]. This approach is novel to this paper, we include it to show the importance of using censored regression rather than standard regression for predicted early termination.
- **Bliss**: ensemble Bayesian optimization [29]. Bliss reduces sample collection time by determining when to update its surrogate model using predictions from that same surrogate. To the best of our knowledge, Bliss is the state-of-the-art of Bayesian optimization in configuration search for computer systems.
- **Cello**: Bayesian optimization with predictive early termination by predicting with censored regression.

4.4 Evaluation Methodology

Following a methodology established in prior work on investigating Apache Spark systems [16], we create a set of 2000 configurations per workload, randomly sampled from both hardware and software configuration parameters. We run these configurations to record their latency and energy consumption. For reference, we used more than 50000 CPU hours to record this test dataset (and we will include it as part of our open source release). We then give each of the above approaches a fixed amount of time to search a combined space of hardware and software configuration parameters and find solutions for two optimization problems: (1) **Latency-Under-Power**: minimizing latency under a power constraint; and
(2) Energy-Under-Latency: minimizing energy under a latency constraint.

We evaluate on a wide range of search time budgets such that at least one of the above approaches converges to the optimal solution. We set a range of constraints: the power and latency constraints are set as $[10, 20, 30, 40, 50, 60, 70, 80, 90]$-th percentiles of the distributions. For all approaches that measure progress of running samples, we set a time interval of 5 seconds; i.e., the system behavior is monitored every 5 seconds. The reported results are averaged over different constraints over 10 runs with different random seeds.

For censored regression from the XGBoost library, we choose the extreme distribution for the loss function. We set num_boost_round, the parameter that controls the number of steps to fit gradient boosting trees in eq. (5) to minimize the loss (i.e., the point at which to early stop) to 20. We tune this parameter by generating predictions that are generally above the current elapsed latency and energy on one workload of dataset, and use this same value on all other datasets without additional tuning. For each distinct trial on each dataset, we run cross validation for distribution_scale with the value range of $[0.2, 0.3, 0.4]$ and learning_rate with the value range of $[0.2, 0.25, 0.3]$ and report the best results.

4.5 Evaluation Metric

RE. We use relative error (RE) between the result from each approach and the optimal for evaluation:

$$RE = \frac{|Y_{\text{pred}} - Y_{\text{opt}}|}{Y_{\text{opt}}}.$$  

where $Y_{\text{pred}}$ is the best value found by the approach, and $Y_{\text{opt}}$ is the optimal measured value. Lower RE is better.

5 EXPERIMENTAL EVALUATION

We evaluate the following research questions (RQs):

- **RQ1**: How well does Cello perform? Cello reduces latency by 1.19–1.90× for Latency-Under-Power (Figure 4 and 5) and energy by 1.18–2.35× for Energy-Under-Latency (Figure 6 and 7).

- **RQ2**: Is prediction or measurement better for early termination? Cello’s predictive early termination outperforms measured early termination approaches by terminating much earlier while producing more accurate predictions (§5.2).

- **RQ3**: How is censored regression beneficial to Cello? Cello’s censored regression reduces prediction error (as mean squared error) for latency and energy by 60% and 82% over standard regression for Latency-Under-Power and Energy-Under-Latency (Figure 8).

- **RQ4**: How many samples are explored? By combining censored regression and predictive early termination, Cello both explores more samples and improves search results compared to other baselines (§5.4).

- **RQ5**: What is the overhead? Within the same amount of search time (learning overhead included), Cello produces the best results by both predicting accurately (§5.3) and updating quickly (0.3 seconds per sample, §5.5).

### 5.1 RQ1: How well does Cello perform?

Figure 4 and 6 show the latency and energy results of different approaches as a function of different search time budgets for Latency-Under-Power and Energy-Under-Latency, respectively, where the x-axis is the search time, and the y-axis is the latency or energy (lower is better). We compare the summarized results averaged over all search times in Figure 5 and 7, and compute the relative error (RE) by comparing to the optimal value (Optimal) in Table 3, where Optimal is the best value found through brute force search. We can see that compared to other approaches, Cello finds the configuration with the lowest latency and energy at almost all search times for almost all workloads. The major exceptions are lr and rf in Latency-Under-Power, and a1s and bayes in Energy-Under-Latency, where Bliss outperforms Cello at some points. It is not surprising since with numerous local optima in the tremendous search space, no single method will dominate. Despite that, Cello still outperforms prior work in the majority of cases and gets much better results on average. In particular, we find that on average:

| Latency-Under-Power | Energy-Under-Latency |
|---------------------|-----------------------|
| RE (%)  | # samples | RE (%)  | # samples |
| RS      | 55        | 23     | 46       | 25       |
| BO      | 52        | 24     | 36       | 28       |
| BO-ST   | 51        | 26     | 31       | 32       |
| BO-TC   | 48        | 30     | 32       | 41       |
| BO-IM   | 51        | 91     | 31       | 69       |
| BO-NN   | 94        | 19     | 54       | 21       |
| BO-GB   | 127       | 385    | 72       | 378      |
| Bliss   | 42        | 36     | 31       | 31       |
| Cello   | 20        | 44     | 16       | 50       |

