Evolutionary Mutation-based Fuzzing as Monte Carlo Tree Search

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Abstract

Coverage-based greybox fuzzing (CGF) has been approved to be effective in finding security vulnerabilities. Seed scheduling, the process of selecting an input as the seed from the seed pool for the next fuzzing iteration, plays a central role in CGF. Although numerous seed scheduling strategies have been proposed, most of them treat these seeds independently and do not explicitly consider the relationships among the seeds.

In this study, we make a key observation that the relationships among seeds are valuable for seed scheduling. We design and propose a “seed mutation tree” by investigating and leveraging the mutation relationships among seeds. With the “seed mutation tree”, we further model the seed scheduling problem as a Monte-Carlo Tree Search (MCTS) problem. That is, we select the next seed for fuzzing by walking this “seed mutation tree” through an optimal path, based on the estimation of MCTS. We implement two prototypes, ALPHAFUZZ on top of AFL and ALPHAFUZZ++ on top of AFL++. The evaluation results on three datasets (the Unistra dataset, the CGC binaries, and 12 real-world binaries) show that ALPHAFUZZ and ALPHAFUZZ++ outperform state-of-the-art fuzzers with higher code coverage and more discovered vulnerabilities. In particular, ALPHAFUZZ discovers 3 new vulnerabilities with CVEs.

1 Introduction

Coverage-based greybox fuzzing (CGF) has been approved to be very effective in finding security vulnerabilities in real-world applications and has been widely studied and used in both academia and industry [9, 19, 27, 38, 48, 49]. In general, CGF starts with several initial inputs (a.k.a. seed inputs). Then, CGF leverages a seed scheduling strategy to select an input as the seed, and generates new inputs by randomly mutating the seed. With lightweight program instrumentation, CGF executes a program with these newly generated inputs and collects code coverage to further guide the next cycle of seed scheduling. In this way, CGF makes progress in discovering vulnerabilities through iterative seed scheduling, mutation, and program states exploration.

Seed scheduling, the process of selecting a seed from the seed pool for the next fuzzing iteration, plays a central role in CGF. First, CGF utilizes a seed scheduling strategy to bridge the gap between limited fuzzing effort and an ever-increasing number of seeds. More importantly, seed scheduling determines the directions of exploring program states. Specifically, CGF explores program states by dynamic execution using the inputs mutated from seeds. As mutations are often slight (e.g., bit-flip or byte-flip in AFL [49]), the newly generated input often differs from the seed only in small input regions. Consequently, the execution using the new input could result in a transition to a path that is a neighbor of the path corresponding to the seed. In other words, dynamic executions using mutated inputs can be regarded as the process of exploring the neighbor paths of the corresponding path of the seed. Therefore, seed scheduling refers to the selection of an execution path for exploring its neighbor paths, which determines the directions of exploring program states.

Numerous seed scheduling strategies have been proposed. Generally speaking, these strategies aim to assign a score to each seed based on certain criteria and then choose the seed with the highest score for the next fuzzing iteration. For example, AFL [49] prefers seeds with the smallest size and shortest execution time. AFLFast [9] assigns more energy to the seed with low frequency. FairFuzz [27] prefers to choose a seed that covers more rare branches. EcoFuzz [48] favors newly generated seeds. These strategies treat these seeds independently and do not explicitly consider the relationships among the seeds.

In this paper, we make a key observation that the relationships among seeds are valuable for seed scheduling, especially the seed mutation relationship (e.g., “A → B” means Seed B is mutated from Seed A). More specifically, a tree structure can be formed for these seeds by following their mutation relationships, which we refer to as “seed mutation tree”. Then we model the seed scheduling problem as a Monte-Carlo Tree Search (MCTS) problem. That is, we select the next seed for fuzzing by walking this seed mutation tree through an optimal path, based on the estimation of MCTS.

The main advantage of the “seed mutation tree” is that it benefits the seed scheduling to balance between exploitation (i.e., repeatedly exercising a high-potential seed and its neigh-
and exploration (i.e., trying a rarely-exercised seed) for optimal performance. As demonstrated above, seed scheduling refers to the selection of an execution path for exploring its neighbor paths. With the relationships among seeds, we can further organize paths corresponding to every seed as a tree structure, which is denoted as execution tree [12]. In this way, we can model the fuzzing process of exploring program states as the growth of the execution tree. Based on this observation, we can leverage the “seed mutation tree” to approximate the execution tree, in which each path corresponds to a seed. For example, the mutation relationship (“A → B”) indicates that the CGF covers a new path corresponding to B by converting the result of a conditional jump on the path of A. As an approximation to the execution tree, the “seed mutation tree” enables the seed scheduling to balance exploitation (the tree’s depth) and exploration (the tree’s width), which indicates the fuzzing progress within a specific direction and multiple directions, respectively.

Moreover, the construction of “seed mutation tree” is lightweight, because mutation relationships are readily available in CGF and do not require extra instrumentation and expensive computation.

