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-based fuzzers who extend the code coverage in an undirected manner, a directed fuzzer spends most of its time budget on reaching specific target locations (e.g., the bug-prone zone) without wasting resources stressing unrelated parts. Thus, directed greybox fuzzing is particularly suitable for scenarios such as patch testing, bug reproduction, and special bug hunting. In this paper, we conduct the first in-depth study of directed greybox fuzzing. We investigate 28 state-of-the-art fuzzers (82% are published after 2019) closely related to DGF, which have various directed types and optimization techniques. Based on the feature of DGF, we extract 15 metrics to conduct a thorough assessment of the collected tools and systemize the knowledge of this field. Finally, we summarize the challenges and provide perspectives of this field, aiming to facilitate and boost future research on this topic.**

I. Introduction

To date, the most scalable and practical approach to software testing has been greybox fuzzing, which draws much attention in recent years [1–4]. Compared to blackbox fuzzing and whitebox fuzzing, greybox fuzzing is efficient and effective. Based on the feedback information from the execution, greybox fuzzers use an evolutionary algorithm to generate new input and explore the paths. Greybox fuzzing is widely used to testing application software, libraries [5], as well as kernel code [6–8], and has been applied in practice to varieties of targets, including protocols [9, 10], smart contracts [11, 12], and multi-threaded programs [13–15].

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, intuitionally, 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.* [16], 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 the code to improve efficiency and save the resources. Thus, directed fuzzing is proposed.

Unlike coverage-based fuzzers who are blindly extending the path coverage, a directed fuzzer spends most of its time budget on reaching specific target locations (e.g., the bug-prone zone) without wasting resources stressing unrelated parts. Thus, directed greybox fuzzing is particularly suitable for scenarios such as patch testing, bug reproduction, and integration with other tools. Traditionally, directed fuzzers are based on symbolic execution [17–20], which uses program analysis and constraint solving to generate inputs that exercise different program paths. Such directed fuzzers cast the reachability problem as iterative constraint satisfaction problem [21]. However, since directed symbolic execution 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) [21]. By specifying a set of target sites in the program under test (PUT) and leveraging lightweight compile-time instrumentation of the PUT, a directed greybox fuzzer calculates the distance between the seed and the target to assist seed selection. By giving more mutation chances to the seeds that are closer to the target, it can steer the greybox fuzzing to reach the target locations. DGF casts reachability as an optimization problem to minimize the distance of the generated seeds to the targets [21]. Compared with directed symbolic execution, DGF has much better scalability and improves the efficiency by several magnitudes. For example, Böhme *et al*. can reproduce Heartbleed within 20 minutes while the directed symbolic execution tool KATCH [20] needs more than 24 hours [21]. For now, DGF has evolved beyond the primary pattern that depends on manually labeled target sites and distance-based metrics to prioritize the seeds. A great number of variations have been realized to boost software testing under different scenarios, such as fuzzers directed by target sequence [22–24], by semantic information [25, 26], by parser [27], by typestate [28], by sanitizer checks [29, 30], by memory usage [31], and by vulnerable probability [32]. Complex deep behavioral testing scenes, such as use-after-free bugs [22, 28], memory consumption bugs [31], memory violation bugs [33], algorithmic complexity vulnerabilities [5], input validation bugs in robotic vehicles [34], and deep stateful bugs [35].

In this paper, we focus on the up to date research progress on DGF and conduct the first in-depth study of it. We systemize the knowledge of DGF by surveying the state-of-the-art directed greybox (hybrid) fuzzers and conducting a comprehensive analysis based on their assessment. In summary, we make the following contributions.

- We investigate 28 state-of-the-art fuzzers (82% are published after 2019) closely related to DGF, which have various directed types and optimization techniques. We extract 15 metrics based on the features of DGF to conduct a thorough assessment of the collected tools and systemize the knowledge of this field.
- Base on the assessment of the known works, we summarize six challenges to the research of DGF, including binary code support, automatic target identification, differentiated weight metric, global optimum deviation, missing indirect calls, and exploration-exploitation coordination. We disclose the deep reasons behind these challenges and propose possible solutions to address them.
- We give perspectives on future directions, aiming to facilitate and boost research of this field.

The rest of the paper is organized as follows: Section 2 reviews the background knowledge of coverage-guided greybox fuzzing and directed greybox fuzzing. Section 3 evaluates the collected state-of-the-art directed greybox fuzzers based on the extracted metrics and systemizes the optimization details of each work for the critical techniques in DGF. Section 4 summarizes the challenges of this field based on the current research progress. Section 5 discusses future perspectives and followed by conclusions.

II. Background

This section provides the background knowledge on CGF and DGF. We use AFL and AFLGo to illstrate the principle, respectively. Then we compare DGF with CGF to show the difference. Finally, we summarize the application scenarios of DGF.

A. Terminology

To avoid the confusion on the presentation of different literature, we unify the terminology in fuzzing.

- *Fuzzing*. In this paper, fuzzing refers to traditional blackbox fuzzing and greybox fuzzing. We exclude whitebox fuzzing as it depends on constraint solving of symbolic execution to generate inputs, which is quite different from evolutionary fuzzers based on mutation.
- *Testcase*. A testcase is an input to the PUT, which is generated by randomly mutating a seed.
- *Seed*. A seed is a testcase that is favored (trigger a new path or close to the target) and retained for the mutation to generate new testcases in the next fuzzing iteration.
- *Seed prioritization*. Seed prioritization means to evaluate and sort the seeds according to its performance. Prioritized seeds would be given more fuzzing chances.
- *Power schedule* Power schedule means to determine the number of fuzzing tests to be applied on a seed (i.e., energy).
- *Fuzzing cycle* All seeds in the seed queue have been fuzzed at least once.

B. Coverage-guide Greybox Fuzzing

Coverage-guide greybox fuzzing is the most prevalent fuzzing scheme that aims to maximize the code coverage to find hidden bugs. AFL (American fuzzy lop) [36] is the state-of-the-art coverage-based greybox fuzzer, and many state-of-the-art greybox fuzzers [1, 2, 4, 37] are built on top of it. Here we use AFL as a representative to illustrate the principle of CGF. AFL uses lightweight instrumentation to capture basic block transitions and gain coverage information during runtime. Then it selects a seed from the seed queue and mutates the seed to generate testcases. If a testcase exercises a new path, it is added to the queue as a new seed. AFL favors seeds that triggered new paths and give them preference over the non-favored ones. Compared to other instrumented fuzzers, AFL has a modest performance overhead.

Edge coverage. AFL obtains the execution trace and calculates the edge coverage by instrumenting the PUT at compile time. It inserts random numbers for each branch jump at compile-time and collects these inserted numbers from the register at run-time to identify the basic block transition. Edge coverage is more delicate and sensitive than basic block coverage as it takes into account the transition between basic blocks. It is also more scalable than path coverage as it avoids path explosion.

Seed prioritization. AFL leverages the edge-coverage information to select seeds. It maintains a seed queue and fuzzes the seed within it one by one. It labels some seeds as "favored" when they execute fast and are small in size. AFL uses a bitmap with edges as keys and top-rate seeds as values to maintain the best performance seeds for each edge. It selects favored seeds from the `top_rated` queue, and gives these seeds preference over the non-favored ones by giving the favored one more fuzzing chances [38].

