Multi-Intention-Aware Configuration Selection for Performance Tuning

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ABSTRACT

Automatic configuration tuning helps users who intend to improve software performance. However, the auto-tuners are limited by the huge configuration search space. More importantly, they focus only on performance improvement while being unaware of other important user intentions (e.g., reliability, security). To reduce the search space, researchers mainly focus on pre-selecting performance-related parameters which requires a heavy stage of dynamically running under different configurations to build performance models. Given that other important user intentions are not paid attention to, we focus on guiding users in pre-selecting performance-related parameters in general while warning about side-effects on non-performance intentions. We find that the configuration document often, if it does not always, contains rich information about the parameters' relationship with diverse user intentions, but documents might also be long and domain-specific.

In this paper, we first conduct a comprehensive study on 13 representative software containing 7,349 configuration parameters, and derive six types of ways in which configuration parameters may affect non-performance intentions. Guided by this study, we design SafeTune, a multi-intention-aware method that preselects important performance-related parameters and warns about their side-effects on non-performance intentions. Evaluation on target software shows that SafeTune correctly identifies 22-26 performance-related parameters that are missed by state-of-the-art tools but have significant performance impact (up to 14.7x). Furthermore, we illustrate eight representative cases to show that SafeTune can effectively prevent real-world and critical side-effects on other user intentions.

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CCS CONCEPTS

• **Software and its engineering → Extra-functional properties**.

KEYWORDS

Performance tuning, user intention, non-performance property

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1 INTRODUCTION

Configuration can change software behavior and thus enable customization to meet different user intentions. Among many possible user intentions, improving performance is one of the most common purposes. However, modern software systems are often equipped with a large number of parameters (e.g., HDFS [46] has 560 parameters) that are impractical to tune by hand. Though existing works have applied various techniques to perform automatic configuration tuning [17, 18, 20, 25, 36, 41–43, 52, 54, 61], they still have two major limitations. First, it is well-known that their efficiency is extremely limited by the huge configuration search space [58, 61]. Second, we find that they only consider performance improvement while **being unaware of** user intentions other than performance (e.g., reliability, security). However, one configuration parameter may impact multiple user intentions at the same time. For example, changing some parameters gain performance by sacrificing reliability [1]. But users of safety-critical systems (e.g., industrial

`innodb_flush_log_at_trx_commit`:
"Controls the balance between strict ACID compliance for commit operations and higher performance... The default setting of 1 is required for full ACID compliance. Logs are written and flushed to disk at each transaction commit. With a setting of 0, logs are written and flushed to disk once per second. You can achieve ***better performance*** *by changing the default value but then you can* ***lose transactions*** *in a crash."*

Figure 1: Configuration documents of MySQL

control systems) may also intend to keep their systems reliable while improving performance. In such cases, the parameter that affects the corresponding intentions should be very carefully tuned.

To reduce the huge search space for those auto-tuners, many recent works have been proposed to *pre-select important parameters*. They run dynamic performance experiments to measure performance changes with parameter value changes, and use statistical [24] or machine-learning [38] methods to select parameters that have significant impacts on performance. Though working in some scenarios, the effectiveness of their dynamic methods depends strongly on both workloads and environment, which often vary from case to case. Moreover, these methods are hard to deploy due to the heavy performance experiments.

In this paper, we propose SafeTune, a multi-intention-aware approach that provides *tuning guidance*, including identifying performance-related configuration parameters in general and warning about potential side-effects on other user intentions. To the best of our knowledge, we are the first to propose multi-intention-aware parameter pre-selection for performance tuning. The insight of SafeTune is that configuration documents often contain rich information about parameters' relationship with multiple user intentions. For example, in Fig. 1, the document of parameter `innodb_flush_log_at_trx_commit` explains if and how the parameter affects performance in general, and warns about the potential side-effect (losing a transaction) on the intention of reliability. SafeTune leverages documents to understand the relationship between performance and other user intentions.

It is non-trivial for SafeTune to automatically select performance-related parameters and warn about side-effects. First, how configuration parameters affect performance and cause side-effects on non-performance intentions is unknown. Second, building a model to learn information from documents (which are written in natural language) requires large-scale training data, but there is no such public dataset. Third, the side-effect information is usually described implicitly, and documents can be very long and domain-specific. For the example shown in Fig. 1, expert knowledge is required to understand that "lose transaction" means hurting reliability in this context.

Therefore, we first conduct an empirical study to comprehensively understand how the configuration parameters can affect performance and cause side-effects on non-performance intentions such as reliability. To determine the general result from the study, we choose 13 software from four categories, including 7,349 parameters, as shown in Table 1. From this study, we obtain three heuristics to precisely filter out parameters unrelated to performance, and derive a categorization that contains six types of ways in which parameters can cause side-effects on non-performance intentions.

Based on these findings, SafeTune predicts the tuning guidance of a parameter for the given configuration document of the parameter. In light of the last two challenges, SafeTune takes two major steps: 1) We design a semi-supervised data expansion approach, which automatically expands the manually labeled training dataset. We manually assign the type of side-effect for parameters in a small-scale training data set during the study. Next, SafeTune uses association rule mining techniques in a progressive manner to mine natural language patterns from the dataset, then uses the patterns to enlarge this dataset with high precision. This step is necessary because manually inspecting all parameters is extremely expensive. 2) SafeTune trains a learning-based hierarchical model to capture important information from the document based on the expanded dataset and provide the final performance tuning guidance.

We evaluate SafeTune on software that has neither previously appeared before in this paper. The results show that SafeTune can accurately identify performance-related parameters and their side-effects, scoring 81.3-85.1% in precision and 67.6-67.7% in recall. Compared with the state-of-the-art pre-selecting method [38], SafeTune can correctly find 117 performance-related parameters that are missed by the method, and some of the these parameters have huge (up to 14.6x) performance impacts. Moreover, SafeTune correctly covers 29 out of 32 performance-related parameters. The false positive rate is 12.7%. Furthermore, we conduct a case study in which we apply SafeTune with a state-of-the-art and popular auto-tuner, OtterTune [50], which has 1.1k `GitHub` stars. The results show that SafeTune can help prevent eight side-effects (covering four types) caused by OtterTune that lead to severe consequences.

Our main contributions can be summarized as follows:

- We conclude six types of ways in which performance-related parameters can affect non-performance user intentions from an empirical study of 13 widely used open-source software from four representative domains.
- We design and implement a multi-intention-aware and semi-supervised approach, SafeTune, to identify performance-related parameters and their side-effects. All data and source code can be found in our public repository:

  https://github.com/TimHe95/SafeTune
- We evaluate SafeTune on the target software. The results show that SafeTune finds 22-26 performance-related parameters that have large performance impacts (up to 14.7x) but are missed by state-of-the-art tools. Further, we illustrate eight representative cases to show that SafeTune can effectively prevent real-world and critical side-effects on other intentions.

