SoK: The Progress, Challenges, and Perspectives of Directed Greybox Fuzzing

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Abstract—Greybox fuzzing has been the most scalable and practical approach to software testing. Most greybox fuzzing tools are coverage-guided as code coverage is strongly correlated with bug coverage. However, since most covered codes may not contain bugs, blindly extending code coverage is less efficient, especially for corner cases. Unlike coverage-guided greybox fuzzing which increases code coverage in an undirected manner, directed greybox fuzzing (DGF) spends most of its time allocation on reaching specific targets (e.g., the bug-prone zone) without wasting resources stressing unrelated parts. Thus, DGF is particularly suitable for scenarios such as patch testing, bug reproduction, and special bug detection. For now, DGF has become a fast-growing research area. However, DGF has general limitations and challenges that are worth further study. Based on the investigation of 42 state-of-the-art fuzzers that are closely related to DGF, we conduct the first in-depth study to summarize the empirical evidence on the research progress of DGF. This paper studies DGF from a broader view, which takes into account not only the location-directed type that targets specific code parts, but also the behavior-directed type that aims to expose abnormal program behaviors. By analyzing the benefits and limitations of DGF research, we try to identify gaps in current research, meanwhile, reveal new research opportunities, and suggest areas for further investigation.

I. INTRODUCTION

To date, greybox fuzzing has been a scalable and practical approach to software testing, which draws much attention in recent years [1–4]. Based on the feedback information from the execution of the program under test (PUT), greybox fuzzers use an evolutionary algorithm to generate new input and explore paths. Greybox fuzzing is widely used to test application software and libraries [5, 6], as well as kernel code [7–9] and protocols [10–12]. Most greybox fuzzing tools are coverage-guided, which aim to cover as many program paths as possible within a limited time budget. This is because, intuitively, code coverage is strongly correlated with bug coverage, and fuzzers with higher code coverage can find more bugs. However, it is not appropriate to treat all codes of the program as equal because most covered codes may not contain bugs. For example, according to Shin et al. [13], only 3% of the source code files in Mozilla Firefox have vulnerabilities. Thus, testing software by blindly extending code coverage is less efficient, especially for corner cases. Since achieving full code coverage is difficult in practice, researchers have been trying to target the vulnerable parts in a program to improve efficiency and save resources. Direct fuzzing is proposed as a means of achieving this aim [14].

Unlike coverage-based fuzzers that blindly increase the path coverage, a directed fuzzer focuses on target locations (e.g., the bug-prone zone) and spends most of its time budget on reaching these locations without wasting resources stressing unrelated parts. Originally, directed fuzzers were based on symbolic execution [14–17], which uses program analysis and constraint solving to generate inputs that exercise different program paths. Such directed fuzzers cast the reachability problem as an iterative constraint satisfaction problem [18]. However, since directed symbolic execution (DSE) relies on heavy-weight program analysis and constraint solving, it suffers from scalability and compatibility limitations.

In 2017, Böhme et al. introduced the concept of directed greybox fuzzing (DGF) [18]. Greybox fuzzing generates inputs by mutating seeds. By specifying a set of target sites in the PUT and leveraging lightweight compile-time instrumentation, a directed greybox fuzzer can use the distance between the input and the target as the fitness function to assist seed selection. By giving more mutation chances to seeds that are closer to the target, it can steer the greybox fuzzing to reach the target locations gradually. Unlike traditional fuzzing techniques, DGF casts reachability as an optimization problem whose aim is to minimize the distance between generated seeds and their targets [18]. Compared with directed symbolic execution, DGF has much better scalability and improves efficiency by several orders of magnitude. For example, Böhme et al. can reproduce the Heartbleed vulnerability within 20 minutes, while the directed symbolic execution tool KATCH [17] needs more than 24 hours [18].

Motivation. For now, DGF has become a research hot spot and grows very fast. It has evolved beyond the original pattern that depends on manually labeled target sites and distance-based metrics to prioritize the seeds. New fitness metrics, such as trace similarity and vulnerability prediction models, are used. Current DGF tools can not only identify targets automatically but also expose target program behavior in a directed manner. A great number of variations have been used to boost software testing under different scenarios, such as patch testing [19, 20], regression testing [21, 22], bug reproduction [23–25], knowledge integration [26], result validation [27–30], energy-saving [12], and special bug detection [12, 25, 31–35]. Though fast-growing and useful, DGF has general limitations and challenges that are worth further study. Under this background, we conduct this work to summarize the empirical evidence on the research progress of DGF. Based on the analysis of benefits and limitations of DGF research, we try to identify gaps in current research, meanwhile, reveal new research opportunities, and suggest areas for further investigation.
Research Questions. We conduct the first in-depth study of DGF in this work. To study DGF from a broader view, we take into account not only the location-directed type that targets specific code parts, but also the behavior-directed type that targets exposing abnormal program behaviors to find bugs. In summary, we design the following research questions:

- RQ1: How the target identification method is changed in the up-to-date research of DGF?
- RQ2: In addition to distance, are there any new fitness metrics in the recent development of DGF?
- RQ3: How the recent DGF tools are optimized regarding the key steps of fuzzing?
- RQ4: What are the challenges of the DGF research? Are there any potential solutions?
- RQ5: What are the typical application of DGF? How to choose a DGF tool for a specific application scenario?
- RQ6: What are the perspectives of the future trends on DGF research?

In this work, we make the following contributions.

- We investigate 42 state-of-the-art fuzzers that are closely related to DGF to systemize recent progress in the field and answer research questions RQ1, RQ2, RQ3.
- Based on the analysis of the known works, a summary of five challenges to DGF research is provided. We discuss these challenges with examples and disclose the deep reasons behind them, aiming to propose possible solutions to address them and answer RQ4.
- Based on the fast-growing of DGF tools, we summarize the typical application scenarios of DGF and provide suggestions on how to choose a DGF tool for a specific application scenario, which answers RQ5.
- We make suggestions in terms of the perspectives for the research points of DGF that are worth exploring in the future, aiming to facilitate and boost research in this field and answer RQ6.

II. Background

A. Coverage-guided Greybox Fuzzing

Coverage-guided greybox fuzzing (CGF) aims to maximize the code coverage to find hidden bugs. Here we take the widely used tool AFL as a representative to illustrate the principle of CGF. AFL uses lightweight instrumentation to capture basic block transitions at compile-time and gain coverage information during run-time. It then selects a seed from the seed queue and mutates the seed to generate test cases. If a test case exercises a new path, it is added to the queue as a new seed. AFL favors seeds that trigger new paths and gives them preference over the non-favored ones. Compared to other instrumented fuzzers, AFL has a modest performance overhead. However, though some tools (e.g., Fairfuzz [36]) try to reach the rare part of a code, most greybox fuzzers treat all codes of the program as equal. Thus, CGF is less efficient as effort is wasted on non-buggy areas.

B. Directed Whitebox Fuzzing

A directed whitebox fuzzer is mostly implemented into a symbolic execution engine such as KLEE [37], KATCH [17], and BugRedux [38]. Directed Symbolic Execution (DSE) uses program analysis and constraint solving to generate inputs that systematically and effectively explore the state space of feasible paths [15]. Once a target path is identified, potential solutions to the path constraints are explored by creating test cases. Since most paths are actually infeasible, the search usually proceeds iteratively by finding feasible paths to intermediate targets. Unlike DGF, which casts reachability as an optimization problem to minimize the distance between generated seeds and their targets [18], DSE casts the reachability problem as an iterative constraint satisfaction problem [18]. DSE is effective in various scenarios, such as reaching error-prone program locations (e.g., critical syscalls [39]), testing code patches [17, 40, 41], exercising corner paths to increase coverage [42], and reproducing failures in-house [38, 43].

However, DSE’s effectiveness comes at the cost of efficiency. The heavy-weight program analysis and constraint solving of DSE is rather time-consuming. At each iteration, DSE utilize program analysis techniques to identify branches that can be negated to get closer to the target. Then, based on the sequence of instructions along these paths, it constructs the corresponding path conditions. Finally, it checks the satisfiability of those conditions using a constraint solver. DGF is capable of producing a far greater number of inputs in a given timeframe than DSE can achieve [18]. Böhme et al. have demonstrated with experiments that DGF outperforms DSE both in terms of effectiveness and efficiency. For example, AFLGo can expose the Heartbleed vulnerability in 20 minutes while the DSE tool KATCH cannot even in 24 hours [18].

