Automated Performance Tuning for Highly-Configurable Software Systems

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Abstract—Performance is an important non-functional aspect of the software requirement. Modern software systems are highly-configurable and misconfigurations may easily cause performance issues. A software system that suffers performance issues may exhibit low program throughput and long response time. However, the sheer size of the configuration space makes it challenging for administrators to manually select and adjust the configuration options to achieve better performance. In this paper, we propose ConfRL, an approach to tune software performance automatically. The key idea of ConfRL is to use reinforcement learning to explore the configuration space by a trial-and-error approach and to use the feedback received from the environment to tune configuration option values to achieve better performance. To reduce the cost of reinforcement learning, ConfRL employs sampling, clustering, and dynamic state reduction techniques to keep states in a large configuration space manageable. Our evaluation of four real-world highly-configurable server programs shows that ConfRL can efficiently and effectively guide software systems to achieve a higher long-term performance.

I. INTRODUCTION

Modern computer systems are highly-configurable, allowing users to customize a large number of configuration options\(^1\) to meet their specific goals. The complexity of the configuration space and the sophisticated constraints among configurations may easily lead to performance issues. Recent studies have shown that performance problems caused by misconfiguration are still prevalent \(^2\). Performance issues can cause significant performance degradation which leads to long response time and a low program throughput \(^7\), \(^17\), \(^24\).

When a performance problem occurs (e.g., a significant slowdown with HTTP responses in a web server), system administrators and developers may need to re-configure the system to find a configuration setting for better performance. However, it is not an easy task to figure out the best settings for a system with a large number of configuration options. For example, the latest version of Apache HTTP Server (Apache) has 600+ configuration options (directives). Even for domain experts, it is not an easy task to configure the software system to get the best performance. For example, as one experienced user complained in HBase Bug #13919\(^2\) “There are current many settings that influence how/when an HBase client times out. This is hard to configure, hard to understand, and badly documented.” Besides, manually changing the configuration can be tedious, inefficient, and impractical. For instance, in the case of a web server, the volume of the web page request level changes at different times of the day. It is not practical to ask administrators to change configurations to keep up with the level of web request changes.

The goal of this research is to develop an approach, ConfRL, that can automatically select and tune configuration options in response to the environment dynamics \(^8\) to achieve better performance. ConfRL is intended to be used by system administrators and developers to tune performance through configurations. The key idea of ConfRL is to use reinforcement learning (RL) techniques to automate performance configuration tuning. RL is a process of interacting with a dynamic environment to generate the optimal control policy on what actions to take for a given state. Therefore, we can formulate the task of performance tuning as a RL problem in which the optimal policy refers to generate a configuration for higher performance. The main benefit of RL is that it does not require domain knowledge of the software system and can update optimal policies continuously in the long run.

ConfRL consists of two stages: performance-influential configuration option ranking and Q-Learning \(^41\). The first stage identifies configuration options that potentially influence the system’s performance. The enormous configuration space leads to a huge number of states that RL must explore, thus apply RL directly to a system with a large number of configuration options hardly scales. To address this challenge, ConfRL uses a clustering method to identify performance-influential options.

The second stage of ConfRL uses Q-Learning for finding a policy to guide on what actions to take in a given state to achieve higher performance gains. There are two challenges in this stage. First, even with fewer options to choose from, the configuration space may still be enormous \(^8\) at runtime. To address this challenge, we utilize adaptive value generation and dynamic state merging techniques to reduce the runtime reinforcement learning states. Another challenge is the inconsistent readings of the performance measurements (e.g., program throughput such as web page requests per

\(^1\)A.k.a., configuration parameters. Configuration used in this context is not to be confused with software configuration management (SCM).

\(^2\)https://issues.apache.org/jira/browse/HBASE-13919
This paper is structured as follows. In Section II, we introduce the technical background. In Section III, we discuss the formulation of ConfRL as an RL problem. We then present the design of ConfRL in Section IV. Our empirical study and the formulation of ConfRL as a RL problem. We then present the results are presented in Sections V and VI, followed by a discussion of threat to validity in Section VII. We present the related work in Section VIII, and then conclude the paper in Section IX.

II. BACKGROUND

In this section, we introduce the background of reinforcement learning (RL) and discuss how to model automated performance tuning as a RL task.

A. Tuning Performance Configuration

Reinforcement learning (RL) [30], as illustrated in Figure 1, is the procedure of learning from interactions between an agent and the environment to determine the best action to take under any given state to achieve the maximum long-term rewards [35]. After the agent initiates an action, the environment reacts to the action by transitioning the agent to a different state. Depending on the current and previous states, the environment grants rewards to the agent. This cycle goes on iteratively until the learning procedure terminates. The output of RL is a policy that guides the agent to take an action that maximizes long-term rewards based on its current state. The value of an action associated in a state is computed by a function that estimates the sum of future rewards by taking this action. The agent performs trial-and-error interactions with the environment to obtain rewards. Therefore, the optimal policy is to select the action that maximizes the reward in each state.