A recent work AFL-HIER [43] also leverages a tree structure to manage all the seeds and uses the UCB algorithm to perform seed scheduling. Our approach differs from AFL-HIER in three aspects. First, the insights are different. AFL-HIER defines different coverage sensitivity metrics and clusters seeds to reduce the impact of similarity. The core of our approach is to construct a seed tree using the mutation relationships, which is a lightweight and practical approximation to the execution tree. Second, the tree structures are different. In AFL-HIER, every internal node means a cluster of seeds that have the same coarse-grained coverage measurement. Every leaf node represents one seed. In our approach, every node in the tree refers to one seed, and the edge represents the mutation relationship between seeds. Third, the performances of seed scheduling are different. As AFL-HIER requires maintaining multiple coverage metrics for clustering, it introduces overhead to seed scheduling and finally results in a negative impact on the fuzzing throughput. By contrast, seed scheduling on our seed tree is lightweight. As throughput is a significant factor for the fuzzing performance, our approach can outperform AFL-HIER.

We implement two prototypes of the MCTS-based seed scheduling, ALPHAFUZZ on top of AFL [49], and ALPHAFUZZ++ on top of AFL++ [18]. To demonstrate the effectiveness of our approach, we conduct a comprehensive evaluation on three datasets, including UniFuzz [28], CGC binaries [15], and 12 real-world binaries. We compare the performance of ALPHAFUZZ with AFL-based techniques AFL, AFLFast, FairFuzz, and EcoFuzz. For AFL++-based techniques, we compare ALPHAFUZZ++ with AFL++ and AFL++-HIER. Evaluation results show that ALPHAFUZZ and ALPHAFUZZ++ outperform other baseline techniques in terms of code coverage and discover more vulnerabilities. Specifically, ALPHAFUZZ achieves higher code coverage on UniFuzz than AFL, AFLFast, FairFuzz, and EcoFuzz on 14, 15, 14 and 16 out of 18 binaries, respectively. ALPHAFUZZ and ALPHAFUZZ++ discover more unique bugs and exploitable vulnerabilities than others. For CGC binaries, ALPHAFUZZ discovers 87 vulnerabilities, whereas AFL, AFLFast, EcoFuzz, and FairFuzz discover 83, 83, 73, and 76 respectively. Moreover, ALPHAFUZZ and ALPHAFUZZ++ can find bugs faster than other fuzzing techniques. In addition, ALPHAFUZZ discovers 3 new CVEs on 12-real-world binaries dataset.

The contributions of this study are as follows:

- **New insight.** We make a key observation that the relationships among seeds are valuable for seed scheduling. We investigate and leverage the seed mutation relationships to construct a “seed mutation tree”, which is an approximation of the execution tree for the fuzzing progress and can further benefit the seed scheduling to balance exploitation and exploration.

- **New fuzzing technology.** With the “seed mutation tree”, we model the seed scheduling problem as a Monte-Carlo Tree Search (MCTS) problem and propose an MCTS-based seed scheduling strategy. This strategy strikes a balance between exploitation and exploration, due to the nature of the MCTS algorithm.

- **Open-source implementation.** We implement two prototypes, ALPHAFUZZ and ALPHAFUZZ++, and conduct comprehensive evaluations to demonstrate their performance. Results show that ALPHAFUZZ and ALPHAFUZZ++ outperform state-of-the-art fuzzers with more code coverage and more vulnerabilities discovered. The source code is available at: https://github.com/zzyyrr/AlphaFuzz.git and https://github.com/zzyyrr/AlphaFuzzplusplus.git.

## 2 Motivation and insight

In this section, we first illustrate our motivation by discussing the limitations of existing seed scheduling strategies with an example and then state our insight.

### 2.1 Motivating example

We use a piece of code in Figure 1 as an example to illustrate our motivation. As shown in Figure 1, $b_i$ represents the basic block in this code, and $(b_i, b_j)$ represents the branch from $b_i$ to $b_j$. In column 3 to 7, $t_1$ to $t_5$ are test cases retained by CGF. The string below each test case is the content of the input file. For example, the content of test case $t_1$ is `'x'`. When executing with different test cases, different basic blocks are covered. The solid circle indicates that the test case covers the corresponding basic block.

In order to describe the seed scheduling process clearly, we suppose that the CGF starts with two initial test cases, $t_1$ and $t_2$. After several fuzzing iterations, CGF generates and retains three new test cases. Test case $t_3$ and $t_4$ are generated via performing mutations on test case $t_1$. Similarly, test case $t_5$ is derived from $t_2$. 

### Test Cases

| Code | Test Cases |
|------|------------|
| int func1 (input) { | t1 t2 t3 t4 t5 |
| b0 if (input[0] == 'x') | 'x' 'y' 'xaf' 'xc' 'ym' |
| b1 if (input[1] == 'a') | 'a' 'b' 'af' 'ac' 'am' |
| b2 if (input[2] == 'f') | 'f' 'g' 'af' 'ag' 'am' |
| b3 if (input[3] == 'c') | 'c' 'd' 'cf' 'cd' 'cm' |
| b4 if (input[4] == 'm') | 'm' 'n' 'mf' 'mn' 'mm' |
| b5 func2(input); | |
| b6 if (input[1] == 'b') | 'b' 'c' 'bf' 'bc' 'bm' |
| b7 else if (input[1] == 'm') | 'm' 'n' 'mf' 'mn' 'mm' |
| b8 else if (input[0] == 'y') | 'y' 'z' 'yz' 'yz' 'zm' |
| b9 else if (input[0] == 'z') | 'z' 'a' 'za' 'za' 'zm' |
| b10 else if (input[0] == 'c') | 'c' 'd' 'cf' 'cd' 'cm' |
| b11 func3(input); | |
| b12 else if (input[1] == 'c') | 'c' 'd' 'cf' 'cd' 'cm' |
| b13 else if (input[1] == 'n') | 'n' 'o' 'no' 'no' 'nm' |
| b14 else exit (0); | |
| b15 | |

| Figure 1: Motivating example.