C. Search-based Software Testing

Search-based Software Testing (SBST) formulates a software testing problem into a computational search problem that can be optimized with meta-heuristic search techniques, such as hill-climbing, simulated annealing, and genetic algorithms [44]. The key to the optimization process is defining a problem-specific fitness function, which guides the search by measuring the quality of potential solutions from a possibly infinite search space. Greater fitness values are assigned to those inputs that provide data closer to the focal point in the program [45]. The original use of SBST was structural coverage testing [46], including path and branch coverage. The path taken through the program under test is compared with some structure of interest for which coverage is sought [45]. The fitness function usually incorporates two metrics—approach level and branch distance [47]. The complete fitness value is computed by normalizing the branch distance and adding it to the approach level [45]. In addition to structural testing, SBST can also be used for functional testing [48, 49], temporal testing [50–52], robustness testing [53], integration testing [54, 55], regression testing [56], stress testing [57], mutation testing [58], interaction testing[59–61], state testing[62–64], and exception testing [65, 66].
Algorithm 1: Directed greybox fuzzing Scheme.

Input: $i$ – Initial input
Input: Target – A set of target locations
Output: BugInput – A set of buggy input
Output: SeedQueue – A set of expected seeds that fulfill the demands.

01 BugInput ← ∅
02 SeedQueue ← $i$
03 while true do
04 $s$ ← select(SeedQueue)
05 $s'$ ← mutation($s$)
06 trace ← execute($s'$)
07 if find_new_path(trace) then
08 SeedQueue ← SeedQueue + $s'$
09 if trigger_crash(trace) then
10 BugInput ← BugInput + $s'$
11 distance ← evaluate_seed(trace, Targets)
12 SeedQueue ← sort_insert(SeedQueue, $s'$, distance)
13 end

D. Directed Greybox Fuzzing

Unlike CGF which blindly increases path coverage, DGF aims to reach a set of pre-identified locations in the code (potentially the buggy parts) and spends most of its time budget on reaching target locations without wasting resources stressing unrelated parts. To describe the DGF principle, we use AFLGo as an example. AFLGo follows the same general principles and architecture as CGF. At compile-time, except for instrumentation, AFLGo also calculates the distances between the input and pre-defined targets. The distance is calculated as the average weight of the execution trace to the target basic blocks. The execution trace weight is determined by the number of edges in the call graph and control-flow graphs of the program. Then, at run-time, AFLGo prioritizes seeds based on distance instead of new path coverage and gives preference to seeds closer to the targets at basic block level distance. Böhme et al. view the greybox fuzzing process as a Markov chain that can be efficiently navigated using a “power schedule”. They leveraged a simulated annealing strategy to gradually assign more energy to a seed that is closer to targets than to a seed that is further away. They cast reachability as an optimization problem to minimize the distance between the generated seeds and their targets [1].

The exploration-exploitation problem. DGF fuzzing is a two-part method, which is readily separated into phases of exploration and exploitation [18]. The exploration phase is designed to uncover as many paths as possible. Like many coverage-guided fuzzers, DGF in this phase favors seeds that trigger new paths and prioritizes them. This is because new paths increase the potential to lead to targets, and it is particularly necessary when the initial seeds are quite far from their targets. Then, based on the known paths, the exploitation phase is invoked to drive the engine to the target code areas. In this phase, Böhme et al. prioritize seeds that are closer to the targets and assign more energy to them. The intuition behind this is that if the path that the current seed executes is closer to any of the expected paths that can reach the target, more mutations on that seed should be more likely to generate expected seeds that fulfill the demands. The exploration-exploitation trade-off lies in how to coordinate these two phases. Böhme et al. use a fixed splitting of the exploration and exploitation phases. For example, in a 24-hour test, AFLGo assigns 20 hours for exploration and then 4 hours for exploitation.

III. Methodology

This section introduces the methodology we adopted when conducting this research. The motivation and research questions have been introduced in Section I, thus, here we only describe the other key elements in a review protocol.

A. Inclusion and Exclusion Criteria

This paper defines a tool as a directed greybox fuzzer from a broader view, namely, that a fuzzer either reaches specific target locations or triggers specific program buggy behavior by optimizing a customized fitness function. The following inclusion criteria are thus specified, which also serve as the definition of DGF in this paper.

- The core mechanism should be greybox fuzzing, which relies on the instrumentation of the PUT and includes the key steps of seed prioritization, power scheduling, and mutator scheduling.
- The directedness is realized by optimizing the fitness metric in the key steps of greybox fuzzing, which includes input optimization, seed prioritization, power scheduling, mutator scheduling, and mutation operations.
- The fitness goal is to reach a specific site or to trigger certain buggy behavior of a program. The site could be a manually labeled target or a potential bug location predicted automatically, such as by machine learning [27–29] or static analysis [30]. The target buggy behavior could be a non-functional property (e.g., memory consumption [31]), or a certain bug type (e.g., algorithmic complexity vulnerability [34]).

We classify a DGF tool as directed for target location type when its object is reaching target sites, and the fitness metric can be measured visibly on a concrete structure, such as on the execution trace, the control-flow graph, or call-graph. The target can be a single location, a set of basic blocks, or a sequence of ordered call sites. Differently, if a DGF tool is directed with a certain fitness metric but without a fixed target, then it is classified as directed for target behavior. For this type, the targets need not or cannot be pre-labeled, and the fitness metric is not as visible as the first type. With the optimization of the fitness function, a target can be reached automatically and the buggy behavior will be exposed.

However, to concentrate on the research of DGF, the following types of papers will be excluded.

- Directed whitebox fuzzing realized only via symbolic execution. However, we still include directed hybrid fuzzing papers that assist DGF with symbolic execution.
- Informal literature reviews and technical reports.
- Too short papers (less than 4 pages) without a clear description of the approach or the evaluation.
B. Search Process

The search process consists of three rounds. The first round is a manual search of specific conference proceedings and journal papers via an academic search engine with keywords, which includes the following steps:

1. The publications are initially collected from the proceedings of the top-level conferences on security and software engineering since 2017. Alphabetically, ACM Conference on Computer and Communications Security (CCS), IEEE Symposium on Security and Privacy (S&P), USENIX Security Symposium (Sec), Network and Distributed System Security Symposium (NDSS), and International Conference on Software Engineering (ICSE), ACM International Symposium on the Foundations of Software Engineering (FSE), IEEE/ACM International Conference on Automated Software Engineering (ASE). We search with “directed greybox fuzzing” and “directed fuzzing”. We have 15 papers collected.

2. Then, we use google scholar to search for works from journals and preprints by searching with keywords including “directed greybox fuzzing”, “directed fuzzing”, “targeted fuzzing”. We have 15 papers collected.

3. After that, we refer to a popular fuzzing paper repository and manually select papers related to DGF. We also refer to another paper repository that only collects papers related to directed fuzzing. We have 21 papers collected.

Then, in the second round, we filter out the duplicates from the collection in the previous round. When a paper has been published in more than one journal/conference, the most complete version will be used. We have 49 papers remaining.

In the third round, we read each paper we collected and filter out the papers based on the research content with the inclusion and exclusion criteria from Section III-A. Finally, 42 papers ranging from 2017.1 to 2022.1 (listed in the appendix) remain for further investigation.

C. Data collection

The data extracted from each paper will be:

- The publication source (i.e. the conference, journal, or preprint) and year.
- The fitness goal. To reach what kind of target sites (e.g., vulnerable function) or to expose what target bugs?
- The fitness metric used in the evolutionary process of fuzzing. For example, the distance to the targets.
- How the targets are identified or labeled? For example, predicted by deep learning models.
- The implementation information. What tool is the fuzzer implemented based on? Is the fuzzer open-sourced?
- Whether the tool supports binary code analysis?
- Whether the tool supports kernel analysis?
- Whether the tool supports multi-targets searching?
- Whether the tool supports multi-objective optimization?
- What key steps in fuzzing are optimized to realize the directedness? Namely input optimization, seed prioritization, power scheduling, mutator scheduling, and mutation operations.
- What techniques are adopted in the optimization? Namely control-flow analysis, static analysis, data-flow analysis, machine learning, semantic analysis, and symbolic execution.