The task of performance tuning fits into the RL framework naturally. Each configuration (i.e., a combination of configuration option values) represents a RL state. When performance tuning occurs, (i.e., issue an action to change configuration), an action receives a reward based on performance measurements. Given sufficient interactions with the environment, RL obtains an estimation of how good an action is for the current configuration (i.e., state).

B. Reinforcement Learning Techniques

Reinforcement learning comes in a few different forms depending on what is available to the problem (e.g., full knowledge of the environment such as the transition function). We discuss briefly two of the most widely adopted methods and explain why we select the Q-Learning method for our problem.

Markov Decision Process. The basic form of a reinforcement learning problem is encapsulated as the Markov Decision Process (MDP) [27]. Formally, MDP is used to describe an environment for reinforcement learning where the environment is fully observable. MDP consists of a finite set of states, a finite set of actions, a state transition matrix: $P_{ss'} = P[S_{t+1} = s'|S_t = s]$ [29], a reward function $R$, and a discount factor $\gamma$. A state has Markov property if and only if each state captures the information from all past states that lead to the current state. A policy $\pi$ gives the probability to take an action given a state $s$: $\pi(\alpha|s) = P[A_t = \alpha|S_t = s]$. The action-value function $q_\pi(s, \alpha)$ is the expected total rewards for taking an action $\alpha$ following the policy $\pi$ in state $s$. The goal
of solving the MDP problem is to find the optimal action-value function: \( q_\alpha(s, \alpha) = \max_\pi R^\pi(s, \alpha) \).

**Model-Free RL.** If a problem can be modeled as MDP, it can be solved analytically through value-iteration and policy-iteration algorithms. Most real-world problems cannot be formulated as MDP since the environment is not fully observable. It is also difficult to describe the rules in a dynamic environment, so the MDP transition function is unknown. There are a set of techniques to estimate the action-value function of an unknown MDP, such methods are referred to as Model-Free reinforcement learning algorithms [29]. The Q-Learning method [41] is one type of Model-Free learning algorithm. It seeks to learn a policy to maximize the total award. ConfRL uses Q-Learning as its reinforcement learning algorithm. Q-Learning is based on the Bellman Optimality Equation [5]:

\[
q_\alpha(s, \alpha) = R^\alpha_s + \gamma \sum_{s' \in S} \max_{\alpha'} q_\alpha(s', \alpha').
\]

The formula contains two parts: \( R^\alpha_s \) is the immediate reward, \( \sum_{s' \in S} \max_{\alpha'} q_\alpha(s', \alpha') \) is the expected future reward to take an action \( \alpha \) in state \( s \), and \( \gamma \) is the discount factor that determines how much RL should value the future reward.

**\( \epsilon \)-Greedy Exploration.**

As RL explores the environment, it takes advantage of its experience interacting with the environment. Internally, RL maintains a state-action table to keep track of rewards received by taking specific actions in a state. This helps RL to select actions to achieve higher performance gains. However, in the early stage of exploration, sticking to the state-action table completely may restrict the number of states that RL could have visited. There may be a chance that RL could have achieved higher performance by visiting different states. As such, RL introduces some randomness into the process. By convention, the degree to which RL acts randomly is denoted as \( \epsilon \) with a range between 0 (i.e., no random actions at all) and 1.

### III. Problem Formulation

We demonstrate how to formulate and solve the problem of performance tuning with RL using an example of the Apache web server. Table [II] shows the configuration options used in the example. Column “Name” lists the names of the selected configuration options. Column “Type” lists the option value types: binary (B) or numerical (N). Column “Range” lists the configuration option value ranges. Column “Constraints” lists imposed constraints on configuration options. The configuration option value ranges and constraints are manually extracted from the documentation of the subject programs.

**State.**

TABLE I: Configuration Options

| Name           | Type | Range       | Constraints                      |
|----------------|------|-------------|----------------------------------|
| KeepAlive      | B    | OFF / ON    | Constraints Not Applicable       |
| MaxClients     | N    | [1,312]     | MaxClients < ServerLimit         |
| StartServers   | N    | [1,100]     | StartServers < MaxSpareThreads    |
| ThreadsPerChild| N    | [1,128]     | ThreadsPerChild < StartServers < MaxClients |

A state is encoded as an instance of the subject program’s configurations. For example, Table [II] illustrates five states in Apache. Each state is a combination of the current configuration option values (Columns “Option”). The “State” column lists the state ID. The default values of configuration options are used as the initial state (S1). We discuss the impact of choosing different initial states in Section VII. The “Meas.” column lists the performance measurements.

It is a metric to quantify program performance. For web servers, we measure the number of concurrent web page requests per second [11] for database servers, we measure the number of transactions per second [10]. The “Action” column lists the next actions to be performed on the subject program. The “Rewards” column lists the immediate performance reward. The reward is used to populate the state-action table, a.k.a, the Q-Table. The “State” column in Table III lists the visited RL states. Column “A1” to “A8” list eight actions associated with four options used in Table II. Each cell in Table III lists the immediate performance reward after taking an action in the corresponding state. By default, the immediate performance reward is set to 0.

