Zeror: Speed Up Fuzzing with Coverage-sensitive Tracing and Scheduling

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ABSTRACT

Coverage-guided fuzzing is one of the most popular software testing techniques for vulnerability detection. While effective, current fuzzing methods suffer from significant performance penalty due to instrumentation overhead, which limits its practical use. Existing solutions improve the fuzzing speed by decreasing instrumentation overheads but sacrificing coverage accuracy, which results in unstable performance of vulnerability detection.

In this paper, we propose a coverage-sensitive tracing and scheduling framework `Zeror` that can improve the performance of existing fuzzers, especially in their speed and vulnerability detection. The `Zeror` is mainly made up of two parts: (1) a self-modifying tracing mechanism to provide a zero-overhead instrumentation for more effective coverage collection, and (2) a real-time scheduling mechanism to support adaptive switch between the zero-overhead instrumented binary and the fully instrumented binary for better vulnerability detection. In this way, `Zeror` is able to decrease collection overhead and preserve fine-grained coverage for guidance.

For evaluation, we implement a prototype of `Zeror` and evaluate it on Google fuzzer-test-suite, which consists of 24 widely-used applications. The results show that `Zeror` performs better than existing fuzzing speed-up frameworks such as Untracer and INSTRIM, improves the execution speed of the state-of-the-art fuzzers such as AFL and MOPT by 159.80%, helps them achieve better coverage (averagely 10.14% for AFL, 6.91% for MOPT) and detect vulnerabilities faster (averagely 29.00% for AFL, 46.99% for MOPT).

KEYWORDS

Coverage-guided Fuzzing, Coverage-Sensitive Tracing, Scheduling

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1 INTRODUCTION

Coverage-guided fuzzing is one of the most popular software testing techniques for bug detection. In the past few years, it has gained significant traction in academic research as well as in industry practice. Most notably, Google's OSS-Fuzz [18] adopts American Fuzzy Lop (AFL) [25], honggfuzz [21] and libFuzzer [34] to continuously test open source applications. Over 16,000 bugs in 250 open source projects are discovered by OSS-Fuzz.

A coverage-guided fuzzer feeds a program with random test cases, collects coverage-increasing test cases (such test cases are called interesting seeds), and generates new test cases by mutating those seeds. The key goal of coverage-guided fuzzers is to maximize coverage and explore deeper paths as fast as possible. Many fuzzing optimizations have been proposed to maximize coverage, including the ones that improve seed selection strategy [5, 14, 41, 42] or mutation strategy [6, 28, 29, 36], the ones that integrate multiple fuzzing optimizations [9, 30, 32], and the ones that leverage taint analysis [2, 7, 8, 41], symbolic execution [40, 46, 49, 52, 53], human knowledge [1, 45, 54], or machine learning [10, 16, 44] to assist fuzzing.

While those above optimizations greatly improve performance, especially in coverage improvements, they do not take fuzzing overhead into consideration, which may hinder them from achieving better scalability. For example, the overhead caused by coverage collection is costly. We conduct experiments on AFL using real-world programs of Google fuzzer-test-suite [17] to investigate the overhead of collecting coverage. To our surprise, AFL spends an average of 71.85% and up to 98.5% of its runtime to trace coverage. Some related works try to decrease overheads from instrumentation. INSTRIM [22] reduces instrumentation cost by instrumenting a part of basic blocks and reconstructing coverage information. Untracer [39] avoids tracing coverage of non-coverage-increasing test cases by removing visited instrumentation points. They can effectively decrease overhead but cannot preserve fine-grained coverage guidance, which limits their vulnerability detection.

To speed up fuzzing and further improve vulnerability discovery, the main challenge is to keep a good balance between instrumentation overheads and the granularity of the collected coverage. Those existing overhead reduction methodologies decrease the overhead

with sacri cing coverage accuracy. For example, our experiments demonstrate that compared with AFL, although improves the speed by 155.75%, Untracer decreases coverage by 8.31%, which results in an unstable ability of vulnerability discovery. Therefore, it is not easy to keep a good balance between overhead reduction and coverage accuracy.

In this paper, we propose a coverage-sensitive tracing and scheduling framework Zeror , which aims at increasing fuzzing speed with diversely-instrumented binaries. The main idea is switching to a self-modifying based zero-overhead-instrumented binary for fuzzing when the normal instrumented binary fails to make better progress Zeror is mainly made up of two parts: (1) A self-modifying tracing mechanism to provide a zero-overhead instrumentation for coverage collection. The self-modifying tracing mechanism reduces the coverage collection overhead by restricting coverage tracing to only coverage-increasing test cases. (2) A real-time scheduling mechanism to support adaptive switch between the zero-overhead instrumented binary and the fully instrumented binary. To choose the optimal binary, it estimates the probabilities of discovering interesting seeds for each binary by Bayesian inference. Instead of doing a tradeo between fuzzing speed and coverage accuracy within a single binary, the scheduler helps fuzzers achieve both by taking advantages of diversely-instrumented binaries.

