

# TOFU: Target-Oriented FUzzer

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## ABSTRACT

Program fuzzing—providing randomly constructed inputs to a computer program—has proved to be a powerful way to uncover bugs, find security vulnerabilities, and generate test inputs that increase code coverage. In many applications, however, one is interested in a *target-oriented* approach—one wants to find an input that causes the program to reach a specific target point in the program. We have created TOFU (for Target-Oriented FUzzer) to address the directed fuzzing problem. TOFU’s search is biased according to a distance metric that scores each input according to how close the input’s execution trace gets to the target locations. TOFU is also *input-structure aware* (i.e., the search makes use of a specification of a superset of the program’s allowed inputs).

Our experiments on `xmllint` show that TOFU is 28% faster than AFLGo, while reaching 45% more targets. Moreover, both distance-guided search and exploitation of knowledge of the input structure contribute significantly to TOFU’s performance.

## KEYWORDS

Fuzz testing, input-structure specification

## 1 INTRODUCTION

Fuzz testing is an automated technique for testing a program by generating random inputs and running the program on those inputs. It is widely used for identifying bugs and security vulnerabilities, and for generating test inputs that increase code coverage.

Even when used for identifying bugs and security vulnerabilities, the focus of *standard fuzz testing* is on increasing code coverage: more code covered generally results in more bugs found. However, in many applications one wants to find an input that causes the program to reach a specific target point in the program (or set of target points). For instance, one might be interested in (i) generating inputs that exercise newly patched code, or (ii) as a way to reproduce a crash, generating inputs that exercise regions of code known to be likely to cause a crash. In other words, one is interested in a directed approach, in which the target points are given a higher priority than other parts of the program. The goal of a *target-oriented fuzzer* is to spend the available computational resources on the task of reaching those specific points in the program.

Given some target locations in the source code, craft a set of inputs that causes these locations to be reached during execution.

Unfortunately, the techniques used in standard fuzzers offer little control over which parts of the program are explored. For example, American Fuzzy Lop (AFL) [38] is a state-of-the-art standard fuzzer. However, AFL does not make use of any information about the structure of the program’s inputs, and thus creates many inputs that are rejected by the program. This approach is less useful for finding

inputs that reach specific locations—particularly if the targets are deep in the part of the program that constitutes its core computation, rather than in the program’s input-validation code.

AFLGo [4] is a system that supports target-oriented fuzzing. However, many of AFLGo’s features are inherited from the American Fuzzy Lop (AFL) [38]; in particular, AFLGo does not use any information about the structure of the program’s inputs.

Most modern fuzzers share the same structure: a loop involving mutation, feedback, and evaluation of fitness. AFL is an example: at each step, the input is mutated; if the mutant causes an execution run that has a new edge-coverage profile, the mutant is retained as a seed for further mutation.

Fuzzing works well because small changes in inputs usually cause a small change in the parts of the program that are exercised. For target-oriented fuzzing, this “stability heuristic” can be used to steer the fuzzer toward an input that reaches the desired target: by focusing on inputs that are closer to the target, the fuzzer might generate inputs that are even closer. The hope is that this process will eventually allow the target to be reached.

Unfortunately, random changes to some bits or bytes of the input can significantly change the program’s execution; for instance, such a change can turn a valid input into an invalid input (leading to an execution run that is usually much farther away from the desired target).

For target-oriented fuzzing, one way to restore the stability heuristic is by taking advantage of known structure of the program’s inputs: the heuristic is now that small *structural* changes in inputs usually cause a small change in the parts of the program that are exercised, and the fuzzer can take advantage of such behavior to steer itself to an input that reaches the desired target.

**TOFU: Target-Oriented FUzzer.** In our work, we have created a new directed fuzzer, called TOFU. The high-level structure of TOFU is similar to that of AFL; however, there are two important differences.

- (1) TOFU’s goal is to produce inputs that reach a specific set of targets in the program. TOFU pre-computes the distance between each pair of basic blocks, and uses these distances, together with the outcome of executing various inputs, to determine the order in which inputs are selected for mutation.
- (2) TOFU leverages knowledge of the program’s input structure, which is provided by the TOFU user in the form of a protobuf specification [12].

We are interested in understanding how much these two aspects of TOFU contribute to its overall effectiveness, which gives rise to the following research questions:

**RESEARCH QUESTION 1:** What is the contribution of distance-guided search to TOFU’s overall effectiveness?

**RESEARCH QUESTION 2:** What is the contribution of structured mutation to TOFU’s overall effectiveness?

The existing AFLGo and Hawkeye [6] tools are also target-oriented fuzzers. Their high-level organization is similar to TOFU’s in that the source code is first analyzed to generate a static metric, and then the metric is used to guide the subsequent process of dynamic exploration. However, TOFU addresses the following issues in a different way than existing tools:

- (1) The input space for both AFLGo and Hawkeye is a single file or `stdin`, as in AFL. However, the input space for many programs is larger than a single file. For instance, a program may use command-line flags to indicate option settings. AFL is designed to maximize coverage, which means that it might need different flag settings: different flag settings can lead to execution runs that cover different parts of the program. However, a directed fuzzer has a different goal, namely, to reach a specific target, or set of targets, in the program.
- (2) One wishes to generate inputs that reach desired targets as quickly as possible. AFLGo introduced scheduling via simulated annealing: i.e., inputs closer to the target get mutated more. Hawkeye adopted scheduling via simulated annealing and added prioritization: i.e., inputs closer to the target are mutated first. The Hawkeye work showed that, without prioritization, an input that nearly reaches a target might wait for a long time before getting mutated (cf. Chen et al. [6]).

TOFU only applies prioritization, but uses a different metric than the ones used in AFLGo and Hawkeye. TOFU’s metric has an intuitive interpretation as a distance (e.g., the number of correct branching decisions needed to reach the target), whereas scheduling in AFLGo (as well as prioritization in Hawkeye) has a complicated relationship to the history of the annealing that has taken place, and has no intrinsic meaning as a distance.

- (3) Both AFLGo and Hawkeye use the mutators from AFL, which is general-purpose, but not structure-aware. The mutation operations can create many invalid inputs. This approach is useful for triggering buggy behavior *somewhere* in the program (which is appropriate for standard fuzzing), but it is hard for a structure-blind fuzzing tool to find an input that passes the input-validation tests typically performed by a program, and even harder for it to find an input that reaches a desired target.

Because TOFU mutates inputs with respect to a specification of the input language, it has an easier time finding valid inputs, which (often) allows it to find inputs that reach a target that is deep in the program.

