AlphaFuzz: Evolutionary Mutation-based Fuzzing as Monte Carlo Tree Search

Yiru Zhao¹, Ruiheng Shi¹, Lei Zhao *¹,² and Yueqiang Cheng³

¹School of Cyber Science and Engineering, Wuhan University, China
²Key Laboratory of Aerospace Information Security and Trusted Computing, Ministry of Education, China
³NIO Security Research

Abstract

Fuzzing is becoming more and more popular in the field of vulnerability detection. In the process of fuzzing, seed selection strategy plays an important role in guiding the evolution direction of fuzzing. However, the SOTA fuzzers only focus on individual uncertainty, neglecting the multi-factor uncertainty caused by both randomization and evolution. In this paper, we consider seed selection in fuzzing as a large-scale online planning problem under uncertainty. We propose AlphaFuzz which is a new intelligent seed selection strategy. In Alpha-Fuzz, we leverage the MCTS algorithm to deal with the effects of the uncertainty of randomization and evolution of fuzzing. Especially, we analyze the role of the evolutionary relationship between seeds in the process of fuzzing, and propose a new tree policy and a new default policy to make the MCTS algorithm better adapt to the fuzzing. We compared AlphaFuzz with four state-of-the-art fuzzers in 12 real-world applications and LAVA-M data set. The experimental results show that AlphaFuzz could find more bugs on lava-M and outperforms other tools in terms of code coverage and number of bugs discovered in the real-world applications. In addition, we tested the compatibility of AlphaFuzz, and the results showed that AlphaFuzz could improve the performance of existing tools such as MOPT and QSYM.

1 Introduction

Fuzzing is one of the most popular vulnerability discovery techniques, which has been widely studied and used in both academic and industry [21] [2] [5]. Among types of fuzzing techniques, evolutionary mutation-based fuzzing (EMF for short), which aims to make fuzzing more effective in path exploration without sacrificing time for program analysis, attracts prominently focuses in recent years [10] [15]. EMF maintains an input set which starts with only a few initial inputs (a.k.a. seed inputs or seeds). Following a specific seed selection strategy, EMF picks one input from the set of inputs as a seed, and generates a number of new test cases (program inputs) by slightly mutating these seeds. Further, EMF uses lightweight program instrumentation to monitor the dynamic execution and determines code coverage exercised by these new test cases. If a test case exercises new code (such as basic blocks and branches that are traversed during dynamic execution), this test case will be retained as a seed candidate for further mutation. In this way, EMF makes progress via iterative seed selection, input generation/mutation, and execution monitoring.

Seed selection plays an important role in EMF. First, as seed inputs are used as the base for mutation, the potential contributions for discovering new program code (we use code explore potential for convenience) varies between different inputs. For example, suppose a program input contains 100 bytes, we want the fuzzing to gener-
ate an input to exercise the code within an \emph{if} condition \texttt{input[0] = 'x'}. Mutating a seed input with the first byte as \texttt{x}, there would be a 99\% chance for a mutated variant to exercise the target code. By contrast, mutating a seed input in which the first byte is not \texttt{x}, the probability for a mutated variant to bypass the \emph{if} condition is only 1\%. Therefore, seed inputs guide the direction of code exploration, which is fundamental to the effectiveness of EMF. Second, as EMF can quickly generate a number of inputs via mutation, it is impractical to take every generated input as a seed due to resource limitation. To bridge the gap, seed selection aims to determine which input should be taken as a seed during the EMF progress.

Previous studies have proposed a variety of seed selection strategies. AFL \cite{24} retains the input with the shortest length and fastest execution time corresponding to the branch that has been covered, so that fuzzing can generate inputs more quickly. Based on the observation that most seeds exercise the same few paths, AFLFast \cite{3} proposes to focus most of the fuzzing effort on low-frequency paths. Fairfuzz \cite{14} focuses on the frequency of branches covered by seeds, and prefers to choose inputs that cover more rare branches. EcoFuzz \cite{22} estimates the path transfer ability of each seed based on the multi-armed slot machine model, and preferentially selects the seed with the highest probability of covering the new path.