Mutation strategies. AFL has two categories of mutation strategies: deterministic strategies and non-deterministic strategies. The deterministic strategies are applied first, which leverage mutators based on bit-flip, arithmetic, token, dictionary, and interest values to sequentially mutate the seeds with different granularity. After doing deterministic strategies, AFL introduces non-deterministic strategies, including the *havoc* stage and *splice* stage. In the havoc stage, AFL mutates the seed by randomly choosing a sequence of mutation operators from the deterministic strategies and apply them to random locations in the seed file. As a result, the generated testcase is significantly different from the original seed. Then, AFL uses the splice strategy to randomly choose another seed from the seed queue and recombine it with the current seed to generate a new seed. Then, the havoc strategies are re-implemented to the new seed.

Power schedule. In the deterministic stage, mutation strategies are involved sequentially, but in the non-deterministic stage, AFL can assign energy to the seed to decide the fuzzing chances of each seed. The energy is assigned according to the performance score of each seed, which is based on coverage (prioritize inputs that cover more paths), execution

Algorithm 1: Directed Greybox Fuzzing.

```
Input:  i − Initial input
Input:  Target − A set of target locations
Output: BugInput − A set of buggy input
BugInput ← ∅
SeedQueue ← i
while true do
    s ← select(SeedQueue)
    s′ ← mutation(s)
    trace ← execution(s′)
    if find_new_path(trace) then
        SeedQueue ← SeedQueue + s′
    if trigger_crash(trace) then
        BugInput ← BugInput + s′
    distance ← evaluate_seed(trace, Targets)
    SeedQueue ← sort_insert(SeedQueue, s′, distance)
end
```

time (prioritize inputs that execute faster), and discovery time (prioritize inputs discovered later) [39] Particularly, if the test case exercises a new path, AFL will double the assigned energy.

C. Directed Greybox Fuzzing

In 2017, Böhme *et al*. introduced the concept of Directed Greybox Fuzzing (DGF) and implemented a tool called AFLGo [21] based on the modern greybox fuzzing framework. Unlike blindly increasing the path coverage in coverage-based greybox fuzzing, 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.

Here we use AFLGo as the representative to illustrate how DGF works. AFLGo follows the general principles and architecture as coverage-guided fuzzing. During the compile-time, in addition to instrument to obtain the execution path and path coverage information, AFLGo also calculate the distances between the input and the pre-defined targets. The distance is calculated based on the average of basic blocks on the input seed's execution trace weight to the target basic blocks, where the weight is determined by the number of edges in the call graph and control-flow graphs of the program. Then, at run-time, AFLGo prioritize seeds based on distance instead of new path coverage and give 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 leverage a simulated annealing strategy to gradually assign more energy to a seed that is closer to the targets than to a seed that is further away. They cast reachability as an optimization problem to minimize the distance of the generated seeds to the targets [1].

The exploration-exploitation problem. For DGF, the whole fuzzing process is divided as the *exploration phase* and the *exploitation phase* [21]. The exploration phase is designed to uncover as many paths as possible. Like many coverage-guided fuzzers, DGF in this phase favors the seeds that trigger new paths and prioritizes them. This is because new paths increase the potential to lead to the targets. It is particularly necessary when the initial seeds are quite far from the 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 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 target. The exploration-exploitation tradeoff lies in how to coordinates these two phases. Böhme *et al* use a fixed splitting of the exploration and exploitation phases. For example, for 24-hour testing, AFLGo uses 20 hours for the exploration and then 4 hours for the exploitation.

D. Difference between CGF and DGF

(1) **Seed prioritization**. A major difference between CGF and DGF lies in the seed prioritization. Since CGF aims to maximize the path coverage, CGF gives preference to seeds that trigger new paths. Differently, DGF aims to reach specific locations in the code. Thus, it prioritizes seeds that are "closer" to the targets. The evaluation metrics of the seeds varies a lot, including distance, coverage, path, and probability.

(2) **Target involvement**. CGF expands code coverage in an undirected manner, which wastes testing resources on code regions do not contain bugs. While for DGF, a set of targets are marked in advance, manually or automatically, to guide the fuzzing process and save the power. The target selection can affect the performance of DGF. For example, selecting critical sites, such as memory allocation function malloc() or string manipulation function strcpy(), as targets are more likely to trigger memory corruption bugs. Besides, we can leverage the relationship among targets to accelerate detecting complex behavioral bugs, such as use-after-free [22, 28]. Thus, the involvement of targets gives more chance to optimize DGF by applying customized techniques that are specific to DGF.

(3) **Exploration-exploitation**. Researchers [38, 40] model the greybox fuzzing process as a "multi-armed bandit problem" where the seeds are considered as arms of a multi-armed bandit. For coverage-based greybox fuzzing, the whole process is essentially a tradeoff of the exploration-exploitation problem, where exploration stands for trying as many seeds as possible while exploitation means mutating a certain seed as much as possible. For DGF, the exploration-exploitation problem lies in coordinating the exploration phase and the exploitation phase. In the exploration phase, DGF try to discover as many seeds as possible and learn information from them to increase the potential to reach the targets. At the same time, the exploitation phase gives more chances of mutation to seeds that are more likely to generate inputs to reach the target.

E. Application of DGF

DGF is a promising direction as it is especially suitable and effective for specific testing scenarios. We summarize the following common practical application of DGF.

- **Patch testing**. DGF can be used to test whether a patch is complete and compatible. A patch is incomplete when a bug can be triggered by multiple inputs [41], for example, CVE-2017-15939 is caused by an incomplete fix for CVE-2017-15023 [42]. Meanwhile, a patch can introduce new bugs [43]. 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.

- **Bug reproduction**. DGF is useful when reproducing a known bug without the buggy input. 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 development team can use DGF to reproduce the crash with the method calls in stack-trace and some environmental parameters [21]. DGF is also helpful when generating Proof-of-Concept (PoC) inputs of disclosed vulnerabilities given bug report information [25, 44]. In fact, DGF is in demand because 45.1% of the usual bug reports cannot be reproduced due to missing information and users privacy violations [45].
- **Knowledge boost**. DGF can boost program testing by integrating the knowledge from a human analyst or auxiliary techniques. Human-in-the loop is commonly used in software testing, which can help to identify the critical syscalls or security-sensitive program sites (e.g., memory allocation function malloc(), string manipulation function strcpy()) based on the previous experience to guide fuzzing to error-prone parts [35]. Auxiliary techniques, such as symbolic execution [44] and tait analysis [46] can be leveraged to overcome roadblocks in the testing. Preliminary results from static analysis [12] and machine learning based detection approach [32] can be used as the potential vulnerable targets for DGF.
- **Energy saving**. Another interesting application of DGF is when the testing resource is limited, for example, fuzzing the IoT devices. Under this circumstance, to save the time and computational resources spent on non-buggy like code regions, identifying critical code areas to guide the testing is more efficient than testing the whole program in an undirected manner.
- **Special bug hunting**. Finally, DGF can be applied to hunting special bugs based on customized indicators. For example, finding uncontrolled memory consumption bugs under the guidance of memory usage [31], find use-after-free bugs under the guidance of typestate violation [28]. With DGF, the efficiency of discovering behavioral complex bugs can be greatly improved.

III. Assessment of the-state-of-the-art Works

During the last three years, DGF has drawn the attention of the whole field, and many followups appear. In this section, we collect and investigate 28 fuzzing works relevant to DGF. To reflect the state-of-the-art research, we choose to include works from top-level conferences on security and software engineering. Alphabetically, ACM Conference on Computer and Communications Security (CCS), IEEE Symposium on Security and Privacy (S&P), USENIX Security Symposium (USEC), Network and Distributed System Security Symposium (NDSS), and International Conference on Software Engineering (ICSE). To reflect the most up to date research progress, we also include works from preprint website arXiv.org. For writings that appear in other venues or mediums, we include them based on our own judgment on their relevance. To conduct a thorough assessment, we extract 15 metrics based on the features of DGF. We further divide the metrics into three categories, including basic information, implementation details, and optimization methods. In the following, we concentrate on properties that related to the critical techniques of DGF, including directed type, input optimization, seed prioritization, power assignment, mutation scheduling, and data-flow analysis. Detailed assessment is listed in Table I

A. Directed Type

Although this paper focuses on directed greybox fuzzing (noted as G in Table I), some of the works we investigated adopt symbolic execution to enhance the directedness, forming directed hybrid fuzzing (noted as H), we also include them in this table.

