CONEX: Efficient Exploration of Big-Data System Configurations for Better Performance

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Abstract—Configuration space complexity makes the big-data software systems hard to configure well. Consider Hadoop, with over nine hundred parameters, developers often just use the default configurations provided with Hadoop distributions. The opportunity costs in lost performance are significant. Popular learning-based approaches to auto-tune software does not scale well for big-data systems because of the high cost of collecting training data. We present a new method based on a combination of Evolutionary Markov Chain Monte Carlo (EMCMC) sampling and cost reduction techniques to cost-effectively find better-performing configurations for big data systems. For cost reduction, we developed and experimentally tested and validated two approaches: using scaled-up big data jobs as proxies for the objective function for larger jobs and using a dynamic job similarity measure to infer that results obtained for one kind of big data problem will work well for similar problems. Our experimental results suggest that our approach promises to significantly improve the performance of big data systems and that it outperforms competing approaches based on random sampling, basic genetic algorithms (GA), and predictive model learning. Our experimental results support the conclusion that our approach has strongly demonstrated potential to significantly and cost-effectively improve the performance of big data systems.

Index Terms—Performance Optimization, MCMC, SBSE, Machine Learning.

1 INTRODUCTION

The use of Big-data frameworks such as Hadoop and Spark have become a de-facto standard for developing large scale data-driven applications. These frameworks are highly configurable and can be tailored to meet a diverse set of needs. In practice, however, it is hard to fully exploit such configurability. Instead, off-the-shelf, or default, configurations are most commonly used [1]. This often leaves significant performance potential unrealized [2]. Configuring for performance is important especially for big data because “even a small performance improvement translate into significant cost savings due to the scale of computations involved [3]”.

Finding high-performing (or good) configurations for big data systems is hard. Their configuration spaces are vast and their configuration-to-performance functions are complex. First of all, they have multiple configurable sub-systems [4]. Hadoop, for example, has about 900 parameters across 4 sub-systems. Some parameters, e.g., numeric ones, have many values. Secondly, parameters also have diverse types, including optional and dependent substructures. For example, setting one Boolean parameter to true can enable a feature, requiring values for all of its parameters. Further, parameters can also be constrained by external values. For example, in a multi-core system, one cannot set the number-of-core value to a number larger than the number of available cores. Configuration-to-performance functions are not well understood: e.g., how parameter values interact. Also, due to its discrete nature, typical mathematical optimization methods do not apply [5]. Finding good configurations ends up as a black-art [6].

For traditional software, the problem of finding better configuration has given rise to a significant body of work [7], [8], [9], [10], [11], [12]. This research share a common general framework shown in Figure 1. They involve the following steps: (i) deploy different sampling strategies to select a set of valid and representative configurations [13], [14], [15], [16], [17], [18], (ii) use the sampled configurations to measure the performance of the system, (iii) use Machine Learning (ML) models to learn the mapping between configuration and performance [7], [8], [12], [19], [20], and finally, (iv) use the learned models to find better configurations. Most notably, the success of these learning-based approaches are contingent on the size and the quality of the sampled configurations used for training.

For big-data systems, however, these existing techniques often struggle to scale due to the following two reasons:

(1) The cost of collecting training data in big data systems is prohibitively large [21]. For example, in a typical Hadoop system, a single run of a simple sorting task for a typical workload (data size=3.2GB) can take up to 14 minutes. A typical learning based approaches need about 2000 samples [22]. For the sorting task in hadoop, this would take 19 days to obtain! Therefore, we seek multiple orders of magnitude cost reduction for such a method to be practical.

(2) The configuration space of big data systems is particularly complex. The configuration-finding problem for big data systems involves significantly larger number of dimensions than addressed in most previous work. Nair et al. [19] showed that for complex, configurable systems the measurement data often do not generalize well, and thus, it is almost

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impossible to find “the best” configuration.

To address this issue, Nair et al. [19] proposed a rank-based learning approach. Instead of focusing on constructing an accurate model, they use a random sampling strategy to build a “bad” model that can learn to predict whether one given configuration is better than another. They showed such predictors can be trained easily with significantly fewer samples. For big-data systems, as we will show in §5, it is hard to learn even such rank-preserving models with high accuracy. One might try Neural Networks (NNs) [23]. However, NNs require large amounts of high-quality samples data for training, and the cost of even collecting such data for big-data systems would be prohibitively high [24].

Hence, given the number of samples needed to train a good model and the cost involved in collecting them for big-data systems, we cannot rely on the popular random sampling + learning based approaches. They must be eschewed in favor of better methods that (a) can give us near-optimal configurations within a sampling budget and more importantly (b) can be scaled much more easily.

To achieve these objectives, in this paper we argue that random sampling is inadequate and we need smarter sampling strategies that can explore diverse configurations with a high discriminatory power. In particular, we show that Evolutionary Markov Chain Monte Carlo (EMCMC) sampling strategy are best suited this purpose. A nice property of EMCMC is that, unlike random sampling, it tries to estimate the target distribution, i.e. draws more samples from important regions while maintaining sample diversity.

The rest of this paper is organized as follows: § 1.2 summarizes our key findings. § 2 provides background and motivation. § 3 introduces the tool CONEX proposed in this paper. § 4 presents the experimental design for evaluating our approach. § 5 highlights our experimental results. § 6 samples some previous related work in this area. § 7 highlights some threats to the validity. § 8 provides some concluding remarks regarding our findings.

1.1 Contributions

Our work makes the following contributions:

- We propose and provide compelling evidence for the Scale-Up hypothesis which states that good configurations found with small workloads work well for significantly larger workloads and saves significant experimental cost.
- We propose and provide compelling evidence for the Scale-out hypothesis which states that good configurations for one kind of job would yield improvements for other dynamically similar jobs, saving further sampling costs.
- We implement a configuration exploration framework for big-data systems called CONEX. We demonstrate experimentally that CONEX outperforms learning-based methods in the case of big-data systems.

1.2 Research Questions

Our experiments were conducted using the Hadoop and Spark frameworks on five canonical jobs defined by the HiBench [25] benchmark suite for three different size of workloads: small (320MB), large (3.2GB), and huge (32GB). We answer the following research question in this paper:

RQ1: Can CONEX find configurations that are better than the baseline default configurations? In the first RQ, we compare CONEX with default configurations as a baseline. We evaluate this RQ for different workloads (small, large, and huge) of bigdata jobs. We break this research question into four sub-questions:

- RQ1-A: How effective is CONEX in finding optimal configurations for small workloads? In this setting, we study Hadoop and Spark jobs on small workloads, we measure the performance of the configurations discovered by CONEX over the default off-the-shelf configurations.

  **Result:** CONEX can find configurations that produce up to 72% and 40% performance gains respectively over the default configurations. On average, we see around 10% and 30% performance gains for Hadoop and Spark.

- RQ1-B: How well does CONEX Scale-Up when exposed to much larger workloads? Although the performance gains above were noteworthy, it would be most beneficial if CONEX can improve performance for larger workloads without incurring additional exploration cost. Thus, here we assess if the configurations found in the exploration phase with smaller workloads can be used as proxies for identifying optimum configurations on workloads that are orders of magnitude (≥ 100x) larger in size.