Existing works only focus on individual uncertainty, such as the input throughput, the number of times each path is covered or the number of new inputs produced after an input has been mutated. However, they ignore the multi-factor uncertainty caused by both randomization and evolution of EMF. EMF tests target programs via execution on randomly mutated inputs. With the impact of randomization, little prior knowledge is available for evaluating or determining \emph{code explore potential}. Besides, EMF evolves by iteratively generating inputs, discovering new code, and selecting seeds for further mutation. Thus the \emph{code explore potential} of an input is also evolutionary. Specifically, with the increasing code coverage, an input that is selected as a seed in the earlier fuzzing stage may not be suitable for further mutation, because all the neighbor branches of the corresponding execution path have already been covered. Therefore, EMF requires an online seed selection strategy that meets the following design objectives. First, it should diversify the selected seed for discovering different code pieces. Second, it should select inputs with higher \emph{code explore potential} as seeds. Third, the \emph{code explore potential} of inputs should be evaluated dynamically as fuzzing evolves.

In this paper, we propose an intelligent seed selection model based on the Monte Carlo Tree Search (MCTS). Inspired by the online planning ability in MCTS that has been successfully applied in active object recognition \cite{16}, wildlife monitoring \cite{11}, and planetary exploration \cite{1}, we treat the seed selection in EMF as a large-scale online planning problem under uncertainty. We propose a new \texttt{tree\_policy} and a new \texttt{default\_policy} to make MCTS more adaptive to solve the problems of fuzzing. First, we leverage the tree structure in MCTS to organize generated inputs according to their evolutionary relationships. The evolutionary relationship between inputs not only clearly shows all the actions taken by the fuzzing in all known states, but also helps us compare the benefits between inputs. During the seed selection stage, the \texttt{tree\_policy} leverages such evolutionary relationship to quantify the \emph{code explore potential} of inputs. Second, in the simulation stage of the traditional MCTS algorithm, random actions are taken according to the default policy until a score or profit is obtained. We replace the default policy with the random mutation process of fuzzing. With the MCTS, our seed selection model aims to select the optimal seeds to achieve maximum code coverage. It deals with the uncertainty of randomization by lightweight \emph{code explore potential} quantification based on run-time information. Besides, our model can deal with the uncertainty of evolution by recognizing the evolutionary relationship between inputs.

We implemented a prototype called AlphaFuzz on the basis of AFL’s source code. We store the inputs in a tree structure according to our model and modify the seed selection strategy. AlphaFuzz does not rely on any additional program analysis. We then evaluated AlphaFuzz with four SOTA fuzzers on the LAVA-M data set and 12 real-world programs. Experimental results show that compared with other fuzzers, AlphaFuzz could find more bugs on lava-M and outperforms other tools in terms of code coverage and number of bugs discovered in the real-world applications. In addition, we tested the compatibility of AlphaFuzz, and the results showed that AlphaFuzz could improve the performance of existing tools such as MOPT and QSYM.

The contributions of our work are summarized as fol-
• New insight. We treat the seed selection in EMF as a large-scale online planning problem under uncertainty, and propose an intelligent seed selection model based on the Monte Carlo Tree Search (MCTS). We have improved the MCTS algorithm to better adapt to the seed selection scenario of fuzzing.

• New fuzzing technology. Based on our model, we implemented a prototype called AlphaFuzz. We replace the traditional queue structure with a tree structure representing the evolutionary relationship between inputs. With the help of the evolutionary relationship represented by this tree structure, we make the fuzzing more efficient.

• Open-source implementation. We implement a prototype and the source code is available at (URL omitted for double-blind reviewing). We evaluate our prototype with four state-of-the-art fuzzers on 12 real-world applications and LAVA-M data set. Results show that AlphaFuzz outperforms state-of-the-art techniques in more code coverage and more unique bugs.

2 Background and Motivation

In this section, we provide a running example to illustrate the process of seed selection in fuzzing. We discuss the shortcomings of existing work and then summarized our research motivation.

2.1 Seed Selection Strategy for Fuzzing

The seed selection strategy is the strategy adopted by the fuzzer when it selects an input from the input set as the base for mutation. To make it easier to understand, we provide a running example. The code in Figure 1 represents a part of the target program, and we use br to represent the branches that connect different basic blocks in this code. At the same time, we provide two initial inputs 'x' and 'c'. The solid circle indicates that the input covers the corresponding branch. Suppose we mutate from the input 'x' into input 'xd' and input 'xe', and we mutate from the input 'c' into input 'ch'.

Existing fuzzers store all input as a queue. When making seed selection, they iterate over all the inputs from the head of the queue, marking the high-priority inputs according to their respective seed selection strategies. The tagged input is then mutated in turn. For AFL, it retains the input with the shortest length and fastest execution time corresponding to the branch that has been covered. For example, for branch br₅, AFL will select input 'c' rather than 'ch'. Since the input 'xd' and the input 'xe' covered the new branch br₁ and br₂, they were both considered the favorite inputs, even though they both covered branch br₀. Fairfuzz calculates how many times each branch has been covered and selects the low-frequency branches, so it will prioritize 'xd', 'xe', and 'ch'. For EcoFuzz and AFLFast, they choose the less selected inputs, which are the three newly generated inputs 'xd', 'xe', and 'ch'.