These differences lead to the following research question:

**RESEARCH QUESTION 3:** How does the performance of TOFU compare to existing tools?

We found that the time taken by TOFU (pre-fuzzing) to compute distance information and to insert instrumentation was  $\frac{1}{40}$  the time

taken by AFLGo. Moreover, the success rate for TOFU, measured by how many target basic blocks are covered, is 45% higher than that of AFLGo (Table 3). TOFU is also 28% faster than AFLGo (Figure 5).

*Command-line Fuzzing and Staged Fuzzing.* In response to the common practice of using command-line flags to specify options to a program, TOFU includes command-line arguments in the input space that it explores. Prior fuzzing tools have not emphasized exploration of these inputs. Command-line flags are commonly used by many programs, while most fuzzing tools focus mainly on one input file used by the program under test (which is often specified by some file argument on the command line). It is often necessary to supply the program with specific flags for particular target basic blocks to be reachable. A user could read the source code to try to understand what flags must be set; however, the targets could be any locations in the source code, and the manual approach could require a big investment of time. To address this issue, TOFU first performs a search—which is really just a variant of its “core search” using a distance metric and structured mutation—to find appropriate flag settings and options to flags that get *close* to the target basic blocks. (In fact, in 60% percent of the cases, command-line fuzzing alone succeeded in reaching one or more of the target basic blocks.)

Our experiment on libxml2[2] showed the effectiveness of dividing the fuzzing process into stages. In particular, fuzzing the flags and fuzzing the primary input file can be carried out in sequence. This approach reduces the dimensionality of the input space for each individual stage of fuzzing, and we found that fuzzing efficiency is improved by doing so. The idea of staged fuzzing also appeared in Zest [21], in which the fuzzing process is divided into syntactic-fuzzing and semantic-fuzzing stages. We believe that the staged-fuzzing idea can be further exploited if the input space can be divided into more fine-grained stages.

*Contributions.* Our work makes three main contributions:

- (1) We use structured mutation to address the problem of target-oriented fuzzing.
- (2) We expand the idea of *staged fuzzing*. TOFU augments the search space for fuzzing to include a program’s command-line flags. To reduce the dimensionality of the search carried out, command-line fuzzing is carried out separately, and prior to, the fuzzing of the program’s primary input file.

To support this task, TOFU provides a *generator of structured mutators* for a family of command-line languages typical of those used by many Linux programs. TOFU—equipped with such a mutator—could be used as a pre-processing step to select appropriate command-line flags, before letting another fuzzing tool take over to fuzz the program’s primary input file.

- (3) The tool chain of TOFU consists of multiple components that can be reused in other tools. For example, TOFU’s phase of distance computation takes only about 2 minutes for libxml2, while AFLGo’s distance computation takes about 80 minutes. Moreover, the distance computation is not a one-time investment—it is needed for each set of targets.

TOFU also comes with specifications of different languages of structured inputs, which can be reused for fuzzing multiple application programs. For instance, the input language for libxml2

```

1  bool is_valid(string input){
2  # validate the input with respect to grammar (1)
3 }
4
5  int num_a(string input){
6  # count how many number of a's in input
7 }
8
9  int main(int argc, char** argv){
10 string input = argv[1];
11 if(!is_valid(input))
12 perror("Invalid input\n");
13
14 ...
15 if(num_a(input) == 10){
16 # target location
17 }
18 }
```

**Figure 1: Example for structured mutator.**

is XML; thus, specification that we created for fuzzing libxml2 can be reused for any application that takes an XML file as input.

*Organization.* The remainder of the paper is organized as follows: §2 presents two examples to motivate the problem that TOFU addresses. §3 gives an overview of how instrumentation and execution is carried out in TOFU. §4 presents the details of the algorithms used in TOFU. §5 presents experimental results. §6 discusses threats to the validity of our results. §7 discusses different aspects of TOFU. §8 discusses related works. §9 concludes.

## 2 EXAMPLES

*Structured Mutator.* Consider the program shown in Fig. 1, and suppose that its input language is described by the grammar

$$S \rightarrow aSa \mid bSb \mid \epsilon \quad (1)$$

The program first validates the input; then performs other computations; and finally counts the number of occurrences of the character a in the input.

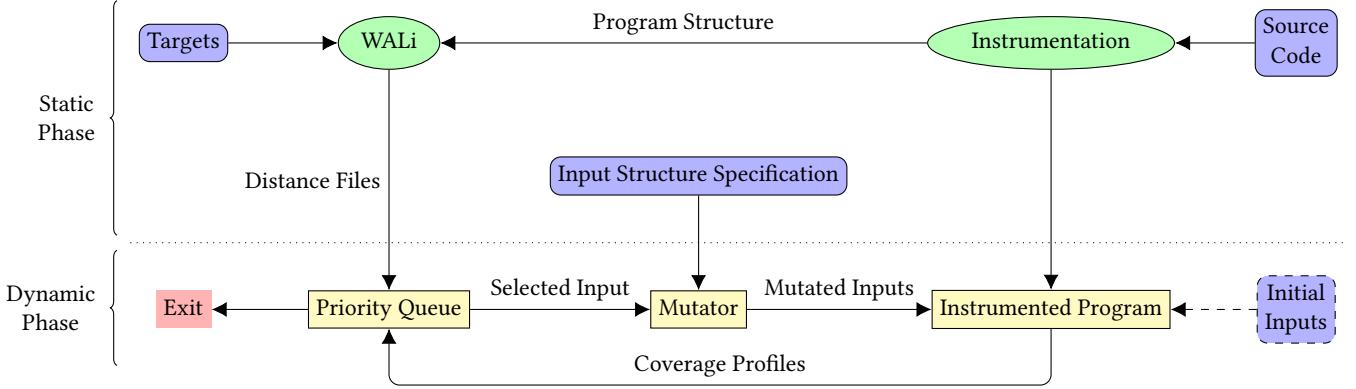
This example illustrates why a fuzzer can perform much better if it mutates the input with respect to the input grammar. For execution to reach the target location in line 16, the input must be grammatically correct—i.e., it must be a string in  $L(S)$  of grammar (1)—and contain exactly 10 occurrences of the character “a”. Any single-character mutation of a grammatically valid input creates an invalid input that will be rejected by the program in line 12. Therefore, even if a valid input yields an execution that gets close to the target location, a single-character mutation will create an input that is never close to the target location. Moreover, for a single-character mutation to create an input that reaches the target location, it must start with an invalid input that would be rejected by the program (and hence one whose execution is never close to the target location).

```

1  static char const shortopts[] =
2  "0123456789abBcC:dD:eEfF:hHi" \
3  "I:lL:nNpPqrsS:tTuU:vwW:x:X:y";
4
5  bool ignore_blank_lines = false;
6
7  int main (int argc, char **argv) {
8    while ((c = getopt_long (argc, argv, shortopts,
9      longopts, NULL)) != -1) {
10      switch (c) {
11        case 'B':
12          ignore_blank_lines = true;
13          break;
14        ...
15      }
16      exit_status = compare_files (...);
17    }
18
19  static int compare_files (...) {
20  ...
21  status = diff_2_files (&cmp);
22  ...
23 }
24
25  int diff_2_files (struct comparison *cmp) {
26  ...
27  if (ignore_blank_lines) {
28    if(analyze_hunk(...))
29      #target location
30  else ...
31 }
32 ...
33 }
```