  **Result:** Configurations found with Scale-Up strategy produces significant performance improvements (average of 10% to 20%) for larger workloads. This strategy is also much more economical saving over 9600 compute hours and over $12,000 in compute cost over baseline, i.e., sampling directly over the large workloads.

- RQ1-C: How well does CONEX Scale-Out across workloads that are dynamically similar to one another? To further save the configuration exploration cost, we check how well CONEX can Scale-out across workloads, i.e., if a good configurations found for one specific job (say WordCount) can be used for a different job type (say NutchIndex).

- RQ1-D: How we should choose configuration? After determining the performance of configurations found by CONEX on a given workload, we need to choose which configuration to use for each type of job. We evaluate this RQ for different workloads (small, large, and huge) of big-data jobs. We break this research question into four sub-questions:

  - RQ1-D-A: How well does CONEX Scale-Out across workloads that are dynamically similar to one another? To further save the configuration exploration cost, we check how well CONEX can Scale-out across workloads, i.e., if a good configurations found for one specific job (say WordCount) can be used for a different job type (say NutchIndex).
Result: The best configuration found with one job can achieve significant performance gains for other jobs having similar dynamic characteristics. By scaling out, CONEX can achieve gains of up to 30% for Hadoop jobs. In the case of Spark jobs, we notice gains of up to 50%.

- RQ1-D: Which parameters have the highest impact on improving performance gain of CONEX?

Lastly, we inspect how sensitive the performance gains are to each of the individual parameters of the big-data system. This ensures that the performance gains are not due to trivial changes to only a certain few parameters.

Result: Performance gains are sensitive to a few parameters. Overall improvements are due to a combination of the most important parameters and not any individual parameter.

RQ2: How does the EMCMC sampling strategy perform compared to random and evolutionary sampling? In this RQ, we investigate the effectiveness of EMCMC-based sampling strategies used by CONEX over other popular sampling strategies used in performance optimization. To this end, we compare EMCMC against two state-of-the-art methods—(i) a baseline random sampling method [19] and (ii) genetic algorithm-based evolutionary sampling methods [26].

Result: EMCMC-based sampling strategy, on average, outperforms random (by up to 105%) and genetic algorithms (by up to 52%) based sampling strategies to find better performing configurations for Hadoop.

RQ3: How does CONEX perform compared to the state-of-the-art Machine Learning-based configuration optimization approaches? In the final research question, we compare EMCMC based sampling with machine learning based approaches. The state-of-the-art methods that attempt to discover optimal configurations most commonly use machine learning based approaches [19], where the training samples are usually collected by randomly sampling based on a uniform distribution. Our tool, CONEX, eschews sampling randomly from a uniform distribution in favor of EMCMC-based sampling. Here, we ask how CONEX is when compared to learning based approaches of Nair et al. [19].

Result: Compared to Nair et al.’s [19] learning-based approach, CONEX finds configurations that are significantly better with performance gains of 1700% (in PageRank).

2 FORMALIZATION

In this section, we begin by defining basic terms used in the rest of this paper (§2.1). Then we discuss formal underpinnings of the current state-of-the-art in configuration optimization and their shortcomings (§2.2). Finally, we discuss our proposal to remedy these issues using Evolutionary Markov Chain Monte Carlo, or EMCMC (§2.3 and §2.4).

2.1 Terminologies

- Configuration parameter $p_i$: Is a configuration variable whose value is set by a system installer or user to invoke certain desired some system property.

- Configuration type $t$: Is an $N$-element record type $[p_1, \ldots, p_N]$, where each element $p_i$ is a configuration parameter and $N$ is the number of parameters representing the dimensionality of the space.

- Configuration $c$: Is a configuration type, $t$, in which valid values are assigned to the configuration parameters $p_i$.

- Configuration space $\zeta$: Is the set of all valid configurations for a given system. The definition of valid varies from system to system. If there are no constraints on a configuration $c$, and if $N$ is the number of parameters and $M$ is the average number of possible values of each parameter, then the size of configuration space $\zeta$ is roughly equal to $M^N$.

- Performance $Y$: The measured performance of the software system given that it is configured according to $c$. A number of performance measurements can be made for a system. For example, we may want to maximize performance measures such as throughput or minimize measures such as latency.

2.2 Identifying optimal configurations with Stochastic Approximation

In the most general sense, the goal of finding the best configuration for a configurable software system can be understood as search problem. The goal of this search problem would be to identify a configuration that maximizes (or minimizes) an objective function. More formally, given a space of all possible configurations $\zeta$ and valid configuration from that space $c$, let us represent the software system as a function $S : c \rightarrow Y$. The function $S$ consumes an input $c$ and returns the performance $Y$. The goal of finding the optimal configuration can be viewed as a search for a configuration $c^* \in \zeta$ such that we obtain the best performance $Y^*$. This can be generalized as follows:

\[
\begin{align*}
Y^* &= \min_{c \in \zeta} Y \equiv \min_{c \in \zeta} S(c) & Y &= \text{Latency, etc.} \\
Y^* &= \max_{c \in \zeta} Y \equiv \max_{c \in \zeta} S(c) & Y &= \text{Throughput, etc.}
\end{align*}
\]

However, the space of configurations, $\zeta$, is exponentially large. Further, the software system $S$ is quite complex and each of the configuration $c \in \zeta$ is highly nonlinear, high dimensional, and are otherwise inappropriate for deploying deterministic optimization strategies. Therefore, we seek alternative strategies to find optimum configurations [27].

A prominent alternative to deterministic optimization is the use of machine learning models in conjunction with stochastic optimization methods to solve the search problem.
of finding the optimum configuration for a given software system [7], [8], [19]. These methods use a three-step approach described below:

(i) **Stochastic Sampling.** This step attempts to overcome the issue of exponentially large space of possible configurations \( c \in \zeta \). The sample of configurations \( c \) are drawn from an underlying probability distribution \( f(c) = f(p_1, p_2, ..., p_N) \forall c \in \zeta \). This distribution is almost always assumed to be uniform in nature, i.e., \( f_\zeta(c) \rightarrow \mathcal{U}(p_1, p_2, ..., p_N) \forall c \in \zeta \). The total number of samples that are drawn are limited by a sampling budget.

(ii) **Modeling with machine learning.** Even with a limited number of samples, the time and cost overhead of having to measure the true performance can be exorbitant. Therefore, from among the sampled configurations, a few representative samples are used to construct a machine learning model to approximate the behaviour of the software system.

More formally, the machine learning model can be represented as a function \( ML \) that takes as input a configuration \( c \) and returns an estimated performance measure \( \hat{Y} \), i.e., \( ML: c \rightarrow \hat{Y} \) where \( ML \) is a machine learning model and \( \hat{Y} \) is the performance predicted by the ML model.

(iii) **Identifying the best configuration.** With the machine learning model from above, the performances of the remaining configuration samples are predicted. The configuration yielding the best performance is returned as being the optimum setting for the given software system.

### 2.2.1 Challenges with the current state-of-the-art

There are a number of challenges associated with using the methodology discussed above. Foremost among them is due to the stochastic sampling step. Since this sampling step precedes the construction of an ML model, the quality of samples directly affects the subsequent steps.