For the directed type, DGF was initially directed by target sites that are manually labeled in the PUT, such as AFLGo [21] and Hawkeye [42]. Then, researchers noticed that the relationship among the targets is also helpful. For example, in order to trigger use-after-free vulnerabilities, a sequence of operations (e.g., allocate memory, use memory, and free memory) must be executed in a specific order. UAFuzz [22] and UAFL [28] leverages target sequences instead of target sites to find use-after-free vulnerabilities. LOLLY [23] also uses target statement sequences to guide greybox fuzzing to trigger bugs that resulted from the sequential execution of multiple statements. Berry [24] uses symbolic execution to enhance the directedness of LOLLY when reaching deep targets along complex paths. Apart from the target sequence, researchers have proposed various mechanisms to direct the fuzzing process. Memlock [31] is directed by memory usage to find uncontrolled memory consumption bugs. V-Fuzz [32] is directed by vulnerable probability, which is predicted by a deep learning model to guide the fuzzing process to potentially vulnerable code area. SemFuzz [25] and DrillerGo [26] leverage semantic information retrieved from CVE description and git logs to direct fuzzing and generate PoC exploits. 1DVUL [44] is directed by patch-related branches that directly change the original data flow or control flow to discover 1-day vulnerabilities. SAVIOR [30] and ParmeSan [29] are directed by information from sanitizers. IJON [35] leverages annotations from a human analyst to guide the fuzzer to overcome significant roadblocks. RVFUZZER [34] is directed by control instability to find input validation bugs in robotic vehicles. PFUZZER [27] is directed explicitly at input parser to cover the space of possible inputs well. DGF has evolved from reaching target locations to hunting complex deep behavioral bugs,

TABLE I

Comparison of directed greybox fuzzers

	Basic information					Implementation details				Optimization methods					
Tool names & publish year	Fuzzing type	Directed type	Open sourced	Kernel support	Specific bug type	Base tool	Binary support	Indirect call support	Multi-targets support	Seed prioritization metric	Target auto-identification	Data-flow analysis	Input optimization	Mutation optimization	Adaptive explore-exploit
'17 AFLGo [21]	G	target sites	✓	×	-	AFL	×	×	✓	distance	×	×	×	×	×
'17 SemFuzz [25]	G	Semantic	×	✓	-	Syzkaller	×	×	✓	-	✓	✓	✓	✓	×
'18 Hawkeye [42]	G	target sites	×	×	-	AFL	×	✓	✓	distance	×	×	×	✓	×
'18 TIFF [47]	G	bug	×	×	IOF, BOF	VUzzer	×	×	✓	-	✓	✓	✓	×	×
'19 ProFuzzer [48]	G	bug	×	×	MCB	AFL	×	×	✓	-	✓	×	✓	✓	×
'19 LOLLY [23]	G	target sequence	×	×	-	AFL	×	×	✓	sequence coverege	×	×	×	×	×
'19 V-Fuzz [32]	G	vulnerable probability	×	×	-	VUzzer	IDA	×	✓	fitness score	✓	×	✓	✓	×
'19 SUZZER [49]	G	vulnerable probability	×	×	-	VUzzer	IDA	×	✓	fitness score	✓	×	×	×	×
'19 TAFL [50]	G	vulnerable probability	✓	×	-	AFL	×	×	✓	semantic metrics	✓	×	×	✓	×
'19 Wüstholz [12]	G	target sites	×	×	-	HARVEY	BRAN	✓	✓	path	×	×	×	×	×
'19 Memfuzz [33]	G	memory access	×	×	-	AFL	×	×	✓	code coverage; new memory access	×	×	×	×	×
'19 TortoiseFuzz [51]	G	vulnerable function	×	×	MCB	AFL	×	×	✓	function, loop, basic block	✓	×	✓	×	×
'19 PFUZZER [27]	G	parser	×	×	-	-	✓	×	×	×	×	✓	✓	×	×
'19 RVFUZZER [34]	G	control	×	×	IVB	-	✓	×	×	control instability	×	×	×	✓	×
'20 RDFuzz [52]	G	target sites	×	×	-	AFL	×	×	✓	distance; frequency	×	×	×	×	✓
'20 TOFU [53]	G	target sites	×	×	-	-	×	✓	✓	distance	×	×	✓	✓	×
'20 UAFuzz [22]	G	target sequence	×	×	UAF	AFL	QEMU	×	✓	UAF-based distance; target similarity; cut-edge coverage;	✓	×	×	×	×
'20 UAFL [28]	G	typestate	×	×	UAF	AFL	×	×	✓	operation sequence coverage	✓	✓	×	✓	×
'20 Memlock [31]	G	memory usage	×	×	MC	AFL	×	×	✓	function & operation memory consumption	✓	×	×	×	×
'20 IJON [35]	G	human annotations	✓	×	-	AFL	×	×	✓	×	×	×	×	×	×
'20 FuzzGuard [54]	G	target sites	×	×	-	AFLGo	×	×	✓	distance	×	×	✓	×	×
'20 ParmeSan [29]	G	sanitizer checks	✓	×	-	Angora	×	✓	✓	distance	✓	✓	✓	×	×
'20 Ankou [55]	G	combinatorial difference	✓	×	-	self-AFL	×	×		execution distance	×	×	×	×	×
'16 SeededFuzz [46]	H	critical sites	×	×	-	KLEE	×	×	×	critical site coverage	✓	×	×	×	×
'19 DrillerGo [26]	H	semantic	×	×	-	AFL	Angr	×	×	×	✓	×	×	×	×
'19 1DVUL [44]	H	binary patches	×	×	-	Driller	QEMU	×	×	diatance	×	×	✓	×	×
'19 SAVIOR [30]	H	sanitizer	×	×	OOB, IOF, OS	AFL	×	✓	✓	bug potential coverage	✓	×	×	×	×
'20 Berry [24]	H	target sequence	×	×	-	AFL	×	×	✓	similarity between the target execution trace and the enhanced target sequence	×	×	×	×	×

* G: greybox fuzzing, H: hybrid fuzzing, UAF: use-after-free, MC: memory consumption, OOB: out-of-boundary, IOF: interger overflow, BOF: buffer overflow, OS: Oversized shift, IVB: input validation bug, MCB: memory corruption bug

B. Input Optimization

Once the targets are marked, DGF needs to generate a seed input to invoke the fuzzing process. 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 the buggy code [54]. Thus, optimizing the input generation has much room to improve the directedness of DGF. SeededFuzz[46] focuses on improving the generation and selection of initial seeds to achieve the goal of directed fuzzing. It utilizes dynamic taint analysis to identify the bytes of seeds which can influence values at security-sensitive program sites and generates new inputs by mutating the relative bytes and feeds them to target programs to trigger errors. FuzzGuard [54] uses a deep-learning-based approach to filter out unreachable inputs before exercising them. It views program inputs as a kind of pattern and uses a large number of inputs labeled with the reachability to the target code learned from previous executions to train a model. Then, FuzzGuard utilizes the model to predict the reachability of the newly generated inputs without running them, which saves the time spent on real execution.