2 UNDERSTANDING PERFORMANCE-RELATED CONFIGURATION

To comprehensively understand which configuration parameters affect software performance, along with what side-effects those performance-related parameters may have on non-performance intentions, we conduct an empirical study on 7,349 parameters from 13 open-source software systems. From this study, we first derive

Table 1: Studied Software and Configuration Parameters

Category	Software	Popularity‡	# Params†
Database	MySQL	6.8k	943
	Cassandra	6.8k	116
	MariaDB	3.9k	274
Web Service	Apache Httpd	2.7k	571
	Nginx	14.5k	710
Distributed Service	Hadoop Common	11.8k	313
	MapReduce	11.8k	198
	Apache Flink	16.8k	441
	HDFS	11.8k	560
	Keystone	4.4k	394
	Nova	2.7k	844
Developer Tool	GCC	5.3k	1,335
	Clang	2.8k	650
Total			7,349

†The number of configuration parameters. ‡ `Github` stars

three heuristic strategies to help filter out parameters unrelated to performance. We then conclude six different types of ways in which those performance-related parameters may cause side-effects. These findings are used to guide the design of SafeTune.

2.1 Data Collection

We study the configuration documents of the software. The configuration document explains the detailed semantics and their relationships with user intentions (e.g., performance). The document has two unique advantages. First, it provides a general but comprehensive understanding of configuration parameters that does not rely on specific workloads; then, it contains multiple user intentions (e.g., text in bold in Fig. 1). We studied 13 open-source software systems from four different domains, as shown in Table 1. These four categories are chosen from the most popular products provided by famous cloud vendors [5, 7, 10] and are representative among highly-configurable software systems [31, 37, 50, 51, 59, 61]. These software systems are: 1) usually located in server-side and accordingly have higher demands in terms of performance, reliability, etc; 2) mature and widely used, with at least 2.7k `GitHub` stars; 3) highly configurable (each has more than 100 configuration parameters) with well-maintained configuration documents. We collected configuration parameters and their documents from two main sources: the official websites and the configuration files (e.g. XML-based configuration files). Each of the collected data point is in the form of *<parameter name, description>*. We filter out parameters without description, and finally collected 7,349 parameters.

Identifying Performance-related Parameters. To understand the side-effects of performance-related parameters, we manually studied the documentation of configuration parameters. Studying all parameters is extremely expensive; accordingly, we conclude three heuristic strategies to filter out parameters that have no impact on the performance of software. 1) Parameters indicating the location of resources. Descriptions of these parameters contain phrases such as "path of", "port of", "address of", and "location of". These typically have little impact on performance. 2) Parameters marked as "unused" or "deprecated" in the documentation. 3) Parameters set for compatibility reasons. These parameters are usually designed to support old behavior in old versions of software. Parameters in this category are filtered by the keywords "version", "compatibility" and "legacy". We apply these heuristics to all 7,349 parameters and filter out 1,071 parameters. Note that these heuristics are set to quickly filter out some of parameters unrelated to performance so that the others still need to be further filtered out by SafeTune. We then randomly sample 1,292 (20%) of the 6,278 parameters to study. Two authors with at least three years of research experience in configuration independently identified each parameter as either performance-related or not according to its description. Once a disagreement occurred, a third author was involved until a consensus is reached. Finally, we obtained 525 performance-related parameters for further study.

2.2 Side-effects on Non-performance Intentions

We study the 525 performance-related parameters to understand the side-effects they may cause. We follow the same methodology as in the above section; additionally, to make the results more consistent, the rest of the authors randomly review a fifth of the parameters studied in weekly meetings. This process took more than 400 working hours and lasted for six weeks. During the process, we use the software quality model [35] as the starting point and refine the classification by our domain knowledge (some software qualities in this model may not be affected by performance-related configurations). Finally, we conclude six different types of ways in which these performance-related parameters may cause side-effects on non-performance user intentions.

As a result, we find that the majority (76.0%, 399/525) of performance-related parameters have side-effects on non-performance intentions. These parameters can affect common user intentions, such as reliability, security and functionality. Table 2 shows the number of parameters falling into each type of side-effects. This result indicates a strong demand for tuning tools to warn about these side-effects for end users. Subsequently, we describe each type and the criteria used to classify it in our study.

Lower reliability. These parameters improve performance at the cost of decreasing the level of reliability. For example, `innodb_flush_log_at_trx_commit` controls the ACID level of MySQL, the value of `"1"` ensures strict data protection by executing *fsync* at every commit. Changing this value to `"2"` improves the performance by reducing the calls to *fsync* at the risk of losing data during a power loss. To avoid affecting user intention of reliability, tuning tools should warn users about the risk associated with improving performance. <u>*Criteria to classify*</u>: These parameters are usually related to the way data are persisted to the hard drive and fault tolerance policies, and they are usually documented as "replication level", "update interval", "write to disk", etc.

Lower security. These parameters improve performance at the cost of a lower level of security protection. For example, the parameter `PrivilegesMode` in Apache Httpd controls the way requests are processed. The value `"SECURE"` means that all requests are run in a secure sub-process, but with more overhead. When changing to `"FAST"`, requests are run in-process, speeding up the software but opening up the chance for malicious attackers to utilize the

Table 2: Side-effects on non-performance intentions

Type of Side-effects	# Params	# Params$_{\text{all}}$
Lower reliability	33	121
Lower security	46	185
Reduced functionality	138	696
Lower performance (for other workloads)	68	379
Higher cost	114	512
Limited side-effect	126	603
Total	525	2,496

# Params: number of parameters in the studied set. **# Params$_{\text{all}}$**: number of parameters in the whole data set.

in-process module to escalate privileges. To avoid affecting user intention regarding security, such parameters should be warned about. *Criteria to classify*: These parameters are usually related to common security policies such as encryption, authentication and privacy protection, and they are usually documented as "enable/disable authentication", "enable/disable SSL", "whether (a kind of data) should be encrypted", etc.

Reduced functionality. These parameters improve performance at the cost of reduced functionality. For example, the parameter `adl.feature.ownerandgroup.enableupn` in Hadoop controls whether an additional process should be performed to convert users and groups in FileStatus/AclStatus response to a user-friendly name. Disabling this function saves a large amount of computation (as documented: "*for optimal performance, false is recommended*"); however users intending to enable this function should be provided with warnings. *Criteria to classify*: These parameters are usually documented as "enable/disable (a feature)", "control output", "collect information of (a component)", etc.

Lower performance (for other workloads). These parameters can improve performance only for specific workloads run by some users, and may hurt others run by other users. Taking the parameter `max_seeks_for_key` in MariaDB as an example, it controls the estimated maximum cost for look-ups on table's index. Decreasing the value makes MariaDB prefer index scan than full table scan. But the index scan is only faster than the full table scan when the cost for index look-ups is low in actual (i.e., low cardinality of the index), which is completely workload-dependent. If another user runs a different workload, the inappropriate value may cause the performance problem [13]. So these parameters should be tuned with caution. *Criteria to classify*: These parameters typically control the internal argument of a specific algorithm, data structure and model, and they are usually documented as "threshold of", "ratio of", "upper/lower bound of", etc.

