Facilitating Database Tuning with Hyper-Parameter Optimization: A Comprehensive Experimental Evaluation

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ABSTRACT

Recently, using automatic configuration tuning to improve the performance of modern database management systems (DBMSs) has attracted increasing interest from the database community. This is embodied with a number of systems featuring advanced tuning capabilities being developed. However, it remains a challenge to select the best solution for database configuration tuning, considering the large body of algorithm choices. In addition, beyond the applications on database systems, we could find more potential algorithms designed for configuration tuning. To this end, this paper provides a comprehensive evaluation of configuration tuning techniques from a broader perspective, hoping to better benefit the database community. In particular, we summarize three key modules of database configuration tuning systems and conduct extensive ablation studies using various challenging cases. Our evaluation demonstrates that the hyper-parameter optimization algorithms can be borrowed to further enhance the database configuration tuning. Moreover, we identify the best algorithm choices for different modules. Beyond the comprehensive evaluations, we offer an efficient and unified database configuration tuning benchmark via surrogates that reduces the evaluation cost to a minimum, allowing for extensive runs and analysis of new techniques.

1 INTRODUCTION

Modern database management systems (DBMSs) have hundreds of configuration knobs that determine their runtime behaviors [16]. Setting the appropriate values for these configuration knobs is crucial to pursue the high throughput and low latency of a DBMS.
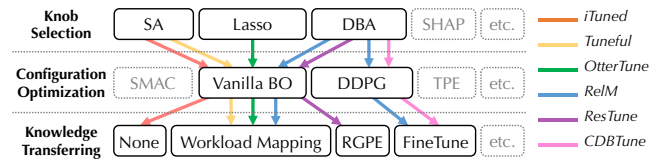
Figure 1: Algorithm Choices of Configuration Tuning Systems: Black boxes denote the algorithms adopted by existing database tuning systems (indicated by colored paths), and grey boxes denote the algorithms in the HPO field.

Given a target workload, configuration tuning aims to find configurations that optimize the database performance. This problem is proven to be NP-hard [79]. To find a promising configuration for the target workload, database administrators (DBAs) put significant effort into tuning the configurations. Unfortunately, manual tuning struggles to handle different workloads and hardware environments, especially in the cloud environment [67]. Therefore, automatic configuration tuning attracts intensive interests in both academia and industry [3, 17, 42, 58, 74, 75, 77, 93, 99].

Recently, there has been an active research area on automatically tuning database configurations using Machine Learning (ML) techniques [4, 19, 25, 30, 46, 50, 58, 96, 98]. We summarize three key modules in the existing tuning systems: *knob selection* that prunes the configuration space, *configuration optimization* that samples promising configurations over the pruned space, and *knowledge transfer* that further speeds up the tuning process via historical data. Based on the techniques used in *configuration optimization* module, these systems can be categorized into two major types: Bayesian Optimization (BO) based [4, 19, 25, 98] and Reinforcement Learning (RL) based [50, 96] systems. Owing to these efforts, modern database systems are well-equipped with powerful algorithms for configuration tuning. Examples includes Lasso algorithm in OtterTune [4], Sensitivity Analysis (SA) in Tuneful [25] for automatic *knob selection*; Bayesian Optimization (e.g., iTuned [19], ResTune [98]), Reinforcement Learning (e.g., CDBTune [96], Qtune [50]) for *configuration optimization*; and workload mapping in OtterTune, RGPE [27] in ResTune [98] for *knowledge transfer*. The various algorithms in each module of the configuration tuning systems enrich the solutions for database optimization and demonstrate superior performance and efficiency compared to manual tuning.

1.1 Motivation

Whilst a large body of methods have been proposed, a comprehensive evaluation is still missing. Existing evaluations [4, 19, 50, 96, 98]

compare tuning systems from a macro perspective, lacking analysis of algorithm components in various scenarios. This motivates us to conduct a comprehensive comparative analysis and experimental evaluation of database tuning approaches from a micro perspective. We now discuss the issues of the existing work.

M1: Missing comparative evaluations of intra-algorithms in different modules. Emerging database tuning systems are characterized by new intra-algorithms (i.e., algorithms in each module) such as OtterTune with Lasso-based knob selection and workload mapping, CDBTune with DDPG optimizer, ResTune with RGPE transfer framework. Figure 1 plots the three key modules and the corresponding intra-algorithms we extracted from the designs of these systems. When designing a database tuning system, we can construct many possible "paths" across the intra-algorithm choices among the three modules, even not limited to existing designs. For example, each *knob selection* algorithm determines a unique configuration space and can be "linked" to any of the *configuration optimization* algorithms. Given so many possible combinations, it remains unclear to identify the best "path" for database configuration tuning in practice. Existing researches focus on the evaluation of the entire tuning systems [4, 25, 96] or limited intra-algorithms in some of the modules [5], failing to reveal which intra-algorithm contributes to the overall success. For example, the choice of intra-algorithms in *knob selection* module is often overlooked, yet important, since different algorithms can lead to distinct configuration spaces, affecting later optimization. To this end, it is essential to conduct a thorough evaluation with system breakdown and fine-grained intra-algorithm comparisons.

M2: Absence of analysis for high-dimensional and heterogeneous scenarios. There are two challenging scenarios for configuration optimization: *high dimensionality* and *heterogeneity* of configuration space. DBMS has hundreds of configuration knobs that could be continuous (e.g., *innodb_buffer_pool_size* and *tmp_table_size*) or categorical (e.g., *innodb_stats_method* and *innodb_flush_neighbors*). We refer to the scenario with knobs of various types as *heterogeneity*. And, the categorical knobs vary fundamentally from the continuous ones in differentiability and continuity. For instance, existing BO-based methods tend to yield the best results for low-dimensional and continuous spaces. However, as for the high-dimensional space, they suffer from the over-exploration issue [73]. In addition, vanilla BO methods assume a natural ordering of input value [86], thus struggling to model the heterogeneous space. Consequently, when analyzing the optimizers, it is essential to compare their performance under the two scenarios.

M3: Limited solution comparison without a broader view beyond database community. The database configuration tuning is formulated as a black-box optimization problem over configuration space. Thanks to the efforts of recent studies, today's database practitioners are well-equipped with many techniques of configuration tuning. However, when we look from a broader view, we can find plenty of toolkits and algorithms designed for the black-box optimization, especially hyper-parameter optimization (HPO) approaches [7, 32, 52, 62, 87, 94]. HPO aims to find the optimal hyper-parameter configurations of a machine learning algorithm as rapidly as possible to minimize the corresponding loss function. Database configuration tuning shares a similar spirit with HPO

since they both optimize a black-box objective function with expensive function evaluations. We notice that recent advances in HPO field have shown promising improvement in high-dimensional and heterogeneous configuration spaces [23, 37, 40, 89, 91]. Despite their success, such opportunities to further facilitate database configuration tuning have not been investigated in the literature.

M4: Lack of cheap-to-evaluate and unified database tuning benchmarks. Evaluating new algorithms in database tuning systems can be costly, time-consuming, and hard to interpret. It requires DBMS copies, computing resources, and the infrastructure to replay workloads and the tools to collect performance metrics. It takes dozens of hours to conduct a single run of optimization with ceaseless computing resources. Moreover, obtaining a sound evaluation of more baselines takes several-fold times longer with expensive computing costs. In addition, the database performance can fluctuate across instances of the same type even though the configuration and workload are the same [5]. Therefore, we cannot run the optimizers in parallel to reduce the evaluation time, making the evaluation more troublesome. These problems pose a considerable barrier to the solid evaluation of database tuning systems. An efficient and unified tuning benchmark is needed.

1.2 Our Contributions

Driven by the aforementioned issues, we provide comprehensive analysis and experimental evaluation of database configuration tuning approaches. Our contributions are summarized as follows:

C1. We present a unified pipeline with three key modules and evaluate the fine-grained intra-algorithms. For **M1**, we break down all the database tuning systems into three key modules and evaluate the corresponding intra-algorithms. We evaluate and analyze each module's intra-algorithms to answer the motivating questions: *(1) How to determine tuning knobs? (2) Which optimizer is the winner? (3) Can we transfer knowledge to speed up the target tuning task?* With our in-depth analysis, we identify design trade-offs and potential research opportunities. We discuss the best "paths" across the three modules in various scenarios and present all-way guidance for configuration tuning in practice.