**Action.** An action is an update issued by ConfRL to modify an individual configuration option value. For numerical option types, an action can be 1) increasing an option value; 2) decreasing an option value. For binary options types, an action can be 1) setting a binary option value to True; 2) setting a binary option value to False. Action is indexed and encoded by an integer number. Each integer is mapped to a specific operation to the option, as shown in the “Action” column of Table III. In this example, action one (A1) is mapped to set the first configuration option KeepAlive to “ON”. Action five (A5) is mapped to increase the value of the third configuration option StartServers.

**Reward.** A reward is calculated based on performance measurement, for example, web servers use the number of concurrent web page requests per second. ConfRL first obtains the performance measurement under the current configuration
options as $M_C$. The subject program follows an action to enter the next state with performance measurement $M_N$. The reward is the relative difference between $M_N$ and $M_C$: $(M_N - M_C) / M_C$, the normalization puts a large measurement range on the same scale.

Since obtaining the performance measurement for each execution is time-consuming and that the measurements may be inconsistent due to environment dynamics, ConfRL caches the performance measurement for each state. The cache can 1) speed up the process of getting performance measurement, and 2) guarantee the performance measurement is consistent throughout the learning process. The details of the performance caching technique will be discussed in Section IV-E.

IV. DESIGN OF CONFRL

Figure 2 gives an overview of ConfRL. ConfRL takes as inputs a program, its configuration options, and the associated constraints. In stage I, ConfRL selects options that influence the program’s performance to reduce the RL states and thus the learning cost. ConfRL employs sampling and clustering techniques to rank the performance-influential options and assign them with appropriate weights. ConfRL differs from prior work [15], [22] on performance-influential configuration option identification in that it is self-contained and it does require any prior knowledge about the software system. In stage II, ConfRL uses an adaptive value generation method to systematically generate configuration option values to cover a wide value range. ConfRL calculates the reward based on the performance measurement obtained in each state and uses the reward to build the Q-Table.

To reduce the learning cost, ConfRL employs a state merging technique to combine reinforcement learning runtime states that share the same performance measurements.

This can effectively reduce the size of the state space and lead to faster learning. In the end, ConfRL outputs a Q-Table to reflect the latest interactions between the agent and the environment.

This procedure goes on until when reaching the stopping criterion. For instance, the learning procedure stops after 24 hours in our experiment.

A. The ConfRL Algorithm

Algorithm 1 illustrates the pseudocode of ConfRL. The algorithm takes as input the subject’s configuration options with default values and outputs a Q-Table. The algorithm starts with a $t$-way sampling technique [43] to get the clustering training data (Line 1). Then, the ranking of performance-influential options is generated from clusters (Line 2). ConfRL creates an action-value table to store the calculated rewards (Line 3). Next, the algorithm initiates the Q-Learning algorithm (Line 4). There are two hyper-parameters involved in the Q-Learning algorithm: the learning rate $\alpha$ and the discount factor $\gamma$. The learning rate “determines to what extent newly acquired information overrides old information” [41], which controls how fast the reinforcement learning converges. The discount factor weighs on how RL perceives future rewards. $\gamma$ has a value between 0 and 1, where 0 indicates RL takes only the immediate rewards without considering future rewards, and 1 indicates RL favors the learning towards long-term rewards.

The $\epsilon$-Greedy explorer (Line 5) is used to control the degree to which RL follows the original policy.

It is a discrete explorer that follows the greedy policy while maintaining a chance to take a random action to explore unknown states. The randomness is controlled by $\epsilon$. The algorithm instantiates the environment and the agent objects (Lines 7–8) and then starts the reinforcement iterations inside a while loop (Line 9). The subject program is reset to the original state at the beginning of each iteration and exploits what it has learned from past in the next iteration.

When the iteration starts, the DoInteractions function (Line 10) controls interactions between the agent and the environment. This is also where the adaptive value generation starts. The algorithm dynamically reduces the value of $\epsilon$ (Lines 11–13) to converge faster. State merging (Line 15) is used at the end of the learning iteration to reduce the number of runtime states. The learning process terminates when it reaches a time-threshold.

B. Ranking Performance-Influential Configurations

This pre-processing step is used to identify the performance-influential configuration options from the target configuration...
Algorithm 1 ConfRL