D. Data Analysis

The extracted data is tabulated to show the basic information about each study. Then we review the extracted data and try to answer the research questions as follows:

RQ1: How the target identification method is changed in the up-to-date research of DGF? This will be addressed by summarizing how the targets of the documented research are identified or labeled.

RQ2: In addition to distance, are there any new fitness metrics in the recent development of DGF? This will be addressed by summarizing the fitness metrics of the documented research.

RQ3: How the recent DGF tools are optimized regarding the key steps of fuzzing? This will be addressed by analyzing the documented research on the optimization of the key steps of fuzzing (i.e., input optimization, seed prioritization, power scheduling, mutator scheduling, and mutation operations) to realize the directedness.

RQ4: What are the challenges of the DGF research? Are there any potential solutions? We will summarize comprehensive challenges for the DGF community based on the design and implementation of the documented research. For the design, we consider the fitness goal, fitness metric, how the targets are identified, and optimizations on the key fuzzing steps, while for implementation, we pay attention to efficiency and whether the tool supports binary, kernel, multi-targets, and multi-objectives.

RQ5: What are the typical application of DGF? How to choose a DGF tool for a specific application scenario? We will summarize the typical application of DGF based on the fitness goals, how the targets are identified, and the implementation details of the documented research.

RQ6: What are the perspectives of the future trends on DGF research? We will summarize future trends based on the analysis of the challenges and limitations of the current DGF research.

IV. Research Progress on Directed Greybox Fuzzing

A. Overview

Recently, DGF has been a fast-growing research area. To provide an overview of the DGF research, we summarize the following progress:

- In addition to the original fitness metric of distance, new fitness metrics have been adopted, such as sequence coverage, which is suitable for satisfying complex bug-triggering paths. Representatives are UAFuzz, UAFL, Lolly, Berry, CAFL. Multi-dimensional fitness metrics...
are also proposed to detect hard to manifest vulnerabilities. Representatives are AFL-HR, HDRFuzz, AFLPro.

- To facilitate target identification, tools based on machine learning can predict and label potential targets automatically, representatives are SUZZER, V-Fuzz, Defuzz, SemFuzz. Meanwhile, CVE information, commit changes, binary differencing techniques, and tools such as UBSan and AddressSanitizer are adopted to label various potential vulnerable code regions. Representatives are DrillerGo, TortoiseFuzz, AFLChrun, GREYHOUND, DeltaFuzz, 1DVUL, SAVIOR, MDPERFFUZZ.

- The fuzzing process has been enhanced with various approaches, such as using data-flow analysis and semantic analysis to generate valid input, using symbolic execution to pass complex constraints. Representatives are TOFU, TIFF, SemFuzz, KCFuzz, 1DVUL, SAVIOR.

- More complex algorithms are adopted to enhance directedness, such as ant colony optimization, optimized simulated annealing, and particle swarm algorithm. Representatives are AFLChrun, LOLLY, GREYHOUND.

- To improve DGF efficiency, target unreachable inputs are filtered out in advance to save execution. Representatives are FuzzGuard, BEACON.

- DGF has been used to detect specific bug types, such as memory consumption bug and algorithm complexity bug. Representatives are Memlock, SlowFuzz, PERFFUZZ, MDPERFFUZZ.

However, current DGF research also suffers some limitations, such as overhead deduction, equal-weighted metric bias, inflexible coordination of exploration and exploitation, source code dependence, lack of multi-object optimization, lack of multi-target coordination. In the following sections, we will discuss the above advantages and disadvantages in detail.

B. Target Identification

According to the definition of DGF, the fitness goal of DGF can be divided into two categories: directed for target locations, and directed for targeted bugs.

1) Target Locations: A barrier to most directed fuzzing strategies is the need for PUT target pre-labelling[18, 67–70]. Manual labeling relies on the prior knowledge of the target sites, such as the line number in the source code or the virtual memory address at the binary level, to label the target and steer the execution to the desired locations. However, obtaining such prior knowledge is challenging, especially for the binary code. In order to set target sites reasonably and effectively, researchers use auxiliary metadata, such as code changes from git commit logs [19], information extracted from bug traces [25], semantics from CVE vulnerability descriptions [12, 23, 24], or deep learning models [27–29] to help identify vulnerable functions [23, 24, 27–29], critical sites [71], syntax tokens [72], sanity checks [30, 73], and patch-related branches [20, 22] in the code and set such vulnerable code parts or sites as targets. Nevertheless, such target identification schemes still rely on additional efforts to process the information and mark the target on the PUT. It is unsuitable when fuzzing a PUT for the first time or when well-structured information is unavailable.

To improve automation, static analysis tools [30, 68, 74–77] are used to automatically find potential dangerous areas in the PUT. However, these tools are often specific to the bug types and programming languages used [30]. Another direction leverages compiler sanitiser passes (e.g., UBSan [78]) to annotate potential bugs in the PUT [30, 73], or uses binary-level comparison (e.g., Bindiff [79]) to identify patch-related target branches [20]. Deep-learning methods have been used to predict potentially vulnerable code at both binary [27, 28] and abstract syntax tree level [29]. Finally, attack surface identification components [80] have also been used to identify vulnerable targets for DGF automatically.

2) Target Bugs: DGF can also be used as a means of specific bug detection. For example, UAFuzz [25] and UAFL [32] leverage target operation sequences instead of target sites to find use-after-free vulnerabilities whose memory operations (e.g., allocate, use, and free memory) must be executed in a specific order. Memlock [31] uses memory usage as the fitness goal to find uncontrolled memory consumption bugs. IION [26] leverages annotations from a human analyst to overcome significant roadblocks in fuzzing and find deep state bugs. AFL-HR [81] triggers difficult-to-manifest buffer overflows and integer overflow bugs via a co-evolutionary approach. RVFUZZER [33] targets input validation bugs in robotic vehicles. GREYHOUND [12] directs a Wi-Fi client to exhibit anomalous behaviors that deviate from Wi-Fi protocols. PERFFUZZ [34] generates pathological inputs to trigger algorithmic complexity vulnerabilities [34, 35]. For DGF type that targets for specific bugs, there is no need to label the target in the PUT, which means the fuzzer can identify and trigger such bugs automatically in an evolutionary way.

C. Fitness Metrics

The crux of DGF is using a fitness metric to measure how the current fuzzing status matches the fitness goal, so as to guide the evolutionary process. We summarize the following fitness metrics used in DGF.

1) Distance: Based on the investigation, 31% (13/42) of the directed greybox fuzzers follow the scheme of AFLGo by using the distance between the input and the target as the fitness metric. AFLGo [18] instruments the source code at compile-time and calculates the distances to the target basic blocks by the number of edges in the call and control-flow graphs of the PUT. Then at run-time, it aggregates the distance values of each basic block exercised to compute an average value to evaluate the seed. It prioritizes seeds based on distance and gives preference to seeds that are closer to the target. Some follow-ups also update this scheme. TOFU’s distance metric is defined as the number of correct branching decisions needed to reach the target [70]. RDFuzz [69] combines distance with execution frequency of basic blocks to prioritize seeds. UAFuzz [25] uses a distance metric of call chains leading to target functions that are more likely to include both allocation
and free functions to detect complex behavioral use-after-free vulnerabilities. Different forms using equal-weighted basic blocks in the traditional distance calculation, AFLChurn [22] assigns numerical weight to a basic block based on how recently or how often it has been changed, WindRanger [82] takes into account deviation basic blocks (i.e., basic blocks where the execution trace starts to deviate from the target sites) when calculating distance. One drawback of the distance-based method is that it only focuses on the shortest distance, and thus longer options might be ignored when there is more than one path reaching the same target, leading to a discrepancy. An example of this problem is depicted in Section V-C. Another shortcoming is the considerable time cost when calculating the distance at the basic block level. On some target programs, users have reported that it can take many hours just to compute the distance file. For example, AFLGo spent nearly 2 hours compiling and instrumenting cxxfilt (Binutils) to generate the distance file, which is a non-negligible time cost.