Higher cost. These parameters improve performance at the cost of consuming more system resources (e.g. CPU cores, memory, bandwidth). For example, `dfs.image.parallel.threads` in HDFS sets the number of threads used to load the image. A higher value of this parameter results in higher parallelism and reduced loading time, while more CPU cores may be used. In Amazon Web Services [5], four more CPU cores for a 32GB memory instance can cost 72$ per month. In cases where a user's budget or hardware resources are limited, changing these parameters may still indirectly affect user intentions (e.g., unexpected bill charges). *Criteria to classify*:

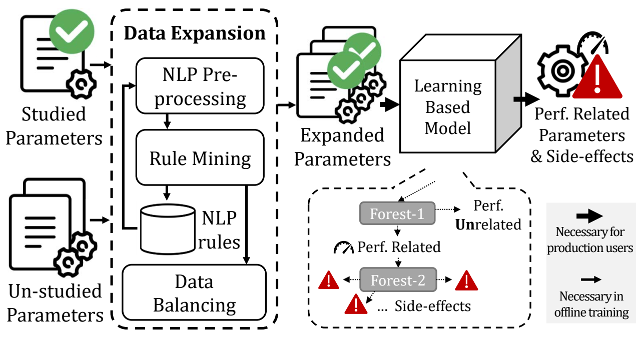


Figure 2: Overview of SafeTune.

These parameters usually control the system resources allocated to the software, and they are usually documented as "size of buffer", "number of workers", etc.

Limited side-effects. These parameters improve performance with limited side-effect on non-performance intentions. Some parameters improve performance by applying certain optimization strategies. For example, when `index_merge` in MySQL is turned on, MySQL can better utilize index and read from a single table rather than across multiple tables. Such optimization has a limited impact on the system, thereby causing limited side-effects on user intentions. It is recommended for tuning tools to tune such parameters in the first place. In other cases, parameters in this category may trade-off other properties (e.g., floating point precision) for performance. *Criteria to classify*: These parameters usually control optimization strategies such as caching, load balancing, compression, and they are usually documented as "enable (a kind of optimization)", "whether to (do optimization)", etc.

In rare cases, one parameter has side-effects on more than one other user intentions. We do not find any case that improving performance brings positive effects on other user intentions.

3 SEMI-SUPERVISED DATASET EXPANSION

Given the side-effects summarized in the study, our goal is to build a model that can automatically identify the performance-related parameters and warn about their side-effects. Training a model to get information from natural language requires data at a large scale. We refer to the configuration parameters and their side-effect types (labels) as training data; hence, SafeTune has seven labels (including six side-effects and performance unrelated parameters). However, the training data obtained from the study is insufficient (i.e., does not exceed 100 for some types), and manual labeling of the unstudied data is extremely expensive.

During the empirical study process in §2, we find that descriptions of parameters of the same type share certain linguistic patterns. For example, parameters that may lead to higher cost are usually documented like "size of buffer" or "number of threads". With these patterns, we will be able to enlarge the dataset with less manual effort. Therefore, we design a semi-supervised data expansion approach that utilizes natural language processing (NLP) and association rule mining (ARM) techniques to automatically mine the patterns (i.e., association rules) in a progressive manner to enlarge the amount of labeled data in the study. As shown in

Table 3: The rule examples of each side-effect types mined by SafeTune (Underlined words are those matched by rules).

Side-effect type	Rule example	Support	Confidence	Matched description
Lower reliability	(NOUN, write), (NOUN, level)	7	0.875	Sets the current transaction's <u>synchronization</u> <u>level</u>.
Lower security	(VERB, check), (NOUN, security)	6	0.857	Sets how deeply `mod_ssl` should <u>verify</u> before deciding that the clients do not have a valid <u>certificate</u>.
Reduced functionality	(NOUN, level), (NOUN, information)	6	0.857	<u>Verbosity</u> of SQL debugging <u>information</u>: 0=None, 100=Everything.
Lower performance (for other workloads)	(NOUN, time), (ADP, for), (NOUN, resource)	6	0.857	The <u>time</u> <u>for</u> which retry <u>cache</u> entries are retained.
Higher cost	(VERB, set), (NOUN, amount), (NOUN, resource)	12	0.923	This value <u>controls</u> the <u>number</u> of <u>cache</u> directives that the NameNode will send over the wire in response to ...
Limited side-effect	(VERB, enable), (NOUN, optimization)	12	0.857	<u>Enables</u> or disables genetic query <u>optimization</u>.

the left part of Fig. 2, the data expansion process contains three main steps: First, SafeTune uses NLP to pre-process the manually studied configuration documents and normalizes words to highlight the most informative words. Second, it mines the pre-processed documents to obtain a set of rules using ARM. With these rules, it matches configuration documents that are not involved in the study to increase the available training data. The above two steps proceed iteratively until no configuration documents can be enlarged by the rules. At the third step, SafeTune balances the data of each type of side-effect to avoid over-fitting to some types.

3.1 Pre-processing

The goal of pre-processing is to normalize words and highlight important information in the description of parameters. Pre-processing contains three steps: lemmatization, reduction, and substitution.

At the lemmatization step, since we are not interested in the grammar features in the documents, we transform each token to its original form to eliminate third-person or plural format effects; for instance, the word "specified" is transformed into "specify".

In the reduction step, we remove the words that are not likely to convey useful information and retain the informative ones. During our study, we find that three kinds of words play an important role in deciding the possible side-effects: 1) *noun*s, which directly point out the entities on which parameters will have an effect; 2) *verb*s, which are actions related to parameters and tend to directly lead to the impact; 3) *adverb*s/*adjective*s, which describe the effects of parameter value changes. We therefore extract the part-of-speech (POS) information of each word and retain words with POS of the types listed above.

In the substitution step, we replace special words to prevent the model from being distracted by unrelated information. For example, we replace the parameter names that appeared in the documentation with "CONFIG" and replace numbers with a fixed number. Moreover, to highlight the semantic knowledge in the documents, we replace words that appear in the synonyms list (the full list can be fond in our public repository) which is built upon domain-specific resources [2, 3, 23]. Examples of synonyms are shown in "*<u>Criteria to classify</u>*" in §2.2. For example, the words "commit", "update" and "sync" are replaced with "write", since they have similar meanings. We implement the pre-processing part using spaCy [33]. We provide an example to demonstrate the above process: the description *"Sets the current transaction's synchronization level"* will be converted to `[(VERB, set), (ADJ, current), (NOUN, transaction), (NOUN, write), (NOUN, level)]`.

3.2 Mining Association Rules

The goal of this step is to find the sub-sequences that appear exclusively and frequently in descriptions of the specific type of side-effect of performance-related parameters. These sub-sequences are association rules that distinguish different types of side-effect. For the pre-processed sentences obtained from § 3.1, we utilize FEAT [28] to mine association rules for each type of side-effect. SafeTune utilizes it by adding the label to the end of the description and mining the most frequent sub-sequences (rules) co-occurring with the label. For example, a rule mined by the algorithm is `[(NOUN, write), (NOUN, level)]`, which is a sub-sequence of the example above. Also, SafeTune outputs the *support* and *confidence* of each association rule, and they are defined as follows:

$$support = |rules_i| \quad \text{where the } rule_i \text{ matches the document of the } i^{\text{th}} \text{side-effect, and}$$

$$confidence = \frac{support}{|rules_i^*|} \quad \text{where the } rule_i^* \text{ matches the document of any type of the side-effect.}$$

The *support* of the $rule_i$ is defined as the number of occurrences of the rule matching i^{th} type given that the rule appears. Moreover, its *confidence* is the conditional probability that a document is the i^{th} type of side-effect when matching this rule. For example, the rule above has a *support* of 7 and *confidence* of 0.857, which represents a strong signal of its side-effect type (i.e. *Lower reliability*). Table 3 presents rule examples mined for each type.