Require: Initial set of configuration options (O)
Ensure: Q-Table
1: trainingData = tWaySampling(O)
2: rankedOps = PerfClustering(trainingData)
3: avt = ActionValueTable()
4: learner = QLearner(a, γ)
5: explorer = EpsilonGreedyExplorer(ε)
6: learner.SetExplorer(explorer)
7: env = ConfigLearnEnv(rankedOps)
8: agent = LearningAgent(avt, learner, env)
9: while TRUE do
10: DoInteractions()
11: if TriggerEpsilonUpdate() == TRUE then
12: ϵ = UpdateEpsilon()
13: explorer = UpdateExplorer()
14: end if
15: env.StateMerging()
16: end while
17:
18: function STATEMERGING
19: perfM = MeasurePerf()
20: if perfM ∈ PerfState.keys() then
21: masterState = PerfState[perfM]
22: UpdatePerfState(masterState, stateID)
23: else
24: PerfState.add(perfM, stateID)
25: end if
26: end function

option space. A t-way covering array samples the set of configurations in such a way that all possible t-way combinations of options appear at least once. Based on a previous study [9], a 3-way covering array is adequate to cover 90% of the number of option value choices is bounded by log(OPT MAX). Therefore, the maximum number of option value choices is bounded by log(OPT MAX). For instance, the MaxClients option has a value range of [1, 1024]. As such, we have at most eleven values choices for MaxClients: 2^0, 2^1, ..., 2^9, 2^10. ConfRL makes sure the selected value satisfies all constraints imposed on the option using the python-constraint library [23].

D. Reducing Runtime States

The adaptive value generation strategy can significantly reduce the number of individual option values without losing adequate coverage for exposing performance problems. However, as the number of configuration options used in the learning process increases, it still poses a challenge to handle a large number of option value combinations, aka, the RL states. To further reduce the number of RL states, ConfRL uses a dynamic state reduction strategy.

At runtime, different states do not always lead to different performances. Many states lead to unnecessary costs in measuring performance without providing any new insights for the reinforcement learning process. Only those performance-influential configuration options tend to result in different performance measurements. ConfRL merges reinforcement learning states that share the same runtime performance. ConfRL implements a cache to store performance measurements for states. At the end of each reinforcement learning iteration (Line 15 in Algorithm 1), a reference list is constructed for
state IDs that have identical performance measurements (Lines 21–22 in Algorithm 1). The first such state in each reference list is referred to as the master state, the rest of the states in the reference list is referred to as slave states. In the following reinforcement learning iteration, ConfRL returns the master state if the current state is in the slave state list.

E. Measuring Performance

Performance measurements (e.g., execution times, throughputs) are used to evaluate if one state is better than another state in terms of achieving higher performance. Performance measurement is essential to calculate rewards in ConfRL for Q-Learning (Section III). Within each reinforcement learning iteration, ConfRL measures the performance by executing benchmark tools (e.g., Apache Benchmark, DBT-2). To provide a reliable and consistent performance measurement, the performance measurement of a state is stored upon the first time ConfRL visits the state. Specifically, the state and its performance measurement are stored in a cache. The cache uses the state ID as the key and the corresponding performance measurement as its value. In each subsequent reinforcement learning iteration, the performance of the same state is queried and retrieved directly from the cache instead of re-running the benchmark utility. This strategy guarantees the performance of the same state is consistent throughout the learning process. Inconsistent performance measurement has a negative impact on the RL reward calculation, therefore confusing ConfRL on which actions to take in a given state. The performance measurement cache also reduces the overall learning time as benchmark tools can take a significant amount of time to collect the performance measurement.

F. An Example

To demonstrate the reinforcement learning design of ConfRL, we use Table II to show how ConfRL works. As the learning iteration advances, the Q-Table gets populated and updated to allow the best action to be returned based on the current state. Table III illustrates the status of Q-Table as the learning progresses. In this example, we assume the StartServers option has a larger weight than other options. Therefore, this option has a higher chance to be selected by the ConfRL (e.g., ThreadsPerChild * StartServers must hold true for StartServers). The adaptive value generation adjusts the option value by finding the first value in the series (i.e., 2^n) that is larger than 24. Therefore, the StartServers option gets a value of 32. Apache is now in the state S3: [ON,102,32,3]. The performance measurement of S3 is 25 r/s. Therefore, the immediate reward for taking action A5 in S2 is 0.25.

In the third interaction, the agent receives the action A6 which is to increase the value of ThreadsPerChild (T.P.C.). ThreadsPerChild gets a value of 4. When the ConfRL validates the constraints, it no longer holds: ThreadsPerChild (4) * StartServers (32) > MaxClients (102). ConfRL uses the Constraint Satisfaction Problems (CSPs) solver. The constraint is passed to the solver as a lambda function lambda T.P.C., S.S., M.C.: T.P.C.* S.S. > M.C., M.C.: [2^0, 2^1, ..., 2^9, 2^10]. One solution to satisfy the constraint is [T.P.C.:4, S.S.:32, M.C.:256]. As such, ConfRL assigns 256 to MaxClients. Apache is now in the state S4: [ON,256,32,4]. S4 has a performance measurement of 30 r/s. The immediate reward for taking action A7 in S3 is 0.2.

In the fourth interaction, the agent receives the action A6, which is to decrease the value of StartServers (S.S.). The StartServers option gets a new option value of 16. The subject is now in the state S5: [ON,256,16,4]. S5 has a performance measurement of 20 r/s. The immediate reward for taking action A6 in S4 is -0.17. After the first iteration finishes, dynamic state reduction looks through states that have identical performance and combines such states.

For instance, states S2 and S5 are to be combined, and the performance-state cache gets a new entry: [20: {MasterState: S2 -> SlaveStates: S5}].