A fuzzer can perform much better if it generates the input concerning the input grammar. TOFU [53] takes advantage of the known structure of the programs inputs in the form of a protobuf [56] specification to generate valid inputs. TOFU augments the input space to include command-line flags by dividing the fuzzing process into syntactic-fuzzing and semantic-fuzzing. However, it usually takes one or two days to implement input-language grammar even if the user is familiar with the input language [53]. SemFuzz [25] leverages information (syscalls and parameters) retrieved from CVE description and git log to build designed seed inputs to increases the probability of hitting the vulnerable functions. TIFF [47] and ProFuzzer [48] identify input types to assist mutation towards maximizing the likelihood of triggering memory corruption bugs. PFUZZER [27] is a syntax-driven approach that specifically targets input parsers to maximize the input space coverage without generating plausible inputs.

C. Seed Prioritization

The crux of DGF is selecting and prioritizing the seeds that perform better in directedness under certain metrics. We summarize three prevalent metrics widely adopted by modern works, including distance, coverage, and probability.

1) Distance: As we can see from Table I, 32% (9/28) of the directed fuzzers prioritize seeds based on distance and give preference to the seeds that are closer to the target. As a groundbreaking work, AFLGo [21] instruments the source code at compile-time and calculates the distances to the target basic blocks by the number of edges in the call graph and control-flow graphs of the PUT. Then at run-time, it aggregates the distance values of each exercised basic block to compute an average value to evaluate the seed. Many followups inherit this distance-based scheme, such as ParmeSan [29], and 1DVUL [44]. TOFU's distance metric is defined as the number of correct branching decisions needed to reach the target [53]. RDFuzz [52] combines distance with frequency to prioritize seeds. The code areas are separated into high-frequency and low-frequency areas by counting the execution frequency. The inputs are classified into high/low distance and high/low frequency four types. In the exploration phase, the low-frequency seeds are prioritized to improve the coverage, and for the exploitation phase, the low distance seeds are preferred to achieve the target code areas. UAFuzz is a tailored directed greybox fuzzer for complex behavioral use-after-free vulnerabilities [22]. Different from the distance based on the control-flow graph, it uses a distance metric of call chains leading to the target functions that are more likely to include both allocation and free functions. Wüstholz *et al* [12] uses an online static lookahead analysis to determine a path prefix for which all suffix paths cannot reach a target location. By stressing the path prefix that might reach the target locations, the power schedule of the fuzzer can allocate its resources more strategically.

One drawback of the distance-based method is that it only focuses on the shortest distance. When there is more than one path reaching the same targets, the longer options might be ignored, leading to a deviation. We will illustrate it with an example in Section IV-D.

2) Similarity & Coverage: In addition to distance, similarity is another useful metric, which indicates the coverage of certain target forms, such as functions, locations, and bug traces. This metric is particularly suitable when there are many targets. Hawkeye [42] leverages a static analysis of the PUT and combines the basic block trace distance with covered function similarity for the seed prioritization and power scheduling. LOLLY [23] uses a user-specified program statement sequence as the target and takes the seed's ability of covering the target sequences (i.e., sequence coverage) as a metric to evaluate the seed. UAFL [28] uses the operation sequence coverage as the feedback to guide the testcase generation to progressively cover the operation sequences that are likely to trigger use-after-free vulnerabilities. UAFuzz[22] also uses a sequenceness-aware target similarity metric to measure the similarity between the execution of a seed and the target UAF bug trace. The sequenceness-aware target similarity metric concretely assesses how many targets a seed execution trace covers at runtime and takes ordering of the targets into account. Berry [24] takes into account the coverage of nodes in the target sequences and their execution context. It enhances the target sequences with necessary nodes, namely the basic blocks required to reach the nodes in the target sequences for all paths. In addition to the branch coverage, Berry also considers the similarity between the target execution trace and the enhanced target sequence to prioritize the seeds. SAVIOR [30] prioritizes seeds that have higher potentials to trigger vulnerabilities based on the coverage of labels predicted by UBSan [57]. TortoiseFuzz [51] differentiates edges that are more likely to be destined vulnerable based on the fact that memory corruption vulnerabilities are closely related to sensitive memory operations. It prioritizes inputs by a combination of coverige and security impact, which is represented by the memory operations on three different types of granularity at function, loop, and basic block.

3) Probability: Probability is another useful metric that prioritizes the seed by how likely to reach the targets. It usually combines the seed prioritization metric with the target identification metric to direct fuzzing towards potentially vulnerable locations. V-Fuzz[32] and SUZZER [49] predicts the vulnerable probability of functions based on a deep learning-based model and gives each basic block in the vulnerable function a static score. Then for each input, it calculates the sum of the static score of all the basic blocks on its execution path and prioritizes the inputs with higher scores. SAVIOR [30] leverage UBSan to label code areas with buggy potentials. TAFL [50] strengthens fuzzing toward regions that have a higher probability of containing vulnerabilities, which is based on static semantic metrics including sensitive, complex, deep and rare-to-reach regions.

D. Power Assignment

After the seeds are selected and prioritized, the preferenced seeds are given more power, namely more chances of fuzzing tests. Although power assignment is crucial for DGF, very few works, try to optimize this step. AFLGo [21] uses a simulated annealing-based power schedule to gradually assign more energy to seeds that are closer to the target locations while reducing energy for further away seeds. Unlike the traditional random walk scheduling that always accepts better solutions which may be trapped in a local optimum, simulated annealing accepts the solution which is not as good as the current one with a certain probability, so it is possible to jump out of the local optimum and reach the global optimal solution [23]. Hawkeye [42] also adopted simulated annealing but added prioritization. Thus, seeds closer to the target are mutated first, which further improves the directedness. LOLLY [23] adopts an optimized simulated annealing-based power schedule to achieve maximum sequence coverage. Controlled by a temperature threshold, the cooling schedule in the exploration stage 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.

E. Mutator Scheduling

Some fuzzers (8 out of 28) optimize mutation strategies to assist directed fuzzing, which is mainly realized by classifying the mutators into different granularities. Hawkeye[42] leverages an adaptive mutation strategy, which categorizes the mutators as coarse-grained and fine-grained. Coarse-grained mutators are used to change bulks of bytes during the mutations, while fine-grained only involve a few byte-level modifications, insertions, or deletions. It gives less chance of coarse-grained mutations when a seed can reach the target function. Once the seed reaches targets, the times of doing fine-grained mutations increase, and coarse-grained mutations decrease. In practice, the scheduling of mutators is controlled by empirical values. Similarly, V-Fuzz [32] classify the mutation strategies into slight mutation and heavy mutation and dynamically adjust the mutation strategy via a threshold according to the actual fuzzing states. SemFuzz [25] performs a resemble classification, except it focuses on the syscall. SemFuzz utilizes coarse mutation on the inputs to find a syscall sequence that can move the execution towards the "vulnerable functions". After that, it switches to a fine-grained mutation on the syscall sequence to monitor the "critical variables". TAFL [50] also adopts granularity-aware scheduling of mutators based on an empirical observation that (1) coarse-grained mutators outperforms fine-grained mutators on path growth; (2) combining multiple mutators performs better than using a single kind of mutator. ProFuzzer [48] entails different mutation policies according to the input field types recognized by input type probing.