In the mining stage, SafeTune may obtain millions of rules. As this set may contain rules with low quality, we retain only the rules that are sub-sequences of other rules with the same *support*, since shorter rules are more general and are thus more likely to expand more data. Moreover, this expanded training data will be directly used to train the SafeTune model. Thus, the soundness of the expanded training data is important. Furthermore, we do not expect the expansion process to expand all parameters to the training data (completeness). Therefore, we drop out the rules whose *confidence*s are lower than 0.85. As we will show in §5.2, with this level of *confidence*, the data expansion method can achieve an optimal balance between precision and recall.

3.3 Expanding Dataset Progressively

The goal of this step is to use rules mined from the studied data to match configuration documents to the greatest extent possible to enlarge the training data. For parameters not involved in the study, SafeTune pre-processes their documents as in §3.1. SafeTune then matches rules mined in the previous step to identify the candidate to be expanded. Note that one parameter document may match multiple rules of different types. SafeTune calculates the sum of matched rules' *confidence* of each type respectively and take the label with the highest score. If no rule is matched, the parameter will not be expanded. If the two steps described in §3.1 and §3.2 are applied only once, the data expanded may still be insufficient. SafeTune expands the dataset in a progressive manner. The process terminates when there is no data remaining that can be expanded.

3.4 Balancing Data

The goal of this step is to make the training data balanced in order to avoid the model being biased towards the majority classes. After the data expansion via rules matching, the parameters that have no impact on the performance account for 72.2% of the entire dataset, while the performance-related parameters that cause *Lower security* contain only 4.1%. This imbalance causes the model to be easily biased towards the performance-unrelated parameters. To avoid this bias, SafeTune over-samples the parameters in the minority types of side-effects to ensure that they are the same as the number of performance-unrelated parameters. Since the soundness of the expanded data is our main concern, we need to lower the probability of incorporating false data. Borderline-SMOTE [30] is a widely used over-sampling method for imbalanced data. Compared with other methods, it can effectively avoid generating samples from the "danger area" (i.e., samples near the borderline of different classes). After balancing the training data, SafeTune applies the pre-processing step as in § 3.1 to the data set to normalize words and highlight important information in the training set.

4 IDENTIFYING PERFORMANCE-RELATED PARAMETERS AND SIDE-EFFECTS

In this section, we introduce how SafeTune predicts the tuning guidance for configuration parameters. As shown in the right part of Fig. 2, SafeTune takes configuration documents that have been expanded and pre-processed from the data expansion step as input, then outputs tuning guidance including performance-related parameters and their side-effects on non-performance intentions.

Random forest (RF for short) [21] is an appropriate algorithm for the text classification task. It can precisely capture the difference between types of side-effects and is more robust than a single decision tree. It is also more lightweight and more interpretable than deep learning models like CNN. More importantly, neural networks usually demand millions of data for training, which is not accessible for configuration documents. The labels of input data in our task are hierarchical (i.e., level-1: performance-related/unrelated; level-2: six different side-effects only for performance-related parameters). However, the classic RF algorithms do not account for hierarchical datasets. Inspired by [29], we build a two-level hierarchical random forest model, as shown in the bottom right part of Fig. 2. RF-1 is used to identify the performance related parameters from unrelated ones. All training data are used to train RF-1. Moreover, RF-2 is used to predict side-effects (among the six side-effects) for the performance-related parameters, while only the performance-related parameters in the training set are used to train RF-2. The label of the data to be predicted is decided by the multiplication of the probabilities given by the two RFs. For example, if the probabilities given by the two RFs of a configuration parameter are RF-1 : $[0.3, 0.7]$ and RF-2 : $[0.04, 0.2, 0.1, 0.5, 0.1, 0.06]$, then the parameter will be labeled as "performance-related" (since $0.7 > 0.3$), as well as the "*Higher cost*" label ($0.7 \cdot 0.5 = 0.35$, which is greater than all the others).

RF requires embedding of the input documents written in natural language. SafeTune embeds each parameter's document using TF-IDF [45], a widely-used method in information retrieval. For its part, TF-IDF treats each document as bag-of-words, ignoring the sequence information. In our task, "write data" and "...data. Write..." can express completely different meanings. Hence, SafeTune considers at most three consecutive words (i.e., unigram, bigram and trigram) when calculating the TF-IDF embedding. Note that the embedding may be sparse (e.g., 2,000 dimensions, with 1,990 zeros), and the RF algorithm only selects several dimensions each time to train a decision tree [21]. Thus, SafeTune applies principal component analysis (PCA) [12] for the TF-IDF embedding. We ensure that the PCA preserves 99% of the information from the initial TF-IDF embedding.

5 EVALUATION

We implement SafeTune with sklearn [22] and randomForest(R) [40]. All experiments are conducted on machines with a 48-core Intel-Xeon 2.2GHz processor, Tesla V100 GPU, 64GB RAM, and 1TB hard disk, with Ubuntu 18.04 LTS, and Python 3.6.8. We evaluate the effectiveness of SafeTune by answering the following questions:

- **RQ1: Accuracy of predicting tuning guidance and data expansion.** How accurate is SafeTune in identifying performance-related parameters and predicting their side-effects on non-performance intentions? How accurate is the automatically expanded data?
- **RQ2: Comparison between SafeTune and the state-of-the-art tool.** Can SafeTune cover performance-related parameters that are identified by the existing tool? Can SafeTune identify performance-related parameters that are missed by the existing tool?
- **RQ3: User study on the effectiveness of SafeTune on helping performance tuning.** Does the existing auto-tuner produces potential side-effects on other user intentions? Can SafeTune help the tool to prevent those side-effects? How severe are these side-effects?

5.1 RQ1: Accuracy of Predicting Tuning Guidance and Data Expansion

To answer RQ1, we evaluate the accuracy of SafeTune in identifying performance-related parameters and predicting their side-effects. To avoid over-fitting, we conduct experiments on software that are neither studied nor included in the training set. Since SafeTune automatically expands the training set, we also evaluate the accuracy of the expanded data.

Table 4: Precision and recall in predicting performance-related parameters and their side-effects

Software	SafeTune				SafeTune$_{\text{w/o exp.}}$				SafeTune$_{\text{ideal}}$			
	PR		SE		PR		SE		PR		SE	
	preci.	recall	preci.	recall	preci.	recall	preci.	recall	preci.	recall	preci.	recall
PostgreSQL	0.873	0.764	0.812	0.629	0.713	0.545	0.623	0.481	0.873	0.777	0.847	0.685
Squid	0.872	0.602	0.830	0.623	0.693	0.426	0.589	0.439	0.891	0.632	0.868	0.652
Spark	0.801	0.669	0.792	0.651	0.611	0.532	0.510	0.389	0.855	0.662	0.820	0.648
Overall	0.851	0.677	0.813	0.676	0.498	0.577	0.553	0.439	0.881	0.691	0.847	0.662

PR: effectiveness of predicting performance-related parameters. **SE**: effectiveness of predicting side-effects. *precis.*: precision. $_{\text{w/o exp.}}$: only using studied data to train SafeTune. $_{\text{ideal}}$: replacing labels of expanded data (may contain incorrect ones) in the training dataset with manually checked labels.