However, the choice of existing fuzzers raises the following problems. First, br₁ and br₂ are both newly covered paths, and they’re the least covered. So the above fuzzers will mark the input 'xd' and the input 'xe' as high priority, and then mutate them in turn. However, due to the high similarity between the two inputs, both of them may mutate to form 'xf'. Then the resources spent on mutating the input 'xe' will be wasted, if we have already mutated 'xd' to get 'xf'.

Second, the new inputs generated from the same round of fuzzing is stored in an adjacent position in the queue. The input 'xd' and 'xe' were mutated by the input 'x' in the same round of fuzzing. Existing fuzzers will select
both of them in turn, and input 'ch' will be selected later. This causes the fuzzing to focus on the branch br0 for a period of time. For large, complex programs, fuzzing will cover only a portion of the program’s path.

Third, the code explore potential of the inputs will change as the fuzzing progresses. The paths covered by some old inputs are also covered by many new inputs. For example, branches covered by the input 'x' are also covered by the new input 'xd'. These inputs can be ignored or have a very low priority in seed selection. Iterating through all the inputs in the current input set each time, whether useful or not, will reduce the efficiency of the entire system.

### 2.2 Motivation

Through the above analysis, we can find that the existing work only focuses on the characteristics of the input and ignores the influence of the relationship between inputs on the efficiency of fuzzing. The path of coverage between the input with an evolutionary relationship has the following characteristics: the path of input execution has great overlap, the time point of input generation has adjacency, and the path of input coverage has substitutability. Ignoring these features will reduce the efficiency of fuzzing and affect the evolution direction of fuzzing. Therefore, we think that the seed selection strategy should achieve the following goals:

First, it should diversify the selected seed for discovering different code pieces. Diverse, unexpected inputs are more likely to trigger vulnerabilities in a program. However, preserving some of the similarities of the input can help the new input pass through some of the constraints of the target program. Therefore, we need to preserve effective similarity while striving for maximum diversity.

Second, it should select inputs with higher potential as seeds. While each round of fuzzing preserves the input that increases code coverage, the benefits of mutating each input are clearly different. With limited time and resources, we cannot mutate all the inputs, in turn, to see if new paths are discovered. Therefore, we should select inputs with higher potential as seeds to improve system efficiency.

Third, the code explore potential of seeds should be evaluated dynamically as fuzzing evolves. During the evolution of fuzzing, the value of every input is not constant. Only by dynamically adjusting the value of the input can we make the optimal choice.

### 3 Seed Selection Based on MCTS

#### 3.1 Challenges

In the motivation section, we describe the design goals of the seed selection strategy. However, the multi-factor uncertainty of fuzzing brings some challenges to the realization of these goals.

First, little prior knowledge creates uncertainty about the code explore potential of the input. The EMF has little prior knowledge and only uses lightweight code instrumentation to obtain the path information of input execution. The relationship between the value of each input field and the constraints on different branches of the program is not known.

Secondly, the random mutation in fuzzing creates uncertainty about the code explore potential of the input. Fuzzing is a random mutation process, the results of one round of fuzzing can not be used as the actual value of the input. How to constantly update input scores based on run-time information is a problem.

Third, evolutionary uncertainty leads to dynamic changes in input code explore potential. With the increasing code coverage, an input that is selected as a seed in the earlier fuzzing stage may not be suitable for further mutation, because all the neighbor branches of the corresponding execution path have already been covered.

#### 3.2 Monte Carlo Tree Search Algorithm

Monte Carlo Tree search (MCTS) is a promising online planning approach because it can effectively search for long-term planning and is anytime [12] [4]. MCTS has been successfully applied to various online planning scenarios, such as real-time games [7], active object recognition [16], wildlife monitoring [11], and planetary exploration [1].

For online planning scenarios with incomplete prior knowledge, the MCTS algorithm can randomly select samples in the decision space and construct a search tree according to the phased decision structure to provide the optimal decision. This means that the algorithm may
often the action is played from that state and reinsert an action, and it holds certain statistics about how much revenue generated each time the system selects this action.