2) Similarity: The similarity is a metric that was first proposed by Chen et al. in Hawkeye [67], which measures the similarity between the execution trace of the seed and the target execution trace on the function level. The intuition is that seeds covering more functions in the “expected traces” will have more chances to mutate and reach the targets. Hawkeye [67] combines the basic block trace distance with covered function similarity for the seed prioritization and power scheduling. LOLLY [83] uses a user-specified program statement sequence as the target and takes the seed’s ability to cover target sequences (i.e., sequence coverage) as a metric to evaluate the seed. Berry [77] upgraded LOLLY by taking into account the execution context of target sequences. This enhances the target sequences with “necessary nodes” and uses the similarity between the target execution trace and the enhanced target sequence to prioritize the seeds. The similarity is then enriched to cover other target forms, such as operations, bug traces, and labeled locations. Formally, the similarity is the degree of overlap between the current status and target status of a certain metric, where the metric includes the length of bug traces, and the number of covered locations, covered operations, or covered functions.

UAFL [32] uses operation sequence coverage to guide the test case generation to progressively cover the operation sequences that are likely to trigger use-after-free vulnerabilities. UAfuzz [25] also uses a sequence-aware target similarity metric to measure the similarity between the execution of a seed and the target use-after-free bug trace. SAVIOR [73] prioritizes seeds that have higher potentials to trigger vulnerabilities based on the coverage of labels predicted by UBSan [78]. TortoiseFuzz [23] differentiates edges that are closely related to sensitive memory operations and prioritizes seeds based on the sensitive edge hit count in their execution paths.

For comparison, similarity-based metrics are better able to handle multi-target fitting than distance-based alternatives. Furthermore, similarity-based metrics can include the relationships between targets, such as the ordering of the targets [25]. Finally, a distance-based metric is measured at the basic block level, which would introduce considerable overheads, while a similarity-based metric can be extracted from a relatively high level to improve overall efficiency.

3) Vulnerability Prediction Models: Researchers also use vulnerability prediction models to quantify how likely a seed can reach a target. Using a deep learning-based model, the vulnerable probability of a functions can be predicted and each basic block in the vulnerable function is given a static vulnerable score to measure the vulnerable probability. Then for each input, the sum of the static vulnerable score of all the basic blocks on the execution path is used as a fitness score to prioritize inputs with higher scores [27, 28]. TAF [76] extracts semantic metrics of the PUT and uses static semantic metrics to label regions, including sensitive, complex, deep, and rare-to-reach regions, that have a higher probability of containing vulnerabilities and strengthens fuzzing towards such regions. Joffe [6] uses crash likelihood generated by a neural network to direct fuzzing towards executions that are crash-prone. The probability-based metric can combine seed prioritization with target identification to direct fuzzing towards potentially vulnerable locations without relying on the source code. Using deep learning models, a probability-based metric can be extended to targeting properties other than crashes, such as information leaks, exploits, as well as specific crash types, and different resource usages. Besides, deep learning methods have been proven to be able to detect several types of vulnerabilities simultaneously [27]. However, a major weakness is that the accuracy at present is to some extent limited.

4) Other: Apart from the above categories, researchers also propose customized metrics for DGF. Wüstholz et al. [68] used online static look ahead analysis to determine a path prefix for which all suffix paths cannot reach a target location. Directed fuzzing is then enabled by strategically scheduling the energy of fuzzing to stress the path prefix that might reach the target locations. KCFuzz [71] defines the parent nodes in the path to the target as keypoints and directs fuzzing using keypoint coverage. CAFL [84] aims to satisfy a sequence of constraints (i.e., the combination of a target site and the data conditions) instead of reaching a set of target sites. It defines the distance of constraints as how well a given seed satisfies the constraints, and prioritizes the seeds that better satisfying the constraints in order. AFL-HR [81] and HDR-Fuzz [85] adopt a vulnerability-oriented fitness metric called headroom, which indicates how closely a test input can expose a hard-to-manifest vulnerability (e.g., buffer or integer overflow) at a given vulnerability location. PERFFUZZZ [34] uses the new maxima of execution counts for all program locations as feedback to generate pathological inputs. To systematically measure fitness, a customized fitness metric also takes into account multiple dimensions simultaneously, including basic code coverage, block weight, number of state transitions, execution time, anomaly count, and so forth [12, 86]. In addition, non-functional properties such as memory usage [31] and control instability of robotic vehicles [33] can also be used to direct fuzzing.
D. Fuzzing Optimization

Since a native fuzzer that uses randomly generated test inputs can hardly reach deep targets and is less effective at triggering deep bugs along complex paths, various program analysis techniques, such as static analysis, control-flow analysis, data-flow analysis, machine learning, semantic analysis, and symbolic execution, have been adopted to enhance the directedness of reaching corner cases and flaky bugs.

Among the tools investigated, 71% of them relied on the control-flow analysis to evaluate seeds and determine the reachability to the targets; 60% of them leverage static analysis to automatically identify targets [73] and extract information from the PUT [67, 68]; 21% use data-flow analysis (mainly taint analysis) to identify the relationship between the input and the critical program variables [20, 87, 88] or to optimize mutator scheduling [32]; 12% use machine learning to predict vulnerable code [27] and filter out unreachable inputs [89]; 12% integrate symbolic (concolic) execution to solve complex path constraints [20, 24, 73, 77]; and finally, 14% adopt semantic analysis to identify vulnerable targets automatically [19, 24, 76] and learn input fields semantics to optimize mutation. The next section will discuss the key steps of greybox fuzzing and how they are optimized for directedness.

1) Input Optimization: A good seed input can drive the fuzzing process closer to the target location and improve the performance of the later mutation process. According to Zong et al., on average, over 91.7% of the inputs of AFLGo cannot reach buggy code [89]. There are thus many opportunities to increase the ability of DGF by enhancing the input generation. Dynamic taint analysis [88] and semantic information [19] can assist in generating valid input that matches the input format [70, 87]. These techniques also increase the probability of hitting vulnerable functions [19] or security-sensitive program sites, such as maximizing the likelihood of triggering memory corruption bugs [88]. Except that, FuzzGuard [89] utilizes a deep-learning-based approach to predict and filter out unreachable inputs before exercising them, which saves time that can then be spent on real execution. BEACON [90] prunes infeasible paths (i.e., paths that cannot reach the target code at runtime) with a lightweight static analysis, which can reject over 80% of the paths executed during fuzzing.

2) Seed Prioritization: The core of DGF is the prioritization of seeds (for mutation) that are closest to the targets. DGF implementation is effectively the act of closest seed-target relation prioritization. No matter what kind of fitness metric it adopts, seed prioritization is mainly realized based on control-flow analysis. Distance-based approaches [18, 20, 25, 30, 67, 69, 70] calculate the distance to the target basic blocks from the number of edges in the call and control-flow graphs of the PUT. Similarity-based approaches [23, 35, 77, 83] take the seed’s ability to cover the target edges on the control-flow graph as a metric to evaluate the seed. Prediction model-based approaches [27, 28] also rely on the attributed control-flow graph (i.e., using a numerical vector to describe the basic block in a control-flow graph, where each dimension of the vector denotes the value of a specific attribute of the basic block) to represent a binary program and extract features for deep learning. A further point to note is that directed hybrid fuzzing [20, 24, 71, 73, 77] combines the precision of DSE and the scalability of DGF to mitigate their individual weaknesses. DGF can prioritize and schedule input mutation to get closer to the targets rapidly, while DSE can reach more in-depth code by solving complex path constraints.

3) Power Scheduling: Post-selection, the seeds nearest to their targets are subjected to greater fuzzing opportunities by assigning more power, i.e., more inputs are produced by mutating them. Whereas AFL uses execution trace characteristics such as trace size, PUT execution speed, and order in the fuzzing queue for power scheduling, most directed greybox fuzzers use simulated annealing to allocate energy. Unlike traditional random walk scheduling, which always accepts better solutions and may be trapped in a local optimum, simulated annealing accepts a solution that is worse than the current one with a certain probability, so it is possible to jump out of local optima and reach the globally optimal solution [83]. AFLGo [18] was the first to use a simulated annealing-based power schedule to gradually assign more energy to seeds that are closer to the target locations while reducing energy for distant seeds. Hawkeye [67] added prioritization to simulated annealing to allow seeds that are closer to the target to mutate first. AFLChurn [22] proposes a byte-level power scheduling based on ant colony optimization which can assigns more energy to bytes that generate more “interesting” inputs. LOLLY [83] and Berry [83] optimized simulated annealing-based power schedules with a temperature threshold to coordinate the cooling schedule in both the exploration and exploitation stages. In the exploration stage, the cooling schedule randomly mutates the provided seeds to generate many new inputs, while in the exploitation stage, it generates more new inputs from seeds that have higher sequence coverage, which is similar to the traditional gradient descent algorithm [83]. In addition to simulated annealing, GREYHOUND [12] also adopts a custom generational particle swarm algorithm, which
is better suited for the non-linear and stochastic behavior of the protocol model.