The problem with sampling arises due to the assumption that the configuration parameters \( p_i \) follow a uniform distribution. This assumption is fraught with risks—

1) Most of the time modeling might be spent exploring suboptimal regions of the configuration space \( \zeta \).
2) The machine learning model built with these samples tend to be severely biased. As a result, they often fail to identify the best configuration if it exists in the regions of the configuration space previously unseen.
3) Consequently, the optimum configuration identified by the ML model is at best only an estimate of the local optima.

Over configuration spaces that are relatively smaller in size, the problem listed above may not be a limiting factor. However, in the case of big data system such as Hadoop and Spark, the configuration space is often too large to ignore these limitations. Thus, in this paper we propose the use of a more judicious sampling scheme with the help of Markov Chain Monte Carlo (MCMC) augmented with an evolutionary search strategy. In the remainder of this section, we discuss our proposed approach in greater detail.

### 2.3 Markov Chain Monte Carlo (MCMC)

When the underlying distribution is unknown, generating samples that comply with the unknown distribution is difficult. To overcome this, we evaluated several heuristic-based optimization techniques including the derivative-free stochastic cyclic coordinate descent method [28] and a genetic algorithm. Having explored these methods, we discovered that a class of algorithms based on Markov Chain Monte Carlo (MCMC) are best suited for our purpose. In essence, MCMC based methods work by utilizing a Markov chain that has the unknown but desired target distribution as its equilibrium distribution. Then, by keeping track of the state transitions of the Markov chain, we may generate samples that resemble the desired distribution. As exemplified in Figure 2, with the increase in the number of state transitions (or steps taken by MCMC), the samples converge more closely to the desired distribution. A number of MCMC based methods exists in literature [29], [30], [31], [32]. For the purposes of this paper, we choose the Metropolis-Hastings algorithm [30], [33] as they are generally well suited for deriving samples from a high-dimensional distributions such as those encountered in configuration optimization.

In order to operationalize MCMC using the Metropolis-Hastings algorithm, we define the following three probability distribution functions:

(a) **Target distribution** \( p(c) \): This is the true probability distribution of the parameters in the configuration \( c \). This distribution is inherently unknowable.

(b) **Surrogate distribution** \( q(c) \): This is an approximate distribution that is proportional to the target distribution \( p(c) \). \( q(c) \) need not be accurate so long as it is proportional to \( p(c) \). In our case, since we don’t know the target distribution \( p(c) \), we follow the principle of maximum entropy [34], [35] to pick a distribution with the largest entropy. The parameters of the configurations always have a finite mean and a finite variance, in such cases the Gaussian distribution will have the maximum entropy relative to all other probability distributions. Thus, we use this as our surrogate distribution.

(c) **Proposal distribution** \( g(c_{t+1}|c_t) \): This is an arbitrary probability distribution function that generates a new configuration \( c_{t+1} \), given a current configuration \( c_t \). Note, since the next configuration at step \( t + 1 \), i.e., \( c_{t+1} \) depends on the immediate predecessor, i.e., \( c_t \), the current configuration at step \( t \), \( c_t \), this makes the sequence of samples belong to a first order Markov chain.

With these three distributions, the Metropolis-Hastings algorithm functions as follows:

1) **Generation:** Here, we use the previous configuration \( c_t \) and the proposal distribution \( g(c_{t+1}|c_t) \) to generate a new configuration sample \( c_{t+1} \).
2) **Acceptance/Rejection:** We compute the probability that the newly generated configuration \(c_{t+1}\) is accepted. This is known as the acceptance probability and is computed using:
\[
A(c_{t+1}|c_t) = \min \left[ 1, \frac{q(c_{t+1})}{q(c_t)} \right]
\]
3) **Transition:** Following this, if the new configuration \(c_{t+1}\) is accepted then we transition to the next state \(c_{t+1}\) from current state \(c_t\), i.e., \(c_t \rightarrow c_{t+1}\). Otherwise, we stay in the same state, i.e., \(c_t \rightarrow c_t\).
4) **Repeat:** The above three steps are repeated until a specified computing budget is exceeded [36].

We observe that, due to the probabilistic nature of acceptance \(A(c_{t+1}|c_t)\), if the new configuration \(c_{t+1}\) is more closer to the target distribution \(p(c)\) than the current configuration \(c_t\), i.e., \(p(c_{t+1}) > p(c_t)\), then we will always accept the new configuration. On the other hand, new configuration \(c_{t+1}\) is less closer to the target distribution, we will sometimes reject the new configuration. The farther away the new point is the target distribution, the more likely we are to reject it. However, since the acceptance probability is usually non-zero, we may sometimes accept some configurations that are not close to target distribution. This maintains the diversity among samples.

As the number of accepted samples increases, the MCMC sampling distribution eventually approaches the target configuration distribution. A good MCMC algorithm is designed to spend most of its time in the high-density region of the target distribution. Consequently, the samples of configurations obtained using MCMC are highly likely to contain the global optima among them. For a detailed description of MCMC, we guide interested readers to [37].

### 2.4 Evolutionary MCMC (EMCMC)

From above, we note that MCMC is inherently not an optimization method. Traditionally, MCMC uses an arbitrary proposal distribution \(q(c_{t+1}|c_t)\) to generate the next sample configuration \(c_{t+1}\) given the current sample \(c_t\). Often, initial candidate configurations are mostly discarded, as they are unlikely to belong to the target distribution. Thus, although MCMC converges, it does so only towards the target distribution; not towards the global optima we seek [38]. In other words, MCMC merely ensures that the samples of configurations are obtained from the most high-density, and therefore the most interesting, regions of the configuration space \(\zeta\). However, our objective is two-fold—not only do we seek to ensure the samples are interesting, but we also would like the samples to be near-optimal.

Therefore, we ought to modify the existing MCMC to behave as an optimization algorithm and not just a sampling algorithm. For this, we leverage the generation step in the Metropolis-Hastings algorithm discussed above. Since \(q(c_{t+1}|c_t)\) is an arbitrary distribution, it may be replaced by an alternative generation function so long as the Markov chain principle is respected, i.e., \(c_{t+1}\) is derived from \(c_t\).

In this paper, we propose a novel Evolutionary-MCMC algorithm (or EMCMC for short). Like evolutionary algorithms (such as genetic algorithms [39], [40], [41]), in EMCMC we start with an initial population of \(N > 1\) configurations. We then follow the steps listed below:

1) **Evolutionary Generation:** We measure the performance of the initial configurations, and pick a random subset of the measured configurations. For each configuration in the subset \(c_i\), we generate a new configuration \(c_{t+1}\) by applying (a) mutation; and (b) cross-over operations. That is:
   - **Mutation:** As described in §2.1, a configuration \(c\) is comprised many parameters \(p_i\). During mutation, some of these parameters are randomly changed (with allowed values) to form a new configuration, say \(c_{t+1}\).
   - **Cross-over:** We randomly selecting two parent configurations, from among all the \(c_i\) and \(c_i'\). Each configuration is bisected, i.e., divided in 2-parts. Then the first part of \(c_i'\) is spliced with the second part of \(c_i'\) and vice versa, generating two offspring configurations \(c_{t+1}\) and \(c_{t+1}'\).