The whole process of our model can be summarized as Formula 1 and Formula 2. For a state \( S_t \) and an optional action set \( A \). Each node in the tree represents an action, and it holds certain statistics about how often the action is played from that state \( N(S_t, a) \), the actual revenue generated each time the system selects this action \( (S_u k = S_t, A_u k = a)G_u \), and the average reward \( Q(S_t, a) \) obtained after applying the action in the state \( S_t \). In each iteration, we perform this action and see if any benefits have been generated. We estimate the average value of rewards by iteratively sampling the actions, and select the action with the greatest benefit.

\[
Q(S_t, a) = \frac{1}{N(S_t, a)} \sum_{k=1}^{K} \sum_{u=t}^{T} 1(S_u k = S_t, A_u k = a)G_u
\]

(1)

\[
a_t = \arg \max_{a \in A} Q(S_t, a)
\]

(2)

We use the UCT (Upper confidence bound apply to tree) algorithm to calculate the value of the action. UCT is a common strategy algorithm in the MCTS algorithm. The calculation method of UCT is shown in Formula 3. Where \( q_t \) represents the average action value of all simulations in the context of \( (S_t, a) \). \( n_i \) represents the number of times the action has been selected. \( N_i \) represents the number of times the parent of the node has been selected. The value of \( c \) is a constant. In our model, we set \( c \) as 1.41.

\[
UCT = \frac{q_t}{n_t} + c \sqrt{\frac{\ln N_i}{n_t}}
\]

(3)

In order to achieve our design goals, our model gives corresponding solutions.

Firstly, we find that the evolutionarily related inputs have a great overlap in the input content and the path branches they covered. We construct a tree structure based on the evolutionary relationships of the inputs. There are large similarities between inputs in the same subtree and small similarities between different subtrees. According to the MCTS algorithm, we start from the root node to search down, and only one node in the same subtree will be selected, thus increasing the diversity of inputs.

Secondly, we leverage the UCT algorithm to quantify the potential of code explore for inputs based on run-time information, which requires little prior knowledge and can reduce the influence of randomness of blind mutation in fuzzing. Besides, the UCT algorithm takes into account the number of times the input is selected. If the number of times the input is selected is too much, the probability of the input being selected will decrease. Therefore, fuzzing does not always focus on exploring the same area of code.

Thirdly, the backpropagation stage of the MCTS algorithm enables the code explore potential of inputs to be dynamically updated. At the end of each round of fuzzing, new inputs are added to the tree as leaf nodes. We update the code explore potential value of the input in the tree based on evolutionary relationships. In this way, we can dynamically update the value of the input.
4 Design and Implementation

We designed a seed selection model based on the MCTS algorithm and implemented a prototype called \( \alpha \)-Fuzz. In this section, we introduce the overall framework and every process of our model.

4.1 AlphaFuzz Overview

![Model Diagram]

Figure 2: The Entire Frame of the Model.

We apply the seed selection strategy based on the MCTS algorithm to fuzzing, and establish the model as shown in Figure 2. The whole model is divided into five parts: tree construction, seed selection stage, seed mutation stage, target program testing stage, and backpropagation stage.

4.2 Tree Construction

Based on the evolutionary relationships between inputs, we construct the tree structure shown in the triangular region in Figure 2. Each node in this tree structure represents an input, and each edge represents the parent-child evolutionary relationship. More specifically, for a node, we record not only its input file, but also the execution path covered by the node itself with node_trace. The node_trace recorded for each input is a collection of all branches containing an execution path. If a node has children, that means it is the root of a subtree. We use tree_trace to record the collection of execution paths covered by the entire subtree. So tree_trace is the union of node_trace for all nodes in this subtree. In addition, we recorded the number of times the input was selected as a seed in the fuzzing.

To facilitate the search, we use a root node as the parent of all the initial input. The input file for the root node is empty, and its node_trace is empty, indicating that it is not a real input. Before the fuzzing starts repeating each round, we test the target program with each initial input, getting their respective node_trace. We then record the union of all initial input’s node_trace on the tree_trace of the root node, and record the number of times each branch is covered. As shown in Figure 3, we have two initial inputs ‘x’ and ‘c’. Their node_trace is \( \{br_0\} \) and \( \{br_5\} \), respectively. Our root node will record tree_trace as \( \{br_0: 1, br_5: 1\} \).