With these test cases in the seed pool, lots of seed scheduling strategies are proposed to guide the direction of CGF. Figure 2 shows how existing seed scheduling strategies manage the test cases in Figure 1. To better understand their principles, Figure 2 (a) shows the execution tree according to Figure 1. Then we distinguish the paths covered by test cases with different colors. For example, the path in blue color is covered by test case t3.

As shown in Figure 2 (b), AFL [49], AFLFast [9], FairFuzz [27], and EcoFuzz [48] propose different criteria for seed scheduling, but they all treat the seeds independently and only consider the individual features of seeds. AFL reserves the seed with the smallest size and shortest execution time for every covered branch to test as many inputs as possible in a limited time. Since the seed t3 covers the new branch \( b_4, b_5 \) and \( b_9, b_6 \), and t4 covers the new branch \( b_4, b_5 \) and \( b_9, b_{10} \), they are both considered interesting, even though they both cover branch \( b_0, b_1 \) and \( b_1, b_4 \).

AFLFast prefers low-frequency paths which fuzzing spent less time and effort exploring them than high-frequency paths. Thus, AFLFast chooses the paths covered by newly generated seeds t3, t4, and t5. FairFuzz calculates the times each branch has been covered and selects the seed that covers more low-frequency branches. So, seeds t4 and t5 are selected by FairFuzz. EcoFuzz gives the highest priority to unfuzzed seeds. So EcoFuzz selects seeds t3, t4, and t5.

The seed scheduling strategies above are unaware of the relationships among seeds. Seeds covering new branches are always given high priority by the above seed selection strategies, regardless of whether the seeds are concentrated in the same code region. For example, seeds t3 and t4 lead fuzzing to constantly explore the region of the `func2`. As a result, as long as new branches are consistently covered in this area of code, fuzzing will focus on this code region, and be difficult to jump out and explore other areas that may have potential vulnerabilities.

AFL-HIER [43] defines many coverage metrics of different sensitivities to cluster the similar seeds together. As shown in Figure 2 (c), AFL-HIER uses function coverage and edge coverage to cluster the seeds together. For example, seeds t1, t3, and t4 are under the same node \( F_7, F_9 \) because they cover the same functions. When performing seed scheduling, AFL-HIER starts from the nodes at function coverage level, and calculates scores for nodes based on their function-level rareness and their rewards. The rewards of the cluster are the average rewards of all the seeds in this cluster. However, elder seeds and newly generated seeds are clustered under the same nodes. The rewards of newly generated seeds can be weakened by the fuzzing effort spent on elder seeds. Therefore, the individual feature of seeds is flattened, which brings a negative impact on fuzzing deeper paths.

As discussed above, the seed scheduling strategy should consider both the relationships among seeds and the individual features of seeds. Therefore, we propose a new seed scheduling strategies which satisfy these two requirements.

### 2.2 Our Insight

In this paper, we consider the seed scheduling as selecting an optimal path in order to explore its neighbor paths. As discussed above, different paths in the execution tree lead fuzzing to explore different directions. In addition, as the execution tree grows, some paths tend to focus on the same region of the program, while some paths tend to explore different regions. The paths covered by seeds with mutation relationships share the same direction on the execution tree in the beginning, and then separate in different directions. Therefore, we can leverage the mutation relationships among seeds to construct a “seed mutation tree”, which can be an approximation of the execution tree. As shown in Figure 2 (d), the relationships among different fuzzing directions are reserved in our “seed mutation tree”. For example, t1, t3, and t4 are in the same sub-tree, because they all covered basic block \( b_0, b_1 \) and \( b_4 \). Similarly, t2, t5 are under the same sub-tree.

In the meantime, the growth of the execution tree can also be represented in “seed mutation tree”, where newly generated seeds are always leaf nodes and elder seeds are usually internal nodes. Thus, the hierarchy of nodes in the tree can show the effort fuzzing spent on different paths, which is an important individual feature in seed scheduling, but is flattened in AFL-HIER.

With this “seed mutation tree”, seed scheduling can guide fuzzing process to exploit in a specific direction or explore in different directions. To balance the exploration and exploitation, we model the seed scheduling as a Monte Carlo Tree Search (MCTS) problem [7, 10, 14, 25, 29]. The following sections give the detail of our “seed mutation tree” and MCTS-based seed scheduling strategy.
3 Seed Mutation Tree

In this section, we present the definition and the construction of the “seed mutation tree”.

3.1 Definition

We leverage the mutation relationships among seeds to construct the “seed mutation tree” as an approximation of the execution tree. The “seed mutation tree” is defined as follows.

Definition 1. A “seed mutation tree” is a directed tree $T = (V, E, \alpha)$, where:

- Each element $v$ in the set of vertices $V$ corresponds to a seed;
- Each element $e$ in the set of edges $E \subseteq V \times V$ corresponds to the mutation relationship between two vertices $v$ and $w$.
- The labeling function $\alpha : E \rightarrow \Sigma$ associates edges among seeds in terms of their mutation relationships.

3.2 Tree construction

According to Definition 1, we construct a “seed mutation tree” during the fuzzing process.