5.1.1 Accuracy of Tuning Guidance. We evaluate SafeTune on PostgreSQL [44], Squid [53] and Apache Spark [57]. These software are not included in our study, but are also popular (at least 1k GitHub stars) and from different domains, written in different programming languages. Thus, we believe they can provide sufficient generality. The three software have 252, 266 and 217 parameters respectively. We follow the same methodology as in § 2.1 to manually label the parameters and use them as the test set. We use the 1,292 studied parameters (not including the above three software) as the initial training set. SafeTune then expands the training set and obtain 24,528 pieces of training data. Each item in this dataset is in the form of *<parameter name, description (embedded), label$_{level\text{-}1}$, label$_{level\text{-}2}$>*, where *label$_{level\text{-}1}$* is one of the two values {"*Performance-related*", "*Performance-unrelated*"}, and *label$_{level\text{-}2}$* is one of: {"*Lower reliability*", "*Lower security*", "*Reduced functionality*", "*Lower performance (for other workloads)*", "*Higher cost*", "*Limited side-effects*"}. Last, SafeTune is trained with this dataset.

To measure the accuracy of predicting performance-related parameters (**PR** for short in Table 4), we use precision and recall. To assess the accuracy of predicting side-effects (**SE** for short in Table 4), we calculate the averaged precision and recall of each type (i.e., Micro-precision/recall [4] of six side-effects) to measure SafeTune as a whole. SafeTune applies data expansion to improve the accuracy. To evaluate the usefulness of this component, we remove it (using only the initial 1,292 parameters as the training set) and conduct experiments with identical test data to draw a comparison. This is denoted as **SafeTune**$_{\text{w/o exp.}}$ in Table 4.

Result and Analysis. First, SafeTune can identify performance-related parameters with a precision of 85.1% and a recall of 67.7%. The false negatives occur because many of them contain technical terms in documents that are difficult for SafeTune to understand. For example, `ssl_ecdh_curve` is documented as "*sets the curve to use for ECDH*", but this does not explain that "ECDH" is an agreement protocol that allows two parties to establish a shared secret, which affects performance. Worse yet, these technical terms rarely appear in the dataset. The false positives occur mainly because some expressions mislead SafeTune. For example, the document of `spark.eventLog.overwrite` is "*whether to overwrite any existing files*", but whether or not "overwrite" is performed does not affect performance in this case; however the word "write" misleads SafeTune into identifying the parameter as related with persisting data to disk, thereby affecting performance. Moreover, technical terms are one of the main causes of false positives.

Table 4 demonstrates the results of predicting side-effects on the non-performance intentions of these performance-related parameters. Overall, SafeTune can reach a precision of 81.3% and a recall of 67.6%. These false positives occur because many parameters have very complex logic described in the long document, making it challenging even for human to identify the type of side-effect. For example, in PostgreSQL, `wal_level` controls "the level of information written to the WAL"; this parameter is falsely identified as *lower reliability*, but all levels of WAL can ensure the "necessary information needed to recover from a crash or immediate shutdown" (reliability). Higher levels is only used to support extra *functionalities* (e.g., logical decoding). It makes challenging for SafeTune to distinguish such subtle logic. Another reason is that some expert knowledge cannot be precisely captured by SafeTune. The false negatives occur mainly because the descriptions may miss context. For example, `cpu_tuple_cost` is described as "*sets the planner's estimate of the cost of processing each row during a query*"; however, the context of this description is that the "planner" is a component that will choose the quickest query plan, while the "cost" is a workload-dependent argument of the choosing algorithm. Without this context, SafeTune will fail to identify it as "*Lower performance (other user)*".

The 6th - 9th columns of Table 4 show the results after removing the data expansion component from SafeTune. Without this data expansion, SafeTune cannot fully learn features in parameter documents, i.e., the precision drop by 26.0-35.3% and the recall drop by 10.0-23.7% respectively. Therefore, data expansion is essential for SafeTune. *In conclusion, the result indicates that SafeTune can achieve good precision and acceptable recall in pre-selecting performance-related parameters and predicting side-effects.*

5.1.2 Accuracy of Data Expansion. SafeTune uses data expansion to enlarge training data. Thus, the quality of enlarged data may affect the effectiveness of the final tuning guidance provided by SafeTune. Therefore, we also evaluate the correctness of the data expanded by the expansion method. To achieve this, we need the ground truth of these data. We therefore manually label all 7,349 parameters and cross-check them in the same way as described in § 2.2. This process took 700+ working hours and lasted 10 weeks. We make all these data publicly available in the repository. Note that this manual work is only needed in this paper to evaluate SafeTune, but not for users of SafeTune. We use precision to measure the correctness of the data expanded by the expansion step, along with expansion rate to measure the rate of the data that can be correctly

Table 5: Precision and expansion rate of the expanded data

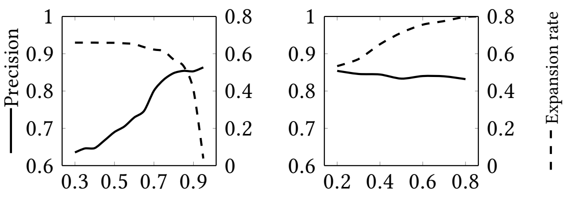
Data Label	Precision	Expansion rate
Lower reliability	0.847	0.393
Lower security	0.808	0.372
Reduced functionality	0.832	0.585
Lower performance (for other workloads)	0.819	0.552
Consuming more resource	0.910	0.670
Limited side-effect	0.801	0.464
Performance-unrelated	0.931	0.702
Overall	**0.854**	**0.534**

expanded to all the unlabeled data (100% expansion rate means all the unlabeled data can be correctly expanded). Moreover, we use averaged precision and expansion rate to measure the overall result. Furthermore, we evaluate the impact of the incorrectly-expanded data on SafeTune. Thus, we replace the labels of expanded data in the training set in § 5.1 with manually annotated labels (ground truth), and keep other experimental settings the same. We denote the model trained by this data set as **SafeTune**$_{\text{ideal}}$ in Table 4.

As described in § 3, SafeTune only keeps rules for which the confidence is higher than a given threshold to improve precision. Therefore, we evaluate the influence of different thresholds (from 0.30 to 0.95) on the precision and expansion rate of the expanded data. Another interesting question is that of how much studied (labeled) data we need to conduct the expansion. Obviously, it is less useful if the expansion approach requires a majority of studied data and can only expand the remaining minority. Therefore, we evaluate the influence of proportion on the precision and expansion rate of the expanded data. Note that, in our evaluation, all data are manually labeled to provide the ground truth, thus, we can simulate any proportion p of studied data against those that need to be expanded. For each p, we apply the approach in § 3 to expand the remaining $1 - p$ data. This process is repeated 10 times to eliminate the occasionality caused by the random sampling. We use averaged precision and expansion rate to measure the remaining $1 - p$ expanded data.