**Figure 2: Example for command-line fuzzing.**

*Staged Fuzzing.* We present a code snippet to illustrate the staged-fuzzing idea and how our flag fuzzer works. The code snippet in Fig. 2 is a slightly modified version of code found in the diff program in diffutils[1]. The input for diff consists of command-line flags with options and two files (or directories, or stdin). Suppose that the target is in the diff\_2\_files function, as shown in the code snippet; to reach the target, it is necessary that ignore\_blank\_lines be set to true, which requires diff be invoked with the flag -B. Consider two executions of diff in which one contains the flag -B in the input, and the other does not. In the first case, execution enters the if condition at line 27, while in the second case, execution does not enter the if condition. Therefore, the basic-block coverage in the first case is closer to the target location than the basic-block coverage in the second case. By measuring the distance, TOFU can decide that, to reach the target, -B is likely needed as part of the command line.



**Figure 3: Workflow of TOFU: Round-cornered nodes indicate inputs for TOFU, where initial inputs are optional. Elliptical nodes denote elements of TOFU’s static phase. Square nodes with a frame indicate TOFU’s dynamic/fuzzing phase. The square node without a frame indicates the exit.**

### 3 OVERVIEW OF TOFU

Figure 3 shows TOFU’s overall workflow. TOFU performs a *static phase*, during which it (i) instruments the source code, and (ii) pre-computes distances in a modified interprocedural control-flow graph. As depicted in Figure 3 via the round-cornered nodes, TOFU takes as inputs the source code, the target lines, and the input-structure specification. During the static phase (above the dotted line), TOFU instruments the program so that at runtime, it can extract the basic-block coverage from each execution run of the program. In addition, TOFU generates distance files that record the pairwise distance from each basic block in the instrumented program to each target basic block. These files are used during the dynamic phase to guide input selection. Moreover, because fuzzing during the dynamic phase is structure-aware, TOFU also takes in a specification of the structure of allowed inputs, and generates the structured mutator that is used in the dynamic phase.

During the dynamic phase (below the dotted line), the fuzzer executes the instrumented program, and assigns scores to the different inputs based on the executed basic blocks and the distance metric. All of the inputs generated are stored in a priority queue, where the priority indicates how close the trace obtained from the input came to the target set. On each round, the closest input is selected from the priority queue for mutation; the structured mutator then generates a user-specifiable number of new mutated inputs.

The dashed frame of the node labeled “Initial Inputs” in Figure 3 indicates that the initial inputs are optional. Because TOFU uses a structured mutator, it does not have to start with initial inputs; instead, it can generate them according to the structural specification. The fuzzing process performs the loop shown in the “Dynamic Phase” portion of Figure 3. Fuzzing terminates when each target basic block is reached by some input, or a timeout threshold is exceeded.

### 4 DETAILED DESCRIPTION

#### 4.1 Gray-Box Fuzzing with Prioritization

The fuzzing process is a repeated loop of mutation and execution, until all target basic blocks are reached or the timeout threshold is exceeded. During each iteration, TOFU selects a seed input and generates multiple new mutated inputs based on the selected input. The number of mutated inputs generated in each mutation round can be defined by the user. The mutated inputs are similar to the seed input, and thus the coverage induced by each mutant is likely to be similar to the coverage induced by the seed input. The hope is that each time TOFU creates mutants from the input selected as the seed, the induced coverage for *some* of the newly mutated inputs will get closer to the target set. In this way, the program’s execution traces are likely to get gradually closer to—and eventually reach—members of the target set.

TOFU uses a priority queue to store candidate inputs, and the priority is a function of both the static distance files generated in the static-analysis phase and the coverage induced by each input. At the beginning of the dynamic phase, TOFU reads the pre-computed distance files generated during the static phase. A distance file  $M_t$  contains the distances from each basic block  $b$  in the program to a target block  $t$ . The distance  $d_{b,t}$  represents the minimum number of choices that would have to be made correctly, for an input that causes execution to reach  $b$ , to continue on to  $t$ .

When a mutant  $j$  is generated from a seed input  $i$ , TOFU executes the instrumented program with  $j$ , and the coverage produced by the program is retrieved by TOFU. The fitness score for a pair  $(j, t)$ , where  $t$  is some target block, is the minimum of the distances induced by all of the basic blocks reached during the execution of  $j$ . The interpretation of this score is that it represents the minimum number of additional choices that a mutation of  $j$  would have to make correctly to reach  $t$ . The priority for  $j$  is the minimum of  $j$ ’s fitness scores across all of the target blocks.

*Distance Computation.* The goal of the distance computation is to count how many constraints remain to reach the target location for each basic block.

Given the inter-procedural control-flow graph (ICFG) of the instrumented program, to compute such distances we label the graph’s edges with lengths—and introduce new edges—as follows: if an edge has no branches, we give the edge the length 0; otherwise, we give the edge the length 1. (The edges involving branches are the control-flow edges that have more than one successor, and the indirect-call edges that have more than one potential callee.) Additionally, we also add edges with length 0 from a basic block to its immediate post-dominators. We then compute the shortest distance in the modified ICFG between each basic block and each target basic block. (If block  $b_2$  is not reachable from  $b_1$ , then the distance from  $b_1$  to  $b_2$  will be  $\infty$ .)

An ideal distance computation would be context-sensitive: when computing the distance from an input  $i$  to a target  $t$ : only feasible paths from each basic block in the execution trace of  $i$  to  $t$  should be considered. However, this approach would require TOFU to record the *call stack* for each element of  $i$ ’s execution trace. Thus, to reduce the run-time overhead of instrumentation, only information about executed *basic blocks* is reported; in particular, the contents of the call stack are *not* reported for each basic block encountered. We use a heuristic to approximate the context-sensitive metric. The intuition for the heuristic is that only functions that can reach the target locations in the call graph are considered in the distance computation. Basic blocks in functions that cannot reach any target location via some call chain are considered irrelevant. Therefore, if there is no call path from `main` to the target locations via a given call edge, we give the call edge the length  $\infty$  in the modified ICFG.