First, before the fuzzing iteration begins, we construct the initial tree structure with the initial seeds and an auxiliary root node. The auxiliary root node is the parent node of all the initial seeds for there might be more than one initial seed. As shown in Figure 2 (d), the root node, node $t_1$ and node $t_2$ form the initial tree structure.

Then, CFG selects a seed as the base of mutation according to the seed scheduling strategy, and performs mutations on it to generate new test cases. We add the newly generated test cases that cover new paths of the program into the “seed mutation tree” as the child of the original seed. For example, CFG performs random mutations on seed $t_1$, and generates test case $t_3$ and $t_4$. They cover two new paths, $t_3$ covers the blue path and $t_4$ covers the green path, respectively. We add the node $t_3$ to the tree as the child node of $t_1$ based on the mutation relationship between them, and node $t_4$ the same.

As CFG continues to explore the targeted application, we continue to add the seeds covering new paths as nodes to the tree structure according to the mutation relationship between the seeds.

Some special mutations may operate on two seeds. For example, the mutation of splice in AFL will splice a seed with a second seed to generate a new input. In such cases, we only construct an edge between the new node and the node corresponding to the first seed, because the first seed is selected by the seed scheduling strategy, whereas the second one is randomly selected for mutations.

4 MCTS-based seed scheduling

With “seed mutation tree”, we regard the seed scheduling as searching for a seed along a tree, and propose an MCTS-based seed scheduling strategy. In this section, we first introduce the MCTS algorithm, and then present the design details of our MCTS-based seed scheduling strategy.

4.1 Monte carlo tree search

Monte Carlo Tree Search (MCTS) [7,10,14,25,29] is a heuristic search algorithm for types of decision processes. In principle, MCTS focuses on the most promising moves via expanding a search tree based on a random sampling of the search space. The process consists of four steps:

Selection. Using a specific selection strategy, usually UCT algorithm, MCTS starts from the root node $R$, recursively selects optimal child nodes until a leaf node $L$ is reached.

Expansion. If $L$ is not a terminal node, then MCTS creates one or more child nodes. Further, it will select one node $C$ from these child nodes. In this step, child nodes refer to any valid moves from the state defined by $L$.

Simulation. A simulation is performed by randomly choosing moves until a result or a predefined state is achieved.

Back propagation. This step back propagates from the new node $C$ to the root node $R$, and updates the simulation results.

Upper confidence bounds for trees. The main challenge in a planning problem is to balance exploitation and exploration. For this challenge, the Upper Confidence Bounds (UCB) algorithm [6] is typically adopted.

$$UCB = v_i + k \sqrt{\frac{\ln N}{n_i}}$$ (1)
4.2 Tree search for seed scheduling

Inspired by the MCTS algorithm, our MCTS-based seed scheduling strategy can calculate and set a score for every node, with both fuzzing rewards as well as fuzzing effort for balancing exploration and exploitation. However, we cannot directly employ MCTS for searching a seed, because the MCTS algorithm always selects the leaf node. In our “seed mutation tree”, an internal node can also be selected as a seed even if it has multiple child nodes. With this impact, the MCTS algorithm is incompatible with “seed mutation tree”.

4.2.1 Variants for internal nodes

To address the problem of incompatible, we update the “seed mutation tree” by inserting a variant node for every internal node. In terms of seed scheduling, there are two different roles for an internal node. First, an internal node refers to a seed. Second, an internal node is also the root node of a sub-tree, from the perspective of the tree structure.

More important, these two different roles indicate different fuzzing scores. As a seed, it refers to the fuzzing score for selecting this seed. As the root node of a sub-tree, it refers to the summary fuzzing score for selecting every seed in the sub-tree. With the impact of such two different roles, the calculations of fuzzing score for an internal node will be also different.

For this problem, we add a variant for every internal node. The internal node refers to the root node of its sub-tree, and the variant refers to the corresponding seed. In this way, the variant will be a leaf node of the internal node. Regarding the fuzzing scores, the internal node delivers the summary fuzzing scores for every seed in the sub-tree. By contrast, the variant delivers the fuzzing score for the corresponding seed.

Let us take the motivating example for illustration. As shown in Figure 3, $t_1$ has two child nodes, $t_3$ and $t_4$, $t_2$ has one child node $t_5$. To distinguish between an internal node itself and its sub-tree, we construct two variants for both $t_1$ and $t_2$, which are denoted as $t_1'$ and $t_2'$, respectively.

With variants, the construction of “seed mutation tree” requires updating for internal nodes. Whenever a leaf node is generated from a node without a variant node, a variant of the parent node will also be created. Then, both the leaf node and the variant node will be inserted into the tree as the child nodes of the parent node.

The design of variants addresses the problem of incompatibility between MCTS and “seed mutation tree”. By setting a variant for every internal node, the variant node will be a leaf node for the internal node. With this design, MCTS is able to search for a promising node until a leaf node is reached.

4.2.2 Seed-mutation-tree search

The process of our seed scheduling strategy is shown in Figure 4. Each fuzzing iteration starts from the root node, we label the currently selected node as the anchor node. Then, we calculate $seed_{scores}$ for every child node of the anchor node. We will present the calculation formula in § 4.3. For example, we calculate the $seed_{scores}$ for $t_m$ and $t_n$. If the $seed_{scores}$ of $t_m$ is higher than $t_n$, the anchor node moves to $t_m$.