Result and Analysis. Table 5 shows the precision and expansion rate of the expanded data of each type of side-effects. SafeTune performs well in expanding the performance-unrelated parameters and those that may cause higher cost. For the remaining types, like *Lower reliability* and *Lower security*, the number of parameters in these types are fewer than in the initially studied data set and thus do not have many distinct features compared with other types. The result of the impact on SafeTune of those incorrectly-expanded data is shown in the last four columns in Table 4. The incorrectly-expanded data cause at most 3.5-5.4% degradation to precision (comparing the **SafeTune** with **SafeTune**$_{\text{ideal}}$ series); without this data expansion approach, however, the precision will reduce significantly. Moreover, with the expansion, we can reduce expensive manual effort by about 73.8% (100% means manual-free). This greatly outweighs the drawback of the incorrectly expanded data.

The result of choosing a proper threshold for rule confidence and proportion of studied data is shown in Fig. 3. First, Fig. 3a shows



(a) Confidence threshold **(b) Proportion(p) of studied data**

Figure 3: The influence of two model arguments on the precision and expansion rate of the expanded data.

the precision and expansion rate changes against different threshold values. As expected, the precision increases as the confidence threshold of the mined rules increases, while the expansion rate is the opposite. As described in § 3, SafeTune honors precision rather than expansion rate. When the threshold increases from 0.85 to 0.9, the precision does not increase while suffering a expansion rate drop of 12.8%; this means that about 640 parameters cannot be automatically expanded but the precision improvement is small. We therefore set the confidence threshold as 0.85 in SafeTune. Fig. 3b shows the averaged precision and expansion rate of different proportions p of studied data. It is shown that, generally, with increasing data studied, the precision of the mined rules will drop slightly while the expansion rate will increase. This is because variety increases alongside increasing studied data, meaning that more rules can be generated and more unlabeled parameters can be expanded. This increases expansion rate but also the likelihood of mistakes. Thus, we use $p = 0.2$ since SafeTune honors precision.

5.2 RQ2: Comparison with State-of-the-art Tool

We compare SafeTune with [38], a state-of-the-art tool for selecting important parameters by running performance experiments and choosing parameters that lead to significant performance changes via machine learning techniques. This work [38] opens up their results, which include the Top-n important parameters (32 in total) in PostgreSQL and Cassandra that they predicted. We therefore evaluate SafeTune on these two software to compare with this work [38]. The two software have 252 and 117 configuration parameters respectively. We train SafeTune on the same dataset (does not include PostgreSQL) as in § 5.1 but excluding Cassandra. To obtain the ground truth of performance-related parameters in the two software, we manually label the parameters in the same way as 2.1. Note that this manual work is only for the evaluation, but is not needed for users of SafeTune.

Note that the existing work [38] predicts the performance-related parameters via concrete performance experiments. For its part, SafeTune is based on configuration documents. To prove that the performance-related parameters predicted by SafeTune do have impacts on performance, we run performance tests under different parameter values; we further measure the performance impact by the factor of performance change before and after the parameter value change. We collect the performance tests from popular benchmarks, including: TPC-C/H [15, 16], tlp-stress [14], NoSQLBench [8] and ca-stress [6]. Each test is repeatedly run 10 times to obtain stable results. We refer to the performance as the tail latency, mean throughput and query execution time.

Table 6: Part of performance-related parameters missed by state-of-the-art tool (full result in public repository).

Parameter Missed	Workload	Chg.	Metric
PG.enable_sort	TPC-H.q17	**14.6**x	Exe. Time[†]
CA.native_transport_max_concurrent	ca-stress.w	**13.5**x	Tail Lat.[‡]
CA.hinted_handoff_throttle_in_kb	ca-stress.w	**6.7**x	Tail Lat.
PG.enable_nestloop	TPC-H.q2	**6.4**x	Exe. Time
PG.enable_indexscan	TPC-H.q13	**3.6**x	Exe. Time

Chg.: Performance change before and after parameter change; **PG**: PostgreSQL; **CA**: Cassandra; [†]Query Execution Time; [‡]Tail Latency.

Result and Analysis. Experimental results show that SafeTune can identify 117 performance-related parameters **that are missed by** the existing work [38]. Among the 117 parameters, 48 show significant performance impacts (up to 14.6x) in our performance testing. Table 6 shows the Top-5 parameters that have large performance impacts on the two software. For example, changing `enable_sort` from 1 to 0 causes the execution time of TPC-H.q17 to degrade from 19.1 seconds to 279 seconds (14.6x). However, this parameter never even appears in the rank-list of the existing work [38]. This occurs because `enable_sort` only affects queries that both contain `GROUP BY` and `ORDER BY` operations, but the workload used by this work [38] does not contain that. Another interesting thing is that the top-ranked parameter `fsync` given by the this work [38] only has 1.7x performance impact and achieves rank-12 during our testing. The reason is similar to the above. Note-worthily, SafeTune gets this result without any heavy performance experiments (the existing work [38] consumes 3,750 machine hours). The performance testing in our evaluation cost about 700 machine hours, while SafeTune only consumes two hours for the one-time-effort training step and less than 10 seconds for the prediction step.

SafeTune can successfully cover 29 out of 32 (90.6%) parameters that are given by the existing work [38]. In total, SafeTune produces 17 false positives (precision: 87.3%), and misses 45 out of 191 parameters (recall: 76.4%) that are manually confirmed from the documents to be performance-related. Most of the false positives are parameters that require a long description to explain the domain knowledge behind the parameter, rather than what turning the parameter on or off will affect. The explanations may also contain phrases that appear frequently in performance-related parameters, thereby misleading SafeTune. For example, turning on `zero_damaged_pages` only reports a warning (performance-unrelated), but its description explains a lot why this warning happens. The three cases that the existing work [38] identifies but that are missed by SafeTune are: 1) `commitlog_segment_size_in_mb`, which controls commitlog file segments; this requires strong domain knowledge to understand, but there are rare similar cases in the training set. 2) `compaction_throughput_mb_per_sec`, whose description is too brief to be understood by SafeTune. 3) `default_statistics_target`, whose description contains too many performance-unrelated explanations that distract SafeTune.

Note that both this existing work [38] and our evaluation are limited by the workload. Some parameters do not trigger substantial performance change under the selected workload. For example, `max_logical_replication_workers` controls maximum workers a logical replication transaction can use. This parameter affects performance only when PostgreSQL is in a replication process, but this workload is not included in any of the selected benchmarks. In the evaluation, we use richer types of workloads in the evaluation, and thus we observe more performance-related parameters than this work [38].

In conclusion, SafeTune can identify many performance-related parameters with large performance impacts that the state-of-art tool [38] fails to detect, and covering most of those identified by this tool. Also, SafeTune is more efficient and lightweight.