In TOFU, the distances used for prioritization are computed by a generalization of Dijkstra’s algorithm [30, §6.5]; it computes interprocedural (context-sensitive) distances in the modified ICFG.

## 4.2 Structured Mutation

Mutation-based directed fuzzing relies on the heuristic that although mutating an input generates a similar input, the coverage of the mutated input can be different from the coverage of the original input. Thus, selecting those mutants whose coverage is closer to one of the target blocks is likely to produce an input that is closer to a desired input (i.e., one that reaches a target block). Iterating this process may eventually generate a desired input.

A structure-blind mutator treats the input as a stream of bytes, modifying the bytes little-by-little, but it can also transform a valid input into a syntactically invalid input. Structured mutation modifies an input with respect to its underlying structure. Structured mutation has recently been used by AFLSmart [25] and Superior [36]. However, the goal of structured mutation in those two tools is to increase the coverage when using fuzzing to test programs. TOFU uses structured mutation to support directed fuzzing.

**4.2.1 Protobuf-Based Structured Mutation.** In TOFU, the structured mutator is based on the Google `libprotobuf-mutator` [11]. Protocol buffers (“protobufs”) are a “language-neutral, platform-neutral extensible mechanism for serializing structured data” [12]. Google also developed `libprotobuf-mutator`, a tool to randomly mutate protobufs.

To use `libprotobuf-mutator` in the context of TOFU, a TOFU user provides a *standard protobuf-specification file* that describes the structure of the inputs to the program. This specification file is then

```

1 --silent|optional|no option
2 -v|optional|no option
3 --version|optional|no option
4 --help|optional|no option
5 file1|required|directory|PATH_TO_DIRECT
6 file2|required|directory|PATH_TO_DIRECT

```

**Figure 4: Example input specification for the generator of command-line-language mutators.**

compiled into a C++ class  $C$ . A program input corresponds to an object of class  $C$ ; the mutator generated via `libprotobuf-mutator` operates on such objects: it modifies a given object into a mutant object.

A user also provides a *renderer function* that transforms an object of class  $C$  into an input (in the form of text). This function renders the mutated object as the corresponding input text, on which TOFU’s dynamic phase can then execute the instrumented program.

If a user wishes to start TOFU with some initial inputs, then they must provide a *parser function* that transforms initial inputs into the corresponding object of class  $C$ .

To summarize, if the user is familiar with the input language, it usually takes one or two days to implement the input-language grammar and the renderer function. In the authors’ experience, the most difficult part is the parser function. In general, however, the program under test contains code that parses the input, which can serve as the starting point for the parser function for TOFU. If the user decides not to use initial inputs, a parser function is not required. Once all the components of a structured mutator have been created, they can be used with all programs that use the same input language. This re-usability is an added bonus when one expends the effort to specify a structured mutator for TOFU.

**4.2.2 Command-Line-Language Structured Mutator.** Command-line flags are commonly used in many programs. In many AFL variants, users must specify these flags when fuzzing the program. Compared to standard fuzzing (i.e., fuzzing intended to increase coverage), having appropriate flag values is more important in target-oriented fuzzing because some target blocks can only be reached when certain flags are given. For efficiency reasons, it is also desirable to use the minimal number of flags and options, so that a fuzzer does not explore irrelevant parts of the program and mutate unnecessary parts of the input.

It is inefficient to use a general-purpose mutator to mutate command-line input. Fortunately, many command-line languages are both simple and highly structured, using flag-names with dashes and taking options listed after the flag. While creating a structured mutator for a command-line language manually is not overly difficult, this task can be tedious and error-prone. To make the task easier, TOFU provides a tool that takes a specification of the command-line flags and options, and generates a structured mutator for the command-line language. This mutator is used in a search-controlled in TOFU’s standard way, by the distance metric and structured mutation—to determine the flag settings and options that cause execution to get closest to the target basic block.

Fig. 4 is taken from the experiment with the `cmp` program from `diffutils`. It shows an example of the kind of input specification that a user provides to create a command-line-language mutator, using TOFU’s command-line-language mutator generator. In Fig. 4, `--silent`, `-v`, `--version`, and `--help` are all optional valid flags without options for `cmd`; `file1` and `file2` are required arguments, which take values from a directory. The directory contains the files that `cmp` compares.

### 4.3 Refinements of Prioritization

TOFU supports two mechanisms beyond basic prioritization of inputs via its priority queue.

- To increase the “diversity” of the kinds of inputs considered during its search, TOFU incorporates a mechanism for suppressing some inputs that “look too much like” inputs already considered. This mechanism uses basic-block coverage as a rough measure of a program’s execution: inputs with different traces may have the same basic-block coverage; the measure of similarity between inputs  $i$  and  $j$  is based on their executions having identical basic-block coverage. Thus, in addition to the priority queue, TOFU’s search uses a dictionary  $D$  of (basic-block set, count) pairs to record how many inputs that cover the same set of basic blocks have been added to the priority queue. When a new mutated input  $i$  is produced, TOFU obtains its coverage set  $c_i$ —the set of basic blocks reached during the execution of the program on  $i$ . By querying  $D$  with respect to  $c_i$ , TOFU obtains the count  $n = D(c_i)$ , and inserts  $i$  in the priority queue with probability  $1/(n+1)$ . This mechanism decreases the probability that TOFU repeatedly works with similar inputs.
- When an input  $i$  with score  $s_i$  is selected from the priority queue,  $i$  is also inserted back into the priority queue, with a new score of  $1.2 \times s_i$ . In this way, TOFU is able to mutate input  $i$  again in the future;  $i$  has an artificially changed priority, but it would still be prioritized over an input whose distance from the target set is 20% greater than that of  $i$ .

## 5 IMPLEMENTATION & EVALUATION

### 5.1 Implementation

TOFU’s uses the Whole-Program-LLVM (WLLVM) [26] tool to compile the subject program on which fuzzing is to be applied to a single LLVM bitcode module for analysis. Several subsidiary analyses are performed, and an instrumented binary is produced that, during an execution of the (compiled) subject program on a particular input, allows determining the set of basic blocks that were reached during execution.

In addition to instrumentation, the main analyses performed serve to compute the static pairwise distances from each basic block in the instrumented program to each target basic block.

- TOFU performs the following simple indirect-call analysis to identify a set of potential callees at each indirect-call site: the analysis assumes that the set of functions possibly called at a given indirect-call site  $s$  consist of (i) each function  $f$  whose address has been taken, for which (ii) the type of  $f$  exactly matches the pattern of argument-type(s) and return-type that occurs at  $s$ .