We implemented the prototype of Zeror and applied it to several state-of-the-art fuzzers, including AFL [25] and MOPT [36]. We evaluated them on Google fuzzer-test-suite, which consists of 24 widely-used real-world applications. The evaluation results demonstrate that Zeror performs better than existing fuzzing speed up frameworks such as Untracer and INSTRIM. Compared with Untracer, it covers 20.84% more branches with almost the same execution time. Compared with INSTRIM, it covers 6.82% more branches with 50.72% less execution time. It improves the execution speed of original AFL instrumentation, which is also adopted in MOPT, by 159.80%, helps them achieve better coverage (averagely 10.14% for AFL, 6.91% for MOPT) and exposure vulnerabilities faster (averagely 29.00% for AFL, 46.99% for MOPT).

In summary, this paper makes following contributions:

- We propose a coverage-sensitive tracing and scheduling framework, which integrates diversely-instrumented binaries and supports adaptive switch between them, to speed up fuzzing as well as maintain the vulnerability detection ability.
- We propose a self-modifying tracing mechanism to reduce coverage collection overhead. By using this mechanism, fuzzers will be sensitive to edge-level coverage granularity and only trace coverage of coverage-increasing test cases.
- We propose a real-time scheduling mechanism, which is able to dynamically choose a proper instrumented binary for fuzzing execution to achieve both speed and accuracy.
- We implemented the prototype of Zeror , which could be applied to most of the state-of-the-art fuzzers such as AFL and MOPT. The results show that Zeror could help boost execution speed and discover vulnerabilities faster than the existing speed-up framework such as Untracer and INSTRIM.

This paper is organized as follows: Section 2 introduces the background of coverage-guided fuzzing and coverage tracing. Section 3 illustrates the motivation of this work through an empirical study on e ciencies of di erent coverage collection methods. Section 4 elaborates the idea and design of Zeror . Section 5 presents the implementation and evaluation. Section 6 shows some related works and the main di erences, and we get the conclusion in Section 7.

2 BACKGROUND

2.1 Coverage-guided Fuzzing

Coverage-guided fuzzing is currently one of the most e ective and e cient vulnerability discovery solution. It aims to automatically generate proof of concept (PoC) exploits by maximizing code coverage. AFL [25], libFuzzer [34] and honggfuzz [21] are some well-recognized coverage-guided fuzzers.

Figure 1 shows the general work ow of a coverage-guided fuzzer. Given a target program and initial inputs, fuzzing works as follows: (1) compile target program into target binary, where coverage instrumentation are injected; (2) execute the binary and spawn target process; (3) queue initial inputs into seeds generator; (4) generate test cases as input; (5) trace coverage to evaluate the test case; (6) save the test case to corpus if there is coverage growth (i.e. the test case is interesting), and goto step 4. During the fuzzing execution loop, performance is highly impacted by execution speed during runtime. Fuzzer's runtime consists of two parts, coverage tracing and fuzzer's internal logic (including child process establishment, seed selection and mutation, coverage comparison, etc.). A simple-but-practical optimization for fuzzer's internal logic is AFL persistent mode, where a long-live process can be reused to try out multiple test cases, eliminating the need for repeated `fork()` calls and the associated OS overhead [26].

Figure 1: The general work ow of coverage-guided fuzzing

2.2 Coverage Tracing

Coverage-guided fuzzers utilize coverage information to guide fuzzing. They track coverage of each execution, compare the coverage with preserved coverage, and check whether current test case is coverage-increasing. The most common approach to gain coverage information for fuzzing is instrumentation, which is taken variously by di erent fuzzers. For OS kernel fuzzing, Syzkaller [47] and

kAFL [43] instrument target kernel by hardware-assisted mechanisms (e.g. Intel PT [23]). For blackbox (source-unavailable) applications fuzzing, VUzzer [41] uses PIN [35] to dynamically instrument black-box binaries. For whitebox (source-available) applications fuzzing, libFuzzer and honggfuzz use SanitizerCoverage [19] instrumentation method provided by Clang compiler, and AFL implements instrumentation by hardcoding basic-block keys into the assembly le of target programs.

(a) code (b) basic-block level (c) edge level

Figure 2: Di erent coverage granularities provided by SanitizerCoverage. Basic-block level focuses on the coverage of each node, while edge level focuses on the coverage of the edge. Furthermore, an empty dummy block is inserted to denote a critical edge between two basic blocks.