2) **Acceptance or Rejection:** For each new configuration generated with the previous step, we compute the acceptance probability according to Equation 2.
3) **Transition:** Using the acceptance probability for each \(c_{t+1}\), we either retain those configurations, or we reject them. All the retained configurations are represent the next state of the EMCMC algorithm.
4) **Repeat:** The above process is repeated until we have exhausted the available budget.

#### 2.4.1 Why EMCMC is better?

It is worth noting that EMCMC offers some marked benefits over both traditional MCMC and genetic algorithms.

**Benefits over traditional genetic algorithms.** Ordinary genetic algorithms are susceptible to getting trapped at local optima [42]. This is because, in a regular genetic algorithms, a new configuration will never be accepted even if its performance is only a little worse than that of its parents and any worse configuration will always be discarded. In contrast, the acceptance or rejection of new configurations in EMCMC is contingent on the acceptance probability alone; this measures how closely the new configurations matches the target distribution and does not use the performance of configuration to make the distinction. This avoids a quick convergence to local optima and increases the chances of eventually reaching the global optima.

**Benefits over traditional MCMC.** As mentioned previously, MCMC is not an optimization algorithm. It only ensures that the configuration samples belong to an unknown target distribution. By using principles of evolutionary algorithms, EMCMC ensures that as the number of transitions increase the samples both belong to an unknown target distribution while also approaching the desired global optima.

### 3 ConEx: Configuration Explorer

Our approach is to use an EMCMC algorithm to sample Hadoop and Spark configuration spaces in search of high-performing configurations, using two additional tactics to reduce the sampling costs dramatically.

1) **Scale-up:** For cost-effectively sampling performance as a function of configuration during sampling processes, we run Hadoop and Spark jobs using inputs that are several orders of magnitude smaller (here, 100X) than those we expect to run in production.
2) **Scale-out:** To amortize the cost of sampling and profiling, we use a dynamic similarity measure of big data jobs to decide when good configurations found for one kind
of job might be used for another kind without any additional sampling activity.

We have implemented our approach in a tool called CONEX. The rest of this section describes our approach in detail.

Overview

Figure 3 presents an overview of CONEX. CONEX takes a big data job as input and outputs the best configuration it found before exceeding a sampling cost budget. CONEX works in three phases. In Phase-I, it reduces the feature space by filtering out the configuration parameters that are not relevant to performance. In Phase-II, it uses EMCMC sampling to find better configurations. Sampling starts with the default system configuration as the seed value. While sampling, CONEX discards invalid configurations generated during sampling using a checker developed by Tang et al. [43] (Phase-III). If a configuration is valid, CONEX runs a benchmark job using it and records the CPU time of the execution. It then compares the result with that of the best configuration seen so far, updating the latter if necessary, per our acceptance criterion (see Equation (2)). Accepted configurations are subjected to cross-over and mutation, as described in Section 2.4, to produce configurations for the next round of sampling. Once CONEX exceeds a pre-set sampling budget, it outputs the best configuration found so far. We now describe each of these steps in greater detail.

Phase-I: Pre-processing the configuration space

Hadoop and Spark have 901 and 212 configuration parameters, respectively (Table 2). Yet most do not affect performance. In this step, we reduce the dimensionality of the configuration space by filtering out the parameters that do not affect the performance—this is similar to standard feature selection technique in Statistics or Machine Learning [44]. We reduce the dimension two ways: we consider only parameters relevant to performance using our domain knowledge; and we select only a few values for sampling for each parameter.

Table 2: Configuration Space Characteristics

| System      | Total Parameters | Total | Bool | Int | Float | Categorical | String | Approx. Total |
|-------------|------------------|-------|------|-----|-------|-------------|--------|---------------|
| Hadoop v2.7.4 | 901              | 44    | 4    | 26  | 6     | 3           | 5      | 3 \times 10^{28} |
| Spark v2.2.0  | 212              | 27    | 7    | 14  | 4     | 2           | 0      | 4 \times 10^{16} |

The first part is manual, and based on a study of technical manuals and other work [45]. For example, we removed Hadoop parameters related to version (e.g., java.runtime.version), file paths (e.g., hadoop.bin.path), authentication (e.g., hadoop.http.authentication.kerberos.keytab), server-address, and ID/names (e.g., mapreduce.output.basename). For Spark, we selected parameters related to the runtime environment, shuffle behavior, compression and serialization, memory management, execution behavior, and scheduling. We ended up with 44 and 27 parameters to consider. See Table 2. We then finely sub-sampled the ranges of integer, float, and string types. In particular, we sub-sample the configuration space by defining small ranges of values for each parameter, varying by parameter type. Boolean parameters are sampled for true and false values. Numerical parameters are sampled within a certain distance from their default. Even these reduced configuration spaces are several orders of magnitude larger than those studied in previous work. For example, most systems studied by Nair et al. [19] have only thousands or at most a few million configurations. Table 2 summarizes the resulting configuration spaces that we dealt with for Hadoop and Spark.

Phase-II: Finding better configurations

This phase is driven by an EMCMC sampling strategy and implemented by Algorithms 1 to 3. Algorithm 1 is the main driver; Line 1 lists inputs and outputs. The algorithm takes a reduced configuration space (ζ) and a given job as inputs. CONEX samples configurations from ζ and evaluates their performance w.r.t. the input job. The routine also requires a seed configuration (confseed), and a termination criterion based on a maximum number of generations (max_gen). We choose max_gen = 30 in our experiment. The tool then outputs the best configuration found (confbest) and its performance (perfbest).

Lines 2, 4 and 5 and ?? initializes some parameters including setting the best configuration and performance to the respective seed values. Line 6 gets the first generation of configurations by randomly sampling n items from ζ. We choose n = 4D where D is the number of parameters, but it could be set to any reasonable value. Lines 9 to 18 are the main procedure for evaluating and evolving w.r.t. each configuration. Given a configuration confp, Line 10 records the job’s performance (perfp) and Line 11 decides whether to accept it based on Equation (2). This function is implemented in Algorithm 2. If accepted, Line 13 stores the accepted configuration to a list confsacepted, which later will be used in generating next-generation configurations (Line 20). If the accepted one is better than the best previously found, Lines 14 to 16 update the state accordingly.

Once all configurations in the first generation are processed, Line 19 computes the performance improvement achieved by this generation w.r.t. the seed performance. Next in Line 20, the algorithm prepares to enter the next generation by generating offspring configurations using cross-over and mutation operations (see Algorithm 3). Line 21 updates the generation number. This process repeats until the termination criterion is satisfied (Line 22). Finally, the last line returns the best found configuration and the corresponding performance.

Algorithm 3 is the evolution sub-routine of the EMCMC
algorithm, as described in Section 2.4. For preparing configurations of the next generation, it takes the best configuration found so far and a list of parent configurations as inputs. There are two main steps: cross-over and mutation. From the best configuration, Line 3 selects half of all parameters as cross-over parameters ($P_{crossover}$), and Line 4 identifies 6% of parameters as mutation parameters ($P_{mutate}$). Next, for each parent configuration, Line 6 exchanges the values of same parameters in two parents with $P_{crossover}$. Note that since the values of the same parameter is exchanged, their types are automatically preserved. It then randomly mutates the values of the mutation parameters at Line 7. The resulting offspring is added into the children set at Line 8. A set of new offspring configurations is returned at Line 10.