F. Data-flow Analysis

Data-flow analysis, such as taint analysis, can reflect the effect of mutation in the generated inputs, thus, it is helpful to optimize mutation strategy and input generation. RDFuzz [52] leverages a disturb-and-check method to identify and protect the distance sensitive content from the input, which is vital to maintain the distance. Preventing such content during mutation can help to approach the target code location more efficiently. UAFL [28] adopts an information flow analysis to identify the relationship between the input and the program variables in the conditional statement, and assigns higher mutation possibility for these input bytes with high information flow strength, as they are more likely to change the values of target statement. SemFuzz [25] tracks the kernel function parameters that the critical variables depend on via backward data-flow analysis. SeededFuzz[46] utilizes dynamic taint analysis to identify the bytes of seeds which can influence values at security-sensitive program sites. PFUZZER [27] uses dynamic tainting of inputs to relate each value processed to the input characters it is derived from. TIFF [47] infers input type by means of in-memory data-structure identification and dynamic taint analysis, which increases the probability of triggering memory corruption vulnerabilities by type-based mutation. Nevertheless, data-flow analysis usually enlarges the run-time overhead.

IV. Challenges and Solutions

In this section, based on the assessment of the state-of-the-art directed greybox fuzzers, we summarize the following challenges in DFG and propose potential solutions.

A. Binary Code Support

Most of the known DGF works [21, 42, 52] are implemented on top of AFL and inherit its compile-time instrumentation scheme to feedback the execution status or calculate the distance-based metric. A significant drawback of such a scheme is the dependence of the PUT source code. Thus, such scheme is unsuitable for testing scenes that the source code is unavailable, such as the commercial off-the-shelf (COTS) software, or the security-critical programs that rely partly on third-party libraries.

The binary-level DGF is less prevalent owing to the following reasons. First, **heavy runtime overhead**. A straightforward solution for the binary code testing is leveraging a full-system emulator. For example, UAFuzz [22] handles binary codes and extract execution paths via QEMU. However, emulator-based tools are usually less efficient. For example, the execution speed of vanilla AFL is 2X - 5X faster than its QEMU mode [58]. Second, **difficulty in collecting target information**. For an open sourced PUT, we can obtain targets information from various channels, such as the CVE vulnerability descriptions, changes made in the git commit logs, and human experience on critical sits in the source code. However, for a PUT in the binary code, we can only extract targets information from bug traces. 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, the thing is much more difficult for the binary-level approach. Since the binary code is hard to read, we have to disassemble it, such as IDA Pro [22], and label the targets with the virtual addresses. However, this is inconvenient and time-consuming.

A viable solution to alleviate the performance limitation is hardware assistance. Intel PT is a lightweight hardware feature in recent Intel processors. It captures tracing data about program execution, which replaces the need for dynamic instrumentation. Intel PT can trace program execution on the fly with negligible overhead. Using the packet trace captured by Intel PT along with the corresponding binary of the PUT, a security analyst could fully reconstruct the PUT's execution path. Averagely, the PT-based approach is 4.3x faster than QEMU-AFL [59]. Previous hardware features such as Intel Last Branch Record also perform program tracing, but its output is stored in special registers instead of the main memory, which limits the trace size. There have been attempts of CGF with PT, such as kAFL [6], PTfuzz [59], Ptrix [58], and Honggfuzz [60]. However, PT has never been used to DGF yet. For the problem of target identification and labeling at binary code level, we can leverage the machine-learning-based approach [32], or heuristic binary diffing approach [30] to automatically identify the vulnerable code.

B. Automatic target identification

Most of the known directed fuzzers require the analyst to mark the targets manually (e.g., AFLGo, Hawkeye). They rely 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 [21, 42]. However, to obtain such prior knowledge is challenging, especially for the binary code. Among the works we investigated, about 43% (12/28) of them try to optimize the way how the targets are identified. Researchers use auxiliary metadata, such as changes made in the PUT code based on git commit logs [25], information extracted from bug traces [22], or information from CVE vulnerability descriptions [26] to identify targets. Nevertheless, they still rely on manual 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 achieve automatic target identification, we can use static analysis tools to find potential dangerous areas in the PUT [46, 61, 62]. However, these tools are often specific to the bug types and programming languages used [29]. Another direction is leveraging the compiler sanitizer passes, such as UBSan [57], to annotate potential bugs in the PUT [29, 30]. For binary code, 1DVUL [44] identifies patch-related target branches by extracting different functions as well as their different basic blocks through binary-level comparison based on Bindiff [63]. A deep learning-based method is also effective in predicting the vulnerability and using the prediction information to guide fuzzing [32]. Finally, attack surface identification component [64] is also useful to identify vulnerable targets for DGF automatically.

C. Differentiated weight metric

In most of the state-of-the-art directed greybox fuzzers, the prioritization of seeds is based on equal-weight metrics. Take the widely used distance-based metric as an example, the ability to reach the target is measured by the distance between the seed and the target. Specifically, the distance

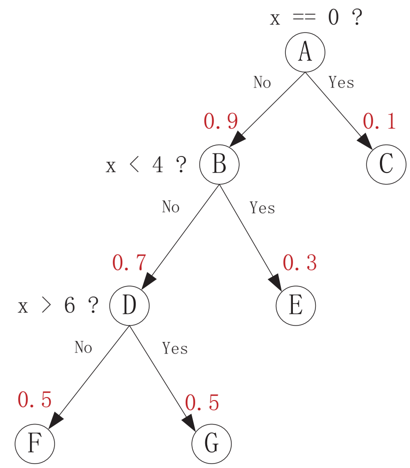

Fig. 1. Probability bias when measuring the distance.

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. Thus, such inaccuracy limits the performance of directed fuzzing.

We use the following example to illustrate the difference. Figure 1 shows a control-flow graph fragment, in which the input x is an integer ranges from 0 to 9. It is easy to know that 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. For the distance calculation based on the number of branch jumps, the distance of $A \rightarrow C$ is shorter than that of $A \rightarrow G$. This is because $A \rightarrow C$ has only one jump but $A \rightarrow G$ has three jumps. However, when we take the branch jump probability into account, the probability of $A \rightarrow C$ is 0.1. However, the probability of $A \rightarrow G$ is $0.9 \times 0.7 \times 0.5 \approx 0.3$, which is more likely to be taken than $A \rightarrow C$ and should be considered as has a "shorter" distance. Thus, it is more reasonable to consider the weight difference as well when calculating the distance to guide the seed prioritization. The other seed prioritization metrics, such as similarity and probability, should follow the same rationale.

One possible solution is taking the branch jump probability into account. When evaluating the reachability of the target based on probability, each seed is prioritized based on how likely the seed can generate an input to reach the target, namely the probability of converting the current execution path of this seed to a target path that goes through the target. Since an execution path can be viewed as a Markov Chain of successive branches [1], the probability of a path can be calculated by gathering the probabilities of all the branches within the path. We can estimate the branch probability by statistically calculating the ratio based on the Monte Carlo method. The density of the stationary distribution formally describes the likelihood that the fuzzer exercises a certain path after a certain number of iterations. A Monte Carlo based method requires two conditions: 1) the sampling should be random; 2) the sample scale should be large [3]. Fortunately, the fuzzing process by nature fulfills these requirements. The execution paths motivated by randomly mutated testcases can be viewed as random samples, which met the first requirement. The high throughput of the testcases generated by fuzzers makes the estimation statistically meaningful, satisfying the second requirement. Thus, regarding fuzzing as a sampling process, we can statistically estimate the branch jump probability in a lightweight fashion.

One possible drawback of such a probability-based approach is the potential run-time overhead. Both the statistical jump counting and the probability calculation introduce extra computation. A simple way to alleviate performance deduction is interval sampling. Another possible solution is to accelerate the computation, which involves how the metadata is stored and accessed. Conventionally, graph-based data is stored in an adjacency table. However, since the probability-based approach updates the jump statistics very often and the reachability judgment also requires a quick edge tracing, thus, the adjacency table is unsuitable owing to its low efficiency when accessing data. Another option is the adjacency matrix [51], which supports quick data access. However, since a jump usually has two branches, the matrix would be vast but the data distribution is relatively sparse, which increases space consumption dramatically. Thus, a pre-condition to leverage a probability-based approach is designing a customized data structure that balances the time complexity and space complexity.