C2. We construct extensive scenarios to benchmark multiple optimizers. For **M2**, we construct specific evaluations and carry out comparative analysis for the two challenges. For *high dimensionality*, we conduct evaluations of the optimizers over configuration spaces of three sizes: small, medium, and large. We specifically analyze the different performances when optimizing over small/medium and large configuration spaces. For *heterogeneity*, we construct a comparison experiment with continuous and heterogeneous configuration spaces to validate the optimizers' support for *heterogeneity*. Such evaluation setting assists us in better understanding the pros and cons of existing database optimizers.

C3. Think out of the box: we apply and evaluate advanced HPO techniques in database tuning problems. For **M3**, we survey existing solutions for black-box optimization. We find that many recent approaches in the HPO field could be borrowed to alleviate the challenges in database tuning. Therefore, besides the configuration tuning techniques proposed in the database community, we also evaluate other advanced approaches in the HPO field under the same database tuning setting. Through evaluations,

| Category	Configuration Tuning System	Application	Design Highlight
BO-based	iTuned [19]	Performance tuning for DBMS	First adopting BO
	OtterTune [4]	Performance tuning for DBMS	Incremental knob selection, workload mapping
	Tuneful [25]	Performance tuning for analytics engines	Incremental knob selection via Sensitivity Analysis
	ResTune [98]	Resourse-oriented tuning for DBMS	Adopting RGPE to transfer historical knowledge
	RelM [46]	Memory allocation for analytics engines	Combining white-box knowledge
	CGPTuner [15]	Performance tuning for IT systems	Adopting Contextual BO to adapt to workload variation
RL-based	CDBTune [96]	Performance tuning for DBMS	First adopting DDPG
	QTune [50]	Performance tuning for DBMS	Supporting three tuning granularities
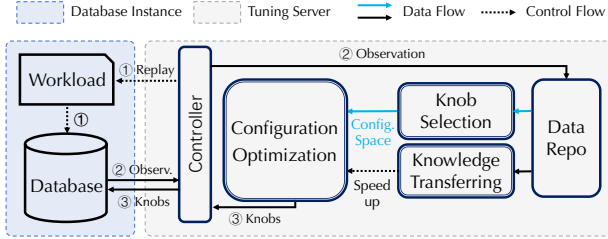
Figure 2: Architecture of Configuration Tuning System.

we have that the best knob selection approach achieves 38.02% average performance improvement, and the best optimization approach achieves 21.17% average performance improvement as well as significant speedup compared with existing methods. We demonstrate that database practitioners can borrow strength from the HPO approaches in an out-of-the-box manner.

C4. We define an efficient database configuration tuning benchmark via surrogates. We summarize the difficulties discussed in **M4** lie in the cost and fluctuation of performance evaluations under configurations. We propose benchmarking database configuration tuning via a regression surrogate that approximates future evaluations through cheap and stable model predictions [22]. Specifically, we train regression models on *(configuration, performance)* pairs collected in an expensive offline manner and cheaply evaluate future configurations using the model's performance predictions instead of replying workloads. The tuning benchmark offers optimization scenarios that share the same configuration spaces and feature similar response surfaces with real-world configuration tuning problems. Significantly, it reduces the evaluation cost to a minimum and achieves 150~311 × overall speedup. The benchmark is publicly available to facilitate future research. With the help of the benchmark, researchers can skip time-consuming workload replay, conduct algorithm analysis and comparison efficiently, and test new algorithms with few costs.

The rest of the paper is organized as follows: Section 2 introduces the preliminaries of this paper, demonstrating the taxonomy and workflow of existing database tuning systems as well as the background knowledge for HPO. Next, we present a survey on algorithms for the three modules in Section 3 and describe the general setup in Section 4. Then, the experimental analysis are presented in Sections 5-7, followed by the the database tuning benchmark in Section 8. We summarize the lessons learned and research opportunities in Section 9. Finally, we conclude the paper.

2 PRELIMINARIES

We first formalize the database configuration tuning problem. Then we review the architecture and workflow of database configuration tuning systems and present the taxonomy and description about the existing systems. Finally, we introduce the background of hyperparameter optimization.

2.1 Problem Statement

Consider a database system having configuration knobs $\theta_1, \ldots, \theta_m$, we define its configuration space $\Theta = \Theta_1 \times \cdots \times \Theta_m$, where $\Theta_1, \ldots, \Theta_m$ denote their respective domains. A configuration knob θ can be continuous or categorical. We denote the database performance metric as f which can be any chosen metric to be optimized, such as *throughput*, *99%th percentile latency*, etc. Given a workload and a specific configuration $\boldsymbol{\theta}$, the corresponding performance $f(\boldsymbol{\theta})$ can be observed after evaluating it in the database. We denote the historical observations as $H_t = \{(\boldsymbol{\theta_i}, y_i)\}_1^t$. Assuming that the objective is a maximization problem, database configuration tuning aims to find a configuration $\boldsymbol{\theta}^* \in \Theta$, where

$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta} \in \Theta} f(\boldsymbol{\theta}). \tag{1}$$

2.2 System Overview and Workflow

The database configuration tuning systems share a typical architecture as shown in Figure 2. The left part shows the target DBMS and the replayed workload. The right part represents the tuning server deployed in the backend tuning cluster. The tuning server maintains a repository of historical observations from tuning tasks. The controller monitors the states of the target DMBS and transfers the data between the DBMS side and the tuning server side. It conducts stress testing to the target DBMS through standard workload testing tools (e.g., OLTP-Bench [18]) or workload runner that executes the current user's real workload [76]. There are three main modules in the tuning system: (1) *knob selection*, (2) *configuration optimization*, (3) *knowledge transfer*. The *knob selection* module prunes the configuration space by identifying important knobs. The pruned configuration space is passed to the optimizer, which suggests a promising configuration over the pruned space at each iteration. Furthermore, the *knowledge transfer* module speeds up the current tuning task by borrowing strength from past similar tasks stored in the data repository or fine-tuning the optimizer's model.

The *configuration optimization* module functions iteratively, as shown in the black arrows: (1) The controller replays the workload to conduct stress testing. (2) After the stress testing finishes, the performance statistics are uploaded to the data repository, and is used

for updating the model in the configuration optimizer. Optionally, the knowledge transfer module can speed up the optimization with historical observations. (3) The optimizer generates a promising configuration over the pruned configuration space, and the configuration is applied to the target DBMS through the controller. The above procedures repeat until the model of the optimizer converges or stop conditions are reached (e.g., budget limits).

2.3 Taxonomy

Table 1 presents a taxonomy of existing configuration tuning systems with ML-based techniques. We classify the systems into two classes based on the algorithms of their optimizers: (1) BO-based systems and (2) RL-based systems.

2.3.1 <u>*BO-based*</u>. The existing BO-based systems adopt BO to model the relationship between configurations and database performance. They follow BO framework to search for an optimal DBMS configuration: (1) fitting probabilistic surrogate models and (2) choosing the next configuration to evaluate by maximizing acquisition function.

iTuned [19] first adopts vanilla BO models to search for a well-performing configuration. It uses a stochastic sampling technique – Latin Hypercube Sampling [63] for initialization and does not use the observations collected from previous tuning sessions to speed up the target tuning task.

OtterTune [4] selects the most impactful knobs with Lasso algorithm, and increases the size of configuration space incrementally. It proposes to speed up the target tuning by a transfer framework via workload mapping. Concretely, it re-uses the historical observations of a prior workload by mapping the target workload based on the measurements of internal metrics in DBMS.

Tuneful [25] proposes a tuning cost amortization model and demonstrates its advantage when tuning the recurrent workloads. It conducts incremental knob selection via Gini score as an importance measurement to gradually decrease the configuration space. Similar to OtterTune, it also adopts the workload mapping framework to transfer knowledge across tuning tasks.

ResTune [98] defines a resource-oriented tuning problem and adopts a constrained Bayesian optimization solver. It uses an ensemble framework (i.e., RGPE) to combine workload encoders across tuning tasks to transfer historical knowledge.

RelM [46] is designed to configure the memory allocation for distributed analytic engines, e.g., Spark. It builds a white-box model of memory allocation to speed up Bayesian Optimization.