Algorithm 2 computes acceptance probabilities as described in Equation (2). It takes two performances as input: a current candidate under test and the best found so far, and returns whether to accept/reject the current candidate. First, Line 2 computes the performance improvement ($\Delta perf$) between the two. If the current configuration is worse than the best value, $\Delta perf$ will be negative. Next, Line 3 computes the acceptance probability of the configuration using an exponential function, which returns a positive value even if $\Delta perf$ is negative. Finally, the acceptance probability is compared with a random number sampled between 0 and 1 exclusively. Thus, even if a configuration is slightly worse than the best one, it still has some chance of being accepted.

Note that Equation (2) is a general concept of how to accept candidates given a distribution P. Algorithm 2 implements P with the exponential function. This is common as used in previous work [36].

**Phase-III: Configuration Validity Checking**

Configuration spaces are often not complete cross-product spaces. Rather, they are subsets defined by constraints on parameter values. A problem that we encountered is that validity constraints on Hadoop and Spark configurations are not well documented, nor statically enforced. For example, the type of Hadoop’s JVM options parameter is string, but not any string will do. The lack of constraint documentation and enforcement makes it easy to make configuration mistakes and also vastly increases sampling space sizes. We thus leveraged an off-the-shelf configuration constraint checker [43] that expresses and checks constraints using the dependent type theory of Coq [46]. It allowed us to avoid costly dynamic profiling of about 8% of all the configurations that we sampled.

## 4 Experimental Design

We implemented ConEx with about 4000 lines of Python code. The tool is available in a public Github repository: https://github.com/ChongTang/sysopt.

### 4.1 Study Subject and Platform

Table 2 summarizes the parameters and their types that we have studied for Hadoop v2.7.4 and Spark v2.2.0.

To evaluate ConEx, we selected big-data jobs from HiBench [25], a popular benchmark suite for big data frameworks. It provides benchmark jobs for both Hadoop and Spark. For Hadoop, we selected five jobs: WordCount, Sort, TeraSort, PageRank, and NutchIndex from the Micro and Websearch categories. These job types only need Hadoop to execute. Some other job types in the suite also require Hive or Spark. For Spark, we selected five Spark jobs: WordCount, Sort, TeraSort, RF, and SVD. HiBench has six different sizes of input workload for each type of job, from “tiny” to “Bigdata”. For our experiments, we used “small (320MB),” “large (3.2GB),” and “huge (32GB)” data inputs. Table 4b shows the CPU times taken by the Hadoop jobs running with default configurations. We used small inputs while sampling but then evaluated the resulting configurations using huge (100X larger) workloads. A HiBench execution has two steps: data preparation and job execution. We prepared the data manually to control the data used for each job.

We conducted our experiments in our in-house Hadoop and Spark clusters. Each had one master node and four slaves, each with an Intel(R) Xeon(R) E5-2660 CPU, 32GB memory, and local storage. We assigned 20GB of memory for Hadoop on each node in our experiments. We also made sure that no other programs were running except core Linux OS processes.

### 4.2 Job Classification

To test our scale-out hypothesis we needed a measure of job similarity. We settled on resource usage patterns rather than HiBench job types for this purpose. HiBench classifies jobs by business purpose (e.g. indexing and page rank jobs fall in Websearch category), which does not necessarily reflect similarity in resource usage patterns. Our approach is based on profiling of run-time behavior using system call traces. Similar approaches have been widely used in the security community [47], [48], [49]. We use a Unix command line tool, strace, to capture system call traces for this purpose.

Based on the system call traces, we represent each job by a four-tuple, $< A, B, C, D >$, where $A$ is a system call sequence, $B$ is a set of unique string and categorical arguments across all system calls, $C$ expresses term frequencies of string and categorical arguments captured per system call, and $D$ is the mean value of the numerical arguments per system call. Table 3 shows an example tuple.

To compute similarity between two jobs, we calculate similarities between corresponding tuple-elements separately. Each contributes equally to the overall similarity measure. For $A$, we use pattern matching—we slice the call sequences and compute the similarity between them. To find similarity between $B$ elements, we compute the Jaccard Index, which is a common approach to compute the similarity of two sets. For $C$ elements, we compute the average difference of each term frequency. Finally, for $D$ elements, we compute the similarity of mean value of numerical ar-

| Example System | Call Sequence |
|---------------|---------------|
| $A$           | $\{\text{foo, bar, foo, foo}\}$ |
| $B$           | $\{\text{foo : ("b", "c"), bar : ("b")}\}$ |
| $C$           | $\{\text{foo : ["b" : 0.66, \"c\" : 0.33], bar : ["b" : 1.0]}\}$ |
| $D$           | $\{\text{foo : [1st arg" : 2.0]}\}$ |
guments as 1 - abs(mean1, mean2)/max(mean1, mean2).
We take the average value of these four scores as the final similarity score between two jobs. We consider two jobs to be similar, if their similarity score is above 0.77 (i.e. from third quartile (Q3) of all the similarity scores).

4.3 Comparing with Baselines

We compare CONEX’s performance with three potentially competing approaches: (i) a random sampling strategy, (ii) a genetic algorithm-based optimization strategy, and (iii) a learning-based approach. The first one evaluates whether EMMC is a good sampling strategy, the second one checks EMMC’s ability to find a near-optimal configuration. The last one evaluates the choice of EMMC over a model-learning approach. Here, we compare CONEX with Nair et al.’s ranking based approach [50], which is most relevant for our problem.

4.4 Evaluation Criterion

Typically, performance optimization models are evaluated based on accuracy or error using measures such as Mean Magnitude of Relative error (abbreviated as MMRE). MMRE is calculated as follows:

\[
\text{MMRE} = \frac{\left| \text{predicted} - \text{actual} \right|}{\text{actual}} \cdot 100
\]

While seemingly intuitive, it has recently been shown that exact measures like MMRE can be somewhat misleading to assess configurations. There has been a lot of criticism leveled against MMRE. MMRE along with other accuracy statistics such as MBRE (which stands for Mean Balanced Relative Error) have been shown to cause conclusion instability [51], [52], [53].

Further, these accuracy measures are best suited for traditional machine learning based performance optimization models. Since this work takes a slightly different approach to performance optimization (using MCMC rather machine learning), we propose an alternative performance measure called performance gain.

Let the performances of a job with the default configuration be denoted as \( perf_d \). Let the best discovered configuration be defined as \( perf_p \). Then the performance gain \( \Delta \text{gain} \) measures the absolute improvement in the performance. It is computed as below: we measure the performance gain as

\[
\Delta \text{gain} = \frac{\text{perf}_d - \text{perf}_p}{\text{perf}_d}
\]

5 EXPERIMENTAL RESULTS

**RQ1. Can CONEX find configurations that are better than the baseline default configurations?**

The first research question seeks to provide a summary of the performance gains that can be achieved with the use of CONEX for three workloads: small, large, and huge of Hadoop and Spark jobs. Specifically, we explore different configurations using CONEX with smaller workloads (in RQ1-A); then we use the configurations obtained from the small workloads to check for performance gains of larger workloads, i.e., through scale-up hypothesis (in RQ1-B); and finally for different jobs that share similar dynamic characteristics (in RQ1-C).