When a new input is generated and a new path is found, the input is added as a child to its corresponding parent node. Then, we need to update the entire tree structure. We find all the parent nodes along the path from the root node to the new node. Union the node_trace of this new node with tree_trace of all parent nodes and update the number of times the branch is covered. As shown in Figure 3, when new inputs ‘xd’, ‘xe’, and ‘ch’ are added to the tree, the node information of the tree structure is updated. In this way, the root node of each subtree records the set of branches and the number of times each branch is covered by all nodes in the subtree.

4.3 Seed Selection Stage

In the selection stage, we start the search from the root node. We use tmp_node to represent the currently se-
lected node. So at the beginning of the search, tmp_node points to the root node, and then tmp_node points to the currently selected node. If the node tmp_node points to has children, we need to select the optimal node among the children. According to Upper Confidence Bound Apply to Tree(UCT) [16] algorithm, we formulated our seed value calculation method, as shown in the formula 4.

$$\text{Seed Score} = \frac{SV_i}{n_i} + c\sqrt{\frac{\ln N_i}{n_i}} \quad (4)$$

In this formula, $SV_i$ is the key to represent the value of the input. In our model, $SV_i$ is calculated in two scenarios. The first scenario is that the children of tmp_node are all leaf nodes. At this point, we first identify the least covered branches in the tree_trace of tmp_node. Then count the number of these branches contained in the node_trace of child node $i$. For example, if the tmp_node points to the node 'x', we need to choose between the node 'xd' and the node 'xe'. We first get the number of times each branch is covered in the tree_trace of the node 'x'. $br_1$ and $br_2$ are covered the least. So the SV value of both 'xd' and 'xe' is 1. When the Seed Score of both nodes are the largest and the same, we select the first one with the largest value, then add its N value by 1, so that its score will decrease the next time you select it. In this way, we can avoid selecting the same node all the time. The second scenario is that some of tmp_node's children are not leaf nodes. In this case, we first identify the least covered branches in the tree_trace of tmp_node. Then count the number of these branches contained in the tree_trace for child node $i$. For the convenience of calculation, we recorded the tree_trace value of the leaf node as the same value as node_trace, so that the calculation method of $SV_i$ value was simplified. When tmp_node is a leaf node, the selection stage ends. Otherwise, the search continues in the same manner.

4.5 Target Program Testing Stage

In this stage, we test the target program with the newly generated input. If a new path is covered. We consider this input to be an interesting input. We add interesting inputs as child nodes to the tree structure. Input 'xf' covers the new branch $br_3$, and input 'xk' doesn’t cover a new branch, so we just add 'xf' to the tree structure. The parent node of the new node is 'xd'.

4.6 Backpropagation Stage

In the backpropagation stage, we update the tree_trace information of the parent node along with the parent node to the root node according to the node_trace of the newly added node. And the N value of all the parent nodes is increased by one. The tree_trace of the nodes 'xd', 'x', and the root node have been updated. And they both add 1 to their N value.

Our tree structure has been updated, and we will repeat the seed selection stage, seed mutation stage, target program testing stage, and backpropagation stage until the system receives a stop command.

5 Experiment

We implemented our prototype based on AFL 2.52b. The core functions are implemented in C language. To verify the performance impact of our seed scheduling strategy on fuzzing, we conduct experiments and compare our model with state-of-the-art fuzzers.

5.1 Experiment Settings

5.1.1 Platform

All the experiments ran on a virtual machine configured with 18 CPU cores of 2.50GHz E5-2670 v2, 64GB RAM, and the OS of 64-bit Ubuntu 16.04 LTS. We ran each fuzzier with each target program for 12 hours, and we repeated all experiments for 5 times.

5.1.2 Data Set

Based on the experiments in previous papers, we have selected target programs that are frequently used, main-
Table 1: Information About The Target Programs.

| Target & Source file | Input format | Parameters |
|----------------------|--------------|------------|
| cjpeg+libjpeg-9b     | jpeg         | @@         |
| exiv2-0.25           | jpg          | @@ /dev/null|
| infotocap+ncurses-6.1| text         | @@         |
| mp3gain-1.5.2        | jpg          | @@         |
| nm-2.26.1            | elf          | -AD @@     |
| objdump-2.26         | elf          | -d @@      |
| pdfimages+xdpdf-4.00 | pdf          | @@ /dev/null|
| pngfix+libpng-1.6.36 | png          | @@         |
| readelf-2.26.1       | elf          | -a @@      |
| size-2.26            | elf          | -At @@     |
| tiff2pdf+lilityf-4.0.10 | tiff       | @@         |
| xmlwf+libxpat-R.2.2.5 | xml          | @@         |