Di erent instrumentation mechanisms provide di erent coverage granularities. SanitizerCoverage and AFL instrumentation method are two most widely-used coverage instrumentation mechanisms. SanitizerCoverage o ers basic-block level and edge level instrumentation. Figure 2 illustrates the mechanisms in a brief example. Basic blocks are the nodes of program's control- ow graph, denoting a piece of straight line code (i.e. there is no jump in or out of the middle of a block). SanitizerCoverage extracts control- ow graph of target program and instruments each basic block in LLVM IR when the basic-block level instrumentation is activated. To enhance instrumentation from basic-block level to edge level, SanitizerCoverage adds dummy blocks to denote critical edges, which is neither the only edge leaving its source block, nor the only edge entering its destination block. Unlike SanitizerCoverage, AFL instrumentation method tracks edge coverage directly. It assigns random keys to target program's basic blocks during static instrumentation, dynamically calculates edge keys through previous basic-block keys and current basic-block keys, and tracks edge counters in a 64K hash table by edge keys [14, 25]. AFL is also compatible with SanitizerCoverage [26].

3 MOTIVATIONS

Di erent coverage collection mechanisms trace di erent coverage granularities. The more accurate information gains through tracing coverage, the more overheads fuzzing faces. However, it is unclear how granularity relates to tracing coverage and overhead. An intuitive impression is that, fuzzers guided by di erent coverage granularities have di erent strengths when fuzzing di erent target programs. To verify our hypothesis, we conducted a preliminary experiment on di erent coverage granularities to evaluate each granularity's e ciency. Three di erent coverage collection instrumentation mechanisms are chosen in our experiment:

AFL (edge): the fuzzer is AFL and target programs are instrumented by original AFL's edge level instrumentation.
AFL (basic-block): the fuzzer is AFL and target programs are instrumented by SanitizerCoverage, using basic-block level instrumentation.
AFL (coarse-basic-block): the fuzzer is AFL and the target programs are instrumented by Untracer [39], which decreases time on handling discarded test cases but only obtains coarse basic-block level coverage without accumulating hit count.

We run above three mechanisms on Google fuzzer-test-suite [17] for 6 hours and select partial results for preliminary illustration (all experiment settings are in line with Section 5.1). From the result of Figure 3 and Table 1, we have the following observations:

Observation 1: tracing accurate coverage is costly . As illustrated in Section 2.1, coverage tracing and internal logic execution are two constituent part of fuzzer's runtime. We record AFL internal logic execution time during each iteration, and calculate edge level coverage tracing time by comparing each test case's execution time in instrumented version and non-instrumented version. As Figure 3 shows, time spent in tracing coverage accounts for averagely 71.85% of AFL's whole runtime. The ratio is even up to 98.5% when fuzzing openssl-1.0.1f .

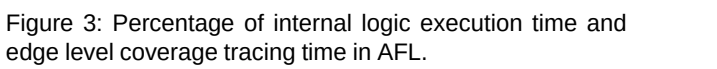

Figure 3: Percentage of internal logic execution time and edge level coverage tracing time in AFL.

Observation 2: the e ciency of each coverage granularity varies with target programs . We record the time spent in triggering known vulnerabilities for each mechanism, and the result is shown in Table 1. Due to the limitation of Dyninst [13], Untracer is incompatible with some projects (denote as N/A). From Table 1, we can see that: AFL (edge) exposes known vulnerabilities faster than others on openssl-1.0.1f and openssl-1.0.2d ; AFL (coarse-basic-block) exposes known vulnerabilities faster than others on guetzli . AFL (basic-block) exposes known vulnerabilities faster than others on lcms, pcre2.

Focus of this Paper: From the observation 1, we nd that tracing coverage is costly. In search for coverage-increasing test cases, fuzzing is based on genetic algorithm, which makes its e ectiveness highly impacted by execution speed. Thus, we focus on improving fuzzing e ciency by reducing the coverage collection overhead. We propose a novel self-modifying tracing mechanism to eliminate needless coverage collection. Besides, inspired by the observation 2, instead of doing a tradeo between fuzzing speed and coverage

Table 1: Time taken to trigger known bugs for fuzzers guided by different coverage granularities. 1 denotes the fuzzer cannot expose known bugs in 6 hours. N/A denotes compatibility issues of Untracer on specific programs.

Project	Average Reaching Time (seconds)		
	AFL (edge)	AFL (basic-block)	AFL+Untracer (coarse-basic-block)
c-ares	5	5	842
guetzli	1	1	16257
json	5	6	5
lcms	20679	4084	11827
openssl-1.0.1f	19	31	N/A
openssl-1.0.2d	8716	10407	N/A
pcre2	822	413	6095

accuracy, we propose a scheduling scheme, which helps fuzzers achieve both goals by integrating diversely-instrumented binaries.

4 ZEROR DESIGN

Figure 4: Overview of Zeror, which mainly includes the self-modifying tracing mechanism implemented with multiple instrumentation and coverage tracer, and the real-time scheduling mechanism implemented with the binary-switching scheduler. Multiple instrumentation means the self-modifying tracing based instrumentation and the full instrumentation of the integrated original fuzzer.