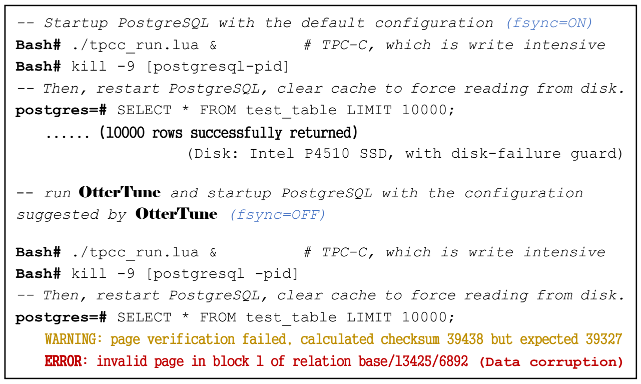
5.3 RQ3: User Study

SafeTune can help tuning tools (e.g., OtterTune [50], BestConfig [61]) avoid potential side-effects on other user intentions. To illustrate the effectiveness of SafeTune, we conduct a user study on one of the auto-tuners and manually validate the result. Among these publicly available auto-tuners, OtterTune is the most popular, with 1.1k `Github` stars. OtterTune supports MySQL and PostgreSQL; thus we run OtterTune in these two software and apply SafeTune (trained in §5.1) to check if SafeTune can warn about potential side-effects. Furthermore, to prove that those side-effects do have severe consequences, we manually validate if the corresponding user intentions are violated. In the case study, we simulate four users who leverage OtterTune to improve performance (with their non-performance intention shown in the end):

- **User A**: military communication service provider who is obligated to preserve data reliably. – *High reliability*
- **User B**: free service provider who uses free cloud instances with limited resources. – *Low cost (resource)*
- **User C**: system administrator who is responsible for monitoring unexpected behavior of the database. – *Functionality*
- **User D**: social network application provider who faces many different user requests. – *Good performance (most workloads)*

Result and Analysis. Overall, SafeTune warns about eight side-effects (covering four types, excluding "lower security" and "limited side-effect", OtterTune does not touch any security related parameters) on other user intentions caused by OtterTune. We discuss how the intentions of **User A-D** are violated in detail, and put the other four cases in the public repository.

For **User A**, `fsync` is turned off by OtterTune during tuning; it is documented [11] as: *"While turning off fsync is often a performance benefit, this can result in* ***unrecoverable data corruption*** *in the event of a power failure or system crash."* Although the workload performance improved by ~70% after tuning by OtterTune, the database becomes unreliable. As shown in Fig. 4(a), we simulate an occasional power loss when PostgreSQL is serving requests normally by issuing `kill -9` to the `postgres` server process and clear the system cache, which would not survive during a power loss. After restarting the process, we observe that **User A**'s data is corrupted (yellow/red text). This is because, by turning off this parameter, PostgreSQL will only persist data once the buffer is full. We also observed that when `fsync` is turned on, simulated power loss never causes data corruption. By applying SafeTune, this parameter is clearly warned about this reliability impact. For **User B**, `innodb_buffer_pool_size` is increased from 128MB to 16.4GB by OtterTune as shown in Fig. 4(b). This is because, using the large `innodb` buffer, more data can be cached, improving the performance. But **User B** uses MySQL in a free cloud virtual machine.

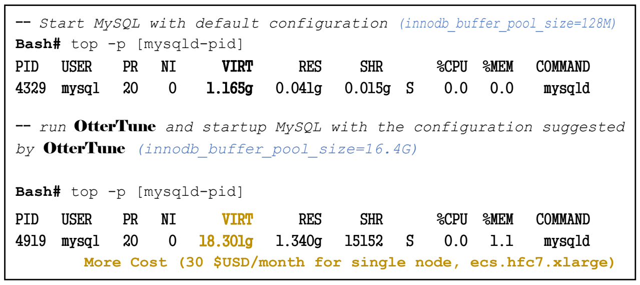


```
-- Startup PostgreSQL with the default configuration (fsync=ON)
Bash# ./tpcc_run.lua &          # TPC-C, which is write intensive
Bash# kill -9 [postgresql-pid]
-- Then, restart PostgreSQL, clear cache to force reading from disk.
postgres=# SELECT * FROM test_table LIMIT 10000;
   ...... (10000 rows successfully returned)
                  (Disk: Intel P4510 SSD, with disk-failure guard)

-- run OtterTune and startup PostgreSQL with the configuration
suggested by OtterTune (fsync=OFF)

Bash# ./tpcc_run.lua &          # TPC-C, which is write intensive
Bash# kill -9 [postgresql -pid]
-- Then, restart PostgreSQL, clear cache to force reading from disk.
postgres=# SELECT * FROM test_table LIMIT 10000;
   WARNING: page verification failed, calculated checksum 39438 but expected 39327
   ERROR: invalid page in block 1 of relation base/13425/6892 (Data corruption)
```

(a) Lower reliability

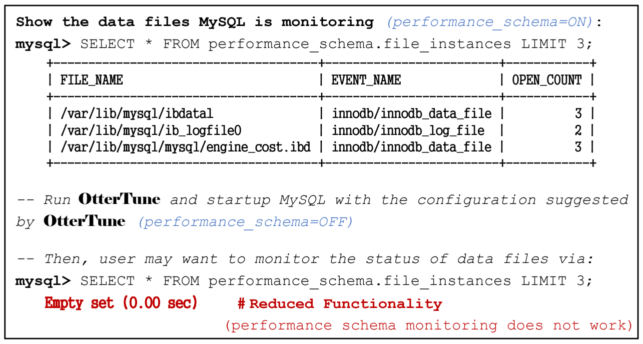


```
-- Start MySQL with default configuration (innodb_buffer_pool_size=128M)
Bash# top -p [mysqld-pid]
PID   USER   PR  NI    VIRT     RES     SHR      %CPU  %MEM  COMMAND
4329  mysql  20   0   1.165g  0.041g  0.015g  S   0.0   0.0   mysqld

-- run OtterTune and startup MySQL with the configuration suggested
by OtterTune (innodb_buffer_pool_size=16.4G)

Bash# top -p [mysqld-pid]
PID   USER   PR  NI    VIRT     RES     SHR      %CPU  %MEM  COMMAND
4919  mysql  20   0  18.301g  1.340g  15152   S   0.0   1.1   mysqld
         More Cost (30 $USD/month for single node, ecs.hfc7.xlarge)
```

(b) Higher cost

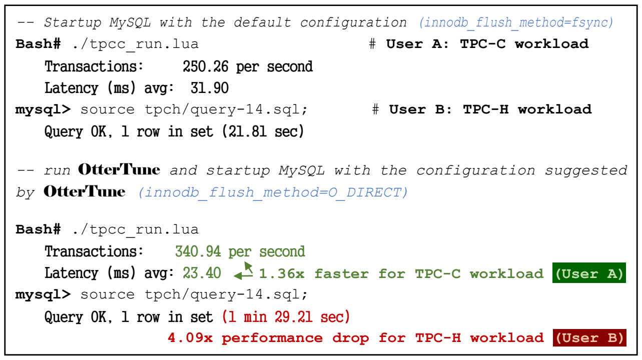


```
Show the data files MySQL is monitoring (performance_schema=ON):
mysql> SELECT * FROM performance_schema.file_instances LIMIT 3;
   +------------------------------------+-------------------------+------------+
   | FILE_NAME                          | EVENT_NAME              | OPEN_COUNT |
   +------------------------------------+-------------------------+------------+
   | /var/lib/mysql/ibdata1             | innodb/innodb_data_file |          3 |
   | /var/lib/mysql/ib_logfile0         | innodb/innodb_log_file  |          2 |
   | /var/lib/mysql/mysql/engine_cost.ibd | innodb/innodb_data_file |        3 |
   +------------------------------------+-------------------------+------------+

-- Run OtterTune and startup MySQL with the configuration suggested
by OtterTune (performance_schema=OFF)

-- Then, user may want to monitor the status of data files via:
mysql> SELECT * FROM performance_schema.file_instances LIMIT 3;
   Empty set (0.00 sec)     # Reduced Functionality
                  (performance schema monitoring does not work)
```