- The distance computation described in §4.1 is performed by (i) extracting the ICFG from WLLVM; (ii) computing immediate-post-dominator information for each procedure’s CFG; (iii) modifying the ICFG as described in §4.1 and labeling its edges with 0 or 1, as appropriate; (iv) encoding the modified ICFG as a weighted pushdown system, using the WALi-OpenNWA [35] library (the encoding is performed via a well-known technique [28, §2.2]); (v) computing interprocedural (context-sensitive) distances using a technique described in Schwoon et al. [30, §6.5].

### 5.2 Evaluation

We aim to answer the research questions posed in §1, specifically:

- (1) What is the contribution of distance guidance to TOFU’s overall effectiveness?
- (2) What is the contribution of structured mutation to TOFU’s overall effectiveness?
- (3) How does the performance of TOFU compare to existing tools?

The goal of directed fuzzing is to cover all the target basic blocks as quickly as possible. We evaluated different tools by checking how many target basic blocks were reached within a timeout limit. For each run of each tool, we also determined how long it took to reach each of the reached targets.

The tested subjects are `space` [33], `diffutils` [1], and `xmllint` from `libxml2` [2]. `Space` is a well-established subject for software-engineering research, and has been studied in several prior papers [3, 5]. `Diffutils` and `libxml2` were used in the experiments reported in the AFLGo paper [4].

To answer research question (1), we created a variant of TOFU, called UG-TOFU (for “Un-Guided TOFU”), which assigns random numbers as scores in the priority queue, instead of using a score based on distance. To answer research question (2), we created another variant of TOFU, called US-TOFU (for “Un-Structured TOFU”), which uses a “dumbed-down” mutator extracted from AFL,<sup>1</sup> in place of TOFU’s structured mutators (which are described in Section 4.2.1). To answer research question (3), we ran TOFU, AFLGo, and Superion—an existing fuzzer with a structured mutator for XML files—on `libxml2`.<sup>2</sup>

Each experiment had same two-phase structure. In phase 1, we ran TOFU to obtain a set of command-line flags and flag options. In phase 2, the command-line information obtained from phase 1 was used for all of the tools in the experiment; during phase 2, the subject program was fuzzed by each of the tools—i.e., each tool was applied to the subject program so that it mutated the program’s primary input file. `space` only uses a single file as input. Consequently, the experiment with `space` had no phase 1: it consisted only of phase 2, using the different tools.

Prior to phase 1 of each experiment, we used TOFU’s generator of command-line-language mutators to create an appropriate command-line-language mutator for the subject program. If there were options available from the program’s test suite, then we used those options as part of the specification provided to TOFU’s generator of command-line-language mutators. Otherwise, we manually

<sup>1</sup>AFL’s mutator consists of three parts, which perform the following steps: (i) deterministic mutation steps, (ii) repeated steps of havoc/random mutations, and (iii) steps that splice two random inputs together at some random midpoint. The “dumbed-down” mutator uses a single havoc step each time it is invoked.

<sup>2</sup>Hawkeye was not available to us due to legal restrictions.

**Table 1: Experimental results for space**

Quantity	Trial		
	1	2	3
Total target basic blocks	119	119	119
Target blocks covered by initial inputs	51	48	50
Uncovered target basic blocks	68	71	69
Commits not totally covered	17	15	16
<b>Basic blocks covered by TOFU</b>	<b>21</b>	<b>65</b>	<b>63</b>
Basic blocks covered by AFLGo	5	6	9
Basic blocks covered by UG-TOFU	2	0	18
Basic blocks covered by US-TOFU	0	0	0

constructed a specification of the subject program’s command-line language by consulting the program’s documentation. During phase 1 fuzzing, TOFU was started from the empty initial input (no flags or options). The names of all input files from the subject program’s test suite are provided to the phase 1 fuzzer as potential elements of the command line that the fuzzer is searching for.

For phase 2 fuzzing, we ran each tool three times to accommodate variance in running times. We call each run of all the tools a *trial*. For each trial, we randomly selected 10 inputs from the subject program’s test suite, and used that set as the initial inputs for each tool for that trial. That is, during a given trial, all tools were started with the same set of initial inputs, flags, and flag options; for a given tool, each trial starts with a different selection of initial inputs.

For a given tool and a given trial, if a target basic block  $t$  was reached by the tool at least once, we say that the tool *covered*  $t$  in that trial; if, for a given commit  $c$ , at least one new target block was covered, we say that the tool *covered*  $c$  in that trial.

### 5.3 Experimental Setup

We ran the experiments on a workstation with twenty-four Intel® Xeon® X5675 CPUs running at 3.07 GHz and 189 GB of memory. All tools in these experiments are parallelizable, and each was given full use of all CPU cores while running.

For the experiment with space (phase 2 only), and diffutils (phases 1 and 2), we limit each phase of each trial to 150 seconds. For the experiment with xmllint (phases 1 and 2), we set the timeout limit for each phase of each trial to 300 seconds. To fully use all the available cores, the number of mutated inputs produced in each round is set to 120 (which is a multiple of the number of cores).

**5.3.1 Space.** The space program is from the Software-artifact Infrastructure Repository [8]. Space consists of 9,564 lines of C code (6,218 executable). It implements an interpreter for an array-definition language (ADL). It has a total of 39 versions. One of the versions is the reference version, and each remaining version contains a single fault. We used each version’s fault location as that version’s target, and hence this set of examples serves as a proxy for the task of reproducing a crash. Most of the faults correspond to less than three target basic blocks. Table 1 summarizes the results.

**5.3.2 diffutils.** We used the GNU diffutils as the subject program. It contains four executables: cmp, diff, diff3, and sdiff,

**Table 2: Experimental results for diff**

Quantity	Trial		
	1	2	3
Total target basic blocks	220	220	220
Target blocks covered by initial inputs	71	71	71
Uncovered target basic blocks	149	149	149
Commits not totally covered	14	14	14
<b>Basic blocks covered by TOFU</b>	<b>57</b>	<b>66</b>	<b>59</b>
Basic blocks covered by AFLGo	24	24	24
Basic blocks covered by UG-TOFU	40	40	38
Basic blocks covered by US-TOFU	24	24	24

which are all related to finding differences between files. We choose all the commits from November 2009 to May 2012, and for the  $n+1^{\text{st}}$  commit, the target blocks were all new code introduced subsequent to the  $n^{\text{th}}$  commit. The total number of target basic blocks is 333. They are in the files util.c, diff.c, io.c, diff3.c, cmp.c, dir.c, context.c, and analyze.c. For the targets in diff.c, diff3.c, and cmp.c, most are reachable by phase 1 fuzzing alone (i.e., by an appropriate choice of flags and options). The files with the most target basic blocks are diff.c, io.c and dir.c, each of which has more than 40 target basic blocks. For each code patch, the target basic blocks are in general close to each other—i.e., the distances between them are small according to the metric used by TOFU.