Figure 4 depicts the basic workflow and main components of Zeror. Different from traditional coverage-guided fuzzing, Zeror will choose a proper binary as fuzzing target (i.e. the running program for fuzzing) among diversely-instrumented binaries. Zeror consists of two main components: coverage tracer and binary-switching scheduler. (1) Coverage tracer collects coverage information from fuzzing target, stores seeds into corpus if the seeds are interesting and sends statistical data to binary-switching scheduler. It will self-adjust when fuzzing target changes: when fuzzing AFL-instrumented binaries, coverage tracer will read coverage from edge-counters hash table; when fuzzing the binaries instrumented by self-modifying tracing, coverage tracer will monitor the status of child process and modify the instructions of child process. (2) Binary-switching scheduler records the statistical data from coverage tracer, restimates efficiency of each instrumented binary based on the statistical data and choose the optimal binary as fuzzing target when time to switch binary. Specially, we leverage empirical Bayesian method to estimate efficiency in a cost-effective way and adopt exponential smoothing to smooth the time-varying efficiency.

4.1 Self-modifying Tracing

As aforementioned, coverage-guided fuzzing spends the majority of its runtime in collecting coverage. It is intuitive that restricting coverage tracing to only coverage-increasing test cases will significantly reduce the overhead. However, how to sense coverage-increasing seeds and ignore discarded test cases is still an open problem. Different with static binary rewriting technique used in Untracer [39], which is coverage-inaccurate, time-consuming and not scalable on many complex programs, our solution, namely self-modifying tracing, adopts self-modifying code technique to address the problem. With the assistance of self-modifying tracing, fuzzers could (1) dynamically remove visited instrumentation points during fuzzing process; (2) sense fine-grained coverage; (3) barely introduce new overhead.

Self-modifying code (SMC) refers to the code that can modify its own instructions during the execution of the program. It is widely used in many of software systems to support runtime code generation [27, 37] and optimization [3], minimize the code size [11], and reinforce dynamic code encryption and obfuscation [24]. There are several advantages in SMC, such as fast paths establishment, repetitive conditional branches reduction and algorithmic efficiency improvement. To apply SMC to coverage tracing, we need to obtain the addresses of instrumentation points at compilation stage, and self-modifying the addresses at runtime stage. A step-by-step example is shown in Figure 5 to elaborate how our solution performs self-modifying tracing with compilation stage and runtime stage.

At compilation stage , we need to generate a zero-overhead binary and obtain the addresses of instrumentation points. However, there are two challenges to be addressed. (1) How to inject instrumentation points into target program? Blackbox instrumentation will obtain redundant and less-accurate coverage information, which impair fuzzing performance. While instrumenting programs in a white-box way like AFL instrumentation [25] or SanitizerCoverage [19] will introduce costly overhead. Besides, using self-modifying code based on AFL instrumentation also obtains coarse-grained coverage because AFL only injects instrumentation points into basic blocks. Thus, an instrumentation approach which obtains fine-grained coverage and introduces less overhead is demanded. (2) How to track the addresses of instrumentation points? Compilers will deactivate some code optimizations as soon as any address of basic block is obtained, and the un-optimized binary will be executed at a low speed. Thus, we need to track the addresses of instrumentation points in a proper way.

Figure 5: A step-by-step demonstration of self-modifying tracing. It eliminates needless overhead spent in tracing coverage of non-coverage-increasing test cases with two stages. It first instruments target programs, obtains addresses of instrumentation points and generates a non-instrumented executable binary file at compilation stage. Then, it does fuzz testing on the binary, detects whether instrumentation points are triggered and removes visited instrumentation points at runtime stage. (The segments in blue rectangles is the text segments of the program's memory layout, the addresses of instrumentation points are highlighted in blue, the modified instructions are highlighted in red, the recovered instructions are highlighted in orange.)

To generate a zero-overhead binary and track the addresses of instrumentation points, it works as follows to compile a program from source code to object file:

> Inject instrumentation points. Before the compiler starts performing platform-independent code optimizations, we construct control flow graph and inject an instrumentation point, i.e. a CALL instruction to invoke callback function, at the start of each basic block. Note that, similar with SanitizerCoverage, the instrumentation could be enhanced from basic-block level to edge level by adding "dummy" blocks to denote critical edges as Section 2.2 illustrates. Instrumenting before code optimizations allows control flow graph to preserve semantics of source code so that coverage information is collected accurately.
> Record & Clear. We record the corresponding basic block symbols of injected CALL instructions and erase all the injected CALL instructions after compiler finishes platform-independent code optimizations at intermediate representation (IR) level. In this way, the generated IR could be non-instrumented while the recorded basic block symbols inherit the fine-grained coverage information from instrumentation points.
> Emit addresses. We obtain addresses of instrumentation points through the recorded basic block symbols, allocate a memory in the generated object file and emit the addresses into the memory after compiler finishes platform-dependent code optimizations at machine-specific intermediate representation (MIR) level. Note that, the addresses are a series of offsets in object file and will be relocated to absolute addresses when a linker generates executable binary. In this way, the addresses of instrumentation points are written in generated binary and could be accessed to perform self-modify tracing during runtime.