D. Global Optimum Deviation

When there are multi-targets in a DGF testing, How to coordinates these targets is another challenge. One strategy is seeking the global shortest distance based on Dijkstras algorithm, as AFLGo does. However, such global optimum might miss the local optimum seed that is closest to a certain target, leading to a deviation. We use the following example to illustrate the situation.

Figure 2 shows a control-flow graph fragment, where node K and O are the target nodes. Here we test three seeds, one exercises path A→B→D→G→K, one exercises path A→C→E→I→M→N→O, and the other exercises path A→C→E→H→L. Based on the distance formula defined by Böhme *et al.* [21], we have calculated the harmonic distances between each node in the three paths to the two targets and label them by the side of each node. The global distances of the three seeds are $d_{ABDGK} = (\frac{4}{3} + 3 + 2 + 1 + 0)/5 \approx 1.47$, $d_{ACEIMNO} = (\frac{4}{3} + \frac{3}{4} + 2 + 3 + 2 + 1 + 0)/7 \approx 1.44$, and $d_{ACEHL} = (\frac{4}{3} + \frac{3}{4} + 2 + 1)/4 \approx 1.27$. Since d_{ACEHL} is the smallest among the three, we should prioritize the seed of path A→C→E→H→L. However, this is unreasonable because path A→B→D→G→K goes through target node K and path A→C→E→I→M→N→O goes through target O, but path A→C→E→H→L does not reach any targets. Intuitionally,

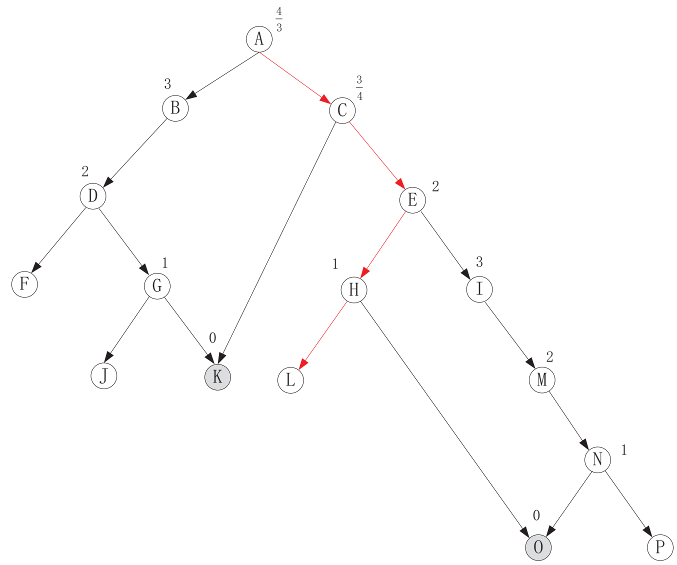

Fig. 2. Deviation introduced by distance-based seed prioritization metric.

path A→C→E→H→L is far away from the targets and should not be prioritized. Therefore, when there are multiple targets, finding the global shortest distance has deviation and affects the directedness of fuzzing.

The reason behind such deviation 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 deviation in the result. In Figure 2, if we consider path A→C→K and path A→C→E→H→O, then $d_{ACK} = (\frac{4}{3} + \frac{3}{4} + 0)/3 \approx 0.69$, $d_{ACEIMNO} = (\frac{4}{3} + \frac{3}{4} + 2 + 1 + 0)/5 \approx 1.02$. As expected, $d_{ACK} < d_{ACEIMNO} < d_{ACEIMNL}$. This is because path A→C→K and path A→C→E→H→O are the shortest paths to targets K and O, respectively. The shortest path is always prioritized. To avoid the bias in the evaluation of seeds, we should take into account all the potential paths to the targets. To achieve this goal, Hawkeye uses adjacent-function distance augmentation based on a lightweight static analysis [42], which considers the patterns of the (immediate) call relation based on the generated call graph.

Another strategy of coordinating multi-targets is separating the targets. For each seed, only selecting the minimum distance among all the targets as the distance of the seed, and prioritize the seed based on this min-distance [44]. In this way, we can avoid the local optimum deviation, but this might slow down the speed of reaching a specific target.

E. Missing Indirect Calls

No matter what metric is adopted, DGF relies on control-flow analysis to prioritize the seed. Take the distance-based metric as an example, the distance is generally measured based on the control-flow graph and call graph. However, most researchers construct the control-flow graph and call graph statically via LLVM's builtin APIs, and such graphs are incomplete due to missing indirect calls. In real-world programs, indirect function calls are prevalent. For example, in `libpng`, 44.11% of the function calls are indirect function calls [42]. For the static analysis approaches, indirect function calls sites, such as passing a function pointer as a parameter in C or using function objects and pointers, cannot be observed directly from the source code or binary instructions. For the binary code, the target address of indirect calls depends on the values in the registers, which cannot be obtained either. Besides, to construct an inter-procedural control-flow graph, we need to combine each function's control-flow graph generated based on LLVM's IR with the call graph of the whole program. Therefore, the distance measurement based on the call graph and control-flow graph is inaccurate without the indirect calls, which affects DGF's ability to reach the targets.

For static approaches, one straightforward solution to this challenge is performing Andersen's points-to analysis for function pointers [30, 42]. However, such inclusion-based context-insensitive pointer analysis causes an indirect call to have many outgoing edges, possibly yielding execution paths that are not possible for a given input. TOFU [53] uses function type-signatures to approximate the callable set at each indirect-call site. However, it does not consider casts, which could allow a differently typed function to be called, introducing imprecision. For the dynamic situation, ParmeSan [29] identifies the missing edges of indirect calls during real executions and compensates the call graph gradually. Finally, the graphs tend to be complete after enough number of fuzzing executions. However, such a solution inevitably enlarges the run-time overhead and cannot guarantee completeness.

F. Exploration-exploitation coordination

The last challenge for DGF lies in coordinating the exploration-exploitation tradeoff. On the one hand, more exploration can obtain and 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. In a word, we do not know when to stop exploration and begin the exploitation can perform the best. AFLGo adopts 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 empirical and inflexible. Since each PUT has a different character, such fixed splitting is less adaptive. Once the exploration phase turns to the exploitation phase, there is no going back even if the direction performance is poor due to not enough paths.

To illustrate how the splitting of the exploration phase and the exploitation phase affects the performance of DGF, we conduct a simple experiment with AFLGo on `libxml`. We use the "-z" parameter of AFLGo to set different time budget for the exploration phase and compare the performance. As Figure 3 shows, the horizontal coordinate shows the time duration of the test, and the vertical coordinate means the

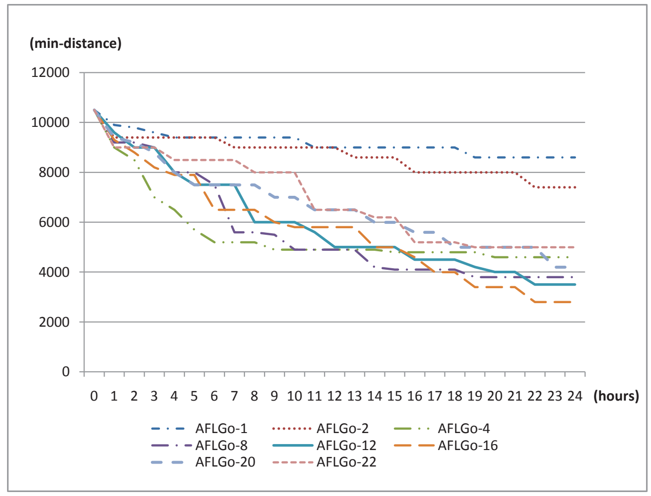

Fig. 3. Comparison on different splittings of the exploration phase and the exploitation phase.