CGPTuner [15] proposes to tune the configuration of an IT system, such as the Java Virtual Machine (JVM) or the Operating System (OS)) to unlock the full performance potential of a DBMS. It adopts Contextual BO [45] to adapt to workload variation, which requires an external workload characterization module.

2.3.2 <u>*RL-based*</u>. RL-based systems adopt Deep Deterministic Policy Gradient (DDPG), which is a policy-based model-free reinforcement learning agent. It treats knob tuning as a trial-and-error procedure to trade-off between exploring unexplored space and exploiting existing knowledge.

CDBTune [96] first adopts DDPG algorithm to tune the database. Its tuning agent inputs internal metrics of the DBMS and outputs

Table 2: Importance Measurements in Knob Selection.

Measure	Category	Brief Description
Lasso [84]	Variance based	Based on coefficient of linear regression, effective for when existing irrelevant features.
Gini score [65]	Variance based	Based on the times a feature is used in tree splits, successful in high-dimensional feature selection.
fANOVA [38]	Variance based	Decomposing the variance of the target function, commonly used in the HPO field.
Ablation analysis[13]	Tunability based	Comparing feature difference between configurations, straightforward and intuitive.
SHAP [56]	Tunability based	Decomposing the performance change additively, solid theoretical foundation derived from game theory.

proper configuration by modeling the tuning process as a Markov Decision Process (MDP) [9].

QTune [50] supports three tuning granularities, including workload-level tuning, query-level tuning, and cluster-level tuning. It embeds workload characteristics to predict the internal metrics for query-level tuning, and clusters the queries based on their "best" knob values for cluster-level tuning.

Scope Illustration. To make our evaluation focused yet comprehensive, we employ some necessary constraints. We focus on evaluating the configuration tuning techniques at the workload level since query-lever or cluster-lever tuning are only available on QTune. In this paper, we concentrate on performance tuning in DBMS. As for the systems targeting the other applications (i.e., performance tuning for analytic engines, resource-oriented tuning), we implement their core techniques (e.g., RGPE transfer framework) and evaluate them in a unified setting.

2.4 Hyper-Parameter Optimization

HPO aims to find the hyper-parameter configurations λ^* of a given algorithm A^i with the best performance on the validation set [31]:

$$\lambda^* = \arg\min_{\lambda \in \Lambda_i} L(A^i, \lambda). \tag{2}$$

HPO is known as black-box optimization since nothing is known about the loss function besides its function evaluations. BO has been successfully applied to solve the HPO problem [8, 60, 90]. The main idea of BO is to use a probabilistic surrogate model to describe the relationship between a hyper-parameter configuration and its performance (e.g., validation error), and then utilize this surrogate to guide the configuration search [72]. It is common to use Gaussian processes (GP) as surrogates [61, 76] and SMAC [37] and TPE [10] are two other well-established methods.

3 METHODOLOGIES

In this section, we survey the methodologies for the three components, respectively. We not only cover the techniques used in existing configuration tuning systems for DBMS but also discuss the representative approaches from the HPO field.

3.1 Knob Selection

The *knob selection* module identifies and selects important knobs to tune. Although the database system has hundreds of knobs, not all of them significantly impact database performance [82]. Selecting important knobs can prune the configuration space and further accelerate configuration optimization.

To conduct knob selection, we first need to collect a set of observations under different configurations. Given the observations, we adopt an algorithm to rank the knobs in terms of their importance. (We refer to the ranking algorithm as "importance measurement" to distinguish it from the other techniques.) Finally, the configuration space is determined by selecting the top-k knobs according to the importance rank. There are various choices for importance measurements, leading to distinct configuration spaces and affecting later optimization. They can be classified into two categories as shown in Table 2: *variance-based* measurements and *tunability-based* measurements [92]. *Variance-based* measurement selects the knobs that have the largest impact on the database performance. It has been adopted by existing tuning systems for DBMS. *Tunability-based* measurement [69] quantifies the tunability of a knob, measuring the performance gain that can be achieved by tuning the knob from its default value. It has been applied successfully to determine the importance of hyper-parameters of ML algorithms, especially when given a well-performing default configuration [92].

3.1.1 Variance-based Measurements. We introduce three variance-based measurements due to their widely-used applications and representativeness, including Lasso [84] adopted in OtterTune, Gini score [65] adopted in Tuneful, and functional ANOVA [38], a state-of-the-art importance measurements from the HPO domain.
Lasso [84] uses the coefficient of linear regression to assess the importance of knobs. It penalizes the L1-norm of the coefficients and forces the coefficients of redundant knobs to be zero. The L1-norm penalization makes Lasso effective when there are many irrelevant knobs in the training samples [20]. However, Lasso assumes the linearity of the knob space [44] and is not able to capture the non-linear dependencies from knobs to the performance metric.
Gini Score [65] is derived from tree-based models, like random forest model [80]. The Gini score of each knob is defined as the number of times the given knob is used in a tree split across all the trees since important knobs discriminate the larger number of samples and are used more frequently in tree splits. Gini score has been successfully applied to high-dimensional feature selection [64].
fANOVA [38] (i.e., Functional analysis of variance) measures the importance of knobs by analyzing how much each knob contributes to the variance of the target function across the configuration space. Based on a regression model (e.g., random forest), functional ANOVA decomposes the target function into additive components that only depend on subsets of its inputs. The importance of each knob is quantified by the fraction of variance it explains. Functional ANOVA is commonly used in the HPO domian due to its solid theoretical foundation [35, 57, 85].

3.1.2 Tunability-based Measurements. While *Variance-based* measurements are interested in the global effect of a knob, *tunability-based* measurements focus on "good" regions of the space which are better than the default configuration. It can be used directly to determine the necessity of tuning a knob from the given default value. We introduce two typical local algorithms that can measure the tunability – ablation analysis [13] and SHAP [56].
Ablation Analysis [24] selects the knob whose change contributes the most to improve the performance of configurations. It identifies the difference between configurations by modifying each knob

Table 3: Algorithms for Optimizers. ✓means the optimizer has specific design for the case in the column and – means the optimizer does not have such design.

Algorithm	High-dimensionality	Heterogeneity
Vanilla BO	–	–
One-Hot BO	–	✓
Mixed-Kernel BO [41]	–	✓
SMAC [37]	✓	✓
TPE [10]	–	✓
TurBO [23]	✓	–
DDPG [55]	✓	–
GA [49]	–	✓

iteratively from its default value to the value of well-performing configurations and evaluating the performance change [24]. For speedup, the evaluations are replaced by cheap predictions obtained from surrogates, e.g., random forest. Given a set of observations, we fit a surrogate and conduct ablation analysis between the default configuration and the better ones.
SHAP [56] (i.e., SHapley Additive exPlanations) is a unified framework to interpret the performance change derived from classic Shapley value estimation [78] in cooperative game theory [36]. The performance change is decomposed additively between knobs. SHAP computes each knob's contribution (i.e., SHAP value) for pushing the default performance to the target one. Given a set of observations, each knob's tunability is calculated by averaging its positive SHAP value (assuming a maximization problem).