In the text segments after step 2 of Figure 5, we highlight four addresses (0x2b1980, 0x2b1984, 0x2b1994 and 0x2b1999) in blue to denote the addresses of instrumentation points. For simplicity, we only show basic-block level instrumentation; however, our solution enhances instrumentation from basic-block level to edge level by adding "dummy" blocks to denote critical edges. After compilation stage, a zero-overhead binary is generated and prepared for fuzzing.

At runtime stage, the coverage tracer of Zeror will execute the zero-overhead binary, inject breakpoints into it and perform fuzzing on this target. Algorithm 1 details the actions of the coverage tracer. First, as presented in lines 2-8, the fuzzer executes the binary, receives the addresses of instrumentation points, and replaces original instructions with 0xcc. The corresponding demonstration is shown in step 3 in Figure 5, the binary codes of instrumentation points are replaced with 0xcc (we highlight the instructions in red). Once the process executes 0xcc, it will trigger SIGTRAP interrupt, and wait for parent process to resume it. After the injection, the fuzzer performs fuzzing on the child process, and monitors the status of it. Once receiving SIGTRAP from child process, the fuzzer stores current input as interesting seed for further mutation, recovers the instruction that belongs to the address, and resumes child process, as presented in lines 11-18. The corresponding demonstration is shown in step 4 in Figure 5.

Within the self-modifying tracing, we maintain a set of instrumentation points which have never been visited (visitedAddrs in Algorithm 1) during fuzzing process. The set will tend to be an empty set as the fuzzer explores target program's states more deeply. Once a instrumentation point is visited, it will be removed and never be collected again. Besides, the self-modifying tracing does not introduce new overhead during fuzzing process. Therefore, along with the fuzzing process, it can theoretically eliminate coverage collection overhead almost down to zero.

Algorithm 1: Action of self-modifying coverage tracer

```
Input : the target binary 1
        Executor G42
/* A map to store (address, instruction) pairs */
033A initial()
G42 run(1)
033AB = receiveInstrumentedAddrs()
D=E8B8C43 3=3A033AB
/* Inject breakpoints into child process */
foreach 033A in 033AB do
    8=BC=A readInstrFromAddr(033A)
    033A"0?.insert(033A, 8=BC A)
    writeInstrIntoAddr(0G22, 033A)
end
async event loop
    if receive SIGTRAP from child process then
        readSeedAndStore()
        /* Recover the instruction */
        033A = readRip()
        8=BC=A 033A"0?.get(033A)
        writeInstrIntoAddr(8=BC, 033A)
        D=E8B8C43 3=3AD=E8B8C43 3=3AC033A
        G42 resume()
    end
end
```

4.2 Binary-switching Scheduling

Section 3 reveals that the e ciency of each coverage granularity varies with target programs. Inspired by this, we believe that switching among diversely-instrumented binaries during fuzzing process will improve fuzzing performance. However, estimating e ciencies of diversely-instrumented binaries is challenging, because: (1) program-dependent e ciency: the e ciency of each binary varies with target programs, thus we cannot share one static set of parameters con guration among di erent programs; (2) time-varying e ciency: even for testing one target program, the e ciency of each coverage granularity changes over time as the fuzzer explores target program's states more deeply; (3) cost-e ective solution: the solution should be cost-e ective and less-frequent due to the high throughput of fuzzing.

We propose a real-time scheduling mechanism to address above problems. In short, it adaptively switches fuzzing binary among diversely-instrumented binaries at set intervals. During fuzzing process, it collects statistical data (i.e. the number of interesting seeds, the number of executions and the time spent on fuzzing), dynamically monitors the number of interesting seeds each binary could discover, and choose an optimal binary as fuzzing target when the switch time is up. We leverage empirical Bayesian method to estimate e ciency in a cost-e ective way and adopt exponential smoothing to smooth the time-varying e ciency.

Estimate e ciency . To simplify the time-varying problem, we discretize continuous time into time periods and assume e ciency is invariant at each time period. For a binary, the e ciency at time period C is de ned as

$$4_C = \frac{C}{)_C} = \frac{C}{"_C} \frac{"_C}{)_C} = A_C \quad B \tag{1}$$

where $_C$ denotes the number of discovered interesting seeds during the time period C, $)_C$ denotes the time spent on fuzzing during the time period C, $"_C$ denotes the number of executions during the time period C, A_C denotes the quotient of $_C$ and $"_C$ (namely, interesting-testcases rate, or ITR), and B denotes execution speed which can be seen as a constant with respect to binary. Given a binary's statistical data $»_1 • _2 • \cdots • _{C¡1}¼$, $»_1 • _2 • \cdots •)_{C¡1}¼$ and $»"_1 • "_2 • \cdots • "_{C¡1}¼$ before current time period C, we aim to estimate ITR A_C, and further calculate the estimation of e ciency 4_C of the binary at current time period C through equation (1).