The diffutils executables that we tested were cmp, diff, diff3.<sup>3</sup> There are a total of 8 commits for diff3, 5 commits for cmp, and 28 commits for diff. During phase 1 fuzzing, all targets for diff3 were reached; all targets but one for cmp were reached; and all targets from 14 of the 28 commits for diff were reached.

There are 14 commits for diff in which not all target basic blocks were completely reached during phase 1 fuzzing.<sup>4</sup> We ran TOFU, AFLGo, UG-TOFU and US-TOFU over the remaining 14 commits, and the result is summarized in Table 2.

**5.3.3 xmllint.** Libxml2 is a project and library for working with XML, and xmllint is a program from libxml2 that can be used to parse and validate XML files. We chose all commits from May 2012 to October 2014, and for the  $n+1^{\text{st}}$  commit, the target blocks were all new code introduced subsequent to the  $n^{\text{th}}$  commit. There are a total of 382 commits, of which 186 are xmllint code changes; TOFU’s distance computation indicated that the new code introduced in 180 of the commits are apparently reachable. The target basic blocks are in 38 files. The files with the most target basic blocks are parser.c, xpath.c, uri.c, encoding.c, tree.c, xmlschemasatypes.c, and buf.c, each of which has more than 200 target basic blocks. Similar to diffutils, basic blocks in the same code patch are generally close to each other.

<sup>3</sup> We excluded sdiff for technical reasons. sdiff is really just a launcher for diff. Rather than exiting normally or crashing, sdiff “terminates” by calling execvp to replace itself with diff. Our coverage-recording instrumentation does not trigger when a process self-replaces in this manner.

<sup>4</sup> The one remaining target of cmp can only be reached when the command-line input contains an error, which lies outside the capabilities of TOFU’s command-line fuzzer. Thus, we excluded this example from this experiment.

**Table 3: Experimental results for xmllint**

Quantity	Trial		
	1	2	3
1. Total target basic blocks	3,064	3,064	3,064
2. Target blocks covered by initial inputs	720	739	772
3. Uncovered target basic blocks	2,344	2,325	2,292
4. Commits not totally covered	127	127	127
5. Basic blocks covered by TOFU	261	270	198
6. Extra commits covered by TOFU	49	50	42
7. Basic blocks covered by AFLGo	160	189	153
8. Extra commits covered by AFLGo	36	37	36
9. Basic blocks covered by Superion	161	140	98
10. Extra commits covered by Superion	32	29	24
11. Basic blocks covered by UG-TOFU	202	214	178
12. Extra commits covered by UG-TOFU	43	44	39
13. Basic blocks covered by US-TOFU	159	143	114
14. Extra commits covered by US-TOFU	33	32	25

During phase 1 fuzzing, all target blocks from 53 commits were completely reached, leaving 127 commits containing targets for phase 2. We ran TOFU, AFLGo, Superion, UG-TOFU, and US-TOFU on these commits; the results are summarized in Table 3.<sup>5</sup>

We also carried out a more detailed analysis of the data, with the goal of evaluating TOFU’s performance against each of the other tools, all as phase-2 fuzzers. The results are shown in Fig. 5. For most commits, it is difficult for any tool to reach all target basic blocks, so we needed a way to understand performance when not all targets are reached. Moreover, we wanted to compare performance on commits that represented a fuzzing challenge of “appropriate difficulty.” We define “appropriate difficulty” in terms of a *coverage threshold*: for each tool and each commit  $c$ , we gathered fine-grained information about how many of the set  $T_c$  of target basic blocks of  $c$  that were *not* covered (by TOFU) during phase 1 *were* covered by the tool during phase 2. Figure 5 shows tool-against-tool plots for the times to reach  $\geq 21\%$  of the targets in  $T_c$ .

We could have used a coverage threshold different from 21%; however, if the threshold is too high, then the study would just show that each tool rarely reaches the threshold within the timeout limit. If the threshold is too low, we only get information about the time needed to reach a single target, which only provides information about well the tools perform on “low-hanging fruit.”

We picked 21% by reasoning as follows: as shown in lines 6, 8, 10, 12, and 14 of Table 3, the tools covered different sets of commits that had not already been completely covered during phase 1; in trial 1, the five tools covered 53 extra commits in total, covering 359 of the 1,689 targets in those commits; in trial 2, they covered 54 extra commits, covering 360 of the 1,677 targets; in trial 3, they covered 49 extra commits, covering 282 of the 1,491 targets. Thus, we set the coverage threshold to  $(359 + 360 + 282)/(1689 + 1677 + 1491) \approx 21\%$ . This methodology—where the threshold was chosen based on

<sup>5</sup> Superion only accepts initial inputs of size less than 10KB. Therefore, when running Superion, we discarded any randomly selected initial inputs that exceeded 10KB.

“performance of the group in aggregate”—ensured that the coverage threshold is challenging for each of the tools.

The results of the study are shown in Fig. 5. Each “ $\times$ ” in a comparison plot in Fig. 5 shows information about the times used by two tools,  $A$  and  $B$ , to reach 21% of the targets for some commit. There are a few additional subtleties in the way this data was gathered.

*Granularity:* Commits vary in their number of targets. For instance, if some commit has eight targets, we plot the time required for tool  $A$  to reach any two targets against the time required for tool  $B$  to reach any two (which are not necessarily the same two).

*Ordering:* As mentioned earlier, we ran each tool three times on each commit, using three different sets of initial inputs. For a given commit, each tool was provided with the same three input sets.

However, because the coverage threshold was set at a non-trivial percentage, many runs of the different tools lead to timeouts. When one tool’s time is below the timeout threshold, and the other tool times out, a natural choice would be to plot the pair on the north or east edge of the comparison plot, as appropriate.