- Cello achieves 20% and 16% REs for Latency-Under-Power and Energy-Under-Latency respectively (Table 3), which represent 1.19× and 1.18× speedups compared to the best baseline Bliss, and 1.90× and 2.35× speedups compared to the weakest baseline BO-GB.

- BO underperforms all approaches with early termination except BO-GB, which indicates the benefits of early terminations in SEML. The reasons that BO-GB performs poorly will be discussed in §5.3.

- As the state-of-the-art Bayesian optimization approach for configuration optimization, Bliss under-performs Cello in most workloads for several reasons. First, Bliss does not incorporate early termination; it runs a few rounds as BO in the beginning and then starts using predictions to update the surrogate model, which means that it does not reduce the cost of collecting samples during early rounds. Second, Bliss uses its surrogate model—i.e., standard regression—to predict, which leads to less accurate predictions compared to censored regression (more details in §5.3). Finally, Bliss updates its surrogate alternating between using predictions and measured system behavior, which produces less accurate model updates. In contrast, Cello combines censored regression and early termination based on predicted behavior to
reduce search costs. When running for a fixed time budget, Cello explores more configurations than Bliss (# sample columns in Table 3), and thus generally achieves better results.
5.2 RQ2: Is prediction or measurement better for early termination?

Here, we focus on comparing predictive early termination (Cello) to measured early termination (BO-ST, BO-TC, BO-IM and BO-NN) to determine if the former significantly improves early termination methods. In Figure 5 and 7, Cello has $1.24 \times$ to $1.61 \times$ and $1.24 \times$ to $1.34 \times$
We compute the mean squared error (MSE) between predicted latency and the true latency. Table 3 summarizes the average number of samples selected for each approach. Therefore, given the same amount of the search time budget, Cello also evaluate more samples than BO-ST, BO-TC, and BO-NN from Table 3, which reflects the fact that Cello terminates more samples earlier. Although BO-IM evaluates more samples than Cello, it underperforms Cello, which suggests that it is terminating both early and accurately that improve results, not just terminating early. These results demonstrate the benefits of predictive early termination over measured early termination; however, the next section shows that achieving these benefits requires an appropriate predictive model.

### 5.3 RQ3: How is censored regression beneficial to Cello?

Here, we analyze the results of BO-GB to Cello. BO-GB uses early termination, but based on a standard regression model rather than Cello’s censored regression. Although BO-GB has predictive early termination, it achieves the worst results. This poor result is due to the low prediction accuracy from standard regression when training on censored data. To illustrate this, we compare the prediction accuracy of each selected sample between BO-GB’s standard regression (gradient boosting trees) and Cello’s censored regression.

We monitor workload execution and predict its latency at each time interval (§4.4). The censoring threshold for censored regression is thus the elapsed latency observed at each time interval. We compute the mean squared error (MSE) between predicted latency and true latency. Figure 8 shows the average MSE over all time intervals, where the x-axis is the workload, the y-axis is the MSE (lower is better), and the last column, Mean, is the arithmetic mean over all workloads. Censored regression almost always has much lower MSE than standard regression, with 60% and 82% reductions for Latency-Under-Power and Energy-Under-Latency respectively. Standard regression has worse prediction accuracy because BO-GB terminates all samples throughout the execution and thus does not update the surrogate model at all. These results suggest that it is important to make accurate predictions so that the poor configurations can be quickly identified. Censored regression achieves high accuracy by considering both uncensored (finished) and censored (running) samples, while standard regression only takes uncensored (finished) samples into account.