V. EMPIRICAL STUDY

To evaluate ConfRL, we conduct an empirical study on four subjects and aim to answer the following research questions:

RQ1: How effective is ConfRL in tuning the configuration options values to achieve long-term performance gains?

RQ2: How efficient is ConfRL for achieving a given performance goal?

A. Implementation

For reinforcement learning, we extend the Python-based library pybrain [51] to conduct Q-Learning. The Bash shell script is used to connect and execute different components of experiments such as updating configurations, monitoring performance measurements, and calculating rewards. We conduct all the experiments automatically on a RedHat Linux system in
B. Subject Programs

We choose four popular open-source server applications: Apache HTTPD Server, Lighttpd Web Server, MySQL Server, and PostgreSQL (PSQL) Server. All subjects are highly configurable server applications, which are prone to performance issues caused by misconfigurations. Table IV shows the characteristics of the subjects. The “Modules” column shows the modules from which the configuration options are collected. We evaluated the modules involving the core functionalities of the programs. The “#Oₐ” column lists the number of numeric options and the “#Oᵦ” column lists the number of binary options.

To evaluate the performance of subject programs, we use the program throughput as the performance measurement similar to other work [6]. Specifically, we use the number of concurrent web page requests (CWR) for web servers and the number of transactions per second (TPS) for database servers. CWR and TPS are commonly used performance measurements for web and database servers [10].

C. Experiment Design

1) Baseline Techniques: We use a random method Mᵦ as the baseline for both effectiveness and efficiency comparison since there are no existing techniques that target the same goal as ConfRL. Mᵦ randomly selects a configuration option from the configuration option pool and then assigns a random value to the configuration option according to its value range. Mᵦ skips state reduction and reinforcement learning steps. To evaluate whether the adaptive value generation and dynamic state merging techniques can affect the effectiveness and efficiency of ConfRL, we consider two “vanilla” versions of ConfRL. The first version is ConfRLᵦ, which does not apply dynamic state merging. The second version is ConfRLᵦ, which does not apply the adaptive value generation. Similar to Mᵦ, ConfRLᵦ assigns a random value to the configuration option. We let each technique run for 24 hours for as many iterations as it can complete before checking the results. To reduce the influence of randomness, we repeat each method 10 times. The null-hypothesis, H₀ states that “the mean of the two methods are equal”, and we reject the null hypothesis if the probability value is less than 5% (p < 0.05). After all methods finish, we conduct the t-test to evaluate if the mean difference in each set of data is statistically significant.

2) RQ1: Effectiveness of ConfRL: RQ1 evaluates whether ConfRL is effective at guiding the applications toward higher performance by adjusting the configuration option values. Since the first step of ConfRL is to identify performance-influential configuration options to reduce the search space, we want to evaluate if the ranking is accurate compared to Mᵦ. Specifically, ConfRL uses a 3-way covering array to conduct configuration sampling for K-Means clustering. The top-10 configuration performance-influential options are returned, such configuration options get a larger weight in reinforcement learning. In other words, ConfRL is biased towards selecting such options for performance tuning. Mᵦ, on the other hand, randomly selects 10 configuration options.

To measure the effectiveness of ranking, the mean average precision (MAP) score is used. MAP is a single-figure measurement of ranked retrieval results independent of the size of the top list [32]. It is designed for general ranked retrieval problems, where a query can have multiple relevant documents. To compute MAP, it first calculates the average precision (AP) for individual query Qᵢ, and then calculates the mean of APs on the set of queries Q:

$$MAP = \frac{1}{|Q|} \sum_{Q_i \in Q} AP(Q_i).$$

To illustrate the MAP calculation, suppose there are two configuration options O₁ and O₂ that are performance influential. If Technique-I ranks the two options at the 1st and 2nd positions and Technique-II ranks the two options at the 1st and 3rd positions, then the MAP score of Technique-I is (1/1 + 2/2)/2 = 1 and the MAP score of Technique-II is (1/1 + 2/3)/2 = 0.8. We say that Technique-I is better than Technique-II in ranking performance-influential configuration options.

Next, we evaluate if ConfRL’s performance tuning algorithm is effective. To build a Q-Table, ConfRL needs to obtain performance measurements. Benchmark tools are used to generate workload and report performance measurements. For instance, the Apache Benchmark (ab) is used to measure Apache’s performance by the following command: “ab -n 1000 -c 10 http:localhost”. -n specifies the number of requests and -c specifies the level of concurrency. The benchmark tools provide an elegant solution to generate synthetic traffic on demand.

In the experiment environment, all non-system processes are terminated to dedicate the system resource to the subject program and to reduce any other activities that may disturb the experiment. We configure each subject program according to the performance tuning guidance [3, 20, 26, 23] and benchmark 1000 times for each subject to record the subject’s performance. The best performance is selected and used as the performance goal P_GOAL.

This performance is established as the maximum performance achievable in the experiment environment.

We look at the mean performance achieved when each method reaches the time limit.