(c) Reduced functionality



```
-- Startup MySQL with the default configuration (innodb_flush_method=fsync)
Bash# ./tpcc_run.lua                      # User A: TPC-C workload
   Transactions:     250.26 per second
   Latency (ms) avg:  31.90
mysql> source tpch/query-14.sql;          # User B: TPC-H workload
   Query OK, 1 row in set (21.81 sec)

-- run OtterTune and startup MySQL with the configuration suggested
by OtterTune (innodb_flush_method=O_DIRECT)

Bash# ./tpcc_run.lua
   Transactions:    340.94 per second
   Latency (ms) avg: 23.40   1.36x faster for TPC-C workload (User A)
mysql> source tpch/query-14.sql;
   Query OK, 1 row in set (1 min 29.21 sec)
                  4.09x performance drop for TPC-H workload (User B)
```

(d) Lower performance (other user)

Figure 4: Side-effects on other intentions caused by OtterTune without the aid of SafeTune.

Using a large amount of memory leads to extra budget of ~30$ per month (depending on the cloud provider). Such a consequence is warned about through the prior use of SafeTune. For **User C**, OtterTune suggests turning off `performance_schema`, because by doing so, the performance improves by ~25%. This parameter enables MySQL monitoring on various entities, including events, opened files, status information, etc. **User C** monitors unexpected behavior (e.g., too many contentions on data files) using this functionality. However, after turning it off, as shown in Fig. 4(c), any monitoring action (i.e., monitoring which files are being opened by how many entities) does not work, hurting **User C**'s initial intention. **User D** is affected by `innodb_flush_method`. As shown in Fig. 4(d), after running OtterTune, this parameter is tuned from `fsync` to `O_DIRECT`. The former value allows each write first touch the kernel's cache and followed by a `fsync` system call. Since MySQL implements buffering itself especially for write [9], the kernel level caching may conflict with MySQL's buffering. The latter value causes MySQL to bypass the kernel cache. Thus, if **User D** uses the configuration suggested by OtterTune, the write workload (green text in Fig. 4(d)) can be improved by ~36%. However, **User D** is facing many kinds of users (i.e., workload). As the red text in Fig. 4(d) shows, the read performance degrades dramatically under this configuration. The reason lies in the ability of the kernel cache to keep more hot data in memory, thereby increasing read speed.

In conclusion, auto-tuners may cause critical side-effects on other intentions; SafeTune is complementary to them, which helps to prevent bad consequences.

6 RELATED WORK

Configuration Tuning. Some works aim to improve software performance by tuning configurations. They can be classified into model-based [17], measurement-based [25], search-based [20, 41, 42, 52, 54, 61] and learning-based [19, 36, 43] methods. These tools tune the parameters using certain heuristics and measure software performance to build a model that can find the fastest configuration. However, they only consider the performance impacts of configurations, meaning that they may cause side-effects such as reducing reliability. SafeTune can help to support these tools; this can be done both by reducing the search space and warning about the side-effects to prevent severe consequences.

Pre-selecting Performance-related Parameters. Some works target on per-selecting important parameters to accelerate the configuration tuning process. They use performance experiments to dynamically select parameters that have a significant influence on performance using statistical [38] or machine learning [24] techniques. Similarly, these works focus only on the performance of software and pay no attention to other users intentions. While SafeTune covers their targets and is also aware of multi-intentions. It fully leverages the document of parameters to predict the performance-related parameters and potential side-effects.

Understanding Relationship between Performance and Configuration. Some works target understanding the relationship between performance and configuration parameters. A group of works has endeavored to understand the relationship from code via static or dynamic code analysis [34, 39, 56]. While they cannot capture the side-effects of configuration parameters from code, but SafeTune leverages documents thus taking multiple intentions into consideration. The other group of works mines useful information related to configuration to help both developers and users improve software performance. Some works mine configuration documents to detect performance bugs [32], and others mine performance constraints of configurations to prevent users from performance misconfigurations [55]. Compared with all these works, SafeTune has a different focus: it utilizes documents to obtain multi-intentions of configuration parameters to pre-select performance-related parameters and warn about potential side-effects. Many works focus on the non-functional properties and feature interactions of software product lines (SPL) configuration [27, 47–49]. SafeTune focuses on run-time configurations, which are different from SPL features. The SPL tools usually rely on expert knowledge from developers as input to ensure non-functional properties. The run-time configurations are tuned by users, so it is hard to provide such input.

7 DISCUSSION

Ability of Generalization. The six types of side-effects on non-performance intentions are concluded from the studied software. To make SafeTune as generalized as possible, we selected 13 widely-used open-source software systems from four representative categories as targets. While our evaluation in §5.1 and §5.2 shows that SafeTune can achieve good results on un-studied software, we still cannot claim that our approach is able to be generalized to all software domains. SafeTune leverages configuration documents to predict tuning guidance. Thus, the tuning guidance that SafeTune provides relies on the quality of the configuration documents of the target software systems. We expect following improvements in documents: 1) explain the context of parameters' functionality, 2) tell user what will result in by changing parameter values, 3) split the description and additional information (e.g., recommendations, constraints) into different paragraphs. Our future work will extend SafeTune by using more information (i.e., source code) as additional input and new techniques to further understand the side-effects on non-performance intentions.

Effectiveness on Reducing the Search Space for Tuning. SafeTune may produce many performance-related parameters (e.g., occupying 38.9% of all parameters in §5.2) for performance tuning, directly using them may still make the search space big during tuning. However, the parameters suggested by SafeTune are labeled with side-effects, thus many of the parameters may not be actually tuned during tuning (when given some of other user intentions as input). In fact, there are only a small proportion (8.4% of all parameters in §5.2) of performance-related parameters that have limited or no side-effects. Also, we argue that SafeTune identifies performance-related parameters in general and independent of workload. So users can further choose parameters according to their workload. Our future works will focus on automatically identifying workloads affected by a given performance-related parameter.

Triggering Conditions of the Side-effects. Tuning parameters with side-effects may not necessarily violate user intentions. The triggering conditions may come from production workloads, system environment and the values of other parameters. For instance, if **User A** of §5.3 turns off `fsync`, but he/she has battery-backed RAM in the event of power failure, the intention of high reliability would not be violated. SafeTune is not able to extract all triggering conditions, while existing tools [26, 55, 60] may help extract some conditions. And we claim SafeTune warns about *potential* side-effects on other user intentions.

8 CONCLUSION

To improve performance, many works automatically pre-select and tune configuration parameters, but only for specific workloads, and are unaware of other user intentions. We argue that the configuration document contains rich information and can be leveraged to pre-select important parameters while retaining other non-performance intentions. We conclude six types of non-performance side-effect of the performance-related parameters from an empirical study on 13 software systems. Based on the findings, we design and implement SafeTune to predict the tuning guidance. Experiments show that SafeTune can identify 22-26 performance-related parameters that have substantial performance impacts but are missed by state-of-the-art tools. Moreover, SafeTune can help auto-tuners to prevent eight potential side-effects that have severe consequences.

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