4) Mutator Scheduling: Optimizing mutation strategies is a viable alternative as means of bettering directed fuzzing. Reasonable scheduling of mutators can enhance the directedness of inputs by improving the precision and speed of seed mutation. A viable approach is to first classify mutators into different granularities, such as coarse-grained and fine-grained [19, 27, 67, 76], and then dynamically adjust them according to the actual fuzzing states. Coarse-grained mutators are used to change bulk bytes during mutations to move the execution towards the “vulnerable functions”, while fine-grained only involves a few byte-level modifications, insertions, or deletions, so as to monitor the “critical variables” [19]. The fuzzer gives a lower chance of coarse-grained mutation when a seed can reach the target function. Once the seed reaches targets, the time for fine-grained mutations increases as coarse-grained mutations decrease. In practice, the scheduling of mutators is controlled by empirical values [27, 67]. Situ et al. [76] gives two empirical observations—that (1) coarse-grained mutators outperform fine-grained mutators on path growth; and (2) the use of multiple mutations offers improved performance compared to each individual mutation.

5) Mutation Operations: Data-flow analysis, such as taint analysis, can reflect the effect of the mutation in the generated inputs, thus, it is helpful to optimize both mutation operations and input generation. RDFuzz [69] leverages a disturb-and-check method to identify and protect “distance-sensitive content” from the input, i.e., the critical content to maintain the distance between the input and the target, and once altered, the distance would become larger. Protecting such content during mutation can help to approach the target code location more efficiently. UAFL [32] adopts information flow analysis to identify the relationship between the input and the program variables in the conditional statement. It regards input bytes that are more likely to change the values of target statement as with higher “information flow strength”, and assigns higher mutation possibility for them. The higher the information flow strength, the stronger this byte influences the values of the variables. SemFuzz [19] tracks the kernel function parameters that the critical variables depend on via backward data-flow analysis. TIFF [88] infers input type by type-based mutation that the critical variables depend on via backward data-flow analysis. TIFF [88] infers input type by type-based mutation to increase the probability of triggering memory corruption vulnerabilities. It leverages in-memory data-structure identification to identify the types of each memory address used by the application and uses dynamic taint analysis to map what input bytes end up in what memory locations. Nevertheless, data-flow analysis usually enlarges the run-time overhead.

V. CHALLENGES FACED BY DIRECTED GREYBOX FUZZING

A. Performance Deduction

To realize directedness in fuzzing, most researchers use additional instrumentation and data analysis, for example, by static analysis, symbolic execution, taint analysis, and machine learning. However, such additional analysis inevitably incurs performance deduction. For the evaluation, researchers usually focus on the ability to reach targets, using metrics such as Time-to-Exposure (the length of the fuzzing campaign until the first testcase that exposes a given error [18]) to measure the performance of directed greybox fuzzers, while ignoring the measurement of performance overhead. However, for a given fuzzing time budget, higher efficiency means more fuzzing executions and consequently, more chance to reach the target. Thus, optimizing efficiency is a major challenge to improve directedness. Based on the investigation, we summarize the following solution to improve DGF efficiency.

- **Move the heavy execution-independent computation from run-time to compile-time.** For example, AFLGo moves most of the graph parsing and distance calculation to the instrumentation phase at compile-time in exchange for efficiency at run-time. Such compile-time overhead can be saved when a PUT is tested repeatedly.

- **Filter out the unreachable inputs to the target before execution.** For example, FuzzGuard [89] utilizes a deep-learning-based approach and BEACON [90] uses a lightweight static analysis to find such infeasible inputs in advance, which can save over 80% of the path execution during fuzzing.

- **Use more light-weight algorithms.** For example, AFLChurn [22] leverages light-weight ant colony optimization instead of expensive taint analysis to find “interesting bytes” and realize a byte-level power scheduling.

- **Leverage parallel computing.** For example, HDR-Fuzz [85] uses another core to run AddressSanitizer in parallel and provides guidance to the directedness. Large-scale parallel fuzzing [91, 92] can also be adopted to improve efficiency further.

B. Equal-weighted Metrics Bias Seed Prioritization

In most of the state-of-the-art directed greybox fuzzers, the seed prioritization is based on equal-weighted metrics, i.e., treat each branch jump in the control-flow graph as having equal probability. Taking the widely used distance-based metric as an example, where the distance is represented by a number of edges, namely the transitions among basic blocks. However, such measurement ignores the fact that different branch jumps have different probabilities to take, and thus, biases the performance of directed fuzzing.

Fig. 2 shows a control-flow graph fragment of a simple example to illustrate the problem. Suppose input x is an integer ranging from 0 to 9. Obviously, the probability of jumping from node A to node C is 0.1, and from node A to node B is 0.9. We can also compute the probabilities of other jumps by the branch conditions. When using a distance-based metric, the distance of A → C is shorter than that of A → G because A → C has only one jump but A → G has three jumps. However, when taking the jump probability into account, the probability of A → C is 0.1, while the probability of A → G is $0.9 \times 0.7 \times 0.5 \approx 0.3$, which is more likely to be taken than A → C and should be considered as “shorter”. Thus, it is reasonable to also consider the weight difference when designing the fitness metric. Though, this is a hypothetical
example, such a problem is realistic and frequent in the real-world program. One common case is when \( A \rightarrow C \) represents an execution path through the error-handling code. The error-handling code is usually short and simple, which is used to retrieve resources, such as free the allocated memory. Thus, the execution path through the error-handling code to the target is usually short in distance (e.g., one jump). However, since error-handling code is rarely executed, such an execution path has a low probability. If we only consider distance, the path through the error-handling code would be over-emphasized, and we would ignore the bug-prone regular code, leading to a bias.

One solution is taking branch jump probability into account to construct weighted fitness metrics. In that case, each seed is prioritized by the probability of converting the current execution path to a target path that goes through the target. Since an execution path can be viewed as a Markov Chain of execution path to a target path that goes through the target, is prioritized by the probability of converting the current target based on probability is the potential run-time overhead. Thus, a customized data structure that balances the time and space complexities is required.

C. Global Optimum Discrepancy in the Distance-based Metric

When measuring multiple targets with a distance-based metric, one strategy is to seek the global shortest distance between the execution path and all the targets using Dijkstra’s algorithm [18, 67–70]. However, such global optimum might miss local optimal seeds that are closest to a specific target, leading to a discrepancy. In order to elucidate this case, an example is depicted in Fig. 3. In this control-flow graph fragment, node K and O are the target nodes. For the three seeds under test, one exercises path \( A \rightarrow B \rightarrow D \rightarrow G \rightarrow K \), one exercises path \( A \rightarrow C \rightarrow E \rightarrow I \rightarrow M \rightarrow N \rightarrow O \), and the last exercises path \( A \rightarrow C \rightarrow E \rightarrow H \rightarrow L \). Based on the distance formula defined by Böhme et al. [18], the harmonic distances were calculated between each node in the three paths to the two targets—these are labelled in the figure. The global distance for each of the three seeds are:

\[
\begin{align*}
    d_{ABDGEK} &= (4/3 + 3/2 + 1 + 0)/5 \approx 1.47, \\
    d_{ACEIMNO} &= (4/3 + 3/4 + 2 + 3 + 2 + 1 + 0)/7 \approx 1.44, \\
    d_{ACEHL} &= (4/3 + 3/4 + 2 + 1)/4 \approx 1.27. \\
\end{align*}
\]

Since \( d_{ACEHL} \) is the smallest of the three, one should prioritize the seed for path \( A \rightarrow C \rightarrow E \rightarrow H \rightarrow L \). However, this is unreasonable because path \( A \rightarrow B \rightarrow D \rightarrow G \rightarrow K \) goes through target node K, while path \( A \rightarrow C \rightarrow E \rightarrow I \rightarrow M \rightarrow N \rightarrow O \) goes through target O, but path \( A \rightarrow C \rightarrow E \rightarrow H \rightarrow L \) does not reach any targets. Intuitively, as path \( A \rightarrow C \rightarrow E \rightarrow H \rightarrow L \) is far from the targets, it should not be prioritized. The efficacy of directed fuzzing is affected when there is more than a single target, as finding the global shortest distance has discrepancy.