3) RQ2: Efficiency of ConfRL: RQ2 evaluates how long it takes for ConfRL to achieve a given performance goal. We
compare ConfRL with three baseline techniques (i.e., M_{RND}, ConfRL_{A}, and ConfRL_{D}) to evaluate the overall efficiency of ConfRL. The mean performance measurement is checked hourly. Ideally, the mean performance measurement should be equal to P_{GOAL}, due to the internal implementation of the benchmarking tool, the uncertainties on the experiment environment, and the nature of reinforcement learning method, it is not always possible to achieve a mean performance measurement equal to P_{GOAL}. We consider ConfRL converges when the mean performance measurement is greater than 90% of the P_{GOAL} and maintains the same level of performance to the end of the experiment. Although measuring performance is the most time-consuming operation in ConfRL, each method uses the same method (benchmark tool). Hence, the time spent on such steps is comparable.

VI. RESULTS AND ANALYSIS

1) RQ1: Table V shows the result of the effectiveness of ranking performance-influential configuration options. The “MAP” column lists the mean average precision scores for both ConfRL and M_{RND}. The MAP score of ConfRL ranges from 0.36 to 0.7, with an average MAP score of 0.52. ConfRL outperforms M_{RND} in three out of four cases. ConfRL successfully identifies at least one performance-influential option [3] and ranks options in the top-10 position. The results show that the option ranking method used in ConfRL is effective.

In the “Effectiveness” column, we report the mean performance measurements across all the iterations for ConfRL, M_{RND}, ConfRL_{A}, and ConfRL_{D}, respectively. As the results suggest, ConfRL outperforms M_{RND} in all four programs, ranging from 14% to 30%, with 24% on average. The t-test shows the difference between the two sets of data is statistically significant. The result shows that ConfRL can effectively select the right configuration options to tune performance.

Figure 3 shows the plotting of four methods in each subject program. The plot shows how well each method works during the time limit. The x-axis indicates the timeline. The y-axis indicates the performance measurement. Due to the space limitation, we place 24 data points in each plot to represent the average performance measurement calculated at each hour. Since there is only a small subset of states that can lead to higher performance, initially, all four methods go hand in hand in terms of the mean performance measurement. As a matter of fact, M_{RND} can often achieve similar and sometimes even better performance.

In early iterations, the performance fluctuations in ConfRL, ConfRL_{A}, and ConfRL_{D} are expected. This is due to explorations in the reinforcement learning states (i.e., states represented by different combinations of configuration option values that as defined in Section IV-F). In the early reinforcement learning iterations, ConfRL needs to explore as many states as possible to understand the environment. Specifically, for $\epsilon$-greedy exploration, ConfRL does not follow exactly the path (i.e., policy) learned from previous iterations to explore more states and hence the performance fluctuations. There is a small chance that the agent strays away from the current policy. The action is selected by following the $\epsilon$-Greedy algorithm. In a nutshell, $\epsilon$ determines the randomness of exploring outside of the learning comfort zone, which allows the agent to have a chance to explore unseen states. The agent either receives a random action in the exploration phase or an action by exploiting the experience. This also prevents the agent from trapping at a local maximum. ConfRL gradually reduces $\epsilon$ to help the learning process converge faster.

Towards the end of the execution, the performance measurement tends to stabilize as the agent figures out what actions to take for a given state. Because ConfRL uses fewer states in the learning process, we observe that ConfRL converges faster than ConfRL_{A} and ConfRL_{D}. On the contrary, M_{RND} does not learn from any previous interactions, the performance of the random method does not have a noticeable improvement. Therefore, ConfRL is more effective in performance tuning than the baseline methods.

2) RQ2: The “Efficiency” column in Table V shows the efficiency of ConfRL. When comparing ConfRL to the baseline random method M_{RND}, in three out of four subject programs, ConfRL uses less time to converge to the target performance. On average, ConfRL uses 20.5 hours to converge whereas all other methods fail to converge within the 24-hours time limit except one occasion in Lighttpd with ConfRL_{D}.

Lighttpd has the smallest number of configuration options in all four subjects. The size of the configuration space hence the number of runtime states is smaller compared to other subjects. We conjecture it is the smaller size of the runtime states that leads to the ConfRL_{D} method to converge faster. Nonetheless, the result shows that the dynamic state reduction technique is useful as the ConfRL_{A} method takes longer to converge.

Table VI shows the results of ConfRL, ConfRL_{A}, and ConfRL_{D} for evaluating the impact of state reduction techniques. The result in Table VI shows the number of states reduced range from 11% to 36% and on average ConfRL reduces reinforcement learning states by 22.8%. When comparing to the ConfRL_{D} method, the states reduced range from 10.7% to 79.8% and on average ConfRL uses 22.8% fewer states. ConfRL uses 26.3% to 82.5% (on average 62.3%) fewer states when compared to the ConfRL_{A} method. As we can see, ConfRL reduces the number of reinforcement learning states without losing learning power. The results show that the reinforcement learning together with state reduction techniques used in ConfRL are efficient.

