Learning Inputs in Greybox Fuzzing

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ABSTRACT
Greybox fuzzing is a lightweight testing approach that effectively detects bugs and security vulnerabilities. However, greybox fuzzers randomly mutate program inputs to exercise new paths; this makes it challenging to cover code that is guarded by complex checks.

In this paper, we present a technique that extends greybox fuzzing with a method for learning new inputs based on already explored program executions. These inputs can be learned such that they guide exploration toward specific executions, for instance, ones that increase path coverage or reveal vulnerabilities. We have evaluated our technique and compared it to traditional greybox fuzzing on 26 real-world benchmarks. In comparison, our technique significantly increases path coverage (by up to 3X) and detects more bugs (up to 38% more), often orders-of-magnitude faster.

1 INTRODUCTION
There is no doubt that test case generation helps find bugs and security vulnerabilities, and therefore, improve software quality. It is also clear that manual test case generation is a cumbersome and very time-consuming task. As a consequence, there has emerged a wide variety of automatic test case generation tools, ranging from random testing [28, 29, 50], over greybox fuzzing [3, 7], to symbolic execution [20, 33].

Random testing [28, 29, 50] and blackbox fuzzing [4, 9] generate random inputs to a program, run the program with these inputs, and check whether any bugs were found, e.g., whether the program crashed or a user-provided property was violated. Despite their practicality, the effectiveness of random testing and blackbox fuzzing, that is, their ability to explore new paths, is limited. The search space of valid program inputs is typically huge, and a random exploration can only exercise a small fraction of (mostly shallow) program paths.

At the other end of the spectrum, dynamic symbolic execution [20, 33] and whitebox fuzzing [19, 31, 34] repeatedly run a program, both concretely and symbolically. At runtime, they collect symbolic constraints on program inputs from branch statements along the execution path. These constraints are then appropriately modified and a constraint solver is used to generate new inputs, thereby steering execution toward another program path. Although these techniques are very effective in covering new paths, they simply cannot be as efficient and scalable as other test case generation techniques that do not spend any time on program analysis and constraint solving.

Greybox fuzzing [3, 7] lies in the middle of the spectrum between performance and effectiveness in discovering new paths. It does not require program analysis or constraint solving, but it relies on a lightweight program instrumentation that allows the fuzzer to tell when an input exercises a new path. In other words, the instrumentation is useful in computing a unique identifier for each explored path in a program under test. American Fuzzy Loop (AFL) [7] is a prominent example of a state-of-the-art greybox fuzzer that has detected numerous bugs and security vulnerabilities [1].

A greybox fuzzer, like AFL, starts by running the program under test with a seed input. During execution of the program, the fuzzer computes the identifier of the path that is currently being explored. It then mutates the seed slightly to generate a new input and runs the program again. If a new path is exercised, the input is added to a set of seeds, otherwise it is discarded. From this set of seeds, the fuzzer picks new inputs to mutate. The process is repeated until a timeout is reached or until the user aborts the exploration.

Despite the fact that greybox fuzzing strikes a good balance between performance and effectiveness in automatic test case generation, the inputs are still mutated in a random way, for instance, by flipping random bits. As a result, many generated inputs exercise the same program paths. To address this problem, there have emerged techniques that direct greybox fuzzing toward low-frequency paths [18], vulnerable paths [54], deep paths [64], or specific sets of program locations [17]. Specifically, such techniques have focused on which seed inputs to prioritize and which parts of these inputs to mutate.

Our approach. In this paper, we present an orthogonal approach that systematically learns new inputs for the program under test with the goal of increasing the performance and effectiveness of greybox fuzzing. In contrast to existing work, our approach suggests concrete input values based on information from previous executions, instead of performing arbitrary mutations. The new inputs are learned in a way that aims to direct greybox fuzzing toward optimal executions, for instance, executions that flip a branch condition and thus increase path coverage. Our technique is parametric in what constitutes an optimal execution, and in particular, in what properties such an execution needs to satisfy.

More specifically, each program execution can be associated with zero or more cost metrics. A cost metric captures how close the execution is to satisfying a given property at a given program location. Executions that minimize a cost metric are considered optimal with respect to that metric. For example, one could define a cost metric at each arithmetic operation in the program such that the metric becomes minimal (i.e., equal to zero) when an execution triggers an arithmetic overflow. Then, any execution that leads to an overflow is optimal with respect to the cost metric it minimizes. Note that cost metrics can either be computed automatically, as in the example above, or provided by the user.

Our algorithm uses the costs that are computed along executions of the program under test to learn new inputs that lead to optimal executions. As an example, consider that method foo, shown below, is the program under test. (The grey box on line 3 should be ignored for now.)
The problem revealed by this code is typical of black- or greybox fuzzers: it is difficult to generate a value for input \( x \) that drives the program through the vulnerable path. For the sake of this example, we assume the cost metric to be the absolute value of \( x - 42 \), shown on line 3, which defines optimal executions as those that cover the then-branch of the if-statement. Now, let us imagine that none of the first few executions of this program cover the then-branch. Although these executions are not optimal with respect to the cost metric of line 3, they are still useful in learning a correlation between the input values of \( x \) and their corresponding costs (as computed on line 3). Based on this approximate correlation, our algorithm proposes a new value for \( x \) (namely 49), which minimizes the cost on line 3. In contrast, existing greybox fuzzing techniques randomly mutate \( x \) hoping to cover the vulnerable path.

Another way to think about our algorithm is the following. Given a set of cost metrics, the program under test is essentially a function from inputs to costs, \( costs = f(inputs) \), which precisely describes the correlation between inputs and the corresponding costs. In this context, our greybox fuzzing algorithm collects data points of the form \( (inputs, costs) \) from executions of the program under test, and it then approximates the function that correlates them. If the approximation is precise enough, this technique is able to suggest inputs that lead to optimal executions by purely reasoning about the much simpler, approximated function.

We implemented our algorithm in a tool architecture that can be instantiated with any cost metric. As a result, our architecture is flexible enough to capture different notions of what constitutes an optimal execution. In our instantiation of the tool architecture, we consider two kinds of cost metrics, (1) ones that are minimized when execution flips a branch condition, and (2) ones that are minimized when execution is able to modify arbitrary memory locations. In comparison to traditional greybox fuzzing, our approach is able to significantly increase path coverage (by up to 3X) and detect many more vulnerabilities (up to 38% more), often orders-of-magnitude faster.

**Contributions.** Our paper makes the following contributions:

- We introduce a greybox fuzzing algorithm that learns new inputs to guide exploration toward optimal program executions.
- We implement this algorithm in a tool architecture that may be instantiated with different notions of optimality.
- We evaluate our technique on 26 real-world benchmarks and demonstrate that it is more effective than traditional greybox fuzzing.

**Outline.** The next section reviews traditional greybox fuzzing and gives an overview of our approach through a running example. Sect. 3 explains the technical details of our approach, while Sect. 4 describes our implementation. We present our experimental evaluation in Sect. 5 and threats to the validity of our experiments in Sect. 6. We discuss related work in Sect. 7 and conclude in Sect. 8.