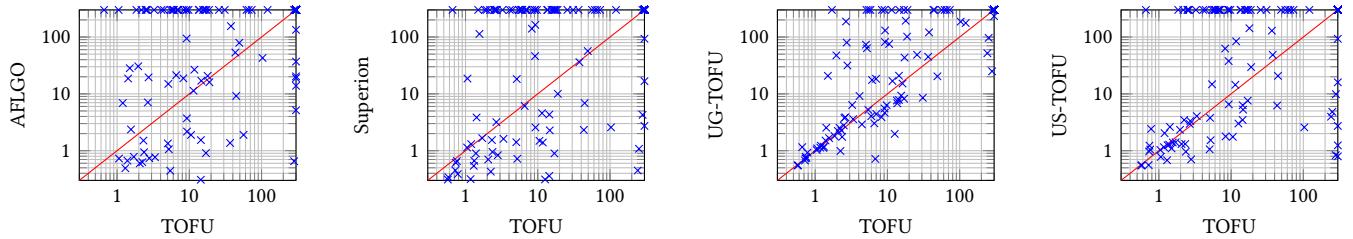
We chose a somewhat different strategy, based on the observation that because each of the tools implements a different search strategy for mutating inputs (including TOFU, UG-TOFU, and US-TOFU), their searches diverge due to the different strategies, and so there is relatively little importance to requiring that the tools’ runs be matched by their input set. For this reason, we compare two tools’ behaviors with respect to achieving the coverage threshold for a commit based on their *ordered times*. That is, when comparing tool  $A$  with tool  $B$ , we create one “ $\times$ ” for  $A$ ’s fastest trial versus  $B$ ’s fastest trial, one “ $\times$ ” for  $A$ ’s median-speed trial versus  $B$ ’s median-speed trial, and one “ $\times$ ” for  $A$ ’s slowest trial versus  $B$ ’s slowest trial.

*Targets not reached:* We also investigated why the targets of some commits were not reached. A large portion of them are not reached because they are not related to the primary input file. For example, patched code from `xmlschemas.c` needs specific XML schema files for the targets to be reachable. Some of the code patches are identified by the distance computation as being reachable from the entry of `xmllint`, but the conditions for reaching them are never satisfied. For example, some patched code is in a procedure that has a formal parameter whose value must be non-NULL for the code to be reachable. However, as called from `xmllint`, the actual parameter is always NULL. This situation arises because the patched code resides in a general-purpose library, but `xmllint` does not exercise that library in its full generality.

## 5.4 Findings

For **Research Question 1**, the experiments show that distance guidance can improve TOFU’s ability to reach more targets. The comparison between TOFU and UG-TOFU in Fig. 5 shows that even without distance guidance, UG-TOFU is able to generate inputs to reach the coverage threshold in many commits; however, the performance of UG-TOFU is worse than that of TOFU.

As noted earlier, the locations of code changes in a commit are generally close to each other; thus, an input that reaches one target is likely to be similar to an input that reaches others, so mutations of a successful input may allow a fuzzer to reach other targets. TOFU prioritizes inputs according to the number of correct branch choices needed to reach some remaining target; in contrast, UG-TOFU does



**Figure 5: Time comparisons (in seconds), for each tool when  $\geq 21\%$  of the uncovered targets for each `xmllint` commit are reached. Each blue “ $x$ ” represents one pair of times. The diagonal red “ $y = x$ ” line shows where equal execution times would appear. Thus, each  $x$  above the red line is a faster result for TOFU; each  $x$  below the red line is a faster result for that plot’s other tool.**

use such distance information, and thus may not explore these “close-to-successful” inputs immediately.

For Research Question 2, the experiments reveal that the structured-mutator component is extremely important to TOFU’s performance. In all experiments, TOFU reaches more targets than US-TOFU, especially for space, where US-TOFU did not reach a new target basic block in any of the three trials. It is also noteworthy that in experiments from both space and `xmllint`, AFLGo’s performance is better than US-TOFU’s. One possible reason is that US-TOFU’s mutator does not implement all of AFL’s mutator: US-TOFU’s mutator only performs AFL’s random-mutation step. These results indicate that if the user does not want to go to the trouble of providing a specification of valid inputs, then it is likely to be better to use AFLGo instead of US-TOFU. (Conversely, it would be interesting to see whether AFLGo would achieve any performance gain if it adopted or incorporated TOFU’s distance guidance.)

For Research Question 3, our experiments show that TOFU outperforms existing tools. For the `xmllint` coverage threshold experiment, TOFU is 28% faster than AFLGo, and 60% percent faster than Superion, computed as the geometric mean of the ratio of each pair. (All timeouts were counted as 300 seconds.) AFLGo does not use prioritization or a structured mutator. Superion is a general-purpose fuzzing tool, aiming to improve coverage, rather than reaching specific locations in the program. For `diff`, TOFU’s mutator includes a filesystem language, allowing TOFU to create new directories and files, which is beyond the capabilities of AFLGo.

On space, TOFU performs much better than AFLGo, while on `xmllint`, TOFU’s advantage is not as dramatic. To understand this difference, we examined `xmllint`’s source code, and looked for differences between the targets covered by TOFU vs. AFLGo. Many of the targets are parsing-related: `parser.c` has the most target basic blocks among all source files. AFLGo is good at reaching those targets. In contrast, for targets that are not in the parsing stage—for example, targets in `xinclude.c`—if the initial inputs do not contain features relevant for reaching the targets, then AFLGo cannot reach them, whereas TOFU is able to construct inputs that allow the targets to be reached. Thus, whether TOFU is a better choice over AFLGo depends on the target: if the target is shallow, and wild or erroneous input is required to reach the target, then AFLGo is better; if the target is deep in the program, and requires features that are not represented in the initial inputs, TOFU is a better choice. In fact, the degree to which the data is scattered

in the plot of TOFU vs. AFLGo in Fig. 5 suggests that TOFU and AFLGo have different strengths when it comes reaching different kinds of targets. As suggested in the Superion paper [36], another reason may be that XML is weakly-structured, whereas the input to space is highly structured. As a point of comparison, our protobuf specification for XML has 142 lines, while our protobuf specification for the input language of space has 300 lines. Thus, it may be that TOFU performs better on space than on `xmllint` (relative to the performance of AFLGo) because it is more difficult for AFLGo to create the more structured inputs needed to fuzz space (cf. the first example in Section 2).

## 6 THREATS TO VALIDITY

Our empirical evaluation tries to adhere to practices recommended by Klees et al. [16]. For example, we evaluated each tool multiple times with randomly selected seed inputs to reduce bias due to any particular selection of inputs. Klees et al. [16] recommend running AFL-like fuzzers for at least 24 hours per trial, but that would take half a year for the 180 `xmllint` commits we used. However, we are not trying to maximize coverage as in general fuzzing, TOFU may be useful for users with limited time, e.g., who want to create coverage tests for code changes.

To compare the performance of TOFU and AFLGo with a longer search time, we selected the ten versions from space with the most uncovered targets. Instead of running for just 150 seconds, we ran the tools for 1500 seconds. The result is that TOFU still reaches 80% more targets than AFLGo (compared with 4x–6x more targets for the 150-second limit—see Table 1).