VII. DISCUSSION

A. Sensitivity of Strength

We evaluate ConfRL with different initial states. Specifically, we conduct an experiment with three sets of initial states: 1) configuration options with default out of the box values; 2) configuration options with random values; 3) configuration options with known best performance values. In the first two cases, ConfRL can guide the subject programs towards better performance after 200+ iterations. However, in the third case
TABLE V: Effectiveness and Efficiency of ConfRL

| Subject | MAP | Effectiveness | Efficiency |
|---------|-----|---------------|------------|
|         |     | ConRL | M_{RD} | ConRL | M_{RD} | ConRL-A | M_{RD} | ConRL-D | M_{RD} | ConRL-A | M_{RD} | ConRL-D |
| Apache  | 0.59| 0.17  | 4607 r/s | 3540 r/s | 4374 r/s | 4422 r/s | 20 h | 24+ h | 24+ h | 24+ h |
| Lighttpd| 0.7 | 0.17  | 3964 t/s | 3094 t/s | 3602 t/s | 3862 t/s | 21 h | 24+ h | 24+ h | 24+ h |
| MySQL  | 0.42| 0.64  | 324 t/s | 257 t/s | 317 t/s | 315 t/s | 20 h | 24+ h | 24+ h | 24+ h |
| PSQL   | 0.36| 0.11  | 248 t/s | 217 t/s | 232 t/s | 235 t/s | 21 h | 24+ h | 24+ h | 24+ h |

MAP: Mean Average Precision; r/s: requests per second; t/s: transaction per second; h: hour;

TABLE VI: RQ3: Impact of State Reduction Techniques

| Subject | States | ConRL | MD | PM | States | ConRL-A | PM | States | ConRL-D | PM |
|---------|--------|-------|----|----|--------|--------|----|--------|--------|----|
| Apache  | 21696  | 7548  | 4607 t/s | 3540 t/s | 4374 t/s | 4422 t/s | 20 h | 24+ h | 24+ h | 24+ h |
| Lighttpd| 15370 | 1844  | 3864 t/s | 3094 t/s | 3602 t/s | 3862 t/s | 21 h | 24+ h | 24+ h | 24+ h |
| MySQL  | 19045 | 2095  | 324 t/s | 257 t/s | 317 t/s | 315 t/s | 20 h | 24+ h | 24+ h | 24+ h |
| PSQL   | 23587 | 7811  | 248 t/s | 217 t/s | 232 t/s | 235 t/s | 21 h | 24+ h | 24+ h | 24+ h |

States: # of states identified when the RL finishes; MD: # of states sharing the same performance; PM: performance measurement;

Other subjects may exhibit different behaviors. We reduce this threat to some extent by using several varieties of well studied open-source projects from different application domains. For programs in the same application domain (e.g., web servers), we select multiple subject programs with different implementations and varying numbers of configuration options.

B. Threats to Validity

The primary threat to the external validity of this work involves the representativeness of the selected subject programs. In which subject programs are configured with known options for best performance, the performance learning plots show a zigzag pattern. ConfRL first takes the subject program to a state with poor performance, and then jumps to a state that results in a good performance. It makes sense to the reinforcement learning algorithm, as this pattern would allow the agent to get more rewards in each iteration. This shows a potential weakness in ConfRL as it may not behave optimally when starting in the optimal state. Experiments have shown that by giving a greater penalty to the agent may alleviate this phenomenon.

The primary threats to the internal validity of this work include possible faults in the implementation of the proposed approach and tools that we use to perform the evaluation. We control this threat by testing our tools extensively and verifying their results against a small-scale program for which we can manually determine the correct results. For each subject program, we start with a small set of manageable configurations to test things out before conducting experiments on a larger scale. The time complexity of dynamic state merging is proportional to the number of runtime states, it could be very expensive when the subject program has an extensive number of runtime states. We control this threat by identifying the performance-influential configuration options and restricting the number of configuration option values to reduce the runtime state space.
C. Limitations

First, this work does not evaluate the impact of multi-layer software systems. Instead, ConfRL treats the other layers in a black-box fashion. For instance, when requesting a web page from Apache, a web page could make calls to render the dynamic content on the web page from a backend database server. ConfRL does not consider the impact of the backend database server when adjusting configuration options to the Apache server. However, in our setup, we make sure other layers in a multi-layer software have the same setup throughout the experiments. Second, this work does not evaluate the impact on a resource sharing server where multiple programs can request hardware resources at the same time. The current setup assumes that the subject program is the only program demanding resources on the host machine. This is a reasonable assumption since in practice many businesses would prefer to deploy web servers and database servers to dedicated machines.

VIII. RELATED WORK

Configuration Auto Fix. Su et al. [34] propose a causality dependency tracking and analysis approach on modified Linux kernels to help users to find a solution to the configuration problem. Swanson et al. [37] design the REFRACT, a self-adaptive framework to find workarounds to fix and prevent future configuration-induced software failures. Whitaker et al. [40] propose Chronus, a tool that utilizes user-provided probes to search through the incremental system checkpoints to find the offending states and diagnose configuration errors that caused software functional problems. Unlike our approach that targets the software performance (non-functional requirement) long-term gain, the aforementioned methods target software failures (functional requirement) which are vastly different than performance issues.