With empirical Bayesian methods, the integrals over conditional probability distributions are substituted by the empirical statistics in the observed data, which allows us to estimate the posterior probabilities, e.g. a binary's ITRs, by leveraging the information from its statistical data. For each binary, there is an underlying probability distribution of ITR, and at each time period C, the binary's ITR A_C could be regarded as a outcome of the distribution. We use Beta distribution to parameterize the generative process, de ned as $4C0U • V$. Besides, obviously, for each binary at time period C, the number of interesting seeds $_C$ obeys the Binomial distribution with parameters $"_C$ and A_C. Thus, we have a Beta-Binomial compound distribution for the statistical data. The generative process of our Bayesian model is described as follows:

$$\text{Sample } A \quad 4C0U • V, ?^1 A j U • V / \frac{^1U, V^o}{^1U^o \ ^1V^o} A^{U \ 1}{}_1 \quad A^{oV \ 1}$$
$$\text{Sample } \quad 8=><80;^1" • A^o, ?^1 j" • A^o / A^{1}{}_1 \quad A^{o"}$$

where $$ is Gamma function. Therefore, the likelihood over all number of interesting seeds is:

$$\begin{aligned} ! &= ?^1{}_1 • {}_2 • \cdots • {}_C j" {}_1 • "{}_2 • \cdots • "_C • U • V \\ &= \ddot{O}_{8=1}^{C \ 1} ?^1{}_8 j" {}_8 • A^o ?^1 A_8 j U • V 3 A_8 \\ &/ \ddot{O}_{8=1}^{C \ 1} \frac{^1U, V^o}{^1U^o \ ^1V^o} A_8{}^{8 \ 1}{}_1 \quad A_8{}^{o" \ 8} \quad {}_8 A_8^{U \ 1}{}_1 \quad A_8{}^{oV \ 1} 3 A_8 \\ &= \ddot{O}_{8=1}^{C} \frac{^1U, V^o}{^1" \ {}_8, U, V^o} \frac{^1 \ {}_8, U^o}{^1U^o} \frac{^1" \ 8 \quad {}_8, V^o}{^1V^o} \end{aligned} \tag{2}$$

Then, the maximum likelihood can be calculated through the fixed-point iteration (FPI) [38, 50]:

$$\begin{aligned} U_{G,\,1} &= U_G \acute{I} \frac{\ddot{O}_{8=1}^{C} »^1 \ {}_8, U_G{}^o \quad {}^1U_G{}^o¼}{\ddot{O}_{8=1}^{C} »^1" \ {}_8, U_G, V_G{}^o \quad {}^1U_G, V_G{}^o¼} \\ V_{G,\,1} &= V_G \acute{I} \frac{\ddot{O}_{8=1}^{C} »^1" \ {}_8 \quad {}_8, V_G{}^o \quad {}^1V_G{}^o¼}{\ddot{O}_{8=1}^{C} »^1" \ {}_8, U_G, V_G{}^o \quad {}^1U_G, V_G{}^o¼} \end{aligned} \tag{3}$$

where $^1G^o$ is the digamma function, and can be quickly calculated through Bernardo's algorithm [4].

With equation (3), the $\hat{U}$ and $\hat{V}$ could be iteratively estimated, furthermore, the posterior estimation of current time period's ITR could be calculated as $\hat{A}_C = \frac{C, \hat{U}}{"_C, \hat{U}, \hat{V}}$. To accelerate the convergence

speed of the iteration method, we use method of moments [26] to calculate the initial values $\hat{U}_0$ and $\hat{V}_0$. Besides, to smooth time-varying observed data, we leverage exponential smoothing [15] to calculate the smoothed number of interesting seeds:

$$s_n = \begin{cases} o_1 & n = 1 \\ \alpha \cdot o_n + (1-\alpha) \cdot s_{n-1} & n > 1 \end{cases} \quad (4)$$

where o_n is the observed number of interesting seeds, s_n is the smoothed number of interesting seeds which is used in equation (3). α $(0 < \alpha < 1)$ is the smoothing factor. As time passes the smoothed s_n becomes the exponentially decreasing weighted average of its past observations, in this way, we can capture time relationship between ITRs.

Once the posterior estimation of ITR R_C of the binary is estimated, the estimation of e ciency λ_C could be calculated through equation (1). Thus, at current time period C, we can estimate e ciencies of every diversely-instrumented binaries $s_C^1, s_C^2, \ldots, s_C^n$ and form a probability distribution by normalizing these e ciencies:

$$P(i) = \frac{s_C^i}{\sum_{j=1}^{n} s_C^j} \quad (5)$$

where s_C^j denotes the e ciency of binary j. When the time to switch, we can select the target binary for fuzzing according to the probability distribution.