As shown in Figure 4 (b), by comparing $seed_{scores}$ between sibling nodes, our MCTS-based seed scheduling strategy will recursively select the promising one with the highest score, until a leaf node is reached. As shown in Figure 4 (c), $t_k$ is a leaf node, therefore the seed scheduling stops and selects $t_k$ as the base for the mutation stage of fuzzing.

4.3 Seed quantification using UCT algorithm

We leverage the UCT algorithm to calculate the score of a seed in terms of the effort and the rewards. We evaluate the fuzzing effort that cost by fuzzing the same seed rapidly and calculate the rewards of a scheduled seed in terms of new code coverage traversed by the mutations based on this seed. With these two factors, fuzzing effort and fuzzing rewards, we design the calculation of $seed_{score}$ as Formula 2.

$$seed_{score} = \frac{q_i}{n_i} + k \sqrt{\frac{lnN_i}{n_i}} \quad (2)$$

In Formula 2, $n_i$ records the number of times this node has been selected. $q_i$ represents the size of the difference set between the branches covered by the current seed and the branches covered by other seeds under the same sub-tree. We will describe the calculation of $q_i$ in detail later. In $k \sqrt{\frac{lnN_i}{n_i}}$, $k$ is a constant, we discuss the value of $k$ in § 5.8. $N_i$ represents the number of times the parent of the node has been scheduled.

We can see that, $\frac{q_i}{n_i}$ represents the mean rewards of this seed. The $k \sqrt{\frac{lnN_i}{n_i}}$ represents the fuzzing effort spent on this seed, we can observe that the increasing value of $n_i$ will decrease $seed_{score}$, while the increasing of $q_i$ will increase $seed_{score}$.

We calculate $q_i$ for every child node of the anchor node. As shown in Figure 4 (b), $t_m$ is the anchor node, the child nodes of $t_m$ have three types, variant node $t'_m$, internal node $t_j$ and
leaf node $t_k$. The variant node represents the path covered by the anchor node. The leaf node $t_k$ represents the path covered by seed $t_k$. The internal node $t_j$ represents a group of paths covered by all the nodes in the sub-tree which are the yellow nodes.

Most of the existing fuzzers leverage branch coverage to guide the evolution. We choose a node which covers more unique branches. Specifically, for each variant node and leaf node, we collect the branches covered by the seed as its branch set, respectively. For the internal node, we count the branches covered by this node and all its descendants as its branch set. We then put these branch sets together and calculate the difference set for each child node. The number of the branches in the difference set means the number of unique branches covered by the child node compared to other child nodes. Then, we assign the number of unique branches to the value of $q_i$.

### 4.4 Seed score update

After each round of seed scheduling, we update the rewards and effort from the selected seed back to the root node.

To update the fuzzing rewards, as shown in the Figure 4 (d), when a new node, $t_q$ for example, is added to a sub-tree, we update the information of newly covered branches of $t_q$ from $t_q$ to all its parent nodes $t_i$ and $t_m$.

To update the fuzzing effort, the selected times of the selected node and all its parent nodes are increased by one. That is to say, the selected times of $t_i$ and $t_m$ are increased by 1. This process goes in exactly the opposite direction to seed scheduling. In this way, we are able to record the rewards and effort of this time’s seed scheduling to guide the next iteration.

### 5 Evaluation

We implement two prototypes, ALPHAFUZZ and ALPHAFUZZ++, on top of AFL [49] and AFL++ [18], respectively. To demonstrate the effectiveness of our approach, we design and conduct experiments to answer the following research questions:

- **RQ1.** How does our approach perform in vulnerability detection on benchmark datasets?

- **RQ2.** How significant is the improvement of code coverage compared to baseline fuzzing techniques?

- **RQ3.** How does our approach affect fuzzing throughput?

- **RQ4.** How does the parameter $k$ in Formula 2 affect fuzzing performance?

- **RQ5.** Can ALPHAFUZZ detect new vulnerabilities in real-world applications?

### 5.1 Datasets

We leverage three datasets: the Cyber Grand Challenge (CGC) dataset [15], UniFuzz [28], and 12 real-world binaries.

The CGC dataset [15] includes binaries from the CGC Qualifying Event and the CGC Final Event, which are widely used in previous techniques [5, 43]. Every CGC binary is injected with one or more memory corruption vulnerabilities. In our evaluation, we exclude programs involving communication with multiple programs, and programs on which AFL cannot work. In total, we use 188 CGC binaries for evaluation.

As the original CGC binaries are customized with specific syscalls, we leverage their compatible Linux versions [33] for evaluation.

UniFuzz [28] is an open-source and pragmatic metrics-driven platform for evaluating fuzzers, which consists of 20 real-world programs. Unfortunately, sqlite3 and ffmpeg failed to run correctly due to frequent timeouts during our evaluation. Thus, we only leverage 18 programs.

To answer the RQ5, we choose 12 real-world binaries based on the following features: popularity, frequency of being tested, and diversity of categories. As shown in Table 1, these 12 real-world binaries include popular tools (e.g., nm,
5.2 Baseline techniques

In recent years, a number of fuzzing techniques have been proposed to improve the performance of fuzzing from different aspects, including coverage sensitivity, mutation algorithms, input generation, and execution monitoring [11, 20, 31, 32, 44, 45, 47, 50]. As ALPHAFUZZ proposes a new seed scheduling strategy, we only select fuzzing techniques focusing on seed scheduling algorithms as baseline techniques. Besides, we exclude fuzzing techniques requiring the source code of the targeted binaries. For AFL-based fuzzing techniques, we choose AFL [49], AFLFast [9], FairFuzz [27] and EcoFuzz [48]. As AFL-HIER [43] only releases their prototype as AFL++-HIRE, which is implemented on top of AFL++ [18], thus we further choose AFL and AFL++ as baseline techniques.