### 5.4 RQ4: How many samples are explored?

Table 3 summarizes the average number of samples selected for each approach. Note that since all approaches are given the same time to explore, exploring more samples is generally better, provided those samples produce useful information for updating the model. We find that:

- Within the same time budgets, BO selects fewer samples than others (except BO-NN) as BO does not use early termination to save extra time for more samples.
- BO-NN selects the fewest samples compared to others; 19 and 21 on average for for Latency-Under-Power and Energy-Under-Latency respectively. The reason is that BO-NN has a surprisingly high overhead for model updates—over 11 seconds per sample (§5.5)—and thus a significant portion of its time is spent on surrogate updates instead of searching new configurations.
- BO-GB selects the most samples; in Table 3, BO-GB selects 385 and 378 samples for Latency-Under-Power and Energy-Under-Latency respectively. It is because BO-GB terminates all samples in the first time interval based on its predictions, and does not update the surrogate model at all. More results can be found in §5.3.
- Cello selects 44 and 50 samples for Latency-Under-Power and Energy-Under-Latency respectively, which are more than RS, BO, BO-ST, BO-TC, BO-NN, and Bliss, while fewer than BO-IM and BO-GB. It indicates that increasing the number of samples is not the key to achieving the best results, but selecting more useful samples matters. Cello is such an example that combines early termination and censored regression to search more high-quality samples.

### 5.5 RQ5: What is the overhead?

We report the learning overhead of processing each sample, including predicting future behavior and updating the surrogate. Figure 9 and 10 show the overhead of processing each sample for different approaches for Latency-Under-Power and Energy-Under-Latency respectively, where the x-axis is the workload, the y-axis is the overhead, and the last column Mean is the arithmetic mean over all workloads. We use the same setting for neural network training as in [18] for BO-NN, and BO-NN has the highest overhead; i.e., over 11 seconds on average. To better visualize other methods properly, we cap the y-axis at 1 second. BO-IM has the second largest overhead due to the high overhead of imputing samples using the Expected-maximization algorithm [17]. The Expected-maximization algorithm is an iterative method and thus needs numerous steps to converge [84]. Cello has the third largest overhead because it uses the gradient boosting trees—which is an ensemble method—to fit the loss function of censored regression. Nevertheless, Cello’s overhead (0.3 seconds on average) is negligible compared to the cost of collecting each sample (22.3 seconds on average), which is key for its applicability to the efficient computer systems optimization problems. All results in this section include learning overhead for all approaches, and Cello still produces the best results, showing that the overhead can be negligible compared to making good decisions about early termination to explore more high-quality samples in the same amount of time.

### 6 DISCUSSION

To understand the impact of each configuration parameter on system design, we visualize the SHAP values of the parameters with the best energy under 50-th latency constraint for Energy-Under-Latency selected by Cello on all and bayes workloads in Figure 11 and 12, respectively. SHAP (SHapley Additive exPlanations) is a state-of-the-art approach to interpret the output of machine learning models [85], which visualizes parameters contributing to push the model output from the base value (i.e., the average model output over the training data we passed) to the model output.

For all in Figure 11, n, socket and cpu, freq have the largest effects (with contributing value -41.87 and -37.46) that push the...
energy prediction lower from the base value to the predictive value. The other high-influence parameters are shuffle.sort.bypassMergeThreshold, uncore.freq, hyperthreading. For bayes in Figure 12, uncore.freq and n.sockets have the largest effects (with contributing value $-27.69$ and $-23.53$) that push the energy prediction lower from the base value to the predictive value. The other high-influence parameters are cpu.freq, n.cores, shuffle.file.buffer, etc.

Two key points can be seen from these examples. First, both hardware (e.g., uncore.freq) and software (e.g., shuffle.sort.bypassMergeThreshold) parameters influence the system behavior, and thus both types of parameters should be tuned to meet the optimization goal. Second, same parameters have different effects on different workloads, which suggests that the optimal configuration is workload dependent. Therefore, we should be careful about the prior knowledge obtained from the existing workloads since information learned for one workload might not transfer directly to a new workload.

7 LIMITATIONS

We recognize the limitations of this work as follows:

- The outcome of predictive early termination and censored regression from Cello depends on the SEML framework. We chose to implement Cello by adding these components to Bayesian optimization because it has proven to provide high-quality samples. Future work can explore how Cello can be generalized to other learning frameworks.
- It is challenging to determine the search time budget in advance to make sure that the search results converge to the optimal. There has been work investigating this topic in the machine learning literature.
learning community [86, 87]. Although it is out of scope in this paper, it is interesting to explore the combination of Cello and this direction.

- The improper setting of num_boost_round, the parameter that controls the number of training steps can result in poor prediction accuracy. Future work can explore more systematic ways to set this parameter, or incorporate its regularizing effect into the loss function.

8 CONCLUSION

This paper presents Cello, a systematic approach to reduce the cost of samples through predictive early termination and censored regression. Evaluations show that Cello improves the system outcomes compared to a wide range of existing SEML and early termination techniques. Finally, we hope that Cello can inspire future research directions on reducing time cost of sample collection rather than the number of samples, and other applications of censored regression in computer systems research.

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Figure 12: SHAP values for the bayes workload.
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