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# Towards a General Framework for ML-based Self-tuning Databases

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## Abstract

Machine learning (ML) methods have recently emerged as an effective way to perform automated parameter tuning of databases. State-of-the-art approaches include Bayesian optimization (BO) and reinforcement learning (RL). In this work, we describe our experience when applying these methods to a database not yet studied in this context: FoundationDB. Firstly, we describe the challenges we faced, such as unknown valid ranges of configuration parameters and combinations of parameter values that result in invalid runs, and how we mitigated them. While these issues are typically overlooked, we argue that they are a crucial barrier to the adoption of ML self-tuning techniques in databases, and thus deserve more attention from the research community. Secondly, we present experimental results obtained when tuning FoundationDB using ML methods. Unlike prior work in this domain, we also compare with the simplest of baselines: random search. Our results show that, while BO and RL methods can improve the throughput of FoundationDB by up to 38%, random search is a highly competitive baseline, finding a configuration that is only 4% worse than the, vastly more complex, ML methods. We conclude that future work in this area may want to focus more on randomized, model-free optimization algorithms.

## 1 Introduction

Optimizing the configuration space of database systems is crucial in improving the performance and latency experienced by their users, as well as for reducing their operational costs. However, optimizing the performance of a database system is far from trivial, since modern databases expose tens to few hundreds of tuning knobs, resulting in a high-dimensional exploration space with significant performance variability across configuration points. Over the last years, machine learning (ML) has emerged as a promising technique to automatically tune database configurations. Two state-of-the-art ML approaches to database tuning are Bayesian optimization (BO) [1] and reinforcement learning (RL) [2], implemented, among others, by the Ottertune [3] and CDBTune [4] systems, respectively. The ultimate goal of these systems is to optimize the performance of a database assuming as little intervention and domain knowledge as possible from the database administrator.

In this paper, we discuss the challenges we have faced, and the results we have obtained, in applying these two ML methods to tune FoundationDB, a distributed transactional database system that backs several critical workloads and cloud data services, such as Apple’s CloudKit [5], IBM Cloudant [6], and Snowflake [7]. We first show that applying existing ML self-tuning techniques to a new database, assuming little domain knowledge, poses several challenges; challenges that are typically overlooked or briefly discussed in related work, and are not accounted for by existing self-tuner prototypes. For example, we show that identifying valid ranges for the parameter values is a critical step in enabling the database tuning process. We also describe how we have overcome these challenges in order to effectively deploy these self-tuning methods on FoundationDB. Then, we analyze the effectiveness of

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the two methods in terms of the performance achieved by FoundationDB in transactions per second, and compare them with a random search baseline. We show that BO and RL methods perform similarly, both finding a configuration that can improve the average throughput of FoundationDB by 38% relative to the default configuration. However, we also show that even simple random search can find a configuration that is only 4% worse than the best configuration found by the, vastly more complex, ML methods. This result echoes recent findings in neural architecture search, that show that random search is competitive with more complex hyper-parameter tuning approaches [8].

Our experience provides twofold insights. First, research on ML-based approaches to self-tuning databases should not only focus on improving the quality of the employed ML models, but also on making the whole self-tuning process more robust and seamlessly applicable to diverse domains. Second, random search should always be considered as a baseline when evaluating a new approach, and new randomized approaches should receive more attention in future research works.

## 2 Background

**FoundationDB.** FoundationDB is an open-source, transactional, strongly consistent, distributed key-value store, and is used as a back-end data-platform for multiple data services. FoundationDB exposes more than 350 tuning knobs, which regulate the behavior of the system at several levels, including networking, storage, and transaction processing.

**Machine learning approaches.** We now introduce two among the most prominent ML approaches to database tuning, which are implemented by the solutions we investigate in this paper.

- *Bayesian optimization.* BO aims to optimize a target function that is unknown in closed form, and that is expensive to evaluate [1, 9]. BO fits a surrogate model of the function to observed points, and picks the next point to evaluate based on an acquisition function. In database tuning, the function to optimize is the database performance (e.g., throughput), and each function point corresponds to a database configuration. Ottertune [3] is a state-of-the-art database tuning system based on BO. It uses Gaussian processes to fit the surrogate model, and uses expected improvement (EI) as the acquisition function. EI carefully balances exploration (i.e., trying points of high uncertainty in the surrogate model) and exploitation (i.e., refining the search around known good points).

- *Reinforcement learning.* In RL an agent interacts with an environment with the goal of maximizing its reward. At every time step  $t$  the agent is in state  $s_t$  within the environment, performs action  $a_t$ , and receives reward  $r_t$ . In database tuning, the environment corresponds to the database system to tune; the state  $s_t$  encodes the internal metrics of the database at step  $t$  (e.g., free memory and resource utilization); an action corresponds to setting the knobs of the database to a specific set of values; the reward  $r_t$  is expressed as the improvement of the performance measured at step  $t$  over the performance of the database with the initial, default configuration. CDBTune [4] is a state-of-the-art database tuning system based on RL. It implements Deep Deterministic Policy Gradient (DDPG) [10], a recent RL algorithm based on neural networks.