Table 2: The number of bugs found by various fuzzer tools on LAVA-M in 5 hours from 5 trials

| LAVA-M       | base64 | md5sum | uniq | who |
|--------------|--------|--------|------|-----|
| AFL          | 1      | 0      | 0    | 2   |
| AFLFast      | 0      | 0      | 0    | 2   |
| FairFuzz     | 0      | 0      | 0    | 3   |
| EcoFuzz      | 0      | 0      | 0    | 2   |
| AlphaFuzz    | 0      | 0      | 1    | 4   |
| Mopt         | 0      | 0      | 0    | 3   |
| AlphaFuzz-Mopt | 9      | 0      | 1    | 4   |
| AFL-QSYM     | 24     | 15     | 15   | 932 |
| AlphaFuzz-QSYM | 48     | 7      | 29   | 944 |

Table 3: The number of bugs found by various fuzzer tools on real-world programs

| program | AFL | AFLFast | EcoFuzz | FairFuzz | AlphaFuzz |
|---------|-----|---------|---------|----------|-----------|
| cjpeg   | 0   | 4       | 4       | 3        | 3         |
| infotocap | 0   | 2       | 2       | 0        | 3         |
| mp3gain | 3   | 2       | 2       | 3        | 4         |
| objdump | 1   | 1       | 1       | 1        | 1         |
| tiff2pdf | 1   | 0       | 0       | 1        | 2         |
| size    | 1   | 0       | 1       | 1        | 1         |
| pngfix  | 0   | 1       | 1       | 0        | 1         |
| nm      | 0   | 0       | 0       | 1        | 1         |
| pdfimages | 0   | 1       | 0       | 0        | 1         |
| Total   | 11  | 12      | 12      | 14       | 17        |

5.1.3 Compared Fuzzers

In selecting the fuzzers for comparison, we collected 12 real-world target programs as the experimental data set. These programs include image parsing and processing libraries, text parsing tools, assembly tools, and so on. Table 1 shows the information of the programs. Furthermore, we also evaluated AlphaFuzz on the LAVA-M data set [9] as other fuzzers. LAVA-M data set has 4 target programs, and each of which is inserted with a known number of bugs. We can get the bug’s ID by simply run the crashes on the corresponding target program.

5.1.4 Randomness Mitigation

In order to reduce the influence of randomness on experimental results, we take the following measures. First of all, we ran each fuzzer with a master instance and a slave instance on each program for 5 times according to [22] [14]. Then, based on previous papers, we ran 12 hours for each program to get consistent performance.

5.1.5 Evaluation Metrics

According to previous papers, we chose vulnerability discovery ability and code coverage ability as two main metrics to compare the efficiency of each fuzzer. We also combined AlphaFuzz with other technologies that did not propose seed selection strategies to evaluate the compatibility of AlphaFuzz.

5.2 Experiment Results

After processing the experimental data, we get the following experimental results.
5.2.1 vulnerability discovery ability

For lava-M data set, we analyzed all crashes to get the corresponding bug ID. Here, we calculated the union set of bugs found in each fuzzer’s 5 experiments. The first five lines of Table2 shows that AlphaFuzz can find more bugs on uniq and who.

For real-world programs, we analyzed the crashes generated by each fuzzer and identified unique vulnerabilities. Table 3 shows that AlphaFuzz can find more bugs.

5.2.2 code coverage ability

The higher the code coverage, the more areas the fuzzer explores, and the more likely the fuzzer is to find potential vulnerabilities. The fuzzers for comparison are all developed based on AFL. In AFL, each branch of the target program’s path is mapped to a bitmap by hashing. When the new branch is covered, the corresponding bitmap position is set to 1. The size of the bitmap increases as the number of new branches increases. So, we use the bitmap size to measure the code coverage of the fuzzers.

First, we unified the time of the five trial’s data to make them started from 0 to 12 hours. Then, we extract each bitmap size from 5 trials and get the average every 10 minutes. We plotted the growth of bitmap size over time, as shown in Figure 4. The red implementation represent the result of AlphaFuzz. AlphaFuzz’s bitmap size surpass other fuzzers early on, and is higher after 12 hours.

In addition, we also drew a boxplot of five fuzzer’s bitmap size for 12 programs. Figure 6 shows that AlphaFuzz is more stable and performs better.

5.2.3 statistical validation

According to the the Janez Demar’s work [8], we plot a critical difference diagram. The ”critical difference” (CD) is based on the Friedman/Nemenyi post-hoc test. Figure 5 shows the significance of the differences of fuzzers. We can see that, AlphaFuzz is marked improvement over EcoFuzz, AFLFast and FairFuzz.