5.3 Experiment setup

We run the experiments on a server configured with 40 CPU cores of 2.50GHz E5-2670 v2, 125GB RAM, and running on the 64-bit Ubuntu 16.04 LTS.

We fuzz each binary for 24 hours as done in previous studies [9,27]. To alleviate the impact of the nature of randomness in fuzzing, we run each experiment for 10 rounds, and report the statistical results for a more comprehensive evaluation.

All the experiments are based on the QEMU-mode in AFL (so as to support binary-only targets) and configured with the same initial seeds and instructions. The initial seeds for CGC binaries come from the examples provided by the CGC challenges [15]. The initial seeds for UniFuzz are provided by UniFuzz [28]. The initial seeds for the 12 real-world binaries come from the default seed examples provided by AFL.

5.4 Vulnerability detection

To measure the vulnerability detection capability of ALPHAFUZZ, we analyse the experimental results on CGC and UniFuzz. As CGC binaries are manually designed and embedded with known bugs, we mainly evaluate the number of unique bugs and the time to first crash. For UniFuzz, we evaluate the number of unique bugs and the number of unique exploitable vulnerabilities.

5.4.1 Unique bugs on CGC dataset

To summarize the evaluation results of the 10-round experiments, we count the number of times each bug is found in 10-round experiments. Then we count the number of bugs in terms of the number of times the bug is found in 10-round experiments by each baseline technique. As shown in Table 2, columns 2-11 list the number of bugs that are discovered in 10 rounds by different metrics. Column 2 reports the number of vulnerabilities that are discovered in every round. Column 3 reports the number of vulnerabilities that are discovered in at least 9 rounds, and so on.

From Table 2, we can observe that in nearly all these 10 metrics, ALPHAFUZZ discovers more bugs than the other AFL-based fuzzing techniques. For example, ALPHAFUZZ discovers 87 bugs through 10 rounds, with 4 more bugs than AFL and AFLFast, 11 more bugs than FairFuzz, and 14 more bugs than EcoFuzz. By examining the numbers of discovered bugs in Table 2, we observe that the performance of AFL is almost the same as AFLFast on CGC binaries. On the contrary, FairFuzz and EcoFuzz work worse than other fuzzing techniques on CGC binaries.

For AFL++-based fuzzing techniques, in nearly all these 10 metrics, ALPHAFUZZ++ discovers more bugs than AFL++ and AFL++-HIER. ALPHAFUZZ++ discovers 88 bugs through 10 rounds, with 4 more bugs than AFL++ and 3 more bugs than AFL++-HIER.

5.4.2 The time to first crash on CGC dataset.

For CGC binaries, we further leverage the time of first crash to evaluate the performances of fuzzing techniques as the previous technique AFL-HIER [43]. The time of first crash refers to the time costed by a fuzzing technique to detect crashes. A fuzzing technique that discovers crashes more quickly than another technique is said to perform better. To calculate the time to first crash, we first calculate the average time it takes for a binary to crash during our 10-round experiments. To ease representation, we compare the performance for each pair of fuzzing techniques in terms of the time to first crash. For example, taking AFL as the baseline, we compare ALPHAFUZZ with AFL by dividing the time to first crash in
Table 3: Numbers of discovered unique bugs.

| Binary       | AFL | AFLFast | EcoFuzz | FairFuzz | AFlPHAFuzz |
|--------------|-----|---------|---------|----------|------------|
| cflow        | 3   | 4       | 2       | 3        | 4          |
| exiv2        | 0   | 1       | 1       | 1        | 1          |
| flvmeta      | 3   | 3       | 3       | 4        | 3          |
| gdk          | 6   | 6       | 2       | 0        | 8          |
| imginfo      | 0   | 1       | 0       | 0        | 1          |
| infotocap    | 2   | 3       | 0       | 2        | 2          |
| jhead        | 0   | 0       | 2       | 0        | 0          |
| jqi          | 0   | 0       | 0       | 0        | 0          |
| lane         | 3   | 2       | 2       | 3        | 3          |
| mp3gain      | 6   | 7       | 4       | 3        | 7          |
| mp42aac      | 2   | 2       | 2       | 2        | 2          |
| musj         | 2   | 2       | 0       | 0        | 0          |
| nn           | 0   | 0       | 0       | 0        | 0          |
| objdump      | 3   | 3       | 2       | 1        | 4          |
| pdftotext    | 1   | 1       | 0       | 1        | 1          |
| tcpdump      | 0   | 0       | 0       | 0        | 0          |
| tiffsplit    | 4   | 5       | 3       | 8        | 6          |
| wav2swf      | 2   | 3       | 2       | 2        | 3          |
| **total**    | **35** | **41** | **25** | **30** | **53** |

Table 4: Number of discovered unique exploitable bugs.