TOFU only selects targets that its distance computation indicates are reachable. Our reachability analysis makes a few assumptions that may not hold for all C programs. For instance, TOFU uses function type-signatures to approximate the callable set at each indirect-call site. TOFU does not consider casts, which could allow a differently typed function to be called. However, the effect of this imprecision is small. For example, there were only 6 of 186 `xmllint` code-change commits for which TOFU considered all targets to be unreachable. TOFU’s indirect-call analysis is still an advance over AFLGo, which performs no indirect-call analysis at all.

## 7 DISCUSSION

*Structured Fuzzing:* Our structured mutator is based on protobuf specifications, which cannot capture all constraints on valid inputs.

We therefore augmented these rough specifications with additional semantic information. For example, for space inputs, one data field contains a number  $k$  followed by exactly  $k$  PORT definitions. Our protobuf approximation of this format does not have a separate integer data field corresponding to  $k$ . Instead, we count PORT definitions and reconstruct  $k$  accordingly when rendering a protobuf instance as a program input. Furthermore, we do not have a full specified set of features for every aspect of the input. For example, for `xmllint` inputs, we do not have a full XML Pointer (XPointer) Language. Instead, we manually construct some XPointers and map each XPointer into an integer option for the XPointer sub-language. One advantage of this approach is that the user might have prior knowledge on what parts in the input are essential to reach certain targets. A restricted implementation can make the fuzzer reach the targets faster. Furthermore, protobufs allow inheritance, so the user can specify different parts of the input separately, then either reuse or extend specification fragments as needed.

*Fuzzing as a Proxy for Symbolic Execution:* In theory, symbolic execution and constraint solving could derive an input to reach a program location. However, it is always difficult for this approach to scale well. TOFU offers fuzzing as a proxy for symbolic execution. TOFU’s distance metric effectively counts how many constraints must be solved to reach some target. But instead of solving those constraints, TOFU uses structured mutation to generate input variants that *may* have fewer constraints to solve.

*Choice of Distance Metric:* The distance metric we used counts how many branches remain to reach the target location. We also ran our experiments using an alternative metric in which distance is the shortest distance in the ICFG from a given basic block to the target basic block. The results were that for most targets, the performance was nearly the same, and the differences observed did not reveal that one metric is preferred over the other.

*Reproducibility:* All randomization in TOFU is governed by a random-number seed, optionally under user control for reproducibility. However, when running a subject program, TOFU imposes a wall-clock time limit. Stopping the execution early can lead to different basic-block coverage, thereby changing distance measurements, ultimately changing the results of fuzzing. We found that multiple TOFU trials with a given random seed yielded similar results. However, AFLGo and US-TOFU (which uses AFL’s random mutator) form random seeds using system-level entropy sources, so AFLGo and US-TOFU results can vary more across trials.

## 8 RELATED WORK

A common criticism of AFL is that it is inefficient at finding bugs deep in a program [7, 23, 27, 31]. Driller [31] uses concolic execution to find deep bugs. VUZZER [27] uses both control-flow and data-flow analysis to decide where and how to mutate inputs. T-FUZZ [23] removes sanity checks in the source code and then uses symbolic execution to select valid inputs. Fairfuzz [17] biases its search in favor of inputs that execute rarely-executed branches, as those branches are often hard to cover. Angora [7] uses taint analysis and gradient descent to solve the path constraints. Godefroid et al. [10] use grammar-based specifications to generate inputs that reach deeper program paths. TOFU’s structured mutator also uses grammars, but differently. Instead of generating inputs from scratch,

TOFU mutates existing inputs with respect to a structure specification. In this way, TOFU can still utilize feedback from execution on test inputs, as do many AFL-like fuzzers.

As pointed out in [39], the command-line arguments and options of a program have an important influence on a program’s behavior. [39] provides a tool to test command-line arguments and options. However, it applies only to Python programs, and is a standard fuzzer (i.e., not target-oriented). It will not provide the appropriate combination of arguments and options to reach a particular target location in the program. In contrast, the generator for command-line languages that TOFU provides is general-purpose, and can support most command-line languages of Unix utilities. A generated command-line fuzzer is also set up to perform directed fuzzing, and thus can generate an appropriate combination of arguments and options to reach—or get close to—a desired target (or set of targets).

Most fuzzers try to maximize program coverage, but a few have been driven by other goals. TIFF [14] specifically focuses on memory-corruption bugs and adds type inference to the input so that the mutation to certain bytes is driven by specific type information. Singularity [37] uses fuzzing to solve the worst-case-complexity problem by transforming the complexity-testing problem to an optimal program-synthesis problems and then performing feedback-guided optimization. SLOWFUZZ [24] applies evolutionary guidance to generate inputs that trigger worst-case performance. RAZZER [15] aims to find race-condition bugs in the kernel by identifying an over-approximation of points at which data races potentially occur, and guides fuzzing by using a pre-defined system-call grammar and thread-interleaving tools to trigger data races. MoonShine [22] works on optimizing the state-of-the-art kernel fuzzer, syzkaller [34]. TOFU also uses fuzzing as a technique to address a non-coverage-maximization problem. TOFU seeks inputs that reach specific targets in the program, which might also be tackled using symbolic execution and constraint solving. TOFU’s approach to reach certain targets in a program could make other tools more efficient. For example, TOFU could guide RAZZER’s subroutine to reach the locations of potential data races. Additionally, inputs for triggering worst-case-performance are in general beyond the parsing stage, so a structured mutator could improve fuzzers’ efficiency as well.

The idea of guided execution is also found in model checking and symbolic execution [9, 18–20, 32]. Groce and Visser [13] describe different heuristics for model checking to deal with state-space explosion, including various search and structural heuristics, which are used to decide what to explore next. This work is useful for us because we can likewise apply different heuristics when we generate the input. However, instead of model checking, which scales poorly with program size, we use guided fuzzing, which may be better suited to handle larger programs. Saxena et al. [29] devised a novel extension of symbolic execution to analyze input that influences loop executions. Their work addresses the flag and option generation problem. In our work, instead of symbolic execution, we used structured mutation and distance guidance, and do not rely on constraint solvers, which can have scalability problems.

## 9 CONCLUSION

TOFU shows that both structured mutation and distance-based guidance are beneficial for generating inputs for reaching specific locations in the program, especially for those deep in the program. Moreover, TOFU’s guidance metric has an intuitive interpretation as a distance, so users can understand each input’s “closeness” to the target. Our experiments also revealed that “shallow” targets, such as ones in input-parsing code, also commonly appeared during the software-development process. Therefore, whether a user chooses either TOFU or AFLGo depends what kind of target they need to reach. An AFLGo user could still benefit from TOFU by using TOFU’s phase 1 fuzzing to select flags and options. AFLGo might also benefit from adopting TOFU’s distance metric (and implementation of the distance computation).

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