3.2 Configuration Optimization

In the *configuration optimization* module, an optimizer suggests promising configurations and updates its model based on the evaluation results iteratively. We introduce six state-of-the-art optimizers used by the database tuning systems or from the HPO community. We also summarize their designs in Table 3.
Vanilla BO denotes the BO-based optimizer that adopts vanilla GP as its surrogate model. Vanilla GP is widely used for objective function modeling in database configuration systems [19, 25], due to its expressiveness, well-calibrated uncertainty estimates and closed-form computability of the predictive distribution [39]. A GP $\mathcal{N}(\mu(\boldsymbol{\theta}), \sigma^2(\boldsymbol{\theta}))$ is fully specified by mean $\mu(\boldsymbol{\theta})$ and a variance function $\sigma^2(\boldsymbol{\theta})$, which is expressed as:

$$\mu(\boldsymbol{\theta}) = k^T \left(K + \sigma^2 I \right)^{-1} y,$$
$$\sigma^2(\boldsymbol{\theta}) = k(\boldsymbol{\theta}, \boldsymbol{\theta}) - k^T \left(K + \sigma^2 I \right)^{-1} k, \tag{3}$$

where $k = [k(\boldsymbol{\theta_1}, \boldsymbol{\theta}), ..., k(\boldsymbol{\theta_n}, \boldsymbol{\theta})]^T$ and K is the covariance matrix whose (i, j)-th entry is $K_{i,j} = k(\boldsymbol{\theta_i}, \boldsymbol{\theta_j})$. The kernel $k(\boldsymbol{\theta}, \boldsymbol{\theta}')$ models the overall smoothness of the target function. For Vanilla BO, the kernel function (e.g., RBF kernel in OtterTune) is calculated based on the Euclidean distance between two configurations, assuming the natural ordering property and continuity of configuration space.
One-hot BO denotes the BO-based optimizer that adopts one hot-encoding for categorical variables, as original GPs assume continuous input variables. Specifically, each categorical feature with k possible values is converted into k binary features.
Mixed-kernel BO [41] denotes the BO-based optimizer that adopts a mixed-kernel GP as its surrogate model. It uses Matérn

kernel for continuous knobs, Hamming kernel for categorical knobs (also one-hit encoded), and calculates their product. Mátern kernel is a continuous kernel that generalizes the RBF with a smoothing parameter. Hamming kernel is based on hamming distance, which is suitable to measure the distance between categorical variables. The mixed-kernel BO has shown promising performance over the heterogeneous configuration space empirically [41].

SMAC [37] (i.e., Sequential Model-based Algorithm Configuration) adopts a random forest based surrogate, which is known to perform well for high-dimensional and categorical input [14]. SMAC assumes a Gaussian model $N(y|\hat{\mu}, \hat{\sigma}^2)$, where the $\hat{\mu}$ and $\hat{\sigma}^2$ are the mean and variance of the random forest. SMAC supports all types of variables, including continuous, discrete, and categorical features. It has been the best-performing optimizer in Auto-WEKA [83].

TPE [10] (i.e., Tree-structured Parzen estimator) is a non-standard Bayesian optimization algorithm. While GP and SMAC modeling the probability $p(y|\theta, H)$ directly, TPE models $p(\theta|y, H)$ by tree-structured Parzen density estimators. TPE describes the configuration space by a generative process and supports categorical features. TPE has been used successfully in several papers [11, 12, 83].

TuRBO [23] (i.e., Trust-Region BO) proposes a local strategy for global optimization using independent surrogate models. These surrogates allow for local modeling of the objective function and do not suffer from over-exploration. To optimize globally, TuRBO leverages a multi-armed bandit strategy to select a promising suggestion from local models. TuRBO exhibits promising performances when solving high dimensional optimization problems [23, 81].

DDPG [55] denotes the Deep Deterministic Policy Gradient (DDPG) algorithm that is adopted to learn the configuration tuning policy for DBMS. It has been successfully adopted by CDBTune and Qtune. While other reinforcement learning algorithms, such as Deep-Q learning [59], are limited to setting a knob from a finite set of predefined values, DDPG can work over a continuous action space, setting a knob to any value within a range. DDPG consists of two neural networks: the actor that chooses an action (i.e., configuration) based on the input states, and the critic that evaluates the selected action based on the reward. In other words, the actor decides how to suggest a configuration, and the critic provides feedback on the suggestion to guide the actor.

GA [49] (i.e., Genetic Algorithm) is a meta-heuristic inspired by the process of natural selection. In a genetic algorithm, a population of candidate solutions to an optimization problem is evolved toward better solutions, iteratively. In each iteration, the fitness of each solution, which is usually the value of the objective function, is evaluated. The candidates with higher fitness will have more chance to be selected, and their features (i.e., encoded configuration) will be recombined and mutated to form new candidates for the next iteration. Genetic algorithms are simple yet effective and naturally support categorical features. They have been applied to various problems [47], including hyper-parameter optimization [70, 95].

3.3 Knowledge Transfer

The *knowledge transfer* module is designed to accelerate the target tuning task by leveraging the experience from historical tuning tasks. We introduce three knowledge transfer frameworks – workload mapping, RGPE, and fine-tuning.

Table 4: Profile information for workloads.

Workload	Class	Size	Table	Read-Only Txns
JOB	Analytical	9.3G	21	100.0%
SYSBENCH	Transactional	24.8G	150	43.0%
TPC-C	Transactional	17.8G	9	8.0%
SEATS	Transactional	12.7G	10	45.0%
Smallbank	Transactional	2.4G	3	15.0%
TATP	Transactional	6.3G	4	40.0%
Voter	Transactional	0.06M	3	0.0%
Twitter	Web-Oriented	7.9G	5	0.9%
SIBench	Feature Testing	0.5M	1	50%

Workload Mapping is proposed by OtterTune. It matches the target workload to the most similar historical one based on the absolute distances of database metrics and reuses the historical observations from the similar workload. This strategy can be adopted by any BO-based optimizers assuming a Gaussian model.

RGPE [27] (i.e., ranking-weighted Gaussian process ensemble) is an ensemble model for BO-based optimizers. RGPE combines similar base GP models of historical tasks via distinguishable weights. The weights are assigned using relative ranking loss to generalize across different workloads and various hardware environments. The ensemble manner avoids the poor scaling that comes with fitting a single Gaussian process model with all the observations from similar tasks. RGPE is adopted in ResTune to accelerate the tuning process of the target tasks.

Fine-tune is used in the RL-based optimizers [50, 71, 96]. For example, CDBTune and Qtune could pre-train a basic DDPG model by replaying historical workloads. During the later practical use of the tuner, the tuner continuously gains feedback information and updates its model by gradient descent (fine-tune). Such a process is claimed to help the optimizer adapt to different workloads with fewer observations instead of training from scratch.

4 GENERAL SETUP OF EVALUATION

Our study conducts experimental evaluation for the three key modules of configuration tuning systems: *knob selection, configuration optimization, knowledge transfer*. The evaluation is driven by the practical questions we encountered when tuning the databases:
Q1: How to determine the tuning knobs? (i.e., Which importance measurements to use and how many knobs to tune?)
Q2: Which optimizer is the winner given different scenarios?
Q3: Can we transfer knowledge to speed up the target tuning task? We describe the general setup of the evaluation in this section and leave the specific setting (e.g., procedure, metrics) when answering the corresponding questions.

4.1 Hardware, Workloads and Tuning Setting

Hardware. We deploy the target DBMS (version 5.7 of RDS MySQL) on a cloud instance with 8 vCPUs and 16 GB RAM. We use the MySQL default configuration as the default in our experiments except that we set a larger and reasonable buffer pool size (60% of the instance's memory [2]), since the default size (128 MB) in MySQL document largely limits the database performance.
Workloads. To answer **Q1** and **Q2**, we use an analytical workload JOB and a transactional workload SYSBENCH. JOB contains

113 multi-joint queries with realistic and complex joins [48]. SYS-BENCH is a multi-threaded benchmark frequently used for database systems. To answer **Q3**, we use three OLTP workloads (SYSBENCH, TPC-C and Twitter) as target workloads, which have been adopted in previous studies [4, 96, 98]. And we construct diverse source workloads, including Smallbank, SIbench, Voter, Seats, and TATP. They cover various size and read-write ratios, as shown in Table 4. **Tuning Setting.** There are 197 configuration knobs in MYSQL 5.7, except the knobs that do not make sense to tune (e.g., path names of where the DBMS stores files). According to the proprieties of black-box optimization [21], we choose three configuration spaces with different sizes: small, medium, and large, where we tune the most important 5, 20, and 197 (all) knobs ranked by the importance measurement, respectively. we run three tuning sessions per optimizer and report the median and quartiles of the best performances. Each tuning session is comprised of 200 iterations without specification. We conduct a three-minute stress testing to replay the given workload. For OLTP workload, we use throughput as maximization objective, and for OLAP workload, we use the 95% quantile latency as minimization objective. For a failed configuration (i.e., the one causing DBMS crash or unable to start), we set its result the worst performance ever seen in order to avoid the scaling problem [5]. Following iTuned and OtterTune, we initialize each tuning session for BO-based optimizers by executing 10 configurations generated by Latin Hypercube Sampling (LHS) [63]. When reporting the results, we calculate the performance improvement against the default configuration.