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**Algorithm 1 Greybox Fuzzing**

**Input:** Program \( prog \), Seeds \( S \)

1. \( PIDs \leftarrow \text{RunSeeds}(S, \text{prog}) \)
2. \( \text{while } \neg \text{Interrupted}() \) do
3. \( \text{input} \leftarrow \text{PickInput}(\text{PIDs}) \)
4. \( \text{energy} \leftarrow 0 \)
5. \( \text{maxEnergy} \leftarrow \text{AssignEnergy}(\text{input}) \)
6. \( \text{while } \text{energy} < \text{maxEnergy} \) do
7. \( \text{input}' \leftarrow \text{FuzzInput}(\text{input}) \)
8. \( \text{PID}' \leftarrow \text{Run}(\text{input}', \text{prog}) \)
9. \( \text{if } \text{IsNew}(	ext{PID}', \text{PIDs}) \) then
10. \( \text{PIDs} \leftarrow \text{Add}(	ext{PID}', \text{input}', \text{PIDs}) \)
11. \( \text{energy} \leftarrow \text{energy} + 1 \)

**Output:** Test suite Inputs(\( \text{PIDs} \))

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2. **OVERVIEW**

In this section, we first describe traditional greybox fuzzing and then compare with our approach through a running example.

### 2.1 Background: Greybox Fuzzing

Fuzzing comes in three main flavors depending on how much the fuzzer is allowed to look at the structure of the program under test. **Blackbox fuzzers** \([4, 9]\), like random testing tools, execute the program under test without leveraging any information about its structure. On the other hand, **whitebox fuzzers** \([19, 31, 34]\), like dynamic symbolic execution tools, use program analysis and constraint solving to understand the entire structure of the program under test and, therefore, explore more paths.

**Greybox fuzzers**, like AFL \([7]\) or LibFuzzer \([3]\), leverage only some structure of the program under test, which they obtain with lightweight program instrumentation. By obtaining more information about the program structure, greybox fuzzing can be more effective than blackbox fuzzing in finding bugs. In comparison to whitebox fuzzing, greybox fuzzing spends less time acquiring information about the program structure and, as a result, it is more efficient.

Alg. 1 shows how greybox fuzzing works. The fuzzer takes as input the program under test \( prog \) and a set of seeds \( S \). It starts by running the program with the seeds, and during each program execution, the instrumentation is able to capture the path that is currently being explored and associate it with a unique identifier \( PID \) (line 1). Note that the \( PIDs \) data structure is a key-value store from a \( PID \) to an input that exercises the path associated with \( PID \). Next, an input is selected for mutation (line 3); the selection can be either random or based on heuristics, for instance, based on the number of times an input has already been mutated. The selected input is then assigned an “energy” value that denotes how many times the selected input should be fuzzed (line 5).

The input is mutated (line 7), and the program is run with the new input (line 8). If the program follows a path that has not been previously explored, the new input is added to the test suite (lines 9–10). The above process is repeated until an exploration bound is reached (line 2), for instance, a timeout, a maximum number of generated inputs or seeds, etc. The fuzzer returns a test suite containing one test case for each program path that has been explored.
int bar(a, b, c: int) {
  var d = b + c;
  minimize(d < 1 ? 1 - d : 0);
  minimize(d < 1 ? 0 : d);
  if d < 1 {
    minimize(b < 3 ? 3 - b : 0);
    minimize(b < 3 ? 0 : b - 2);
    if b < 3 {
      return 1;
    }
    minimize(a == 42 ? 1 : 0);
    minimize(a == 42 ? 0 : abs(a - 42));
    if a == 42 {
      return 2;
    }
    return 3;
  } else {
    minimize(c < 42 ? 42 - c : 0);
    minimize(c < 42 ? 0 : c - 41);
    if c < 42 {
      return 4;
    }
    return 5;
  }
}

Figure 1: Running example.

As shown here, the program instrumentation is useful in determining which inputs to retain for inclusion in the test suite and further fuzzing.

2.2 Running Example

Fig. 1 shows a simple, constructed program that we will use throughout the paper to demonstrate the benefits of our approach. Function bar takes as input three integers a, b, and c and returns an integer. There are five paths in this function, all of which are feasible. Each path is denoted by a unique return value. (The grey boxes are discussed below and should be ignored for now.)

When running traditional greybox fuzzing (more specifically, AFL) on function bar, only four out of five program paths are explored within 12h. During this time, greybox fuzzing constructs a test suite of four inputs, each of which explores a different path in bar. The path with return value 2 remains unexplored even after the fuzzer generates about 311M different inputs. All but four of these inputs are discarded as they exercise a path in bar that has already been covered by a previous test case.

The path with return value 2 is not covered because greybox fuzzers randomly mutate program inputs (line 7 of Alg. 1). More generally, it is challenging for fuzzers to generate inputs that satisfy “narrow checks”, that is, checks that only become true for very few input values, like the check on line 13 of the running example. In this case, the probability that the fuzzer will generate the value 42 for input a is 1 out of 2^{32} for 32-bit integers. Even worse, to cover the path with return value 2 (line 14), the sum of inputs b and c needs to be less than 1 (line 5) and b must be greater than or equal to 3 (line 8). As a result, several techniques have been proposed to guide greybox fuzzing to satisfy such narrow checks, for instance, by selectively applying whitebox fuzzing [65].

In contrast, our greybox fuzzing approach is able to guide test case generation toward optimal program executions without any program analysis or constraint solving. For instance, to ultimately maximize path coverage, the grey boxes in Fig. 1 define cost metrics that are minimized when execution flips a branch condition. For this example, our algorithm explores all five program paths within only 0.27s and after generating only 372 different inputs.

2.3 Approach

This effectiveness of our technique on the running example becomes possible by making traditional greybox fuzzing a lighter shade of grey. In other words, our fuzzing algorithm has access to more information about the program under test than traditional greybox fuzzing, which is enough to guide exploration toward specific executions.

The workflow and tool architecture of our greybox fuzzer is shown in Fig. 2. The fuzzer takes as input the program under test prog, a set of seeds S, and a partial function $f_{cost}$ that maps program states to cost metrics. When execution of prog reaches a state $s$, the fuzzer evaluates the cost metric $f_{cost}(s)$. For example, the grey boxes in Fig. 1 practically define a function $f_{cost}$ for the running example. Each minimize statement specifies a cost metric at the program state where it appears. In other words, function $f_{cost}$ essentially constitutes an instrumentation of the program under test, which is typically derived automatically (see Sect. 4). In comparison to traditional greybox fuzzing, this function is all the additional information that our technique requires.

As shown in Fig. 2, the fuzzer passes explored inputs and the corresponding costs, which are computed during execution of prog with these inputs, to a learning component. Based on the given inputs and costs, this component learns new inputs that aim to minimize the cost metrics of $f_{cost}$, and therefore, lead to optimal executions.

As mentioned earlier, the cost metrics of Fig. 1 define optimal executions as those that flip a branch condition. Specifically, consider a program execution along which variable d evaluates to 0. This execution takes the then-branch of the first if-statement, and the cost metric defined by the minimize statement on line 3 evaluates to 1. This means that the distance of the current execution from an execution that exercises the (implicit) else-branch of the if-statement is 1. Now, consider a second program execution that also takes the then-branch of the first if-statement (d evaluates to -1). In this case, the cost metric on line 3 evaluates to 2, which
indicates a greater distance from an execution that exercises the else-branch.