The reason behind such discrepancy is that the distance-based seed measurement only focuses on the shortest path. When there are multiple paths reaching the same target, the longer ones might be ignored, causing discrepancy in the result. In Fig. 3, if the paths \( A \rightarrow C \rightarrow K \) and \( A \rightarrow C \rightarrow E \rightarrow H \rightarrow O \) are considered, then \( d_{ACK} = (4/3 + 3/4 + 0)/3 \approx 0.69 \),

![Fig. 2. Equal-weighted metric incurs bias in distance-based seed prioritization.](image)

![Fig. 3. Discrepancy introduced by distance-based seed prioritization metric.](image)
For exploration and exploitation are divided. To elucidate this, performance is poor due to insufficient exploitation phase, there is no going back even if the direction is less adaptive. Once the exploration phase gives way to the exploitation phase, the separation point is inflexible and relies on the human. The time budgets are pre-set in the test configuration. This is because path A→C→K and path A→C→E→H→O are the shortest paths from A to targets K and O, respectively. The shortest path is always prioritized. Such discrepancy is realistic and frequently occurs when three conditions are all met: (1) Multiple targets are measured by distance; (2) At least one target has more than one viable path; (3) A seed exercises the longer path and is measured by this distance. Multi-targets testing is a frequently used scenario when applying DGF. For example, testing patches by setting code changes as targets. Thus, condition 1) is easy to meet. For condition 2), we also use the error handling code as an example. The error-handling code can be the destination of many functional modules, which means a target in the error-handling code is usually reachable via many paths, thus, condition 2) is also easy to meet. Finally, the satisfaction of condition 3) is uncertain as we cannot guarantee the longer path is exercised. Only when a seed exercises the longer path, it would be measured by this distance, and a discrepancy occurs.

To avoid such discrepancy, all potential paths to the targets must be accounted for. For example, under a different context, the distances from the calling function to the immediately called function may not be exactly the same. To solve this problem, Hawkeye uses “adjacent-function distance augmentation” based on a lightweight static analysis [67], which considers the patterns of the (immediate) call relation based on the generated call graph to augment the distance that is defined by immediate calling relation between caller and callee. Another strategy for coordinating multi-targets is separating the targets. For each seed, only the minimum distance for all targets is selected as the seed distance, and the seeds are prioritized based on this min-distance [20]. The effect of this is to negate the possibility of biasing into global optimal solutions but at the cost of increasing the time required to hit a given target.

D. Inflexible Coordination of Exploration Phase and Exploitation Phase

Another challenge of DGF lies in coordinating the exploration-exploitation trade-off. On one hand, more exploration is necessary to provide adequate information for the exploitation; on the other hand, an overfull exploration would occupy many resources and delay the exploitation. It is difficult to determine the boundary between the exploration phase and the exploitation phase to achieve the best performance.

Most directed greybox fuzzers, such as AFLGo, adopt a fixed splitting of the exploration phase and the exploitation phase. The time budgets are pre-set in the test configuration before testing. Such a scheme is preliminary because the separation point is inflexible and relies on the human experience. Since each PUT is different, such fixed splitting is less adaptive. Once the exploration phase gives way to the exploitation phase, there is no going back even if the direction is incorrect. The efficacy of DGF is determined by how the resources for exploration and exploitation are divided. To elucidate this with a case study, AFLGo was applied to libxml using the “-z” parameter of AFLGo to set different time budgets for the exploration phase and compare the performance. As Fig. 4 shows, the horizontal coordinate shows the time duration of the test, and the vertical coordinate shows the minimum distance of all the generated inputs to the target code areas (min-distance). A small “min-distance” indicates a better-directed performance. The experiments last for 24 hours, and AFLGo-1 means 1 hour of exploration with 23 hours of exploitation, and the rest are similar. From the results, it can be concluded that the splitting of the exploration and exploitation phases affects the performance of DGF, and that the best performance (AFLGo-16) requires adequate time for both of the two phases. However, it is difficult to get optimum splitting.

Among the directed fuzzers investigated, only one work tries to optimize the coordination of exploration-exploitation. RDFuzz [69] combines distance and frequency to evaluate the inputs. Low-frequency inputs are required in the exploration phase to improve the coverage, while short-distance inputs are favored in the exploitation phase to achieve the target code areas. Finally, an inter-twined testing schedule is used to conduct the exploration and exploitation alternately. However, the classification of the four input types (short/long distance and low/high frequency) is preliminary, and the performance heavily depends on the empirical threshold values.

E. Dependence on the PUT Source Code

Most of the known DGF works [18, 67, 69] are implemented on top of AFL and inherit AFL’s compile-time instrumentation scheme to feedback the execution status or calculate distance-based metrics. A significant drawback of such a scheme is the dependence on the PUT source code. Thus, it is unsuitable for testing scenarios where the source code is unavailable, such as commercial off-the-shelf (COTS) software, or the security-critical programs that rely partly on third-party libraries.

There are multiple reasons that hinder the application of DGF at the binary level. First, heavy run-time overhead. A straightforward solution to binary-level testing is through a full-system emulator, such as QEMU [25]. However, emulator-based tools are usually less efficient. For example, the execution speed of vanilla AFL is 2–5 times faster than its...
QEMU mode [93]. Second, difficulty in collecting target information. An open-source PUT can be used to obtain target information from various channels, such as the CVE vulnerability descriptions [23, 24], changes made in the git commit logs [19], and human experience on critical sites in the source code. However, for binary code, we can only extract target information from bug traces [25]. Third, difficulty in labeling the targets. For the source code instrumentation approach, the targets can be labeled based on the source code (e.g., cxxfilt.c, line 100). However, it is much more difficult for the binary. Since the binary code is hard to read, it must be disassembled using tools such as IDA Pro [25], and the targets labeled with virtual addresses, which is both inconvenient and time-consuming.

A viable solution to alleviate the performance limitation is hardware assistance, such as Intel Processor Trace (PT). Intel PT is a lightweight hardware feature in Intel processors. It can trace program execution on the fly with negligible overhead (averagely 4.3x faster than QEMU-AFL [94]), which replaces the need for dynamic instrumentation. Using the packet trace captured by Intel PT along with the corresponding binary of the PUT, the execution path of the PUT could be fully reconstructed. There have been attempts of fuzzing with PT [7, 93–95], but it has never been used to DGF yet. For the problem of target identification and labeling at the binary code level, machine-learning-based approach [27, 28] and heuristic binary diffing approach [73] can be leveraged to automatically identify the vulnerable code.

VI. Application of Directed Greybox Fuzzing

DGF has a good application prospect. When a practitioner chooses a directed greybox fuzzer, the first thing to consider is the application scenario. We summarize the following typical scenario for the DGF application.

Patch testing. DGF can test whether a patch is complete and compatible. A patch is incomplete when a bug can be triggered by multiple inputs [96], but the patch only fixes a part of them. For example, CVE-2017-15939 is caused by an incomplete fix for CVE-2017-15023 [67]. Meanwhile, a patch can introduce new bugs [97]. For example, CVE-2016-5728 is introduced by a careless code update. Thus, directed fuzzing towards problematic changes or patches has a higher chance of exposing bugs. For example, DeltaFuzz [21] and AFLChurn [22] are designed for regression testing. SemFuzz [19] uses code changes from git commit logs and lduv [20] uses binary-level comparison to identify patch-related target branches, which are particularly suitable for this scenario.

Bug reproduction. DGF can reproduce a known bug when the buggy input is unavailable. For example, due to concerns such as privacy, some applications (e.g., video player) are not allowed to send the input file. With DGF, the in-house test team can use DGF to reproduce the crash with the method calls in stack-trace and some environmental parameters [18]. DGF is also helpful when generating Proof-of-Concept (PoC) inputs of disclosed vulnerabilities with given bug report information [19, 20]. In fact, DGF is in demand because 45.1% of the usual bug reports cannot be reproduced due to missing information and user privacy violations [98]. TortoiseFuzz [23] and DrillerGo [24] utilize CVE vulnerability descriptions as target information, while UAFuzz [25] extracts target information from bug traces, both of which are suitable for this scenario.

Knowledge integration. DGF can boost program testing by integrating the knowledge from a human analyst. Human-in-the-loop can help to overcome roadblocks and explore the program’s state space more thoroughly. For example, IJON [26] use human experience to identify the security-sensitive program sites (e.g., call site of malloc() and strcpy()) to guide fuzzing towards error-prone parts [26], which are suitable for this scenario.