| Binary       | AFL | AFLFast | EcoFuzz | FairFuzz | AFlPHAFuzz |
|--------------|-----|---------|---------|----------|------------|
| cflow        | 0   | 0       | 0       | 0        | 0          |
| exiv2        | 0   | 1       | 1       | 1        | 1          |
| flvmeta      | 1   | 1       | 1       | 1        | 1          |
| gdk          | 4   | 3       | 2       | 0        | 3          |
| imginfo      | 0   | 0       | 0       | 0        | 0          |
| infotocap    | 0   | 0       | 0       | 0        | 0          |
| jhead        | 0   | 0       | 2       | 0        | 0          |
| jqi          | 2   | 1       | 1       | 1        | 2          |
| lane         | 1   | 1       | 0       | 0        | 1          |
| mp3gain      | 1   | 1       | 0       | 0        | 1          |
| mp42aac      | 0   | 0       | 0       | 0        | 0          |
| musj         | 0   | 0       | 0       | 0        | 0          |
| nn           | 0   | 0       | 0       | 0        | 0          |
| objdump      | 2   | 2       | 0       | 1        | 2          |
| pdftotext    | 0   | 0       | 0       | 0        | 0          |
| tcpdump      | 0   | 0       | 0       | 0        | 0          |
| tiffsplit    | 1   | 1       | 1       | 1        | 1          |
| wav2swf      | 2   | 3       | 2       | 2        | 3          |
| **total**    | **13** | **14** | **10** | **6** | **17** |

Table 5: Number of discovered unique bug and exploitable vulnerabilities found by AFL++-based techniques.

| Binary       | Unique bugs | Exploitable bugs |
|--------------|-------------|-----------------|
| cflow        | 3           | 1               |
| exiv2        | 2           | 1               |
| flvmeta      | 4           | 1               |
| gdk          | 10          | 6               |
| imginfo      | 0           | 0               |
| infotocap    | 2           | 0               |
| jhead        | 3           | 0               |
| jqi          | 0           | 0               |
| lane         | 2           | 2               |
| mp3gain      | 6           | 1               |
| mp42aac      | 2           | 0               |
| musj         | 0           | 0               |
| objdump      | 2           | 2               |
| pdftotext    | 2           | 2               |
| tcpdump      | 1           | 1               |
| tiffsplit    | 3           | 2               |
| wav2swf      | 3           | 2               |
| **total**    | **44**      | **20**          |

5.4.3 Unique bugs on UniFuzz.

For the UniFuzz dataset, we first calculate the number of unique bugs discovered by each fuzzing technique. According to UniFuzz [28], we leverage the report produced by ASAN [37] and GDB [2] to de-duplicate bugs.

Table 3 shows the numbers of discovered unique bugs by AFL-based fuzzing techniques. Among the 18 binaries, 3 of them have not been detected with any fuzzing techniques. We can observe that AFlPHAFuzz finds no less unique bugs than other fuzzing techniques on 11 out of the 15 binaries. In total, AFlPHAFuzz finds 18, 12, 28, and 23 more unique bugs than AFL, AFLFast, EcoFuzz, and FairFuzz, respectively.

Table 4 shows the numbers of discovered unique exploitable bugs. Among the 18 binaries, 2 of them have not been detected with any fuzzing techniques. We can observe that AFlPHAFuzz finds no less unique bugs than AFL++ on 14 binaries, and no less unique bugs than AFL++-HIER on 12 binaries.
Exploitability reflects the severity of the vulnerability [28]. In this paper, we leverage the GDB Exploitable [1] to identify exploitable vulnerabilities. GDB Exploitable classifies crashes into four categories: EXPLOITABLE, PROBABLY_EXPLOITABLE, PROBABLY_NOT_EXPLOITABLE and UNKNOWN. Table 4 and Table 5 show the number of crashes that are classified as EXPLOITABLE and PROBABLY_EXPLOITABLE. We can observe that ALPHAFUZZ finds 4, 3, 7, and 11 more exploitable vulnerabilities than AFL, AFLFast, EcoFuzz, and FairFuzz, respectively. ALPHAFUZZ++ finds 4 and 9 more exploitable vulnerabilities than AFL++ and AFL++-HIER, respectively.

5.5 Code coverage

Code coverage is a critical metric for evaluating the performance of a fuzzing technique [42]. Basically, the more code a fuzzing technique can cover, the more likely it is to find the hidden bugs. We use the bitmap maintained by AFL, a variant of branch coverage, to measure the code coverage. Specifically, AFL maps each branch transition into an entry of the bitmap. If a branch transition is explored, the corresponding entry in the bitmap will be filled and the size of the bitmap will increase.

As an in-depth analysis, we present the average bitmap size of the 10-round experiments for every binary in UniFuzz dataset. As shown in Figure 6, we can observe that ALPHAFUZZ can achieve higher or at least the same bitmap size than other techniques on 14 out of 18 binaries. For nm, ALPHAFUZZ works worse than FairFuzz. For pdftotext, ALPHAFUZZ works worse than AFLFast and AFL. For tiffsplit, ALPHAFUZZ works worse than AFL and FairFuzz.

By comparing the performance of ALPHAFUZZ with every baseline technique as shown in Figure 6, we can also observe that ALPHAFUZZ outperforms AFL, AFLFast, EcoFuzz, and FairFuzz on 15, 16, 14, and 16 binaries, respectively. As shown in Table 7, ALPHAFUZZ++ achieves higher or at least the same bitmap size than AFL++ on 14 out of 18 binaries, AFL++-HIER on 15 out of 18 binaries.