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, we can conclude that the splitting of the exploration phase and the exploitation phase affects the performance of DGF, and the best performance (AFLGo-16) requires adequate time for both of the two phases. However, it is difficult to get an optimum splitting.

Among the directed fuzzers we investigated, only one work tries to improve the coordination of exploration-exploitation. RDFuzz [52] uses an intertwined schedule to conduct exploration and exploitation alternately. It counts the branch-level statistics during the execution to separate the code areas into high-frequency and low-frequency areas. Based on the two evaluation criterias of frequency and distance, the inputs are classified into high/low distance and high/low-frequency types. Low-frequency inputs are helpful to improve the coverage, which is required in the exploration; Low distance inputs are helpful to achieve the target code areas, which are favored in the exploitation. Finally, it uses an intertwined testing schedule to conduct the exploration and exploitation alternately.

Another possible solution to this challenge is leveraging a dynamic strategy to coordinate the splitting of the exploration phase and the exploitation phase, which can adaptively switch between the exploration phase and the exploitation phase. To realize this scheme, we suggest to *cast the splitting of fuzzing phases to the dividing of seeds*, namely dividing the seeds into two groups: coverage seeds for exploration and directed seeds for exploitation. The number of seeds in each group indicates the energy spent on the corresponding phase. The coordination of the two phases is implemented by controlling the number of seeds in each group. We use a variable called *dp* to represent the percentage of directed seeds among all the seeds, which also indicates the percentage of energy that spends on the

Algorithm 2: DGF with adaptive splitting of exploration and exploitation.

```
seedQ ← i    /* initial seeds*/
dp ← 0
directedQ ← ∅    /* Queue for directed seeds */
noPathCycles ← 0
noCloserCycles ← 0
while true do
  findPath ← false
  getCloser ← false
  for s in seedQ do:
    assign_power_by_labels(s)
    s′ ← mutate(s)
    feedback ← execute(s′)
    if find_new_path(s′, feedback) then
      findPath ← true
      noPathCycles ← 0
      label_coverage(s′)    /*set coverage label*/
      seedQ ← seedQ + s′    /* add new seed*/
      min_distance ← evaluate(s′)
      directedQ ← sort_insert(s′, min_distance)
      if getting_closer(min_distance) then
        getCloser ← true
        noCloserCycles ← 0
        dp ← dp + 0.01
  end
  /*when a fuzzing cycle is done*/
  if not findPath then
    noPathCycles + +
  if not getCloser then
    noCloserCycles + +
  if noPathCycles > 100 and dp < 0.5 then
    dp ← 0.9    /* move to exploitation phase */
  if noCloserCycles > 100 and dp > 0.9 then
    dp ← 0.1    /* move back to exploration phase */
  dNum ← len(seedQ) ∗ dp
  label_directed(directedQ, dNum)    /*set directed label*/
end
```

exploitation phase. We give labels to the coverage seeds during seed evaluation, and we give labels to directed seeds after every fuzzing cycle, adjusted by *dp*. We use Algorithm 2 to illustrate this design. A DGF with adaptive splitting should start from the exploration phase ($dp = 0$) that focuses on discovering new paths. Then, with the increasing of known paths, we gradually increase *dp* to invoke the exploitation phase, in which high-valued directed seeds are selected and prioritized to enhance the reachability based on *dp*. When the fuzzer can not find any new paths for a long duration, the exploration phase has come to a bottleneck, and we should quickly move to the exploitation phase by dramatically increasing *dp*. Similarly, we also need to move from the exploitation phase back to the exploration phase occasionally. For example, we are already at the exploitation phase and *dp* is very large (e.g., $dp > 0.9$) but we cannot get any closer to the target for many fuzzing cycles, we should decrease *dp* dramatically to move back to the exploration phase. This is because the directed seeds in hand perform poorly, and we should enlarge path coverage to discover more potential directed seeds. With this scheme, both of the two phases can coexist to achieve the best performance and adaptiveness. It worth noting that the thresholds in the algorithm are used to illustrate the principle. Reasonable values should be generated based on a heuristic algorithm.

V. Discussion

According to Table I, 82% (23/28) of the works were published after 2019, indicating that DGF is currently a research hotspot. With the rapid development of DGF, apart from target sites, various of indicators have been proposed to direct DGF, including target sequence [22–24], semantic information [25, 26], typestate [28], sanitizer checks [29, 30], memory usage [31], and vulnerable probability [32]. DGF has evolved from reaching target locations to hunting complex deep behavioral bugs, such as used-after-free bugs [22, 28], memory consumption bugs [31], memory violation bugs [33], and deep stateful bugs [35].

A. Multi-targets Relationship Exploitation

Although 86% (24/28) of the directed fuzzers we investigated support multi-targets, only 4 pay attention to the relationship among targets. When there are multiple targets, we can optimize DGF via the relationship among the targets. If they are unrelated, we can assign weights to them to differentiate the importance or probability. Otherwise, the hidden relationship can be extracted and exploited to improve directedness. For example, UAFL [28] takes into account the operation sequence ordering when leverageing target sequence 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 long sequence of edges in a particular order. Such a method can be extended to detect semantic bugs, such as double-free and API misuse. Berry [24] enhances the target sequences with execution context (i.e., necessary nodes required to reach the nodes in the target sequences) for all paths. Here we propose the following relationships that can be further included.

- The spatial relationship. The relative position of targets on the execution tree. Suppose we have two targets, we can consider the relationship including whether they are on the same execution path, how many execution paths are shared by them, and which one is the ancestor or the successor of the other.
- The stateful relationship. For targets that involve the program state, we could consider their position in the state space. For example, whether two targets share the same states, and whether two states can convert to each other on the state transition map.
- The interleaving relationship. For multi-threaded programs, the thread scheduling affects the execution ordering of events in different threads. Targets that can be reached under the same thread interleaving should be a close relationship in the interleaving space.

Based on the above discussion, we recommend taking into account the relationship among targets when selecting and prioritizing targets. The targets with higher reachability should

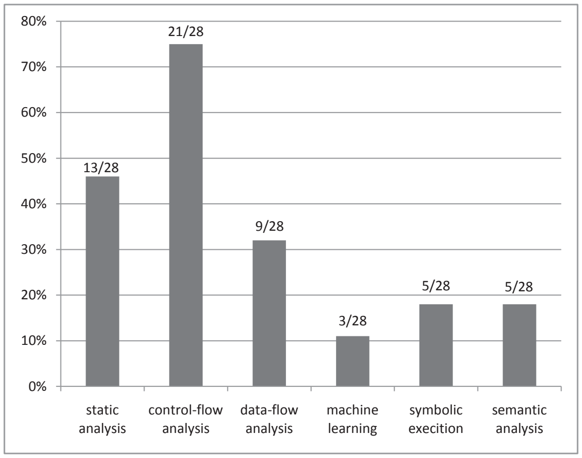

Fig. 4. Statistics of mainsteam techniques used in DGF.

```
400643: mov    eax, dword ptr [rbp - 0xc]
400646: add    eax, 1
400649: mov    dword ptr [rbp - 0xc], eax
40064c: mov    rax, qword ptr [rbp - 8]
400650: movsx  ecx, byte ptr [rax + 1]
400654: cmp    ecx, 0x61
400657: jne    0x400666
```

path 1 path 2

```
40065d: mov    eax, dword ptr [rbp - 0xc]
400660: add    eax, 1
400663: mov    dword ptr [rbp - 0xc], eax
400666: mov    rax, qword ptr [rbp - 8]
40066a: movsx  ecx, byte ptr [rax + 2]
40066e: cmp    ecx, 0x64
400671: jne    0x400680
```

Fig. 5. Differentiate execution path at instruction level.

have higher priority. Targets with a closer relationship should be covered with fewer test runs.