4.2 Implementation

Importance measurements. We compare the five importance measurements listed in Table 2. For Lasso [84], we adopt the implementation in OtterTune, which includes second-degree polynomial features to enable Lasso to detect interactions between pairs of knobs. For ablation analysis, we use random forest implemented by scikit-learn [68] as the surrogate. For fANOVA [38], we adopt its official library [1]. As for SHAP [56], we adopt the implementation released by the authors except that we use the given default as the base configuration when calculating performance gain.
Optimizers. We compare the optimizers in Table 3. For Vanilla BO and one-hot BO, we use a similar design with OtterTune [4]: Gaussian process as the surrogate and Expected Improvement as the acquisition function. We implement they via Botorch library [6]. We adopt the OpenBox [53]'s implementation for mixed-kernel BO and GA. For SMAC and TurBO, we adopt the implementation released by the authors [23, 37]. We implement DDPG via PyTorch [66] with the same neural network architecture as CDBTune [96].
Knowledge transfer frameworks. For workload mapping, we implement the methodology in OtterTune. For RGPE [27], we adopt the implementation in OpenBox [53]. We fine-tune DDPG's pre-trained models' weight when obtaining the target observations.

5 HOW TO DETERMINE TUNING KNOBS?

In order to conduct configuration tuning, we need to choose tuning knobs that decide the configuration space. Specifically, it connotes the following two questions:
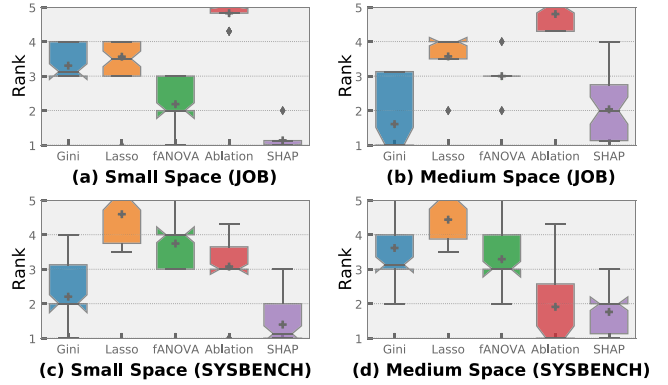

Figure 3: Performance ranking of importance measurements. (Notch denotes medium and plus sign denote mean.)

Table 5: Overall performance ranking (bold values are best).

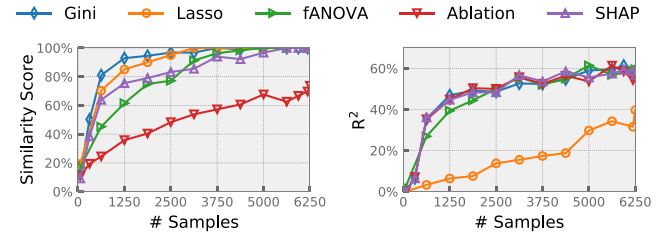| Measurement	Gini	Lasso	fANOVA	Ablation Analysis	SHAP
Average Ranking	2.62	4.18	3.06	3.45	**1.67**

Figure 4: Sensitivity analysis for importance measurements.

Q5.2: Which importance measurement to use to evaluate the importance of configuration knobs?
Q5.3: Given the importance measurement, how many knobs to choose for tuning?

5.1 Setup

To conduct knob selection, we first collect 6250 samples (i.e., observations) respectively for the two workloads SYSBENCH and JOB via Latin Hypercube Sampling (LHS) [63]. LHS attempts to distribute sample points evenly across all possible values over the 197-dimensional space. Then, we apply different importance measurements to generate knob importance rankings and compare the tuning performances on each importance ranking. We perform configuration optimization on small spaces (top-5 knob sets) and medium spaces (top-20 knob sets), using the eight optimizers in Table 3. We collect the performance rankings of the importance measurements in terms of the best configuration found by each optimizer. To further understand the performances of different important measurements, we conduct sensitivity analysis varying the number of training samples to compare their stability and model accuracy. Finally, we vary the number of tuning knobs to analyze the effect of configuration space with different sizes.

5.2 Which Importance Measurement to Use?

Figure 3 presents the performance ranking over the knob sets generated by different importance measurements, and Table 5 summarizes their overall performance ranking. We observe that the
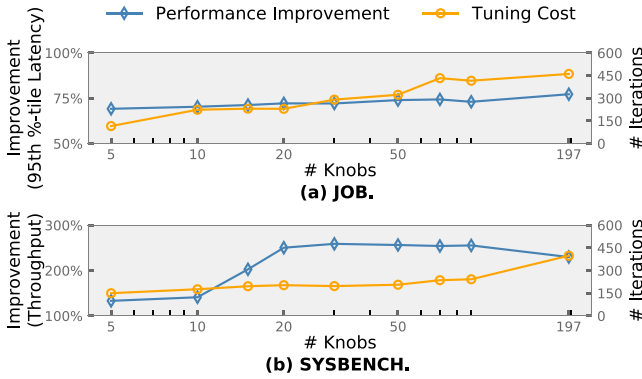
Figure 5: Performance improvement and tuning cost when increasing the number of tuning knobs.

tunability-based method SHAP achieves the best performance. This is due to that SHAP recommends the knobs worthy tuning. When changing a knob's value from the default only leads to the downgrade of database performance, SHAP will recommend not to tune the knob, while variance-based measurements will consider this knob to have a large impact on the performance and need tuning. The default values of database knobs are designed to be robust and can be a good start. Therefore, the variance-based measurements will be less effective. Ablation analysis yields the second last overall performance since it largely depends on the high-quality training samples better than the default and its performances are unstable as shown in Figure 3. Among the variance-based measurements, Gini score performs the best overall, while Lasso tends to yield the worst improvement. Lasso assumes a linear or quadratic configuration space, while in reality there exist complex dependencies from configurations to database performance.

To further understand the different performance of importance measurements, we conduct sensitivity analysis on the number of training samples for SYSBENCH workload as shown in Figure 4. The samples are randomly chosen from the 6250 samples, and the final result is the average of 10 executions for each importance measurement. The y-axis in the left figure is the similarity score (intersection-over-union index [34]) of the top-5 important knobs ranked using the subset of training samples against that of the baseline (6250 samples). A larger similarity score indicates that the importance measurement is more stable since the measurement can find the final important knobs with fewer observations. The right figure plots the Coefficient of Determination [33] (i.e., R^2) on the validation set. A larger R^2 indicates that the surrogate can better model the relationship between configurations and database performance. We have that Lasso fails to model this relationship, while it is very stable. Ablation analysis has the lowest stability, and its calculation highly depends on the high-quality samples. Gini score has the highest similarity score, indicating its sample efficiency. In the meantime, SHAP has a similarity score comparable to the variance-based measurements. Considering that SHAP has the best overall performance and comparable stability, we use SHAP as the default measurement for the remainder of our study.

5.3 How Many Knobs to Choose for Tuning?

We further conduct experiments to explore the effect of different numbers of tuning knobs. To measure the effect, we observe the tuning performance of vanilla BO over knob sets of different sizes ranked by SHAP. For each set, we conduct tuning for 600 iterations on SYSBENCH and JOB. We report the maximum performance improvement and the corresponding tuning costs (i.e., the iterations needed to find the configurations with the maximum improvement).

As shown in Figure 5, for JOB, the improvement is relatively stable, but the tuning cost increases when increasing the number of knobs. For SYSBENCH, the improvement is negligible at the beginning because a small number of tuning knobs have little impact on the performance. As the number of knobs grows from 5 to 20, the improvement increases from 133.10% to 250.33% since a larger configuration space leads to more tuning opportunities. Afterward, the improvement decreases as the tuning complexity increases. We conclude that it is better to tune the top-5 knobs for JOB and to tune the top-20 knobs for SYSBENCH. There is a trade-off between performance improvement and tuning cost. Given more knobs to be tuned, the tuned performance is better, and more tuning iterations are required to achieve it. With a limited tuning budget, it is vital to set the number of tuning knobs to an appropriate value since a small set of knobs only has a minor impact on the database performance, and a large set would introduce excessive tuning cost. **Incremental Knob Selection.** Previously, we have enumerated the number of tuning knobs and conducted extensive tuning experiments. Using such a procedure to determine the configuration space is not practical in production due to the high costs. As discussed in Section 2.3, there are two incremental tuning heuristics to determine the number of knobs: (1) increasing the number of knobs, proposed in OtterTune [4], and (2) decreasing the number of knobs, proposed in Tuneful [25]. We implement the two methods. For increasing the number of knobs, we begin with tuning the top four knobs and add two knobs every four iterations. For decreasing the number of knobs, we begin with tuning all the knobs and remove 40% knobs every 20 iterations. Figure 6 presents the results. For JOB, neither increasing nor decreasing the number of knobs surpass tuning the fixed 5 knobs. In contrast, for SYSBENCH, increasing the number of knobs has better performance, but decreasing the number limits the potential performance gain. As previously discussed, the number of important knobs for JOB is relatively small, thus the incremental knob selection on a larger space will not bring extra benefits. Instead, on SYSBENCH, the increasing method allows optimizers to explore a smaller configuration space of the most impacting knobs before expanding to a larger space.