**RQ1-A. How effective is CONEX in finding optimal configurations for small workloads?** We investigate this RQ for Hadoop by exploring the configuration space using small workloads. HiBench generates a detailed report after each
run, with performance information including CPU time. For Spark jobs, we intentionally refrained from using small workload. This is because, for small workloads, the the runtime in Spark was negligibly low compared the Hadoop. Therefore, in order to enforce a fair comparison, we used Spark “large” workloads, tailored to take as long as small jobs did in Hadoop (about 30 seconds per run). This ensures the cost of sampling are comparable between both systems.

Our findings are tabulated in Table 4a. The best configurations found by CONEX achieved between 7% to 72% improvements over the default configurations for five Hadoop jobs. On average, we notice a performance gain of 30.3% for Hadoop jobs operating on a small workload. For Spark jobs, CONEX produced 0.4% to 40.4% performance improvements for all five jobs with an average improvement of 10.6%. Thus, we conclude that:

**Result:** For Hadoop and Spark jobs with small workload, CONEX can find configurations that produce up to 72% and 40% performance gains over the default configurations in Hadoop and Spark respectively.

Even if CONEX manages to find a better configuration with smaller workloads, CONEX will be most effective if it can improve performance for larger workloads. It will obviate the need for making additional performance measurements thereby saving significant cost. We address this below.

**RQ1-B. How well does CONEX Scale-Up when exposed to much larger workloads?**

We investigate this RQ in two steps: (i) Evaluate the performance gain of Hadoop and Spark jobs using larger workload, and (ii) Perform a cost analysis to assess whether Scale-Up hypothesis can save configuration exploration cost.

(i) **Evaluating Performance Gain.** Here, with no additional sampling, we run the same HiBench jobs as used in RQ1-A, but now with “Large” and “Huge” inputs for Hadoop jobs—10X and 100X times larger workloads respectively (i.e. more than 3-GB and 30-GB inputs), to determine whether good configurations found for small jobs provide comparable benefits for much larger jobs.

To test for potential variations in scale-up performance (how well gains on small jobs scale up to similar gains on large jobs), we evaluated how well each of the top 50 best performing configurations found in the small-job RQ1 samples performed on the much larger data sets. Table 4a presents the results. For all five jobs, we see an average of 20.5% and 19% improvements under large and huge workloads. In fact, somewhat to our surprise, for WordCount, PageRank, and NutchIndex jobs, large workloads exhibited better performance gains than the improvements under the small ones used to find the improved configurations.

For scale-up evaluation of the Spark jobs, we used huge workload jobs as large data is used in the exploration phase (See Table 4a). We saw performance improvements for all five jobs, ranging from 1.6% to 16.8%. However, for Sort and SVD, there were limited improvements: 1.6% and 1.9% respectively. Spark jobs run very fast compared to Hadoop jobs. Although we have scaled up the workload 10 times, it seemed to be hard to achieve significant gains. Additional research is needed to better understand the scale-up potential of Spark jobs. Nevertheless, we saw an average performance improvement of 6.6%, which we still believe is significant if it holds in practice at this scale.

One could argue that running fifty production-scale jobs as a final step of our approach would significantly increase its costs and push out the point of break-even by many pro-
production runs. We therefore conducted a limited sensitivity analysis, plotting performance gains for each of the top fifty jobs. What we found was basically noise around the mean improvement with a low variance. The conclusion we reach based on our limited data is that simply picking the top candidate would not incur much opportunity cost, and in any case one could find a configuration very close to the best of fifty by sampling a small handful of top configurations.

(ii) Cost Analysis. The first three columns in Table 4b show the total execution time (in seconds) across the master-slave nodes for each Hadoop job while our test-bed is configured with default configurations. For example, WordCount under small workload takes about 33 seconds per cluster (166.2/5, where 5 is the number of nodes of our cluster). However, it takes around 1873 seconds with “huge” data, with the time difference of 1840 seconds. The last column shows the number of dynamic evaluations of sampled configurations before CONEX achieves the best configuration. Thus, for WordCount job, our scale-up strategy saves 1656 hours ((1873 − 33) * 3241 seconds) to find a better configuration using scale-up strategy. In total, for all the five jobs, the scale-up strategy saves about 9,600 hours or 39.6 times. In monetary terms, that amounts to about $12,480 on the AWS EMR service with m4.xlarge EC2 instances.

**Result:** Our data support the scale-up hypothesis: configurations found using small workloads as proxies for sampling production-scale performance do tend to produce significant performance improvements (from 10% to 20%, on average) for much larger workloads and thus, save significant amount of exploration cost.

Further exploration cost can be saved if our scale-out hypothesis holds, i.e. configuration found for one kind of job, A (e.g., Word Count), will also produce performance gains for a similar kind of job, B (e.g., Sort). Thus, we ask:

**RQ1-C. How well does CONEX Scale-Up when exposed to much larger workloads?** We test this RQ by evaluating performance gains for jobs of some job type, B, using configurations found for a job of some type, A, where the similarity between A and B is measured using Section 4.2. Among the five Hadoop jobs, we found WordCount, Sort, TeraSort to be highly similar, that PageRank is somewhat similar, and that NutchIndex has low similarity with this group. Table 4c shows the results of Scale-Out hypothesis.

For example, Section 5 shows that CONEX found a configuration for WordCount (WC) that improves its performance by 21.5%. When the same configuration is used for the similar target jobs: Sort, TeraSort, PageRank, the performance gains achieved (10.7%, 28.1%, and 20.6% respectively) are close to the improvements found by their own best configurations. However, for NutchIndex, which is not so similar, we see a performance gain of only 7.1%, while it achieved 14.2% gain while experimenting with its own best configuration. Similar conclusions can be drawn for Spark jobs (Section 5). A surprising outcome was that, in few cases, a better configuration found for one job, e.g., NutchIndex, yielded greater gains for another job, e.g., Sort (27.6%) than the gain achieved by its own improved configuration (15.8% for Sort). We have left the analysis of such surprising behavior for future work.

**RQ1-D. Which parameters have the highest impact on improving performance gain of CONEX?** Here we study how sensitive performance gains are w.r.t. individual configuration parameters. From each best-found configuration, we set the value of each parameter back to its default value leaving all other improved parameter values unchanged and check to see how much the performance reverts to the baseline.