## 3 Challenges and solutions

We now describe the challenges we faced in applying BO and RL to optimize FoundationDB, and how we mitigated them. We start by running the two techniques out-of-the-box as much as possible, and assuming as little knowledge as possible about the internals of FoundationDB.

### 3.1 Unknown tuning parameters and valid value ranges

The first step towards optimizing FoundationDB is identifying the parameters to tune and their value ranges. This is hard to do without domain knowledge. In previous work [11, 4, 3], the tuning parameters and their value ranges are determined by exploiting knowledge about the internals of the target database. FoundationDB exposes the tuning parameters and their default values in a few source files. From those files, we programmatically extract 350 tuning parameters and their default values. Setting the ranges for the parameters poses some challenges. On the one hand, defining small value ranges around the default values reduces the possibility of exploring some parameters widely enough, possibly leaving potential performance gains on the table. On the other hand, large value ranges around the default values increase the size of the domain, and hence the complexity of the optimization problem. In addition, as we have witnessed in FoundationDB, parameter values with a very large distance from the default ones are prone to define database configurations that are invalid – e.g., by setting a timeout so high that the database becomes non-responsive.

We resort to a heuristic in order to define the parameter value ranges without relying on domain knowledge. Specifically, for each parameter  $p$ , we define its domain as  $[d_p/x, d_p x]$ , where  $d_p$  is the default value of  $p$  and  $x$  is a scalar. For our tests, we set  $x = 10$ .

### 3.2 High-dimensional configuration space

After defining the domain of the optimization problem, we run BO and RL to maximize the performance of FoundationDB. To our surprise, both techniques fail to run successfully. These techniques, in fact, start by sampling at random the configuration space to fit an initial surrogate model of the FoundationDB performance function. However, they could not select any initial configurations to try that would result in a functional database deployment. Indeed, we argue that it is hard to pick randomly a valid configuration in a configuration space defined over 350 parameters, with unknown semantics and with highly intertwined performance and functionality dynamics. We note that this problem is not endemic to FoundationDB: the parameters of RocksDB, for example, can also be set in such a way that its internal data structures outgrow the available memory or storage resources [12].

To overcome the problem we decide to reduce the size of the domain space by performing feature selection. This, however, requires to sample the configuration space of FoundationDB, running again in the aforementioned problem. We mitigate this issue by sampling configurations in which we change only a subset of the parameters. We use a variant of Latin hypercube sampling [13] where the number of parameters with non-default value is 50. This number is high enough to capture joint performance dynamics of different parameters, and low enough to yield a high number of valid random configurations. By this approach, we successfully test 200 random configurations and gather initial training data. We use this data to perform feature selection using a random forest regressor, and select the most impactful parameters according to the ranking output by the regressor. Similarly to recent work [11], we find that a few parameters (10 in our case) account for the vast majority (90 % in our case) of the overall importance score. Hence, we use only these knobs to run the optimization phase of the two database tuning approaches.

## 4 Experimental results

We now describe the results we obtain when running the two self-tuning techniques. Figure 1 depicts the full optimization pipeline we execute.

**FoundationDB.** We use FoundationDB 6.2.20, using three server machines and two client machines. The machines are equipped with Intel(R) Xeon(R) CPU E5-2690 @ 2.90GHz CPUs, 251Gi of RAM, run Ubuntu 19.10 with a 5.3 Linux kernel, and are connected over a 100GBps network. We load the database with 1M key-value pairs. Each key is 16 bytes, and each value is 512 bytes. The clients generate transactions composed of 5 operations, according to a 60:40 read:write mix, and select keys according to a uniform random distribution.

**ML techniques.** We use CDBTune to evaluate the RL-based approach, by adapting the code available at [14]. To evaluate the BO-based approach we use the BO implementation of scikit-optimize [15]. We configure the BO algorithm to use Gaussian processes, as in Ottertune. Last, we evaluate a random search approach based on scikit-optimize. We let the three techniques run for 200 steps; we repeat each optimization process three times. Running the experiments took a total of 9 days.

**Results.** In Figure 2a we report the best throughput achieved (in thousands of transactions per second) as a function of the number of optimization steps, averaged over the three repetitions. We observe that BO and RL have a similar behavior, finding a configuration with a higher throughput than random

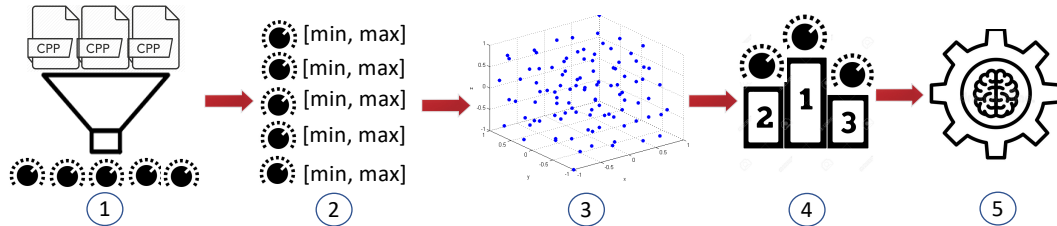


Figure 1: Optimization pipeline. (1) Extraction of the tuning parameters from source code. (2) Definition of value ranges. (3) Random sampling of the configuration space. (4) Feature selection. (5) ML-based self-tuning.