Switch among binaries . Based on the e ciency estimation, we can implement the binary-switching scheduler, as detailed in Algorithm 2. First, as presented in lines 1-3, the scheduler randomly chooses several (in line with the con gurations) binaries and performs fuzzing on these binaries through executor. For each binary, the executor will fork a child process to test them, which is similar to AFL's fork server [26]. Then, the scheduler asynchronously listens events from executor and timer. Executor will periodically report statistics (number of executions, number of interesting seeds, time spent on fuzzing during the time period), and scheduler will record these statistics when receive them from executor as presented in lines 5-8. As presented in lines 10-18, when it is time to switch binary, the executor will stop its child processes, and then, the scheduler will calculate the posterior estimation of each binary's ITR and choose optimal binaries for fuzzing according to the probability distribution of equation (5). Note that, the scheduler supports not only running in single mode (i.e. single-core fuzzing) but also running in parallel mode (i.e. multi-cores fuzzing), which is more common in real industrial practice [31, 33].

Algorithm 2: Action of binary-switching scheduler

```
Input : List of diversely-instrumented binaries
        Executor G42
        Con gurations
1  B2 43D;4Initial( )
2  C0A64€B2 43D;4ChooseRandom(numCores)
3  G42run(C0A64)CB
4  async event loop
5      if receive statistics from executor then
6          18=0A~•BC0C8=BC82Bead()
7          B2 43D;4Record(18=0A~•BC0C)8BC82B
8      end
9      if time to switch binary then
10         G42stop()
11         foreach 1 in  do
               /* calculate the posterior estimation
                  of the binary's ITR                  */
12             U0• V0 = B2 43D;4CalByMoment1()
13             U• V= B2 43D;4CalByFPI(U0• V0)
14             A= betaExpectation(U• V)
15             B2 43D;4Update(1• A)
16         end
17         C0A64€B2 43D;4ChooseOptimal(.numCores)
18         G42run(C0A64)CB
19     end
20 end
```

5 EVALUATION

We implemented the framework Zeror . The instrumentation mechanism in self-modifying tracing is implemented on the top of LLVM 10.0.0 [18]. The Record&Clear procedure is implemented in the initialization of llvm::MachineModuleInfo and the Emit addresses procedure is implemented in the EmitBasicBlockStart method of llvm::AsmPrinter . We create a global variable to record the mapping of MBB Symbol (MCSymbol type) and MBB id (uint32_t type). The runtime logic of monitoring status of process and modifying instructions of memory in self-modifying tracing is based on ptrace . For scalability, the scheduler component contains the self-modifying based zero-overhead binary and the original fully instrumented binary of the integrated fuzzers such as AFL and MOPT. The interval of switching binaries and reporting statistical data are set to 600s and 60s respectively, which barely introduces new overhead and brings best performance after multiple attempts with di erent values. Inspired by the AFL persistent mode [26], our framework sets up a thread which runs ptrace task to monitor the status of child process. Once the child process triggers a crash or exceeds timeout limit, the thread will terminate and re-spawn the child process.

We evaluated Zeror in three aspects. First, we applied Zeror to AFL and compared the performance with two state-of-the-art fuzzing speed up frameworks, Untracer [39] and INSTRIM [22], to assess the e ciency. Then, we generalized Zeror to MOPT [36], a state-of-the-art fuzzer, to study the scalability. Finally, we evaluated the e ectiveness of each component of Zeror .

5.1 Experiment Settings

To reveal the practical performance of Zeror , the evaluation was conducted on fuzzer-test-suite [17], a widely-used benchmark from Google. This test suite consists of 24 popular real-world applications which have interesting known vulnerabilities, hard-to- nd code paths, or other challenges for bug nding tools. The initial seeds were collected from the built-in test suite and each source code inside the test suite was compiled with -O2 ag. To reduce the side e ect caused by AFL's le I/O overhead [51], all fuzzers were running in tmpfs. All experiments were performed on a 64-bit

Table 2: Fuzzing performances of di erent AFL-based fuzzing-speed-up methods.

Project	average execution time for each test case (ms)				number of covered branches			
	AFL	AFL+INSTRIM	AFL+Untracer	AFL+Zeror	AFL	AFL+INSTRIM	AFL+Untracer	AFL+Zeror
boringssl	96.69	69.68	N/A	33.05	2661	2694	N/A	2549
c-ares	43.34	25.42	13.95	16.32	57	57	55	57
freetype2	44.68	25.17	25.13	20.33	8255	9268	7007	10059
guetzli	99.92	67.98	45.80	41.00	4757	4845	4748	4987
harfbuzz	149.82	80.36	66.06	55.73	8148	8048	7195	9168
json	145.82	100.03	64.33	98.39	1315	1333	1152	1346
lcms	97.71	70.92	44.18	63.96	2115	2244	1436	2077
libarchive	193.44	112.50	112.90	112.72	1208	1119	1082	1618
libjpeg	1469.47	668.96	261.30	337.36	2364	2564	2399	2857
libpng	15.34	5.48	5.27	7.54	1092	1096	1029	1140
libssh	638.00	340.52	309.62	309.29	867	867	867	867
libxml2	268.07	135.05	N/A	88.13	4063	4318	N/A	4745
llvm-libcxxabi	137.61	81.61	43.75	42.04	6488	6005	6000	7012
openssl-1.0.1f	3418.66	1998.27	N/A	1948.43	4748	6745	N/A	7372
openssl-1.0.2d	161.09	92.48	N/A	63.23	1825	1828	N/A	1769
openssl-1.1.0c	210.70	89.74	N/A	50.60	1712	1711	N/A	1658
openthread	145.51	91.17	64.80	85.16	3561	3537	3279	3591
pcre2	199.12	102.21	53.86	49.11	6890	6888	6597	6890
proj4	23.22	14.24	8.47	7.86	2541	2584	2347	3886
re2	640.24	391.97	260.19	235.40	4608	4647	4533	4725
sqlite	221.18	160.84	136.01	141.40	1892	1997	1986	1972
vorbis	96.14	58.08	36.45	25.48	2035	2152	1817	2079
wo 2	31.55	20.12	11.80	8.67	2119	2152	1453	2157
wpantund	1921.02	2019.62	1544.89	1789.23	7959	7892	7802	8781
Zeror improvement	+159.80%	+50.70%	-0.46%		+10.14%	+6.82%	+20.84%	