For example, if $\text{perf}_{\text{det}}$ and $\text{perf}_{\text{best}}$ are the default and best performances (i.e., CPU times) obtained by CONEX for a job, then, the performance improvement is

$$\Delta_{\text{best}} = \frac{\text{perf}_{\text{det}} - \text{perf}_{\text{best}}}{\text{perf}_{\text{det}}}$$

Next, to measure how sensitive the gain is w.r.t. a parameter $p_i$, we set $p_i$’s value back to default without changing the other parameter values from the best configurations. We measure the new performance w.r.t. to the default; Thus, $\Delta_i = (\text{perf}_{\text{det}} - \text{perf}_{i})/\text{perf}_{\text{det}}$. Then the sensitivity of parameter $p_i$ is the difference of performance improvement:

$$\text{sensitivity}_{i} = \Delta_{\text{best}} - \Delta_i$$

We conducted this analysis for all the parameters one by one for the Hadoop benchmark jobs using “huge” workloads. Table 5 shows the results. The second row is the overall performance gain. The results suggest that performance improvement is sensitive to only few parameters. However, no single parameter is responsible for most of the improvement. That is,

**Result:** The influences of individual parameters are limited and that overall improvements arise from the combinations of, or interactions between, multiple parameters in the configuration.

1. We used a different cluster to do sensitivity analysis. So the overall performance could be slightly different from those in Table 4a.
Table 6: Performance* gain of EMCMC over Genetic Algorithm (GA) and Random Sampling for Hadoop jobs

| Job          | Genetic Algorithm | Random          |
|--------------|-------------------|-----------------|
|              | Small             | Large           | Huge            | Small | Large | Huge |
| WordCount    | 92.31%            | 58.38%          | 84.61%          | 123.21%| 61.66%| 47.26%|
| TeraSort     | 2.12%             | -32.81%         | 53.75%          | 18.98%| 44.53%| 16.96%|
| NutchIndex   | 26.85%            | -6.96%          | 15.09%          | 136.21%| 85.96%| 64.72%|
| PageRank     | 23.95%            | 62.26%          | 5.95%           | -31.83%| 29.31%| 18.96%|
| Average      | -0.67%            | 272.52%         | 77.75%          | 25.33%| 105.34%| 45.39%|

*Percentage performance improvement is computed as 

\[
p_{EMCMC} - p_{GA} / p_{GA}/random \times 100%
\]

Figure 5: EMCMC compares with other approaches in performance improvement for Hadoop Huge Workload.

These results suggest that, at least for Hadoop, higher-order interactions are present in the objective function and that these will need to be addressed by algorithms that seek high performing configurations. Also, further improvements in sampling efficiency might be possible by focusing on an smaller subset of performance-critical parameters. However, we leave this to be explored in our future work.

**RQ2. How does the EMCMC sampling strategy perform compared to random and evolutionary sampling?**

Here we compare EMCMC with (i) random and (ii) genetic algorithm (GA) based evolutionary sampling strategies. A random approach samples a parameter value from the uniform distribution, *i.e.* each value in the value range has the same probability to be selected. We have also implemented a GA based optimization strategy with the same cross-over and mutation strategies and the same fitness function as of EMCMC (See Section 2.4). For comparison, we run the baseline strategies to generate the same number of configurations and profile their performances with “Small” data sets. We then conduct the scale-out validation to evaluate the performance gain in larger workloads. Table 6 shows the performance gain of EMCMC over these two strategies.

In general, for all the jobs, EMCMC based sampling performed better. For example, on average, EMCMC performed 52.20% and 31.16% better than GA for large and huge jobs. In comparison to random sampling, EMCMC performed 105.34% and 45.39% better, on average. Figure 5 pictorially represents the results for “Huge” workload. The improvement of performance of EMCMC over GA also gives us an estimate of how much the evolutionary part of EMCMC contributes to CONEX’s performance.

**Result:** EMCMC based sampling strategy, on average, outperforms random (by upto 105%) and genetic algorithm (by up to 52%) based evolutionary sampling strategies to find better performing configurations for Hadoop.

**RQ3. How does CONEX perform compared to the state-of-the-art Machine Learning based configuration optimization approaches?**

To compare our approach with learning-based approaches, we choose previous work of Nair et al. [19] published in FSE 2017. We carefully choose this work as they also intended to find a near-optimal configuration rather than the best one, which is the most practical approach for big-data job. They used a rank-based performance prediction model to find better configuration. The authors argued that such a model works well when the cost of sampling is high, such as ours. They showed that compared to residual based approaches, their model saves a few orders of magnitude of sampling cost and achieves similar and even better results.

In their experiments with larger systems having millions of configurations (e.g. SQLite), the training pool covered 4500 configurations, including 4400 feature-wise and pairwise sampled and extra 100 random configurations. We used the same approach—we randomly collected the same number of configurations (e.g. of configurations (e.g. SQLite)), the training pool covered 4500 configurations, including 4400 feature-wise and pairwise sampled and extra 100 random configurations. We used the same approach—we randomly collected the same number of configurations as CONEX to profile their performances (similar to RQ4) and used them as training. We directly used the model published by Nair et al. As they did, we ran each model 20 times to find improved configurations.

For a fair comparison, following Nair et al., we evaluated both approaches by measuring rank difference (RD) between the predicted rank of a configuration and the rank of the training data (the profiled performance in our case). Table 7 shows the result. Here we ran each model 1000 times to get enough data for the descriptive analysis. The results show that although the minimum RD is 0, the average and maximum RDs are 13.2 and 408 respectively, and the standard deviation is 24.4. It means that this model could be largely wrong when trying to find high-performing configurations.

Table 7: Descriptive rank differences of 1000 tests

| Job      | Mean | Std  | Min | Max |
|----------|------|------|-----|-----|
| WordCount| 13.2 | 24.4 | 0   | 408 |
| Sort     | 28.7 | 42.6 | 0   | 391 |
| TeraSort | 14.3 | 19.1 | 0   | 171 |
| NutchIndex| 16.4 | 24.0 | 0   | 296 |
| PageRank | 9.5  | 16.7 | 0   | 158 |
None of the approaches we evaluated guarantee to find truly optimal configurations. So we discuss which approach can find the best candidate from all configurations checked. As we see from Table 7, although a learning-based approach can find good configurations, it cannot guarantee the resulting one is the best. In some cases, the ranking mistake could be as large as 408. On the other hand, our sampling-based approach can accurately find the best thanks to the dynamic evaluation and guided sampling strategy.

How much performance improvement one can gain by using Nair et al.'s approach? While our final goal is to improve system performance, we studied which approach can find better configurations, concerning how much performance one can gain. Suppose an engineer wants to use their approach to find a good configuration. She knows that all learning-based approaches have prediction errors. One possible way is to run such a model multiple times to rank configurations and then find the one with the best ranking in average across all tries. In this paper, we modified the tool released by Nair et al. to get the predicted ranking of configurations. We ran the above-described procedure 20 times and find out the configuration with the highest rank in average. The last bar in Figure 5 shows the performance improvement of the rank-based approach w.r.t. the default configuration. CONEX performs 5.4% to 1,700% better than the ranked-based approach across five Hadoop jobs.

To understand why Nair et al.’s approach doesn’t perform well in finding good Hadoop configurations, we studied the accuracy of the trained models. In their implementation, the ranked-based model wraps a decision tree regressor as the under-hood performance prediction model. We checked the $R^2$ scores of these regressors, and it turns out that all scores are negative for all five jobs. It means that the trained model performs arbitrarily worse. This is not surprising because Hadoop’s configuration space is complex, hierarchical, and high-dimensional; it is hard to learn a function approximating the objective function for such a space. A neural network based regression model might work better. However, that would incur more sampling cost to gather adequate training samples.