Based on this information, the learning component of Fig. 2 is able to learn new program inputs that force execution of prog to take the else-branch of the first if-statement and minimize the cost metric on line 3 (i.e., make the cost metric evaluate to zero). For instance, the learned inputs could cause d to evaluate to 7. Then, although the cost metric on line 3 evaluates to zero, the cost metric on line 4 evaluates to 7, which is the distance of the current execution from an execution that exercises the then-branch of the if-statement.

Similarly, the minimize statements on lines 6–7, 11–12, and 18–19 of Fig. 1 define cost metrics that are minimized when a program execution flips a branch condition in a subsequent if-statement. This instrumentation aims to maximize path coverage, and for this reason, an execution can never minimize all cost metrics. In fact, the fuzzer has achieved full path coverage when the generated test cases cover all feasible combinations of branches in the program under test; that is, when they minimize all possible combinations of cost metrics.

As shown on the left of Fig. 2, the fuzzer may still generate program inputs without the learning component, for instance, when there are not enough executions from which to learn. In the above example, the inputs for the first two program executions (where d is 0 and -1) are generated by the fuzzer. Because the learner can only approximate correlations between inputs and their corresponding costs, it is possible that certain learned inputs do not lead to optimal executions. In such cases, it is up to the fuzzer to generate inputs that cover any remaining paths in the program under test.

3 GREYBOX FUZZING WITH LEARNING

In this section, we present the technical details of our approach. In particular, we describe our algorithm and explain how learning works.

3.1 Algorithm

Alg. 2 shows how greybox fuzzing with learning works. The grey boxes indicate the differences between our technique and traditional greybox fuzzing (Alg. 1).

In addition to the program under test prog and a set of seeds S, Alg. 2 takes as input a partial function $f_{\text{cost}}$ that, as explained earlier, maps program states to cost metrics. The fuzzer first runs the program with the seeds, and during each program execution, it evaluates the cost metric $f_{\text{cost}}(s)$ for every encountered program state s in the domain of $f_{\text{cost}}$ (line 1). Like in Alg. 1, each explored path in the program is associated with a unique identifier $PID$. Note, however, that the $PID$s data structure now maps a $PID$ both to an input that exercises the corresponding path as well as to a cost vector, which records all costs computed during execution of the program with this input. Next, an input is selected for mutation (line 3), and it is assigned an energy value (line 5).

The input is mutated (line 12), and the program is run with the new input (line 13). For simplicity, we assume that the new input differs from the original input (which was selected for mutation on line 3) by the value of a single input parameter. As usual, if the program follows a path that has not been previously explored, the new input is added to the test suite (lines 14–15).

On line 17, the original input and the new input are passed to the learning component along with their cost vectors. The learner inspects $input$ and $input'$ to determine the input parameter by which they differ. Based on the given cost vectors, it then learns a new value for this input parameter such that one of the cost metrics is minimized. In case a new input is learned, the program is tested with this input, otherwise the original input is mutated (lines 8–10). The former happens even if the energy of the original input has run out (line 7) in order to ensure that we do not waste learned inputs.

The above process is repeated until an exploration bound is reached (line 2), and the fuzzer returns a test suite containing one test case for each program path that has been explored.

Running example. In Tab. 1, we run our algorithm (Alg. 2) on the running example of Fig. 1 step by step. The first column of the table shows an identifier for every generated test case, and the second column shows the path that each test exercises identified by the return value of the program. The highlighted boxes in this column denote paths that are covered for the first time, which means that the corresponding tests are added to the test suite (lines 14–15 of Alg. 2). The third column shows the test identifier from which the value of variable $input$ is selected (line 3 of Alg. 2). Note that, according to the algorithm, $input$ is selected from tests in the test suite. The fourth column shows a new input for the program under test; this input is either a seed or the value of variable $input'$ in the algorithm, which is obtained with learning (line 9) or fuzzing (line 12). Each highlighted box in this column denotes a learned value. The fifth column shows the cost vector that is computed when running the program with the new input of the fourth column. Note that we show only non-zero costs and that the subscript of each cost denotes the line number of the corresponding minimize statement in Fig. 1. The sixth column shows which costs (if any) are used to learn a new input, and the last column shows the current energy...
value of the algorithm’s input (lines 4 and 18). For simplicity, we consider \textit{maxEnergy} of Alg. 2 (line 5) to always have the value 2 in this example. Our implementation, however, is inspired by an existing energy schedule [18].

We assume that the set of seeds \( S \) contains only the random input \((a = -1, b = 0, c = -5)\) (test \#1 in Tab. 1). This input is then fuzzed to produce \((a = -1, b = -3, c = -5)\) (test \#2), that is, to produce a new value for input parameter \( b \). Our algorithm uses the costs computed with metric \( C_6 \) to learn a new value for \( b \). (We explain how new values are learned in the next subsection.) As a result, test \#3 exercises a new path of the program (the one with return value 3). From the cost vectors of tests \#1 and \#3, only the costs computed with metric \( C_3 \) may be used to learn another value for \( b \); costs \( C_6 \) and \( C_7 \) are already zero in one of the two tests, while metric \( C_{12} \) is not reached in test \#1. Even though the energy of the original input (from test \#1) has run out, the algorithm still runs the program with the input learned from the \( C_3 \) costs (line 7). This results in covering the path with return value 4.

Next, we select an input from tests \#1, \#3, or \#4 of the test suite. Let’s assume that the fuzzer picks the input from test \#3 and mutates the value of input parameter \( a \). Note that the cost vectors of tests \#3 and \#5 differ only with respect to the \( C_{12} \) costs, which are therefore used to learn a new input for \( a \). The new input exercises a new path of the program (the one with return value 2). At this point, the cost vectors of tests \#3 and \#6 cannot be used for learning because the costs are either the same (\( C_5 \) and \( C_7 \)) or they are already zero in one of the two tests (\( C_{11} \) and \( C_{12} \)). Since no input is learned and the energy of the original input (from test \#3) has run out, our algorithm selects another input from the test suite.

This time, let’s assume that the fuzzer picks the input from test \#4 and mutates the value of input parameter \( c \). From the cost vectors of tests \#4 and \#7, it randomly selects the \( C_{18} \) costs for learning a new value for \( c \). The learned input exercises the fifth path of the program, thus achieving full path coverage of function \( \text{bar} \) by generating only 8 test cases.

Note that our algorithm makes several non-systematic choices, which may be random or based on certain heuristics, such as when function \textsc{PickInput} picks an input from the test suite, when \textsc{FuzzInput} selects which input parameter to fuzz, or when function \textsc{Learn} decides from which costs to learn. For illustrating how the algorithm works, we made "good" choices such that all program paths are exercised with a small number of test cases. In practice, the fuzzer achieved full path coverage of function \( \text{bar} \) with 372 test cases, instead of 8, as we discussed in Sect. 2.2.

### 3.2 Learning

We now explain how the learning component of our approach works. Even though this component is relatively simple, we found that it is very effective in practice (see Sect. 5). Note, however, that our architecture (Fig. 2) is configurable, and the learning component may be replaced with any technique that learns new inputs for the program under test from already explored inputs and the corresponding costs.