5.2.4 Compatibility Analysis

Inspired by Mopt [15], we studied the compatibility of AlphaFuzz.

We combined our seed selection strategy Mopt. Mopt is the first fuzzer that presented a mutation scheduling
scheme based on Particle Swarm Optimization. We implement AlphaFuzz-Mopt, and compared it with Mopt on LAVA-M data set. The six and seven line of Table 1 shows that AlphaFuzz-Mopt can find more bugs than Mopt.

We also combined AlphaFuzz with QSYM [23]. QSYM is a concolic execution engine tailored to support hybrid fuzzers. According to the experimental setup in QSYM’s paper, we run QSYM with a master AFL and a slave AFL as the baseline. Then we ran QSYM with a master AlphaFuzz and a slave AlphaFuzz. The last two lines of Table 1 shows that AlphaFuzz-QSYM performs better except for md5sum.

6 Related Work

6.1 Seed Selection Strategy of Fuzzing

Fuzzing is becoming more and more popular as an automated vulnerability detection technique. Because seed selection strategy plays an important role in the evolution direction of fuzzing, many researches have proposed various methods. These methods can be divided into two categories according to whether extra program analysis is needed for the target program.

Some studies do not carry out additional analysis of the target program, but only uses lightweight program instrumentation to determine code coverage. AFL [24] selects short and fast inputs in order to generate a large number of new test cases in a short time. AFLfast [3] prioritizes seeds with less mutation. Fairfuzz [14] focuses on the frequency of branches covered by seeds, and prefers to choose inputs that cover more rare branches. EcoFuzz [22] estimates the path transfer ability of each seed based on the multi-armed slot machine model, and preferentially selects the seed with the highest probability of covering the new path.

Some studies use program analysis techniques to analyze potentially vulnerable branches of programs, increase the priority of those branches, and then select inputs related to those branches as seeds. AFLgo [2] prioritizes seeds that are closer to the target point to be tested. QTEP [20] prioritizes seeds that trigger more sensitive codes. Honggfuzz [19] and libfuzzer [18] also 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, and achieved good results. GreyOne [10] uses data flow analysis to determine the relationship between input fields and constraint-related variables, and selects the input with the highest number of relevant key fields.

Since our model also does not require additional program analysis, we chose AFL, AFLFast, EcoFuzz, and FairFuzz when choosing the fuzzers to compare.
6.2 MCTS
Monte Carlo Tree Search (MCTS) is a promising online planning approach because it can effectively search for long-term planning and is anytime [12] [4]. The MCTS algorithm has achieved great success in the field of artificial intelligence. The application field of MCTS algorithm is very extensive, such as active object recognition [16], wildlife monitoring [11], environment exploration [6] [13], and planetary exploration [1]. MCTS has been proposed in many different forms [4], but currently, the most common one is the upper-confidence bounds applied to trees (UCT) algorithm [12]. Therefore, the UCT algorithm is also used in our model.

7 Conclusion
In this paper, we analyze the problems caused by ignoring the multi-factor uncertainty caused by both randomization and evolution of fuzzing. In order to solve these problems, we set the design goals of the model and discuss the challenges we face. We propose a new seed selection strategy based on the MCTS algorithm. Compared with four state-of-the-art fuzzers, the experimental results show that $\alpha$-Fuzz is better at improving code coverage, discovering program paths, and detecting program vulnerabilities.

References
[1] Akash Arora, Robert Fitch, and Salah Sukkarieh. An approach to autonomous science by modeling geological knowledge in a bayesian framework. In 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 3803–3810. IEEE, 2017.

[2] Marcel Böhme, Van-Thuan Pham, Manh-Dung Nguyen, and Abhik Roychoudhury. Directed greybox fuzzing. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, pages 2329–2344, 2017.

[3] Marcel Böhme, Van-Thuan Pham, and Abhik Roychoudhury. Coverage-based greybox fuzzing as markov chain. IEEE Transactions on Software Engineering, 45(5):489–506, 2017.

[4] Cameron B Browne, Edward Powley, Daniel Whitehouse, Simon M Lucas, Peter I Cowling, Philipp Rohlfshagen, Stephen Tavener, Diego Perez,Spyridon Samothrakis, and Simon Colton. A survey of monte carlo tree search methods. IEEE Transactions on Computational Intelligence and AI in games, 4(1):1–43, 2012.

[5] Mingi Cho, Seoyoung Kim, and Taekyoung Kwon. Intriguer: Field-level constraint solving for hybrid fuzzing. In Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security, pages 515–530, 2019.