5.4 Main Findings

Our main findings of this section are summarized as follows:

- Given a limited tuning budget, tuning over the configuration space with all the knobs is inefficient. It is recommended to pre-select important knobs to prune the configuration space.
- Configuration spaces determined by different importance measurements will impact tuning performance significantly.
- SHAP is the best importance measurement based on our evaluation. Compared with traditional measurements (i.e., Lasso and
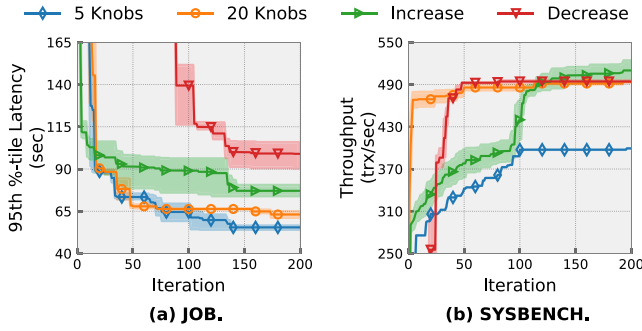
(a) JOB.

(b) SYSBENCH.

Figure 6: Best performance of incremental knob selection methods over iteration (for JOB, bottom left is better; for SYSBENCH, top left is better). We use top-5 knobs tuning and the top-20 knobs tuning as baselines.

Gini score), it achieves 38.02% average performance improvement. When training samples are limited, Gini score is also effective.

- When determining the number of tuning knobs, there is a trade-off between the performance improvement and tuning cost. Increasing/decreasing the number of tuning knobs has good performances in some cases. However, how to determine the number theoretically is still an open problem with research opportunities.

6 WHICH OPTIMIZER IS THE WINNER?

In this section, we aim to find the best optimizer regarding the different sizes of configuration spaces. Furthermore, we construct two scenarios - continuous configuration space and heterogeneous configuration space to validate the optimizers' support for heterogeneity. In addition, the algorithm overheads are also studied.

6.1 Setup

We first evaluate the eight optimizers' performance over different spaces on workloads – JOB and SYSBENCH. To further validate the support for heterogeneity, we focus on the well-performing optimizers and construct a comparison experiment on JOB where we use the configuration space of top-20 integer knobs as a control group (continuous space) and the space of top-5 categorical knobs and top-15 integer knobs as a test group (heterogeneous space). In addition, we measure the execution time of recommending a configuration (i.e., algorithm overhead) of different optimizers.

6.2 Performance Comparison

6.2.1 Performance over configuration spaces of different sizes. Figure 7 presents the results, where each solid line denotes the mean of best performance across three runs, and shadows of the same color denote the quartile bar. We summarize the average ranking of optimizers in terms of the best performance they found in Table 6.

We have that SMAC achieves the best overall performance, and TPE performs worst. SMAC adopts random forest surrogate, which scales better to high dimensions and categorical input than other algorithms. TPE fails to find the optimal configuration, and the main reason could be the lack of modeling the interactions between knobs [12]. It is almost certain that the optimal values of some knobs

(a) Small Space (JOB)

(d) Small Space (SYSBENCH)

(b) Medium Space (JOB)

(e) Medium Space (SYSBENCH)

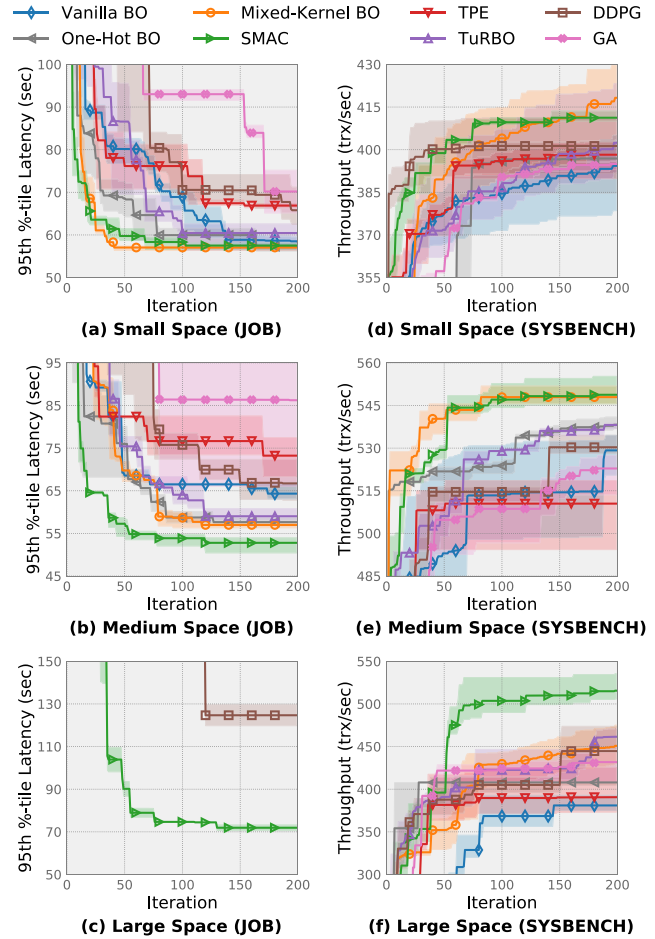**(c) Large Space (JOB)**

(f) Large Space (SYSBENCH)

Figure 7: Best performance of optimizers over iteration (for JOB, bottom left is better; for SYSBENCH, top left is better).

depend on the settings of others. For instance, the tuning knobs *tmp_table_size* and *innodb_thread_concurreny* define the maximum size of in-memory temporary tables and the maximum number of threads permitted. Intuitively, the larger number of threads running, the more in-memory temporary tables created. The relationship can be modeled by the considered optimizers, while TPE does not. In addition, the meta-heuristic method – GA also performs poorly.

Over small and medium configuration spaces, SMAC and mixed-kernel BO exhibit outstanding performance. While both adopting the Gaussian Process, the BO-based optimizers have distinct performance due to their different design with the categorical knobs (see the detailed analysis in Section 6.2.2). One-hot BO performs better than vanilla BO, but is inferior to mixed-kernel BO. In addition, DDPG has relatively bad performance on the small and medium spaces. It learns a mapping from internal metrics (state) to configuration (action). However, given a target workload, the optimal configuration is the same for any internal metrics, leading to the fact that action and state are not necessarily related [98]. We also notice that the tuning cost of DDPG is constantly high due to the requirement of learning a great number of neural network parameters, which is consistent with the existing evaluation [5].

Table 6: Average ranking of optimizers in terms of the best performance. VBO, OHBO, MBO denote vanilla BO, one-hot BO, mixed-kernel BO respectively. (bold values are the best.)

Optimizer	VBO	OHBO	MBO	SMAC	TPE	TuRBO	DDPG	GA
Small	5.33	4.00	**2.17**	3.33	5.83	3.83	5.00	6.50
Medium	5.17	3.83	2.33	**1.33**	7.17	4.00	5.50	6.67
Large	7.33	6.50	5.17	**1.00**	6.50	5.00	3.17	5.83
Overall	5.94	4.78	3.22	**1.89**	6.50	4.28	4.56	6.33

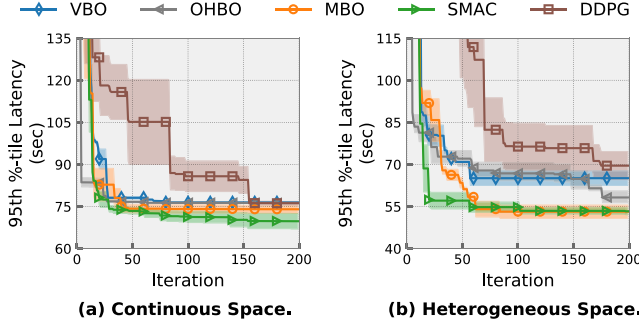**(a) Continuous Space.**   **(b) Heterogeneous Space.**

Figure 8: Comparison experiment for knobs heterogeneity (bottom left is better).