Our algorithm passes to the learning component the input vectors \( \text{input} \) and \( \text{input}' \) and the corresponding cost vectors \( \text{cost} \) and \( \text{cost}' \) (line 17 of Alg. 2). The input vectors differ by the value of a single input parameter, say \( i_0 \) and \( i_1 \). Now, let us assume that the learner selects a cost metric to minimize and that the costs that have been evaluated using this metric appear as \( c_0 \) and \( c_1 \) in the cost vectors. This means that cost \( c_0 \) is associated with input parameter \( i_0 \), and \( c_1 \) with \( i_1 \).

As an example, let us consider tests \#3 and \#5 from Tab. 1. The input vectors that are passed to the learner differ by the value of input parameter \( a \), so \( i_0 = -1 \) (value of \( a \) in test \#3) and \( i_1 = 7 \) (value of \( a \) in test \#5). The learner chooses to learn from cost metric \( C_{12} \) since the cost vectors of tests \#3 and \#5 differ only with respect to this metric, so \( c_0 = 43 \) (value of \( C_{12} \) in test \#3) and \( c_1 = 35 \) (value of \( C_{12} \) in test \#5).

Using these two data points \((i_0, c_0)\) and \((i_1, c_1)\), we compute the straight line \( c(i) = m \cdot i + k \) that connects them, where \( m \) is the slope of the line and \( k \) is a constant. This line approximates the relationship of the input parameter with the selected cost metric. The line is computed (using basic algebra) as follows. The slope of the line is:

\[
m = \frac{c_1 - c_0}{i_1 - i_0}
\]

Once computed, we can solve for constant \( k \). Next, to compute the value that the input parameter should have in order to minimize the cost metric, we solve the following equation for \( i \):

\[
m \cdot i + k = 0 \implies i = -\frac{k}{m}
\]

From the data points \((-1, 43)\) and \((7, 35)\) defined by tests \#3 and \#5, we compute the slope of the line to be \( m = -1 \) and the constant to be \( k = 42 \). Therefore, the equation of the line connecting the two data points is \( c(i) = -i + 42 \). Now, for the cost to be zero, the value of parameter \( a \) must be:

\[
i = -\frac{42}{-1} \implies i = 42
\]

Indeed, when \( a \) becomes 42 in test \#6, cost metric \( C_{12} \) is minimized.

However, as discussed earlier, the computed line \textit{approximates} the relationship between an input parameter and the cost. This is because costs are evaluated locally, at every branch condition, without taking into account the structure of the program until that point. As a result, our technique is very efficient in practice, but
there may be situations where the predicted value for an input parameter fails to flip the target branch. For example, consider the random seed input \( (a = 0, b = 0, c = 0) \) to the running example \( (C_0 = 3) \). Assume that input parameter \( b \) is then fuzzed to produce \( (a = 0, b = -1, c = 0) \) with \( C_0 = 4 \). According to the above, the line that connects the two data points, involving parameter \( b \) and costs \( C_0 \), is \( c(t) = -i + 3 \), which means that for \( C_0 \) to be minimized, \( b \) should have value 3. However, if \( b \) becomes 3, the branch condition that we aimed to flip (on line 8 of Fig. 1) is not even reached; the condition on line 5 is flipped instead. We discuss the success rate of our technique in flipping the target branches in Sect. 5.

Our learning technique resembles linear regression with the difference that we learn from only two data points. Our fuzzer could learn from all previously explored inputs that differ by the value of the same input parameter. However, storing all these inputs and then performing look-up operations would most likely not scale for real programs, where fuzzing can generate tens or hundreds of thousands of inputs in only a few minutes (Sect. 5).

Selecting a cost metric for minimization. Recall that, in order to generate test \#8 in Tab. 1, our algorithm learns a new input from the cost vectors of tests \#4 and \#7, comprising the \( C_0 \) and \( C_{18} \) costs. In principle, the algorithm could use the costs evaluated with either metric for learning. In practice, however, it could use heuristics that, for instance, pick from which costs to learn such that new branches are flipped (like the branch on line 20 of Fig. 1, which is flipped only by test \#8 after learning from the \( C_{18} \) costs).

Alternatively, minimize statements could be augmented with a second argument that specifies a weight for the cost metric. A comparison between such weights would then determine from which costs to learn first, for instance, if \( C_4 \) had a greater weight than \( C_{18} \), the algorithm would prioritize the \( C_4 \) costs for learning. Weights would also make it possible to impose a search strategy on the greybox fuzzer, such as depth- or breadth-first search.

4 IMPLEMENTATION

In this section, we present the details of our implementation. We describe the characteristics of the code that we target, namely of Ethereum smart contracts, and discuss the specific cost metrics that our fuzzer aims to minimize.

4.1 Smart Contracts

In recent years, there have emerged various general-use, blockchain-based [53, 66, 67], distributed-computing platforms [14], the most popular of which is Ethereum [2, 10]. A key feature of Ethereum is that it supports contract accounts in addition to user accounts, both of which publicly reside on the Ethereum blockchain. Contract and user accounts store a balance and are owned by a user. A contract account, however, is not directly managed by users, but instead through code that is associated with it. This code expresses contractual agreements between users, for example, to implement and enforce an auction protocol. A contract account also has persistent state (stored in a dictionary) that the code may access, for instance, to store auction bids. In order to interact with a contract account, users issue transactions that call functions of the account’s code, for instance, to place an auction bid. Executing a transaction requires users to pay a fee, called gas, which is roughly proportional to how much code is run.

Contract accounts with their associated code and persistent state are called smart contracts. The code is written in a Turing-complete bytecode, which is executed on the Ethereum Virtual Machine (EVM) [70]. Programmers, however, do not typically write EVM code; they can instead program in several high-level languages, like Solidity, Serpent, or Vyper, which compile to EVM bytecode.

We have implemented a greybox fuzzer for smart contracts, which works on the EVM-bytecode level and is being used commercially. We implemented our learning technique on top of this fuzzer, and in our experiments, we compare against the vanilla version (without learning). It is generally difficult to compare against other popular off-the-shelf fuzzers, like AFL or LibFuzzer, since we target EVM code. However, on the running example, AFL does not achieve full path coverage after generating 311M inputs in 12h, whereas our vanilla fuzzer exercises all paths after generating 37’354 inputs in 21.64s.

To test a smart contract, our tool generates, executes, and fuzzes sequences of transactions, which call functions of the contract. We consider sequences of transactions since each transaction may have side effects on the contract’s persistent state, which may affect the execution of subsequent calls to the contract.

Note that function \( f_{\text{cost}} \), introduced in Sect. 2.3, constitutes a runtime instrumentation of the contract under test. Although the minimize statements in Fig. 1 give the impression that we instrument the code at compile-time, we only use these statements for illustration purposes. The design decision to use a runtime instrumentation was taken because a compile-time instrumentation would increase the gas usage of the contract and potentially lead to false positives when detecting out-of-gas errors.

In this paper, we focus on two types of vulnerabilities in smart contracts: (1) crashes, which cause a transaction to be aborted and waste assets paid as gas fees, and (2) memory-access errors, which may allow attackers to modify the persistent state of a contract. We discuss these in more detail in the following sections.