[6] Micah Corah and Nathan Michael. Efficient online multi-robot exploration via distributed sequential greedy assignment. In Robotics: Science and Systems, volume 13, 2017.

[7] DeepMind. Deepmind. Accessed August 18th, 2020. https://deepmind.com/research/publications/Static-and-Dynamic-Values-of-Computation-in-MCTS, 2017.

[8] Janez Demšar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine learning research, 7(Jan):1–30, 2006.

[9] Brendan Dolan-Gavitt, Patrick Hulin, Engin Kirda, Tim Leek, Andrea Mambretti, William K. Robertson, Frederick Ulrich, and Ryan Whelan. LAVA: large-scale automated vulnerability addition. In IEEE Symposium on Security and Privacy, SP 2016, San Jose, CA, USA, May 22-26, 2016, pages 110–121, 2016.

[10] Shuitao Gan, Chao Zhang, Peng Chen, Bodong Zhao, Xiaojun Qin, Dong Wu, and Zuoning Chen. Greyone: Data flow sensitive fuzzing. In 29th USENIX Security Symposium (USENIX Security 20). USENIX Association, Boston, MA. https://www. usenix. org/conference/usenixsecurity20/presentation/gan, 2020.

[11] Benjamin Heffner, Oliver M Cliff, and Robert Fitch. Adversarial patrolling with reactive point processes. In Proceedings of the ARAA Australasian
Conference on Robotics and Automation (ARAA, 2016), pages 39–46, 2016.

[12] Levente Kocsis, Csaba Szepesvári, and Jan Wilemsen. Improved monte-carlo search. *Univ. Tartu, Estonia, Tech. Rep.*, 1, 2006.

[13] Mikko Lauri and Risto Ritala. Planning for robotic exploration based on forward simulation. *Robotics and Autonomous Systems*, 83:15–31, 2016.

[14] Caroline Lemieux and Koushik Sen. Fairfuzz: A targeted mutation strategy for increasing greybox fuzz testing coverage. In *Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering*, pages 475–485, 2018.

[15] Chenyang Lyu, Shouling Ji, Chao Zhang, Yuwei Li, Wei-Han Lee, Yu Song, and Raheem Beyah. {MOPT}: Optimized mutation scheduling for fuzzers. In *28th USENIX Security Symposium (USENIX Security 19)*, pages 1949–1966, 2019.

[16] Timothy Patten, Wolfram Martens, and Robert Fitch. Monte carlo planning for active object classification. *Autonomous Robots*, 42(2):391–421, 2018.

[17] Diego Perez, Spyridon Samothrakis, and Simon Lucas. Knowledge-based fast evolutionary mcts for general video game playing. In *2014 IEEE Conference on Computational Intelligence and Games*, pages 1–8. IEEE, 2014.

[18] Kostya Serebryany. libfuzzer—a library for coverage-guided fuzz testing. *LLVM project*, 2015.

[19] Robert Swieciki. Honggfuzz: A general-purpose, easy-to-use fuzzer with interesting analysis options. URL: https://github.com/google/honggfuzz (visited on 06/21/2017), 2017.

[20] Song Wang, Jaechang Nam, and Lin Tan. Qtep: quality-aware test case prioritization. In *Proceedings of the 2017 11th Joint Meeting on Foundations of Software Engineering*, pages 523–534, 2017.

[21] Yanhao Wang, Xiangkun Jia, Yuwei Liu, Kyle Zeng, Tiffany Bao, Dinghao Wu, and Purui Su. Not all coverage measurements are equal: Fuzzing by coverage accounting for input prioritization. *NDSS*, 2020.

[22] Tai Yue, Pengfei Wang, Yong Tang, Enze Wang, Bo Yu, Kai Lu, and Xu Zhou. Ecofuzz: Adaptive energy-saving greybox fuzzing as a variant of the adversarial multi-armed bandit. In *29th USENIX Security Symposium (USENIX Security 20)*, 2020.

[23] Insu Yun, Sangho Lee, Meng Xu, Yeongjin Jang, and Taesoo Kim. QSYM : A practical concolic execution engine tailored for hybrid fuzzing. In *27th USENIX Security Symposium, USENIX Security 2018, Baltimore, MD, USA, August 15-17, 2018*, pages 745–761, 2018.

[24] Michał Zalewski. American fuzzy lop. Accessed August 18th, 2020. http://lcamtuf.coredump.cx/afl, 2014.