Result validation. DGF can validate the result of other software testing approaches. Testing approaches such as static analysis and machine learning can help to identify potentially vulnerable targets, though the results are inaccurate. DGF can be used to refine the results by removing false positives. Tools like V-Fuzz [27], SUZZER [28], DeFuzz [29], ParmeSan [30] are suitable for this scenario.

Energy saving. Another interesting application of DGF is when the testing resource is limited. For example, when fuzzing IoT devices. Under this circumstance, identifying critical code areas to guide testing is more efficient than testing the whole program in an undirected manner, which can save time and computational resources being spent on non-buggy code regions. GREYHOUND [12] and RVFUZZER [33] are designed for Wi-Fi client and robotic vehicles respectively, and are both suitable for this scenario.

Special bug detection. Finally, DGF can detect special bugs based on customized indicators. For example, it can find uncontrolled memory consumption bugs under the guidance of memory usage [31], use-after-free bugs under the guidance of type-state violation [25, 32], and find algorithmic complexity vulnerabilities under the guidance of resource usage [35, 99].

The second thing to consider is the test conditions. Of these, the source code availability is paramount. In order to realize directed fuzzing, researchers use additional instrumentation and data analysis in the fuzzing process. Taking AFLGo as an example, when instrumenting the source code at compile-time, the control-flow and call graphs are constructed via LLVM’s link-time-optimization pass. After this, AFLGo measures the distance between each basic block and a target location by parsing the call graph and intra-procedure control-flow graph of the PUT. For the tools reviewed herein, 81% rely on the PUT source code.

Since both parsing graphs and calculating distances are very time-consuming, pre-processing is required. AFLGo moves most of the program analysis to the instrumentation phase at compile-time in exchange for efficiency at run-time. Notwithstanding this, AFLGo still spent nearly 2 hours compiling and instrumenting cxxfFilt (Builtin) [25], which is a non-negligible time cost. For cases where the source code is unavailable, there are three challenges to consider—the heavy run-time overhead caused by QEMU [25], the difficulty in
collecting target information, and the difficulty in labeling targets, all of which result in inconvenience and reduced efficiency (this is discussed in detail in Section V-E).

Last but not least, the number of targets and the number of testing objectives also affect the choice of a tool. When there are multiple targets, the relationship among targets is also exploitable. Most of the tools investigated tend to only focus on optimizing a single objective, such as covering specific targets. Multi-objective optimization is a practical option that meets the demand of optimizing more than one fitness metric simultaneously.

VII. Perspectives on Future Trends

The coming section provides an overview of the prevailing trends in DGF studies.

A. Exploitation of Relationship between Targets

When there are multiple targets in a targeted fuzzing task, how to coordinate these targets is another challenge. Although 86% (36/42) of the fuzzers we investigated support multi-targets, only five of them paid attention to the relationship among targets. For multiple targets to be reached, exploiting the relationship among targets is meaningful for optimizing DGF. If the targets are unrelated, weights can be assigned to them to differentiate the importance or probability. Alternatively, the hidden relationship can be extracted and exploited to improve directedness. For example, UAFL [32] takes into account the operation sequence ordering when leveraging target sequences to find use-after-free vulnerabilities. This is because, to trigger such behavioral complex vulnerabilities, one needs not only to cover individual edges but also to traverse some longer sequences of edges in a particular order. Such a method can be extended to detect semantic bugs, such as double-free and API misuse. Berry [77] enhanced the target sequences with execution context (i.e. necessary nodes required to reach the nodes in the target sequences) for all paths. Similarly, KCFuzz [71] regards the parent nodes in the path to the target as keypoints to cover. CAFL [84] regards the data conditions along the path to the target as constraints (more like a kind of sub-targets) and drives the seeds to satisfy the constraints in order to finally reach the target. Herein, we suggest that the following relationships can be considered for DGF research.

The spatial relationship. Namely the relative position of targets on the execution tree. Consider the relation between two targets, including whether they occupy the same branch, the level of shared executions, and their relative precedence if any.

The state relationship. For targets that involve the program state, consider their position in the state space. For example, whether two targets share the same state, and whether two states can convert to each other on the state transition map.

The interleaving relationship. For multi-threaded programs, thread scheduling also affects the execution ordering of events in different threads. Targets that can be reached under the same thread interleaving should have a close relationship in the interleaving space.

B. Design Multi-dimensional Fitness Metric

Current fuzzing approaches mainly focus on the coverage at the path level, such as maximizing the overall path coverage or reaching specific code parts, which neglects the fact that some bugs will not be triggered or manifest even when vulnerable code is exercised. For example, a buffer overflow vulnerability will be exhibited at a buffer access location only when the buffer access pointer points outside the buffer. Similarly, an integer overflow vulnerability will be observed at a program location only when the variable being incremented has a large enough value. To detect such “hard-to-manifest” vulnerability, the fitness metric must be extended to be multi-dimensional, such as the state space.

In practice, exploring a complex state machine is difficult, and most fuzzing-based approaches only make progress when exercising certain code, neglecting the update of the state machine and would not fuzz the corresponding test input further. However, some vulnerabilities may not get revealed for every visit to the program point. Only certain executions that reach the vulnerability point with the right state may exhibit the vulnerable behavior. To expose such vulnerability, we need inputs that not only reach the vulnerability location but also match the vulnerable state [81]. AFL-HR [81] defines a fitness metric ranging from 0 to 1 called headroom to indicate how closely a test input can expose a potential vulnerability at a given vulnerability location. For example, for buffer overflow vulnerabilities, the headroom is defined as the minimum distance between the location pointed to by the buffer access pointer and the end of the buffer across all visits to this location, divided by the size of the buffer. ION [26] leverages an annotation mechanism that allows a human analyst to help overcome roadblocks and explore the program’s state space more thoroughly. Thus, state space is a dimension that is worth taking into account as a fitness metric alongside the reachability of the vulnerability location.

C. Multi-objective Optimization

For simplicity, the vast majority of contemporary studies have opted to ignore the possibility of multi-objective targeting through the simultaneous application of a range of metrics. For example, a tester might be interested in achieving higher coverage, but while also targeting unusually long execution times, security properties, memory consumption, or energy consumption. Multi-objective optimization provides an advantage over traditional policies that are only capable of achieving one goal. It formulates the trade-off among multiple properties, such as usability and security [100]. For example, multi-objective optimization can generate test sets that cover specific targets while also maximizing overall coverage, or prioritizing tests that cover as much of the software as possible whilst minimizing the amount of time that tests take to run [45]. The result of a multi-objective search is a set of Pareto-optimal solutions, where each member of the set is no better than any of the others for all of the objectives [45].

Multi-objective optimization is an open problem in the SBST community [45], which also is a challenge for DGF.
A general solution of optimizing multiple objectives is co-evolution, where two (or more) populations of test inputs evolve simultaneously in a cooperative manner using their own fitness functions [101]. For example, in order to find hard-to-manifest vulnerability (e.g., buffer overflow and integer overflow), AFL-HR [81] defines a vulnerability-oriented fitness metric called headroom, which indicates how closely a test input can expose a potential vulnerability at a given vulnerability location. After this, it uses a co-evolutionary computation model to evolve test inputs for both coverage-based and headroom-based fitness metrics simultaneously. Similarly, other fitness metrics such as memory consumption [31] and new maxima of execution counts [34] have also been applied in a co-evolutionary manner. In contrast, FuzzFactory [102] provides a framework that supports multiple domain-specific objectives that are achieved by selecting and saving intermediate inputs from a custom predicate, which avoids the non-trivial implementation of mutation and search heuristics.

D. Target for New Domains

Among the tools evaluated, only one (SemFuzz [19]) supports kernel code testing. Thus, introducing DGF to kernel code and guiding fuzzing towards critical sites such as syscalls and error handling codes to find kernel bugs should be a productive direction. Except for kernel testing, protocol testing is also suitable for DGF. Directed testing can strengthen the critical fields of the protocol message, such as the message length and control information. Zhu et al [103] utilize DGF to constructing more complete control flow graphs by targeting and exercising indirect jumps. It is delighted to see that DGF has been applied in the targeted testing for Register Transfer Level (RTL) designs [104]. Hopefully, DGF would be applied to more domains in the future.