4.2 Cost Metrics

We focus on two different kinds of cost metrics, (1) ones that are minimized when execution flips a branch condition, and (2) ones that are minimized when execution is able to modify arbitrary memory locations.

Branch conditions. We have already discussed cost metrics that are minimized when execution flips a branch condition in the running example. Here, we describe how the cost metrics are derived from the program under test.

For the comparison operators \( \geq, \leq \), and \( \neq \), we define the following cost functions:

\[
C_{eq}(l, r) = \begin{cases} 
1, & l = r \\
0, & l \neq r
\end{cases}
\]

\[
C_{eq}(l, r) = \begin{cases} 
0, & l = r \\
|l - r|, & l \neq r
\end{cases}
\]

\[
C_{lt}(l, r) = \begin{cases} 
0, & l \geq r \\
|l - r|, & l < r
\end{cases}
\]

...
where logical operators, such as \(a \neq b\), denote the value of a \(\neq b\) comparison operator used in the branch condition. The cost functions for the \(= (ne)\) operator are derived as follows:

\[
C_{eq}(l, r) = \begin{cases} 
0, & l < r \\
l - r + 1, & l \geq r 
\end{cases}
\]

\[
C_{eq}(l, r) = \begin{cases} 
0, & l < r \\
1 - l + 1, & l \leq r 
\end{cases}
\]

\[
C_{eq}(l, r) = \begin{cases} 
0, & l < r \\
l - r, & l > r 
\end{cases}
\]

Function \(C_{eq}\) from before is non-zero when a branch condition \(l = r\) holds; it defines the cost metric for making this condition false. On the other hand, function \(C_{ne}\) defines the cost metric for making the same branch condition true. The arguments \(l\) and \(r\) denote the left and right operands of the operator. The notation is similar for all other functions.

As an example, consider the branch condition on line 13 of Fig. 1, \(a = 42\). According to function \(C_{eq}\), when this condition holds, the cost metric to make it false is 1, as specified in the \(\text{minimize}\) statement on line 11. This means that the distance from an execution where the condition does not hold is 1, or in other words, if the value of a changes by 1, the condition no longer holds. For an execution where the condition on line 13 does not hold, function \(C_{eq}\) defines the cost metric to make it true as \(|a - 42|\) (see \(\text{minimize}\) statement on line 12).

Based on the above cost functions, our instrumentation evaluates two cost metrics before every branch condition in the program under test. The specific metrics that are evaluated depend on the comparison operator used in the branch condition. The cost functions for other comparison operators, namely \(!= (ne), > (gt)\), and \(>= (ge)\), are easily derived from the functions above. For instance, the cost functions for the \(!= (ne)\) operator are defined as follows:

\[
C_{ne}(l, r) = \begin{cases} 
l - r, & l \neq r \\
0, & l = r 
\end{cases}
\]

In other words:

\[
C_{ne}(l, r) = C_{eq}(l, r) - C_{eq}(l, r) 
\]

Similarly:

\[
C_{ge}(l, r) = C_{eq}(l, r) - C_{eq}(l, r) 
\]

Note that our implementation works on the bytecode level, where logical operators, such as \&\& and | |, are typically expressed as branch conditions. We, therefore, do not define cost functions for such operators.

**Memory locations.** Recall that a smart contract may store persistent state in a dictionary. If, however, users or other contracts manage to access memory in this dictionary (either accidentally or intentionally), they may endanger the crypto-assets of the contract leading to critical security vulnerabilities.

As an example, consider the smart contract (written in Solidity) shown in Fig. 3. (The grey box should be ignored for now.) It is a simplified version of code submitted to the Underhanded Solidity Coding Contest (USCC) in 2017 [8]. (In the next section, we refer to the original code of this submission as USCC2, with benchmark identifier 22.) The USCC is a contest to write seemingly harmless Solidity code that, however, disguises unexpected vulnerabilities.

The smart contract of Fig. 3 implements a wallet that has an owner and stores an array (with variable length) of bonus codes (lines 2–3). The constructor (on line 5) initializes the owner to the address of the caller and the bonus codes to an empty array. The empty function on line 10 ensures that assets can be paid into the wallet. The following functions allow bonus codes to be pushed, popped, or updated. The last function (on line 27) must be called only by the wallet owner (line 28) and causes the wallet to self-destruct (line 29), that is, to transfer all assets to the owner and then destroy itself.

The vulnerability in this code is caused by the precondition on line 17, which should require the length of the array to be greater than zero (instead of greater than or equal to zero) before popping an array element. Consequently, when the array is empty, the statement on line 18 causes the (unsigned) array length to underflow; this effectively disables the bound-checks of the array, allowing elements to be stored anywhere in the persistent storage of the contract. Therefore, by setting a bonus code at a specific

\[
\begin{align*}
C_{ne}(l, r) & = 0, & l < r \\
C_{ne}(l, r) & = 1 - l + 1, & l \leq r \\
C_{ne}(l, r) & = 0, & l = r \\
C_{ne}(l, r) & = l - r, & l > r \\
\end{align*}
\]
index in the array, an attacker could overwrite the address of the wallet owner to their own address. Then, by destroying the wallet, the attacker would transfer all assets to their account. In a slightly more optimistic scenario, the wallet owner could be accidentally set to an invalid address, in which case the assets in the wallet would become inaccessible.

To detect such vulnerabilities, a greybox fuzzer can, for every assignment to the persistent storage of a contract, pick an arbitrary address and compare it to the target address of the assignment. When these two addresses happen to be the same, it is very likely that the assignment may also target other arbitrary addresses, perhaps as a result of an exploit. A fuzzer (without learning) is only able to detect these vulnerabilities by chance, and chances are extremely low that the target address of an assignment matches an arbitrarily selected address, especially given that these are 32 bytes long. In fact, our greybox fuzzer without learning does not detect the vulnerability in the code of Fig. 3 within 12h.

To direct the fuzzer toward executions that could reveal such vulnerabilities, we define the following cost function:

$$C_{st}(lhsAddr, addr) = |lhsAddr - addr|$$

In the above function, $lhsAddr$ denotes the address of the left-hand side of an assignment to persistent storage (that is, excluding assignments to local variables) and $addr$ an arbitrary address. Function $C_{st}$ is non-zero when $lhsAddr$ and $addr$ are different, and therefore, optimal executions are those where the assignment writes to the arbitrary address, potentially revealing a vulnerability.

Our instrumentation evaluates the corresponding cost metric before every assignment to persistent storage in the program under test. An example is shown on line 23 of Fig. 3. (We use the $@_s$ operator to denote the address of $bonusCodes[1]$ and we do not show the instrumentation at every assignment to avoid clutter.) Our fuzzer with learning detects the vulnerability in the contract of Fig. 3 within a few seconds.

Detecting such vulnerabilities based on whether an assignment could target an arbitrary address might generate false positives when the arbitrary address is indeed an intended target of the assignment. However, the probability of this occurring in practice is extremely low (again due to the address length). In fact, we did not encounter any false positives during our experiments.

## 5 EXPERIMENTAL EVALUATION

In this section, we evaluate the effectiveness of greybox fuzzing with learning on real-world smart contracts. First, we explain how we selected our benchmarks (Sect. 5.1) and describe the experimental setup we used (Sect. 5.2). We then show the results of comparing to traditional greybox fuzzing (Sect. 5.3).