Result: Compared to Nair et al’s learning-based approach, our approach finds configurations with higher (from 5.4% to 1,700%) performance gains.

6 Related Work

The related work broadly fall under two categories: (i) tuning big-data systems, and (ii) tuning traditional software.

(i) Tuning big data framework. Starfish [54] is one of the initial works on Hadoop auto-tuning. It tunes parameters based on the predicted results of a cost model. However, the success of such a model depends largely on the underlying cost model, which is often hard to build. In fact, Liao et al. [55] have already proved that the predicted results of Starfish’s cost model could vary largely under different tasks settings. They used a vanilla GA with only six important parameters to identify high-value configurations and beat [54]. We empirically showed EMCMC strategy is performing better than a GA based approach. We further selected all parameters related to performance tuning, as without knowing how parameters interact, we cannot exclude any relevant parameter.

Another line of work by Babu et al. [56] tune MapReduce parameters by sampling data from actual production, and thus, they optimize a job given a cluster and a fixed workload. In contrast, CONEX is more suitable to configure clusters where diverse set of jobs are running. Our assumptions are more generic (e.g. scale-up and scale-out).

(ii) Tuning Generic Software. A large body of research exist on configuring generic software that use different sampling+learning strategies. The main challenge to apply them directly to our case is the cost of dynamic profiling at the scale of big-data and the complexity of the configuration space. Here we systematically summarize these related work.

Configuration Sampling. This step selects a subset of configurations based on different sampling strategies. For example, variations of random [12], [13], [27] sampling are used to draw configurations uniformly from the configuration space. We have shown that CONEX works much better than random sampling. Researchers also sampled test inputs targeting different regions [14], [57], or covering all the configurations satisfying some predefined constraints [15], [16], [17]. Kaltenecker et al. [18] further propose a distance-based sampling to sample the whole space uniformly. Since big-data configuration space is quite complex and huge than previously studied systems, partitioning the configuration space is challenging and will require a significant amount of dynamic traces. Further, uniform sampling from different regions may not be necessary if the configurations that will lead to better performance is sparse. Instead, EMCMC based sampling strategy theoretically can approximate the global configuration space, and we showed that the guided approach can help to find a near-optimal configuration. Sampling-based approaches often select invalid configurations [58]. To handle this problem, researches used constraint solvers to sample valid configurations [14], [59]. Instead, we used an off-the-shelf configuration constraint checker [43] (see Line 10).

Learning-based approaches. A large body of previous works estimates system performance by learning prediction models [7], [12], [19], [60], [61]. The accuracy of these models depends on the representativeness of training data. As shown in RQ5, for big-data systems, because of the complex high-dimensional configuration space, it is challenging to find a representative model. Also, collecting training samples is costly [21]. Existing logs from industrial uses of such systems are not necessarily useful as users tend to use default, or at least very few, configuration settings [1].

Learning-based approaches often encounter the effect of parameter interactions and they adopt different strategies to address them. For example, Zhang et al. [9] assume all Boolean parameters are independent and formulate the performance prediction as learning Fourier coefficients of a Boolean function. In contrast, Meinicke et al. [62] studied parameter interactions by running multiple configurations and comparing differences in control and data flow. Siegmund et al. [8] added interaction terms in learning models. We have also seen evidence of parameter interactions in RQ2. However, unlike learning-based approaches, our sampling
strategy is less affected as the strategy makes no assumptions about parameter interactions.

**Other Applications.** Many software engineering applications use sampling and optimization strategies in the past. For example, researchers used automated search to find valuable test cases [63], [64] and increase test coverage [65]. Weimer et al. [66] used genetic programming for program repair. Le [36] used MCMC techniques to generate program variants with different control- and data-flows. Whittaker and Thomason [67] used a Markov Chain model to generate test inputs to study software failure causes. Oh et al. [27] worked to find good configurations for software product lines. Vizier [68] was developed at Google for optimizing various systems like machine learning models. Our work demonstrates the promise of similar approaches for performance tuning of critical big-data systems.

There are some researches related to detecting software performance issues [69], [70]. However, finding a better configuration for performance improvement and identifying performance issues in software are orthogonal problems. Tăpăuș et al. [71] propose a distributed tool to optimize a system’s resource utilization. We are interested in gaining higher performance given such resource.

### 7 Threats to Validity

**Internal Validity.** Threats to the internal validity arise from the experimental setup. First, it is possible that the experimental results are affected by uncontrolled factors on hardware platforms. In our experiments, we adopted some strategies to mitigate such unseen factors. For example, we make sure that no other programs are running while we are running experiments. We also choose a subset of all parameters to study with domain knowledge. It is possible that we missed some important ones. To mitigate this threat, we referred to many previous works cited in this review paper [45] on Hadoop, and have included all parameters studied by other researchers in our parameter set.

**External Validity.** In this work, we report results only for Hadoop and Spark framework using 10 representative jobs. Since these two are most widely used big-data frameworks and we used a popular benchmark tool from Intel, we believe the results will be representative in other settings.

**Cost Saved.** With the scaled-down strategy, we saved about 9,600 hours for all five studied jobs. In monetary terms, that amounts to about $12,480 on the AWS EMR service with m4.xlarge EC2 instances. If one adopts the resulting configurations of our approach, she could start to save the cost of running jobs after reaching the break-even points. We got 21.5% improvement for the WordCount job in our experiment. That means one will start to save cost after five runs in production.

**Other Limitations.** In this work, we had a scalar objective function: CPU time for Hadoop and wall-clock time for Spark. Other applications may have multi-dimensional objectives, with trade-offs among multiple dimensions of performance. Evolutionary algorithms are known to perform less well in multi-attribute settings. In the general case of system design, one may have dozens of interacting quality attributes that contribute to system value. Whether techniques such as ours can be adapted to work in or such situations remains a question for further study.

**Threats from external factors.** Due to the nature of dynamic evaluation, it is possible that the experimental results are affected by uncontrolled factors on hardware platforms. In our experiments, we adopted some strategies to mitigate such unseen factors. For example, we make sure that no other programs are running on the experimental platform while we are running experiments. We also run each dynamic evaluation three times to get average performance as a final result.

**Threats in our approach.** In this work, we choose a subset of all parameters to study with domain knowledge. It is possible that we missed some important ones. To mitigate this threat, we referred to many previous works [45] on Hadoop, and have included all parameters studied by other researchers in our parameter set.

### 8 Conclusions

In this work, we proposed an EEMCMC-based sampling strategy in combination with scale-up and scale-out tactics to cost-effectively find high-performing configurations for big-data infrastructures. We conducted and have reported results from carefully designed, comprehensive, and rigorously run experiments. The data that emerged provides strong support for the hypothesis that our approach has strong potential to significantly and cost-effectively improve the performance of real-world big data systems. The data also strongly support the hypothesis that our approach outperforms several competing approaches.

In this work, we had a single scalar objective function for each system: reducing CPU time for Hadoop and wall-clock time for Spark. However, in reality, there might be tradeoffs between performance improvements and other constraints (e.g. cost). For example, user has to pay more money to Amazon EC2 for renting high performing systems. Whether techniques such as ours can be adapted to work in such situations remains a question for further study.

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