B. Technology Integration

Owing to that, DGF depends on the random mutation to generate test inputs, it can hardly reach deep targets and is less effective at triggering deep bugs along complex paths. In order to enhance the directedness of reaching corner cases and flaky bugs, various program analysis techniques, such as static analysis, control-flow analysis, data-flow analysis, machine learning, semantic analysis, and symbolic execution, have been adopted (statistics are shown in Table 4).

Among the tools we investigate, 75% of them rely on control-flow analysis to evaluate seeds and determine the reachability to the targets; 46% of them leverage static analysis to automatically identify targets [30] and extract information from PUT [12, 42]; 32% use data-flow analysis (mainly taint analysis) to identify the relationship between the input and the critical program variables [27, 44, 47] and optimize mutation strategy scheduling [28, 46]; 11% use machine learning to predict vulnerable code [32] and filter out unreachable inputs [54]; 18% adopt semantic analysis to identify vulnerable targets automatically [25, 26, 50] and learn input fields semantics to optimize mutation; finally, 18% integrate symbolic (concolic) execution to solve complex path constraints [24, 26, 30, 44]. In a personal view, directed hybrid fuzzing is a promising direction that can leverage the precision of symbolic execution and the scalability of DGF to mitigate individual weaknesses. Directed fuzzing can prioritize and schedule input mutation to get closer to the targets rapidly, and directed symbolic execution can help to reach more in-depth code guarded by sophisticated checks on the execution traces from program entry to the targets. Nevertheless, we should be aware that anti-fuzzing techniques [65, 66] can insert fake paths, add delays in error-handling code, and obfuscate codes to slow down dynamic analyses such as symbolic execution and taint analysis [51].

C. Implementation Limitation

According to Table I, about 57% (16/28) of the tools are implemented on top of AFL. Thus, the performance is, to some extent, limited by the implementation of AFL. We illustrate such limitation from two aspects.

Since the edge coverage of AFL is based on the basic block transitions, thus, it is only sensitive at the basic block level and cannot distinguish the path difference at the instruction level. Figure 5 shows an example of a jump between two nearby basic blocks. Since a traditional control-flow graph is only path-sensitive at the basic block level, we cannot differentiate whether the jump at address 0x400657 is taken (path 2) or not (path 1) because there will be the same edge in the control-flow graph, namely 0x400657 → 0x400671. Thus, general basic block level control-flow graph is not sensitive enough to precisely reflect the code coverage at the instruction level.

Another problem lies in the path collision. AFL inserts random numbers for each branch jump at compile-time and collects these inserted numbers from the register at run-time to identify the basic block transition (i.e., the edge in the control-flow graph). Then it maps such transitions to a 64KB bitmap by $cur\_location \wedge (prev\_location >> 1)$]. This scheme incurs path collision because different edges might have the chance to share the same location.

Both of the two limitations of AFL can import imprecision to the control-flow graph, which eventually affect the seed prioritization based on the control-flow graph analysis, no matter it is based on distance or other metrics. Although such limitation can be alleviated by constructing finer-grained control-flow graph or designing a customized hash scheme [67], however, additional work inevitably increases the runtime overhead. Thus, the implementation is essentially a tradeoff between the effectiveness and the efficiency.

D. Efficiency Improvement

As we have discussed in last subsection, in order to realize directedness in fuzzing, most researchers use additional instrumentation and data analysis. However, such additional analysis inevitably incurs performance deduction. For the evaluation, researchers usually focus on the ability to reach targets, using metric such as *Time-to-Exposure* (the length of the fuzzing campaign until the first testcase that exposes a given error [21]) to measure the performance of directed greybox fuzzers, while ignoring the run-time overhead. However, for a given fuzzing time budget, higher efficiency means more fuzzing executions and, consequently, more chance to reach the target. Thus, optimize fuzzing efficiency is another direction to improve the directedness.

One solution is moving the execution-independent computation from run-time to compile-time. For example, 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. Since both parsing graphs and calculating distances are very time consuming, AFLGo moves most of the program analysis to the instrumentation phase at compile-time in exchange for efficiency at run-time. Another optimization is at the implementation level. Since most of the data we use during the analysis is graph-based, how such metadata is stored and accessed is vital to the efficiency. We can design an optimized data structure to store such data, which should facilitate the frequent and quick access to the data when searching based on the topological structure of the graph. For example, using the graph database model [68]. Finally, we can leverage parallel computing to improve efficiency further. Prior works [69, 70] have successfully applied parallelism to CGF but not yet to DGF. For DGF, we can use a central node to maintain a seed queue that holds and prioritizes all the seeds for DGF. Then, distributing the seeds to parallel fuzzing instances on computational nodes to test the PUT and collect feedback information.

E. Future research suggestions

Based on the assessment and analysis of known works, we point out the following directions for future research.

- Among the tools we evaluated, only one (SemFuzz [25]) of them supports kernel code testing. Thus, introducing DGF to kernel code and guiding fuzzing towards critical sites such as syscalls [71] and error handling codes [72, 73] should be a productive direction.
- Although DGF has been trying to discover new bug types, such as use-after-free and memory consumption bugs, many commonly seen bugs have not been included yet. Thus, another research direction is applying DGF to specific bug types, such as information leakage bugs [74], concurrency bugs [13–15], semantic bugs (TOCTTOU [75], double fetch [43, 76]).
- As for the seed prioritization metric, most of the works leverage distance and coverage (similarity) based methods, which facilitate quantitive seed evaluation without introducing much overhead. However, a smaller distance or broader coverage does not necessarily mean closer to the target owing to the differentiated weight reason (discussed in Section IV-C) and global deviation reason (discussed in Section IV-D). We argue that probability-based metrics should be more reasonable.
- Finally, staged fuzzing [53, 77] is a feasible approach that can be further exploited for DGF. By dividing the path to the target into sequential stages, staged directed fuzzing can get to the target step by step by reaching the sub-target in each stage. Moreover, we can leverage different fuzzing strategies to satisfy the requirements in different stages. For example, TOFU [53] uses syntactic-fuzzing for command-line flags and semantic-fuzzing for primary input files. Thus, staged fuzzing can reduce the dimensionality of the input space for each individual stage of fuzzing and improve fuzzing efficiency.

VI. Conclusions

Directed greybox fuzzing is a practical and scalable approach to software testing under specific scenarios, such as patch testing and bug reproduction. The modern DGF has evolved from reaching target locations to hunting complex deep behavioral bugs. However, DGF still faces challenges, including binary code support, automatic target identification, differentiated weight metric, global optimum deviation, missing indirect calls, and exploration-exploitation coordination. In this paper, we conduct the first in-depth study of directed greybox fuzzing by investigating 28 state-of-the-art fuzzers. Based on the feature of DGF, we extract 15 metrics to conduct a thorough assessment of the collected tools and systemize the knowledge of this field. According to the assessment, we suggest paying more attention to apply differentiated weight in seed prioritization, to overcome the global optimum deviation, to exploit the relationship among targets, and to coordinate the splitting of the exploration phase and the exploitation phase. We also point out research directions for future work.

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