### 5.1 Benchmark Selection

First, we collected all smart contracts from 16 GitHub repositories. We selected the repositories based on two main criteria to obtain a diverse set of contracts. On the one hand, we picked popular projects in the Ethereum community (e.g., the Ethereum Name Service domain auction, the Consensys wallet, and the MicroRaiden payment service) and with high popularity on GitHub (3’675 stars in total on 2018-05-02, median 106.5). The majority of the contracts in these projects have been reviewed by independent auditors and are deployed on the Ethereum blockchain, managing and transferring significant amounts of crypto-assets on a daily basis. On the other hand, we also selected repositories from a wide range of application domains (e.g., auctions, token sales, payment networks, and wallets) to cover various features of the Ethereum virtual machine and of the Solidity programming language. We also included contracts that had been hacked in the past (The DAO and the Parity wallet) and five contracts (incl. the four top-ranked entries) from the repository of the USCC to consider some malicious or buggy contracts.

Second, we identified one or more main contracts from each of the repositories that would serve as contracts under test, resulting in a total of 26 benchmarks. Note that many repositories contain several contracts (incl. libraries) to implement a complex system, such as an auction. Tab. 2 gives an overview of all benchmarks and the projects from which they originate. The first column lists the benchmark IDs (BIDs) for each project, while the second column provides the project name. The third and fourth columns show two source code metrics to provide some indication of the complexity of the contracts under test: the number of public functions in the benchmarks and the lines of code (LOC). Note that all contracts were written in Solidity. Finally, we provide a short description of each project in the last column. Appx. A provides more details about the repositories and the tested changesets.

### 5.2 Experimental Setup

We ran our fuzzer both with and without learning on each of the 26 benchmarks. To compare the effectiveness of both approaches for different usage scenarios, we selected three time limits: 5m (e.g., coffee break), 30m (e.g., lunch break), and 3h (e.g., over night). We focus our comparison on the following two key metrics: path coverage and number of detected bugs within a given time limit.

| BIDs | Name     | Functions | LOC  | Description                                      |
|------|----------|-----------|------|-------------------------------------------------|
| 1    | ENS      | 24        | 1205 | ENS domain name auction                         |
| 2-3  | CMSW     | 49        | 503  | Consensys multisig wallet                      |
| 4-5  | GNSW     | 49        | 704  | Gnosis multisig wallet                         |
| 6    | BAT      | 23        | 191  | BAT token (advertising)                        |
| 7    | CT       | 12        | 206  | Consensys token library                        |
| 8    | ERCF     | 19        | 747  | ERC Fund (investment fund)                     |
| 9    | FRT      | 34        | 385  | FirstBlood token (e-sports)                    |
| 10-13| HPN      | 173       | 3065 | Havven payment network                         |
| 14   | MR       | 25        | 1053 | MicroRaiden payment service                    |
| 15   | MT       | 38        | 437  | MOD token (supply-chain)                       |
| 16   | PC       | 7         | 69   | Payment channel                                |
| 17-18| RNTS     | 49        | 749  | Request Network token sale                     |
| 19   | DAO      | 23        | 783  | The DAO organization                           |
| 20   | VT       | 18        | 242  | Valid token (personal data)                    |
| 21   | USCC1    | 4         | 57   | USCC `17 entry                                 |
| 22   | USCC2    | 14        | 89   | USCC `17 (honorable mention)                   |
| 23   | USCC3    | 21        | 535  | USCC `17 (3rd place)                           |
| 24   | USCC4    | 7         | 164  | USCC `17 (1st place)                           |
| 25   | USCC5    | 10        | 188  | USCC `17 (2nd place)                           |
| 26   | PW       | 19        | 549  | Parity multisig wallet                         |
The lowest success rate is observed for benchmark 26. Manual inspection of this benchmark revealed that the contract makes extensive use of cryptographic hashes (even during input sanitization), which makes it very challenging when \( x \) is an input. Column \( R_L \) provides the success rate of learning. We can see that the success rate is 0.81 on average (between 0.47 and 0.9), which suggests that it is very effective.

The lowest success rate is observed for benchmark 26. Manual inspection of this benchmark revealed that the contract makes extensive use of cryptographic hashes (even during input sanitization), a known obstacle for most fuzzers. For instance, exploring a branch with condition \( sha(x) = 42 \) is very challenging when \( x \) is an input. Learning does not help in this case since the cost of flipping the above branch cannot be approximated using a polynomial, let alone a linear function. Note, however, that learning can be very effective for a branch with condition \( sha(x) = y \), if both \( x \) and \( y \) are inputs.

To evaluate the potential overhead of learning, the sixth and seventh columns also provide the total energy (i.e., number of generated inputs) spent without (E) and with learning (E\(_L\)). There are only 9 benchmarks where learning is able to explore more inputs. This could suggest that our approach generates fewer inputs within the time limit due to the overhead of learning. However, note that, for most benchmarks where fuzzing with learning achieves higher path coverage, it does so with less energy. This shows that the quantity of inputs alone is not a good indication of the effectiveness of these techniques; better-quality inputs help achieve better results in the same amount of time. Moreover, because the two approaches explore different program inputs, with varying running times, it is difficult to draw any meaningful conclusion about their overhead based on the total energy.

The last three columns of the table provide more details on how often learning succeeds in minimizing the intended cost. Columns \( S_L \) and \( F_L \) show the number of successful and failed minimizations, respectively. A failed minimization indicates that our approximation of how inputs relate to costs is imprecise. Column \( R_L \) provides the success rate of learning. We can see that the success rate is 0.81 on average (between 0.47 and 0.9), which suggests that it is very effective.

The lowest success rate is observed for benchmark 26. Manual inspection of this benchmark revealed that the contract makes extensive use of cryptographic hashes (even during input sanitization), a known obstacle for most fuzzers. For instance, exploring a branch with condition \( sha(x) = 42 \) is very challenging when \( x \) is an input. Learning does not help in this case since the cost of flipping the above branch cannot be approximated using a polynomial, let alone a linear function. Note, however, that learning can be very effective for a branch with condition \( sha(x) = y \), if both \( x \) and \( y \) are inputs.
When looking at how converge increases over time. In Fig. 4, we can see a head-to-head comparison between the two approaches within the same time. The former can be observed even more clearly where we achieve marginally higher coverage without learning.

Finally, the results when running both fuzzers for 3h (Tab. 5) confirm the same trends observed for shorter running times. With learning, we achieve higher coverage for 21 benchmarks and we find more bugs in 6 benchmarks. Benchmark 15 is the only one where we achieve marginally higher coverage without learning.

Overall, our results demonstrate the effectiveness of our approach in achieving higher coverage and detecting more bugs within the same time. The former can be observed even more clearly when looking at how converge increases over time. In Fig. 4, we can see a head-to-head comparison between the two approaches for a few benchmarks. In all cases, our approach surpasses the final coverage of greybox fuzzing without learning within a fraction of the allocated time.

We also compare average percentages of covered paths in the Venn diagram of Fig. 5. In general, each approach covers paths that are not covered by the other for some benchmarks. On average, 7.1% of paths are only covered without learning and 23.7% with learning.