Although DGF has been trying to discover new bug types, such as use-after-free and memory consumption bugs, many commonly seen bug types have not yet been included. Thus, another research direction is applying DGF to bug types with specific feature, such as information leakage, time-of-check to time-of-use [105], and double-fetch bugs[97, 106]. For example, to detect a double-fetch bug, DGF would be useful to guide the testing towards code parts that launch continuous kernel reads of the same user memory address.

VIII. Conclusions

Directed greybox fuzzing is a practical and scalable approach to software testing, which can be applied to specific scenarios, such as patch testing, bug reproduction, and special bug detection. Modern DGF has evolved from reaching target locations to detecting complex deep behavioral bugs. This paper conducts the first in-depth study of DGF based on the review of 42 state-of-the-art tools related to DGF. It systemizes recent progress in the field and summarizes the challenges faced by DGF. Suggestions are made in terms of the perspectives for the application scenarios and future trends of DGF, aiming to facilitate and boost research in this field.

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| Category | Tools | Publication | Fitness goal | Fitness metric | Target identify | Base tool | Binary support | Kernel support | Open source | Multi-targets | Multi-objective |
|----------|-------|-------------|--------------|---------------|----------------|-----------|----------------|----------------|-------------|---------------|----------------|
| Directed for target location | AFLGo [18] | CCS’17 | target sites | distance | manual label | AFL | × | ✓ | ✓ | ✓ | × |
| | SemFuzz [19] | CCS’17 | target function/site | distance | automatic by NLP | Syzkaller | × | ✓ | ✓ | ✓ | × |
| | Hawkeye [67] | CCS’18 | target site | distance | manual label | AFL | × | × | ✓ | ✓ | × |
| | LOLLY [83] | ICPC’19 | target sequence | sequence coverage | manual label | AFL | × | × | ✓ | ✓ | × |
| | TAFL [76] | ICSE’19 | vulnerable region | customized path weights | static semantic analysis | AFL | × | × | ✓ | ✓ | × |
| | DrillerGo [24] | CCS’19 | vulnerable function | coverage | manually based on CVE info | AFL | × | x | x | x | x |
| | IDVUL [20] | DSN’19 | binary patches | distance | binary differ | Driller | QEMU | × | ✓ | ✓ | × |
| | Wüsthofl [68] | Arxiv’19 | target sites | path reachability | static analysis | HARVEY | BRAN | × | × | ✓ | × |
| | SUZZER [28] | ICISC’19 | vulnerable function | vulnerable probability | predict by deep learning | VUzzer | IDA | × | × | ✓ | x |
| | V-Fuzz [27] | TCM’20 | vulnerable function | vulnerable probability | predict by deep learning | VUzzer | IDA | × | × | ✓ | x |
| | DeFuzz [29] | Arxiv’20 | vulnerable location | vulnerable probability | predict by deep learning | AFLGo | × | x | x | ✓ | x |
| | AFLPro [86] | JISA’20 | sanity checks | multi-dimensional fitness | sensitive edge hit rate | automatic | AFLGo | QEMU | × | × | ✓ | ✓ |
| | TortoiseFuzz [23] | NDS’S20 | vulnerable function | sensitive edge hit rate | manually based on CVE info | AFLGo | × | x | x | ✓ | ✓ |
| | Berry [77] | SANER’20 | target sequence | execution trace similarity | static analysis | AFL | × | × | x | ✓ | x |
| | RDfuzz [69] | MIP’20 | target sites | distance, frequency | manual label | AFL | × | × | ✓ | ✓ | x |
| | TOFU [70] | Arxiv’20 | target sites | distance | manual label | - | × | x | x | ✓ | ✓ |
| | GTFuzz [72] | PRDC’20 | guard tokens | distance | static analysis | AFLGo | × | x | x | ✓ | ✓ |
| | ParmeSan [30] | Sec’20 | sanitizer checks | distance | static analysis | Angora | × | × | ✓ | ✓ | ✓ |
| | UAFuzz [25] | RAID’20 | use-after-free | sequence coverage | automatic | AFLGo | QEMU | × | × | ✓ | ✓ |
| | UAFL [32] | ICSE’20 | use-after-free | operation sequence coverage | automatic | AFLGo | × | x | ✓ | ✓ | ✓ |
| | FuzzGuard [89] | Sec’20 | target sites | distance | manual label | AFL | × | × | ✓ | ✓ | ✓ |
| | BEACON [90] | S&P’21 | target sites | distance | manual label | AFLGo | × | x | ✓ | ✓ | ✓ |
| | CAF | Sec’21 | target sites | conditions to the target | manual label | AFL | × | × | ✓ | ✓ | ✓ |
| | AFLChurn [22] | CCS ’21 | target sites | distance | all commits | AFL | × | x | ✓ | ✓ | ✓ |
| | DeltaFuzz [21] | JCST ’21 | target sites | distance | change point | AFL | × | x | x | ✓ | ✓ |
| | DirectFuzz [104] | DAC’21 | target sites | distance | manual label | AFLGo | × | x | ✓ | ✓ | ✓ |
| | Constructor [103] | MDPT’21 | target sites | distance | indirect jump | AFLGo | × | x | x | ✓ | ✓ |
| | KCFuzz [71] | ICAS’21 | target sites | keypoint coverage | static analysis | AFLGo | × | x | x | ✓ | ✓ |
| | WindRanger [82] | ICSE’22 | target sites | distance | static analysis | AFLGo | × | x | x | ✓ | ✓ |
| | SlowFuzz [35] | CCS’17 | algorithmic complexity | vulnerability | resource usage | automatic | LibFuzzer | × | x | x | x |

*continued on next page*
| Category                          | Tools                  | Publication | Fitness goal | Fitness metric           | Target Identify | Base tool | Binary support | Kernel support | Open sourced | Multi-targets | Multi-objective |
|----------------------------------|------------------------|-------------|--------------|--------------------------|-----------------|-----------|----------------|----------------|--------------|---------------|----------------|
| Directed for target behavior    | PERFFUZZ [34]          | ISSTA’18    | algorithmic complexity, vulnerability | coverage and edge hit count | automatic       | AFL       | ×              | ✓              | ✓            | ✓             | ✓              |
|                                 | TIFF [88]              | ACSAC’18    | buffer overflow, integer overflow, crash | new coverage | manual label | VUzzer   | ×              | ×              | ×            | ×             | ×              |
|                                 | Joffe [6]              | ICST’19     | crash         | crash likelihood          | identified by machine learning | AFL       | ×              | ×              | ✓            | ✓             | ×              |
|                                 | FuzzFactory [102]      | OOPSLA’19   | domain-specific goal | domain-specific, multi-dimensional objectives | automatic       | AFL       | ×              | ✓              | ✓            | ✓             | ✓              |
|                                 | RVFUZZER [33]          | Sec’19      | input validation bug | control instability       | automatic       | -         | ✓              | ×              | ×            | ×             | ×              |
|                                 | SAVIOR [73]            | S&P’20      | out-of-boundary, integer overflow, oversized shift | bug potential coverage | Annotate by UB-San | AFL       | ×              | ×              | ✓            | ✓             | ×              |
|                                 | AFL-HR [81]            | ICSEW’20    | buffer overflow, integer overflow | coverage and headroom | automatic       | AFL       | ×              | ×              | ✓            | ✓             | ✓              |
|                                 | GREYHOUND [12]         | TDSC’20     | vulnerable behavior | multi-dimensional cost functions | manually by CVE report | AFL       | ×              | ×              | ✓            | ✓             | ✓              |
|                                 | Memlock [31]           | ICSE’20     | memory consumption bug, deep stateful bug | memory usage and path coverage | automatic       | AFL       | ×              | ×              | ✓            | ✓             | ✓              |
|                                 | IJON [26]              | S&P’20      | buffer overrun | coverage and headroom | human annotation | AFL       | ×              | ✓              | ✓            | ✓             | ×              |
|                                 | HDR-Fuzz [85]          | Arxiv ’21   | buffer overrun | coverage and headroom | ASAN            | AFL       | ×              | ×              | ✓            | ✓             | ✓              |
|                                 | MDPERFFUZZ [99]        | ASE’21      | algorithmic complexity, vulnerability | coverage and edge hit count | automatic       | PERFFUZZ  | ×              | ×              | ✓            | ✓             | ✓              |

**TABLE III.** Collection of directed greybox fuzzers