Several techniques have been proposed to find optimal configurations using learning techniques [11], [12], [14], [21], [22]. Diao et al. [11] propose an approach to use the fuzzy controller to automatically tune configuration options that were known to have a concave upward effect to optimize response time. One big limitation with this approach is that the method relied on the qualitative knowledge of selecting such configuration options. Elkhodary et al. [12] develop a general-purpose framework for a self-adaptive system through a feature-oriented system model. Hoffmann et al. [14] use instrumentation to trace and adjust configuration parameters. Liu et al. [21] conduct experiments to find the best optimization techniques to reduce response time by adopting online optimization methods, such as Newton’s Method, to configuration options in the Apache web server. However, hill climbing techniques based on Newton’s method can be used to find the optimal value only when the problem has a concave upward effect on the parameter, therefore, limiting its adaptability. Reinforcement learning used in ConfRL, on the other hand, is known to solve the problem of determining what actions to take without requiring any prior knowledge of the environment. Naturally, it is suitable for performance tuning.

Reinforcement Learning Techniques. Other literature [6], [28] explore the use of reinforcement learning in the context of dynamically adjusting resource allocations (e.g., CPU and Memory) on the resource sharing virtual machine environment. Such efforts are mainly focused on optimizing the hardware-level resource configurations on the virtual machine environment where guest systems may compete for shared resources. In such cases, the size of the configuration space is relatively smaller since only a handful of resources are needed to be considered. Also, the best practice for tuning performance on the hardware level is well established compared to the software level configurations. Bu et al. [6] propose RAC, a reinforcement learning approach to automatically update the application configuration in response to the web traffic and virtual machine changes. Rao et al. [28] propose a reinforcement learning approach to automatically configure resources on virtual machines (VM). In their work, the configuration space is defined in terms of the system resource allocations in the VM environment. The number of configuration options (CPU, MEM) to change is small. The configuration space is much bigger in our subjects, for instance, Apache has hundreds of configuration options. Also, the prior work focuses on managing resources on the VM-level to maximize throughput whereas we focus on achieving long-term performance gains on the application-level with fixed hardware resources.

Control Theory Techniques. Previous literature [2], [25], [39], [44] use the control theory to manipulate configurations. The control theory works particularly well when certain constraints must not be violated. However, the use of the control theory requires extensive knowledge of the underlying system and a lot of effort in the hyper-parameters tuning. As previous performance bug empirical studies [39], [44] show, application-level configurations may have a great impact on the overall application performance. Wang et al. [39] design SmartConf to use the control theory to build a prediction model for each option to maximize software performance while maintaining the required operating constraints. SmartConf requires code modification whereas our method does not rely on the source code to work. Zhang et al. [44] apply convergent control rules to design a framework that enables friendly virtual machines that can adjust their demands based on feedback on the hardware resource usage and availability. Because of the differences in the project goals, authors of SmartConf agree that machine learning based techniques are “better than controllers in deciding optimal settings”. Abdelzaher et al. [2] use a feedback control theory to achieve response time and throughput guarantees to different classes of clients in a general web server. Padala et al. [25] use classical control theory to allocate resources dynamically to meet the application-level quality of service in a virtual data center environment. Our work, on the other hand, uses reinforcement learning to train the agent to automatically adjusting configuration option values to achieve long-term performance gains.

Elkhodary et al. [12] develop a general-purpose framework for a self-adaptive system through a feature-oriented system model. Hoffmann et al. [14] use instrumentation to trace and adjust configuration parameters. Liu et al. [21] conduct experiments to find the best optimization techniques to reduce response time by adopting online optimization methods, such as Newton’s Method, to configuration options in the Apache web server. However, hill climbing techniques based on Newton’s method can be used to find the optimal value only when the problem has a concave upward effect on the parameter, therefore, limiting its adaptability. Reinforcement learning used in ConfRL, on the other hand, is known to solve the problem of determining what actions to take without requiring any prior knowledge of the environment. Naturally, it is suitable for performance tuning.
IX. CONCLUSIONS

Performance is crucial to the success of software systems. While modern software provides great flexibility through configuration options, the large number of configuration options can be difficult to understand and even more intimidating to setup properly. In this paper, we present ConfRL, a reinforcement learning approach that automatically tunes performance-influential configuration options to achieve long-term performance gains. We evaluate ConfRL with four large-scale server projects. Our evaluation shows that ConfRL can efficiently achieve higher long-term performance gains up to 30%. Our experiment shows that ConfRL can effectively reduce the number of reinforcement learning states up to 82.5%. On average, ConfRL converges in 20.5 hours. In the future, we plan to study additional factors that may influence the effectiveness and efficiency of ConfRL, such as the context of the system environment. We also plan to study if ConfRL can be used to correct performance bugs caused by misconfiguration.
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