The effectiveness in finding bugs is even more apparent when comparing the time until the same bug is detected (see Tab. 6 for the time limit of 3h). With learning, we find all bugs detected by the fuzzer without learning as well as 13 bugs more, for a total of 18 benchmarks. In contrast, the fuzzer without learning only finds one additional bug. The main difference between Tabs. 3 and 4 is that we now observe a slightly lower success rate of 0.73 on average. We suspect that this is due to the fact that we are in a later fuzzing phase where deeper execution traces are explored. This can decrease the probability of minimizing an intended cost when inputs also affect earlier branches in the program (see Sect. 3.2 for an example). However, as observed earlier, the effectiveness of learning does not seem to hinge on very high success rates.

Figure 4: Coverage increase over time. These plots show how coverage increases over time for several benchmarks (1, 4, 10, and 26 from top to bottom) without (dotted line) and with learning (solid line). The light grey horizontal lines illustrate at which point in time one fuzzer surpasses the final coverage of the other.

Table 5: Results of greybox fuzzing without and with learning (time limit of 3h).

| BID | P | Pt | B | Et | Lt | St | Ft | Rt |
|-----|---|----|---|----|----|----|----|----|
| 1   | 1676| 2333| 0 | 2078| 19| 9 | 2679| 3071| 26319| 15197| 9010| 0.68|
| 2   | 254 | 452 | 2 | 260 | 0 | 0 | 1046123| 1079040| 30588| 33326| 0.48|
| 3   | 306 | 422 | 2 | 260 | 0 | 0 | 865133| 800498| 23655| 33444| 0.41|
| 4   | 268 | 498 | 2 | 260 | 0 | 0 | 833864| 1229650| 36689| 33242| 0.52|
| 5   | 256 | 320 | 2 | 260 | 0 | 0 | 904658| 891458| 26586| 33119| 0.45|
| 6   | 52  | 52  | 0 | 0 | 0 | 4097566| 4011683| 57385| 14074| 0.80|
| 7   | 28  | 28  | 0 | 0 | 0 | 1391220| 1330754| 14011| 6759| 0.67|
| 8   | 116 | 141 | 9 | 13 | 9 | 3507219| 3229561| 48816| 18105| 0.73|
| 9   | 85  | 88  | 0 | 0 | 0 | 3021580| 2799495| 72604| 15824| 0.82|
| 10  | 143 | 383 | 1 | 3 | 3 | 1083042| 887115| 35173| 23128| 0.60|
| 11  | 230 | 362 | 1 | 1 | 1 | 1161930| 1006539| 56058| 21007| 0.73|
| 12  | 93  | 95  | 0 | 0 | 0 | 1316578| 1254882| 49935| 15647| 0.72|
| 13  | 77  | 86  | 7 | 7 | 7 | 1220964| 1185722| 27033| 9146| 0.74|
| 14  | 178 | 200 | 2 | 2 | 2 | 924258| 952175| 35087| 27784| 0.56|
| 15  | 247 | 244 | 3 | 3 | 3 | 2271856| 1987588| 66959| 31137| 0.68|
| 16  | 18  | 18  | 0 | 0 | 0 | 5660256| 5555393| 42573| 5048| 0.89|
| 17  | 122 | 132 | 0 | 0 | 0 | 1368845| 1144578| 38296| 17339| 0.69|
| 18  | 74  | 90  | 3 | 4 | 4 | 2079860| 2083114| 45293| 21378| 0.68|
| 19  | 94  | 104 | 7 | 7 | 7 | 1762548| 2072935| 49674| 6948| 0.88|
| 20  | 149 | 194 | 1 | 1 | 1 | 1862167| 1533119| 45512| 21766| 0.68|
| 21  | 24  | 28  | 2 | 2 | 2 | 4753217| 6518330| 27986| 3770| 0.88|
| 22  | 41  | 42  | 2 | 3 | 3 | 5892858| 5216357| 63959| 15279| 0.81|
| 23  | 86  | 86  | 4 | 4 | 4 | 2954445| 2578311| 4565| 25320| 0.64|
| 24  | 20  | 34  | 5 | 9 | 9 | 7292754| 638068| 34142| 35656| 0.86|
| 25  | 22  | 34  | 0 | 0 | 0 | 5313742| 5559319| 59849| 11199| 0.84|
| 26  | 118 | 130 | 23 | 23 | 23 | 540616| 638028| 13361| 99340| 0.12|
6 Threats to Validity

We have identified the following threats to the validity of our experiments.

External validity. With regard to external validity [61], our experimental results may not generalize to all smart contracts or to other types of programs. However, we evaluated our technique on a diverse set of contracts from a wide range of application domains. We, therefore, believe that our benchmark selection significantly aids generalizability. In an effort to further improve external validity, we also provide the versions of all smart contracts we used in our experiments in Appx. A so that others can test them. Independently, our technique is not tailored to target smart-contract code specifically; for this reason, we believe that our contributions generalize to other languages.

Moreover, our comparison to greybox fuzzing without learning focuses on one fuzzer, which we implemented. We discuss this below, as a way of ensuring construct validity.

Internal validity. Another potential issue has to do with the internal validity [61] of our experiments, that is, with whether systematic errors are introduced in the experimental setup. A common threat to the internal validity of experiments with fuzzing techniques is the selection of seeds. During our experiments, when comparing greybox fuzzing with and without learning, we always used the same seed inputs in order to avoid bias in the exploration.

Construct validity. Construct validity ensures that the experimental evaluation indeed measures what it claims, in our case, the effect of our learning technique on greybox fuzzing. It is, for instance, possible that engineering improvements to a tool provide...
There are several techniques that aim to direct greybox fuzzing or constraint solving and our instrumentation is more patches \[16, 45, 58\], complementing static analyzers \[27\], killing been tried in various application domains, such as testing software and comes in different flavors, such as probabilistic symbolic ex-
Pex \[68\], BitBlaze \[62\], Apollo \[12\], S2E \[26\], and Mayhem \[22\], been implemented in many tools, such as EXE \[21\], jCUTE \[59\],
der test and, therefore, explore more paths. This approach has
straint solving to understand the structure of the program un-
combination with these techniques. In comparison, our approach learns
concrete input values from previous inputs, instead of performing arbitrar
inputs. To achieve this, we rely on additional, but still lightweight, instrumentation.

**Whitebox fuzzing.** Whitebox fuzzers \[19, 34\], like dynamic symbolic execution tools \[20, 33\], use program analysis and con-
stRAINT solving to understand the structure of the program un-
test and, therefore, explore more paths. This approach has been
implemented in many tools, such as EXE \[21\], jCUTE \[59\],
Pex \[68\], BitBlaze \[62\], Apollo \[12\], S2E \[26\], and Mayhem \[22\],
and comes in different flavors, such as probabilistic symbolic exec-
ution \[32\] or model-based whitebox fuzzing \[52\]. It has also been tried in various application domains, such as testing software patches \[16, 45, 58\], complementing static analyzers \[27\], killing higher-order mutants \[37\], and reconstructing field failures \[38, 57\).

As discussed earlier, our technique does not rely on any program analysis or constraint solving and our instrumentation is more lightweight, for instance, we do not keep track of a symbolic store and path constraints.