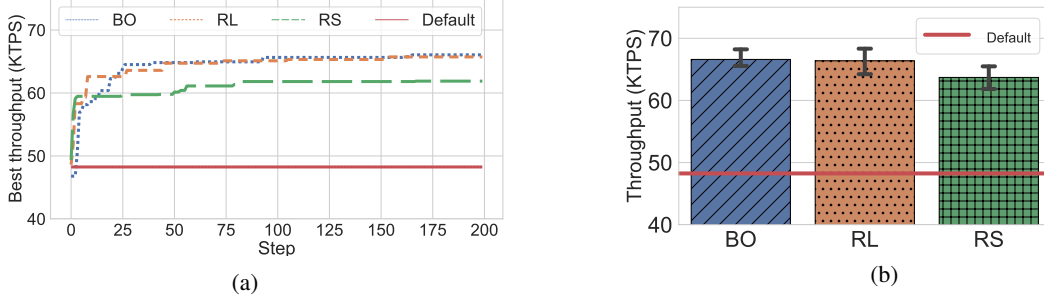


Figure 2: (a) Throughput of the best configuration found over time (average of the three runs). (b) Average throughput and standard deviation corresponding to the best configurations identified by each optimization method.

search. Since evaluating the throughput of a given configuration is inherently noisy, we then took the best configuration found by each optimization run and re-evaluated it 5 times to obtain a more reliable estimate of the throughput, resulting in a total of 15 measurements for each optimization method. We report in Figure 2b the mean throughput and standard deviation achieved. We observe that, while BO and RL achieve a mean throughput of around 66 KTPs (38% better than the default configuration), simple random search achieves a mean throughput of 63.7 KTPs, which is only around 4% lower. In fact, when we apply the standard two-sided pairwise t-test we find that the null hypothesis (i.e., that there is no statistical difference between the configurations) cannot be rejected when comparing the configuration found by random search with that found by BO ( $p > 0.10$ ) and RL ( $p > 0.17$ ).

## 5 Discussion and Conclusions

We now describe the main insights we obtain from our study, and we outline some research directions.

**i) The research community should focus on building self-tuning frameworks that work with as little knowledge as possible about the target database.** The main focus of existing research works is to identify the ML technique that achieves the best performance for a specific database taken as a use-case. We have shown, however, that there are challenges to the adoption of such techniques when applied to a new database. These challenges can jeopardize the optimization process altogether, making the effectiveness of the employed ML model a second-order concern. Crucially, overcoming these challenges requires knowledge about the target database. We advocate that a primary goal of researchers should be making the adoption of self-tuning techniques easily applicable to new databases, without requiring domain knowledge, with the ultimate goal of delivering push-button optimization to the ordinary user. Achieving this goal requires solving several issues, including automatically identifying the tuning parameters, determining their domains and inferring valid value ranges, or designing optimization algorithms that are robust in the face of unknown ranges [16, 17].

**ii) Databases should be built with self-tuning in mind.** Database are extremely complex systems, and hence they are very hard to tune as a black box. We advocate that databases should be built from the ground up with the goal of being amenable to self-tuning. For example, database designers could annotate tuning knobs to expose them, and could define valid value ranges. The designers should also encode invariants that have to be maintained among parameters (e.g., one parameter has to be lower than another one), and specify when tuning a certain parameter has implications not only on performance but also on correctness (e.g., consistency and fault tolerance tuning knobs).

**iii) Model-free approaches warrant more attention.** Our results indicate that random search is a competitive baseline in the context of self-tuning databases, achieving results comparable to more complex ML techniques such as BO and RL. Similar results have been shown in recent work on hyper-parameter tuning [8], and random search is in general considered as a standard baseline by the ML community [18]. However, random search is often not considered in the evaluation of frameworks that use ML to optimize databases [3, 4]. We argue that random search should always be considered as a baseline, since it helps to put performance gains into perspective. Random search is also relatively easy to use since it is *model-free*: it makes no assumptions regarding the structure of the unknown function being optimized. In contrast, ML approaches such as BO and RL both rely on some mathematical model (typically Gaussian processes or neural networks respectively) leading to hyper-parameters that must be tuned. Our results also suggest that other model-free optimization algorithms, such as successive halving [19] and Hyperband [20], may be of significant interest in the context of self-tuning databases.

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