Over the large space of JOB, only SMAC and DDPG have found the configurations better than the default latency (about 200s) within 200 iterations. The success of DDPG can be attributed to the good representation ability of the neural network to learn the high dimensional configuration space. Over the large space of SYS-BENCH, all methods have found improved configurations, among which SMAC still performs the best. And TuRBO ranks the second-best since its local modeling strategy avoids the over-exploration in boundaries, especially in the high dimensional space. The effectiveness of global GP methods (vanilla BO and mixed-kernel BO) further decreases when the number of tuning knobs increases.

6.2.2 Comparison Experiment for Knobs Heterogeneity. Figure 8 demonstrates the performance of vanilla BO, one-hot BO, mixed-kernel BO, SMAC, and DDPG on continuous and heterogeneous spaces, respectively. While the BO-based optimizers perform similarly on continuous space, they reach quite different performances on heterogeneous space. Mixed-kernel BO could find better configurations and with a faster convergence speed than the others. The reasons are as follows: vanilla BO cannot handle categorical knobs since it assumes a partial order between the different values of a categorical knob [86]. Although one-hot encoding converts categorical knobs into binary ones, its RBF kernel struggles to capture the distance between categorical knobs. Mixed-kernel BO adopts different kernels for the integer and categorical knobs, thus better measuring the distance in heterogeneous spaces. In addition, SMAC performs well over the two spaces due to its random forest modeling, and DDPG has high tuning costs for finding good configurations.

6.3 Algorithm Overhead Comparison

Algorithm overhead is the execution time taken by an optimizer to generate the next configuration to evaluate per iteration, and does not include the evaluation time. Precisely, it consists of the time for statistics collection, model fitting, and model probe [46]. Figure 9 shows the statistics when tuning workload - JOB over
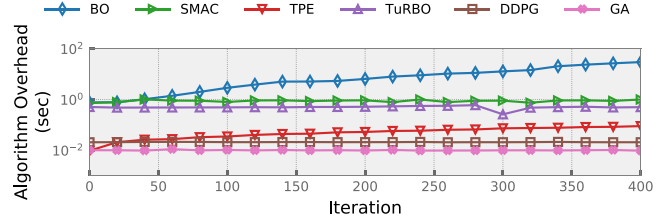

Figure 9: Algorithm overhead for different optimizers.

medium configuration space. GA has the lowest algorithm overhead. DDPG, SMAC, and TPE also have negligible overhead (< 1 second). However, due to the cubic scaling behavior of GP, the overhead of BO-based methods become extraordinarily expensive as the number of iterations increases. In particular, it takes > 10 seconds to select the next configuration after 200 iterations and > 1 minute after 400 iterations. TuRBO's overhead is comparable to SMAC. TuRBO uses a collection of simultaneous local GPs instead of a global GP and terminates unpromising GPs, which mitigates the scaling problem.

6.4 Main findings

Our main findings of this section are summarized as follows:

- SMAC has the best overall performance and could simultaneously handle the high-dimensionality and heterogeneity of configuration space. Compared with traditional optimizer (i.e., vanilla BO, DDPG), it achieves 21.17% average performance improvement.
- TPE is worse than other optimizers in most cases since it struggles to model the interaction between knobs.
- DDPG has considerable tuning costs (more iterations) in small and medium configuration spaces due to its redundant MDP modeling and complexity of the neural network. Meanwhile, it has a relatively good performance in a large configuration space.
- On small and medium configuration spaces, SMAC and mixed-kernel BO rank the top two, while on the large configuration space, SMAC, DDPG, and TuRBO all have good performance rankings. The effectiveness of global GP methods decreases as the number of tuning knobs increases.
- Mixed-kernel BO outperforms other BO-based optimizers in heterogeneous space due to its Hamming kernel measurement.
- Global GP-based optimizers (i.e., vanilla BO, one-hot BO and mixed-kernel BO) have cubic algorithm overhead.

7 CAN WE TRANSFER KNOWLEDGE TO SPEED UP THE TARGET TUNING TASK?

In the previous sections, different optimizers are compared from scratch without knowledge transfer. In this section, we test whether we can utilize the historical data to speed up target tuning tasks and compare the applicability of different transfer frameworks.

Baselines. The transfer learning framework is used to speed up base optimizers. To narrow down the candidate baselines, we evaluate workload mapping and RGPE accelerating the best-performing BO-based optimizers – SMAC and mixed-kernel BO.

Metrics. We use three metrics to evaluate the performance of transfer frameworks: performance enhancement, speedup, and absolute performance. The performance enhancement and speedup focus

Table 7: Evaluation results for different transfer frameworks (the bold values are the best). We report speedup, performance enhancement (i.e., PE) against the base optimizers and the absolute performance ranking (i.e., APR).

Transfer Framework	RGPE						Workload Mapping						Fine-Tune		
Base Optimizer	Mixed-Kernel BO			SMAC			Mixed-Kernel BO			SMAC			DDPG		
Metric	Speedup	PE	APR	Speedup	PE	APR	Speedup	PE	APR	Speedup	PE	APR	Speedup	PE	APR
TPCC	**98.28**	**10.44%**	**1**	8.03	2.18%	2	×	-2.48%	4	0.35	2.43%	3	1.71	3.75%	4
SYSBENCH	**4.76**	0.53%	4	0.78	**13.32%**	**1**	×	-0.51%	5	3.08	2.23%	2	0.93	4.59%	3
Twitter	**28.42**	1.56%	**1**	28.42	0.02%	2	×	-1.70%	5	×	-0.12%	4	0.83	**3.12%**	3
Avg.	**51.52**	4.18%	2	12.41	**5.17%**	**1.67**	×	-1.56%	4.67	1.14	1.51%	3.00	1.32	3.82%	3.33

Table 8: Regression performance (bold values are the best).

Model	RF		GB		SVR		NuSVR		KNN		RR	
Metric	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
SYSBENCH	**26.5**	**93.0%**	27.2	92.6%	97.4	5.6%	97.4	5.6%	54.6	70.2%	64.1	59.1%
JOB	11.8	97.4%	**11.1**	**97.7%**	41.7	67.9%	41.7	67.9%	27.5	86.0%	52.3	49.5%

on whether the transfer framework can speed up the tuning process compared with non-transfer. We denote the best performance within 200 iterations for the base optimizer without transfer as $f(x^*_{base})$ and the best performance with transfer as $f(x^*_{tran})$. The performance enhancement (PE) is defined as

$$PE = \frac{f(x^*_{tran}) - f(x^*_{base})}{f(x^*_{base})}; \qquad (4)$$

and the speedup (η) is calculated as:

$$\eta = \frac{steps\ to\ find\ x^*_{base}\ without\ transfer}{steps\ to\ find\ config.better\ than\ x^*_{base}\ with\ transfer}. \qquad (5)$$

The absolute performance focuses on the performance of the combination of base learner and transfer framework (e.g., the best performance Mapping (SMAC) achieved within 200 iterations).

Main Procedure. We conduct experiments on three target workloads – SYSBENCH, TPC-C, and Twitter. As for the knobs we tune, we use SHAP to select top-20 impacting knobs across OLTP workloads and hardware instances and more details can be found in our technical report [97]. To gather historical tuning data, we collect observations from five source workloads – SEATS, Voter, TATP, Smallbank, and SIBench. Since fine-tune (DDPG) relays on a pre-trained model, we pre-train DDPG's network 300 iterations on the five source workloads in turn. We use DDPG's training observations as the historical data for workload mapping and RGPE frameworks. Such a setting follows the evaluation of CDBTune for data fairness. With the pre-trained models and source observations, we compare the five baselines and obtain absolute performances. To calculate performance enhancement and speedup, we also run base optimizers on the target workloads without knowledge transfer.