**Hybrid fuzzing.** Hybrid fuzzers combine fuzzing with other techniques to join their benefits and achieve better results. For example, Dowser \[36\] uses static analysis to identify code regions with potential buffer overflows. Similarly, BuzzFuzz \[31\] uses taint tracking to discover which input byte processes by “attack points”. Hybrid Fuzz Testing \[51\] first runs symbolic execution to
find inputs that lead to “frontier nodes” and then applies fuzzing on these inputs. On the other hand, Driller \[65\] starts with fuzzing and uses symbolic execution when it needs help in generating inputs that satisfy complex checks.

In contrast, our approach extends greybox fuzzing without relying on static analysis or whitebox fuzzing. It could, however, complement the fuzzing component of these techniques to reduce the need for other analyses.

**Optimization in testing.** Miller and Spooner \[48\] were the first to use optimization methods in generating test data, and in particular, floating-point inputs. It was not until 1990 that these ideas were extended by Korel for Pascal programs \[41\]. In recent years, such optimization methods have been picked up again \[46\], enhanced, and implemented in various testing tools, such as FloPSy \[43\], CORAL \[63\], AUSTIN \[42\], and CoverMe \[30\].

Most of these tools use fitness functions to determine how close the current input is from a target. For instance, Korel uses fitness functions that are similar to our cost metrics for flipping branch conditions. The above tools search for input values that minimize such functions. The search is typically iterative, for instance, by using hill climbing or simulated annealing \[40, 47\], and it may not necessarily succeed in finding the minimum. While our technique also aims to minimize cost metrics, it does so in a single shot. As a consequence, it may succeed faster, but it may also fail to minimize the target metric altogether, in which case it falls back on traditional greybox fuzzing.

**Program analysis for smart contracts.** The program-analysis and verification community has already developed several bug-finding techniques for smart contracts, including debugging, static analysis, symbolic execution, and verification \[5, 6, 11, 13, 15, 24, 25, 35, 39, 44, 49, 60\].

In contrast, our technique is the first to apply greybox fuzzing to smart contracts.

**8 CONCLUSION**

In this paper, we have proposed a novel greybox fuzzing approach that learns new inputs from existing program runs. These inputs are learned such that they guide exploration toward optimal executions, as defined by the given cost metrics. We demonstrate that learning significantly increases the effectiveness of greybox fuzzing, both by achieving higher path coverage and by detecting more bugs within the same time. On a high level, our technique is an instance of a more general idea: leveraging the large number of inputs explored by fuzzing to learn more about the program under test.

In future work, we plan to investigate other instances of this general idea by considering different cost metrics and by exploring alternative learning techniques, such as decision-tree learning.
[64] Sherri Sparks, Shawn Embleton, Ryan Cunningham, and Cliff Changchun Zou. 2007. Automated Vulnerability Analysis: Leveraging Control Flow for Evolutionary Input Crafting. In ACSAC. IEEE Computer Society. 477–486.

[65] Nick Stephens, John Grosen, Christopher Salls, Andrew Dutcher, Ruoyu Wang, Jacopo Corbetta, Yan Shoshitaishvili, Christopher Kruegel, and Giovanni Vigna. 2016. Driller: Augmenting Fuzzing Through Selective Symbolic Execution. In NDSS. The Internet Society.

[66] Melanie Swan. 2015. Blockchain: Blueprint for a New Economy. O’Reilly Media.

[67] Don Tapscott and Alex Tapscott. 2016. Blockchain Revolution: How the Technology Behind Bitcoin is Changing Money, Business, and the World. Penguin.

[68] Nikolai Tillmann and Jonathan de Halleux. 2008. Pex—White Box Test Generation for .NET. In TAP (LNCS), Vol. 4966. Springer, 134–153.

[69] Maverick Woo, Sang Kil Cha, Samantha Gottlieb, and David Brumley. 2013. Scheduling Black-Box Mutational Fuzzing. In CCS. ACM, 511–522.

[70] Gavin Wood. 2014. Ethereum: A Secure Decentralised Generalised Transaction Ledger. http://gavwood.com/paper.pdf
A SMART CONTRACT REPOSITORIES

All analyzed smart contracts are available on GitHub. We provide changeset IDs and links to the repositories in Tab. 7.

| BIDs | Name | Changeset ID | Repository |
|------|------|--------------|------------|
| 1    | ENS  | 510851d656e6201dc005c55751d000d00e9fe3 | https://github.com/ethereum/ens |
| 2–3  | CMSW | 2582787a14dd61b51df6815fab127f51f5b74 | https://github.com/ConsenSys/MultiSigWallet |
| 4–5  | GMSW | 8ac8ba7e6f6c384571e480defb5f2e4f2fd3fe4 | https://github.com/gnosis/MultiSigWallet |
| 6    | BAT  | 15bebdc9642de814d5679477c7c31d5e993ae1 | https://github.com/brave-inl/basic-attention-token-crowdsale |
| 7    | CT   | 1f62e1ba35f2dc22622d9fe94ee4866d67edef2 | https://github.com/ConsenSys/Tokens |
| 8    | ERCF | c7d025220a13832e6926d8983e471844c29f979 | https://github.com/Scja/ercfund |
| 9    | FBT  | ae71053e0656b6c0eba7e22e1d67c09f7217191dc | https://github.com/Firstbloodio/token |
| 10–13| HPN  | 540006e0e2e5ef729482adb8bebec7eaefdc5198c2 | https://github.com/Havven/havven |
| 14   | MR   | 527eb90c6414f8178b269d486e063eb9ee0f254 | https://github.com/raiden-network/microraiden |
| 15   | MT   | 7009c95a5a2a14a013b85903b1602c23bf4f | https://github.com/modum-io/tokenapp-smartcontract |
| 16   | PC   | 515c1b993ac43f65b5f4af86e8f8321595b0b | https://github.com/mattdf/payment-channel |
| 17–18| RNTS | 6c39082ef6b52d3035a89a3f3d9bde69ca80f | https://github.com/RequestNetwork/RequestTokenSale |
| 19   | DAO  | f347c0e177e4cd99d66f589d2d36754a375658 | https://github.com/slockit/DAO |
| 20   | VT   | 30ede971bb68f245e5be11f54e4e5035e933a765 | https://github.com/valid-global/token |
| 21   | USCC1| 3b2664a85d182a9b8f0b6fedc1153fbd510a96 | https://github.com/Arachnid/uscc |
| 22   | USCC2| 3b2664a85d182a9b8f0b6fedc1153fbd510a96 | https://github.com/Arachnid/uscc |
| 23   | USCC3| 3b2664a85d182a9b8f0b6fedc1153fbd510a96 | https://github.com/Arachnid/uscc |
| 24   | USCC4| 3b2664a85d182a9b8f0b6fedc1153fbd510a96 | https://github.com/Arachnid/uscc |
| 25   | USCC5| 3b2664a85d182a9b8f0b6fedc1153fbd510a96 | https://github.com/Arachnid/uscc |
| 26   | PW   | 657da22245dfcfe0e1ccc58e8ec8d86924d65cdd | https://github.com/paritytech/contracts |

Table 7: Smart contract repositories.