5.6 Statistical Significance

To quantify whether there is a significant difference between ALPHAFUZZ and other techniques, we leverage the Mann-Whitney U test to calculate the $p$ value [3, 24] using ALPHAFUZZ as the baseline. According to Mann-Whitney U test [3], a $p$ value less than 0.05 indicates a significant difference between the two fuzzers.

As shown in Table 6, Column 2 shows the average code coverage of ALPHAFUZZ. Column 3-6 show the $p$ values calculated by taking the code coverage of ALPHAFUZZ as the baseline. We can observe that ALPHAFUZZ significantly outperforms AFL, AFLFast, EcoFuzz, and FairFuzz on 7, 9, 8, and 10 binaries, respectively.
Figure 6: Average bitmap size for every binary of UniFuzz. Each graph represents a binary, with the abscissa representing the time and the ordinate representing the size of the average bitmap size.

Figure 7: Throughput comparison.

Table 8: The averaged edge coverage on CGC and UniFuzz with different values of the parameter $k$.

| Dataset | Value of $k$ | 0  | 0.014 | 0.14 | 1.4 | 14 |
|---------|--------------|----|-------|------|-----|----|
| CGC     | 2.59%        | 2.61% | 2.65% | 2.75% | 2.58% |
| UniFuzz | 8.38%        | 8.46% | 8.38% | 8.23% | 8.22% |

5.9 Vulnerability detection on real-world binaries.

To answer RQ5, we run the fuzzing techniques on 12 real-world binaries listed in Table 1. We collect the crashes discovered by each fuzzing technique, and then leverage AddressSanitizer [41] and GDB to distinguish redundant crashes and identify unique vulnerabilities. Table 9 shows that these fuzzing techniques totally discover 12 vulnerabilities. We report the 12 vulnerabilities to upstream vendors. Among these vulnerabilities, 7 of them are confirmed by the vendors with the CVE-ID, 4 of them are confirmed but without a CVE-ID, and 1 of them has not been confirmed yet. Notably, we discovered 3 new vulnerabilities and obtained 3 NEW CVEs, which are CVE-2021-25792, CVE-2021-25793, and CVE-2021-25794. The POCs of the above vulnerabilities are available at (URL omitted for double-blind reviewing).

Table 9 shows that ALPHAFUZZ discovers more vulnerabilities than baseline techniques. Specifically, ALPHAFUZZ discovers 5 vulnerabilities that are never detected by other techniques, and misses a vulnerability that is detected by FairFuzz.
6 Related work

Fuzzing. In this paper, we mainly focus on seed scheduling for Coverage-based greybox fuzzing (CGF). Lots of fuzzing techniques leverage additional program analysis to improve the performance of fuzzing. Honggfuzz [40] and libfuzzer [38] introduced a data flow feature—the degree of matching of the operands of branch statements, and prioritized the selection of seeds that more satisfies the branch constraints. GreyOne [19] uses data flow analysis to determine the relationship between input fields and constraint-related variables, then schedules the input with the highest number of relevant key fields.

Besides CGF, lots of bug-driven seed scheduling strategies are proposed. TortoiseFuzz [36] targets memory corruption vulnerabilities and prioritizes branches containing memory operations. QTEP [46] prioritizes seeds that trigger more sensitive codes, so as to Dowser [21]. AFLgo [8] prioritizes seeds that are closer to the target point to be tested.

Besides the seed selection strategies, there are a lot of advanced fuzzing techniques focusing on seed generation [44], seed mutation [31], coverage sensitivity [42], and execution monitoring [11]. MOPT [31] proposes a seed mutation strategy to determine the proper distribution for mutation operators. NEUZZ [39] identifies the significance of program smoothing and uses an incremental learning technique to guide the mutation of fuzzing. Untracer [32] removes unnecessary instrumentation in basic blocks that have been explored to reduce the overhead of fuzzing. Redqueen [5] solves magic bytes and checksum tests via inferring input-to-state correspondence based on lightweight branch tracing.

Monte Carlo Tree Search. Monte Carlo Tree Search (MCTS) is a promising online planning approach [7, 10, 14, 25, 29]. The MCTS algorithm has achieved great success in Go [16] and has had a profound impact on the field of artificial intelligence [17, 23, 34]. The application field of MCTS algorithm is very extensive, such as active object recognition [35], wildlife monitoring [22], environment exploration [13, 26], and planetary exploration [4]. MCTS has been proposed in many different forms [10], but currently, the most common one is the Upper-Confidence Bounds Applied to Trees (UCT) algorithm [25]. Therefore, we choose to use the UCT algorithm in our model.

MCTS algorithm also attracts the attention of researchers who focus on fuzzing. AFL-HIER [43] proposes a multi-level coverage metric, and leverages UCT algorithm to perform seed selection. Legion [30] leverages MCTS algorithm to maintain a balance between concolic execution and fuzzing, and improves the performance of hybrid fuzzing.

7 Conclusion

In this study, we make a key observation that the mutation relationships among seeds are valuable for seed scheduling. To investigate the seed mutation relationships, we design a “seed mutation tree” and further propose MCTS-based seed scheduling strategy by modeling the seed scheduling problem as a Monte-Carlo Tree Search (MCTS) problem. Evaluation shows that our approach outperforms other seed scheduling strategies with higher code coverage and more discovered vulnerabilities.

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