7.1 Performance Comparison

Table 7 shows the results. If a baseline fails to find configurations better than x^*_{base}, we put "×" in the speedup column. We observe that fine-tune and workload mapping hinder the optimization (i.e., "negative transfer") in some cases where the speedup is smaller than one or the improvement is negative. Workload mapping always maps a similar workload and combines its observations in the surrogate model together with the target observations, which may be problematic since the source workloads may not be entirely identical to the target one. RGPE solves this problem by assigning adaptive weights to source surrogates and utilizing them discriminately. As for fine-tune, the performance is not stable since the neural network may over-fit the source workloads, and fine-tuning
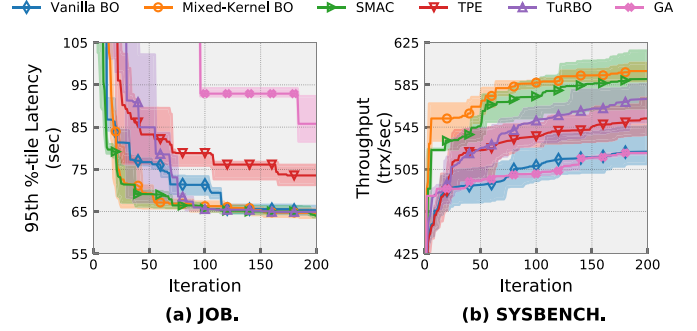

(a) JOB.　　　**(b) SYSBENCH.**

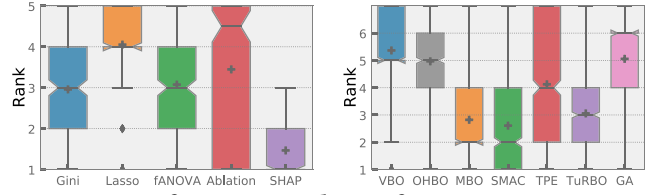Figure 10: Tuning Performance over surrogate benchmark.

Figure 11: Performance ranking of importance measurements and optimizers evaluated by the tuning benchmark. (Notch denotes medium and plus sign denote mean.)

the over-fitted network may be less efficient than training from scratch. Overall, the RGPE framework has the best performance. RGPE (mixed-kernel BO) has shown impressive speedup accelerating, which may come from the inferior performance of mixed-kernel BO compared with SMAC. In terms of absolute performance, RGPE (SMAC) achieves the best overall performance.

8 EFFICIENT DATABASE TUNING BENCHMARK VIA SURROGATES

As discussed previously, to ease the burden of evaluating tuning optimizers, we propose to benchmark the database tuning via surrogate models that approximate expensive evaluation through cheap and stable model predictions. A user can easily test optimizers by interacting with the surrogate models (i.e., input the configuration suggested by the optimizer and output the corresponding database performance). We present the construction of the tuning benchmarks and the evaluation results based on the benchmarks.

To construct the tuning benchmarks, we first collect extensive training samples and then select a regression model with high accuracy as the surrogate. To collect the training data, we run existing database optimizers to densely sample high-performance regions of the configuration space and sample poorly-performing regions [22] via LHS. As for the regression model, we consider a broad range of commonly used models as candidates, including Random Forest

(RF), Gradient Boosting (GB), Support Vector Regression (SVR), NuSVR, k-nearest-neighbours (KNN), Ridge Regression (RR). We evaluate their performance via 10-fold cross-validation, and Table 8 presents the resulted RMSE and R^2. We have that the two tree-based models, RF and GB, perform the best. Since RFs are widely used with simplicity, we adopt RF as the surrogate for the benchmark.

We first focus on the small configuration space of JOB and medium space of SYSBENCH. Figure 10 depicts the best performance found by different optimizers using the tuning benchmark based on RFs. We report means and quartiles across ten runs of each optimizer. We observe that our tuning benchmark yields evaluation results closer to the result in Figure 7 – SMAC and mixed-kernel BO have the best overall performance. In addition, the experiments on our tuning benchmarks are much faster. For example, as previously mentioned, a single function evaluation on SYSBENCH workload requires at least 3 minutes, while a surrogate evaluation needs 0.08 seconds on average. When considering the algorithm overhead of optimizers, the previous 200-iteration experiment takes at least 10 hours, while the same experiment on the tuning benchmark takes about 2~4 minutes. The tuning benchmark brings 150~311 × speedups. We leave the benchmarking RL-based optimizers as future work, since it requires constructing a surrogate to learn the state transaction (i.e., internal metrics of DBMS).

In addition, using surrogates could enlarge the number of evaluation cases of tuning algorithms To achieve this goal, we collect samples over the large (197-dimensional) configuration space and fit a surrogate. In the previous evaluation, we conduct experiments over three configuration spaces since evaluating the enumeration of all dimensions is expensive. And when evaluating the optimizers, we fix the importance measurement to be SHAP. With the surrogate benchmark, we could conduct extensive experiments over all the dimensions of configuration spaces (from top-1 to top-197) and all the importance measurements. Then, we conduct 11820 experiments (197 knob sets × 5 importance measurements × 6 optimizers × 2 workloads) to benchmark the *knob selection* and *configuration optimization* modules. Since the *knob selection* aims to prune the configuration space, we report its performance on 20 knob sets (top-1 to top-20). And we report the performance of optimizers on the 197 knob sets. As shown in Figure 11, SHAP remains the best importance measurement, and ablation study has significant performance variance. SMAC performs the best, followed by mixed-kernel BO. The evaluation results further validate our conclusions.

9 DISCUSSION

9.1 Answers to the Motivating Questions

We summarize our answers to the motivating questions.

A1: We recommend the tunability-based method – SHAP as an importance measurement since it indicates the necessity of tuning a knob when the DBMS has relatively reasonable default knob values. We can determine the number of knobs to tune by exhaustive and expensive enumeration. How to determine the number theoretically with fewer evluations is still an open problem. In practice, with a limited tuning budget, we could resort to incremental tuning.

A2: When comparing different optimizers, we need to consider the size and composition of configuration space. SMAC and DDPG are recommended for high-dimensional configuration spaces, although it is better to first conduct knob selection to prune the configuration space. SMAC is the winner that can handle the high dimensionality and heterogeneity of configuration space.

A3: For RL-based optimizers, we can fine-tune its pre-trained model to adapt to the target workload. However, we find that it might suffer from the negative transfer issue empirically. For BO-based optimizers, RGPE exhibits excellent speedup and improvement since it avoids negative transfer via adaptive weight assignment.

9.2 Research Opportunities

An End-to-End Optimization for Designing Database Tuning Systems. The *end-to-end optimization* can be viewed as optimizing over a joint search space, including the selection of importance measurements, knobs, optimizers, and transfer frameworks. Because of the joint nature, the search space of the *end-to-end optimization* is complex and huge. In our evaluation, we decompose the joint space reasonably to narrow the search space. Meanwhile, a class of methods in the HPO field treats the selection of algorithms as a new hyper-parameter to optimize. They optimize over the joint search space with probabilistic models [26, 29, 43, 51, 54], which could be another research direction.

Tuning Budget Allocation. How to allocate a limited tuning budget between different modules (e.g., knob selection and knobs optimization) is a problem that needs exploring [28, 88]. For example, an accurate ranking of knobs can facilitate later optimization but comes with the cost of collecting extensive training samples. There is a trade-off between the budgets for sample collection and the latter optimization. In addition, as discussed, a larger configuration space gives us more tuning opportunities but with higher tuning costs. There still remains space when determining the number of tuning knobs wisely, given a limited tuning budget.

10 CONCLUSION

Given emerging designs and algorithms for configuration tuning systems of DBMS, we are curious about the best solution in different scenarios. In this paper, we decompose existing systems into three modules and comprehensively analyze and evaluate the corresponding intra-algorithms to construct optimal design "paths" in various scenarios. Meanwhile, we identify design trade-offs to suggest insightful principles and promising research directions to optimize the tuning systems. In addition, we propose an efficient database tuning benchmark that reduces the evaluation overhead to a minimum, facilitating the evaluation and analysis for new algorithms. It is noted that we do not restrict our evaluation within the database community and extensively evaluate promising approaches from the HPO field. Our evaluation demonstrates that such an out-of-the-box manner can further enhance the performance of database configuration tuning systems.

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