Table 3: Time to expose known bugs, 1 denotes the fuzzer cannot expose the known bugs in 6 hours and the projects whose bugs can not be triggered by any fuzzer are removed.

Project	AFL	AFL+INSTRIM	AFL+Untracer	AFL+Zeror
c-ares	8	26	842	8
guetzli	1	1	16257	6001
json	5	5	5	5
lcms	20679	1	11827	10953
llvm-libcxxabi	788	2197	2347	709
openssl-1.0.1f	19	19	1	21
openssl-1.0.2d	8716	6877	1	6013
pcre2	822	1375	6095	439
re2	1	1	1	8194
wo 2	3565	1535	1	3260

machine with 40 cores (Intel(R) Xeon(R) Gold 6148 CPU @ 2.40GHz), 128 GiB of RAM and Linux 5.5.13. Due to the random e ects in fuzzing, we conducted each experiments for six hours and repeated it ten times. And we reported average performance.

In terms of metrics, we evaluate the performance of fuzzers in three aspects, namely execution time, branch coverage and time to expose known bugs. The execution time is the average time the `LLVMFuzzerTestOneInput` function consumed. Di erent fuzzers are guided by di erent coverage granularity, for fair comparison, we collect their generated seeds, feed the seeds to original AFL and gather the number of covered branches through AFL's `bitmap`. The time to expose known bugs is the time consumed by the fuzzer to trigger the rst crash.

5.2 E ciency of Zeror

We applied Zeror to AFL (namely AFL+Zeror) by switching between AFL-instrumented binary and self-modifying tracing instrumented binary based on binary-switching scheduler. We evaluated it on all the 24 programs of Google fuzzer-test-suite and compared it with two state-of-the-art fuzzing speed-up techniques, INSTRIM and Untracer. Speci cally, for the baseline AFL, the version used is 2.52b and the compilation tool chain is `afl-clang-fast` [26], which is the most e cient instrumentation method that AFL provide; for INSTRIM, we activate INSTRIM-APPROX mode, which shows best performance in their evaluations [22].

The results are presented in Table 2 and Table 3. The 2-5 columns of Table 2 show the average execution time per test case and the Zeror improvement in the last row refers to the execution speed increase. The 6-9 columns of Table 2 show the number of branches covered by each fuzzer and the Zeror improvement in the last row refers to branch increase. Table 3 shows the time taken by each fuzzer to expose known bugs, the projects whose bugs cannot be triggered by all the fuzzers in 6 hours are removed from the table. Note that, due to the limitation of Dyninst [3], Untracer is incompatible with some projects (including `boringssl`, `libxml2`, `openssl-1.0.1f`, `boringssl-1.0.2d` and `openssl-1.1.0c`), we denote the corresponding table cell as N/A. From the two tables, we can deduct the following conclusions:

- Zeror increases the execution speed of AFL. In Table 2, the average execution time of AFL+Zeror is less than AFL for every benchmark projects. Speci cally for `libjpeg`, the average execution time of AFL and AFL+Zeror are 1469.47 and 337.36 respectively, which indicates that Zeror increases the execution speed of AFL by 335.58%. Averagely, Zeror increases the execution speed of AFL by 159.80%.
- Zeror helps AFL cover more branches. In Table 2, AFL+Zeror outperforms AFL on 17 out of 24 projects. Specially, AFL+Zeror improves the number of covered branches by 55.27% on `openssl-1.0.1f` and 33.94% on `libarchive`. Averagely, AFL+Zeror increases the number of covered branches of AFL by 10.14%.
- Zeror helps AFL expose bugs faster. In Table 3, AFL+Zeror exposes known bugs faster than original AFL on 8 out of 10 projects.

Specially, AFL+Zeror is 1.87x faster than AFL in term of triggering the bug in pcre2, and exposes the bugs of c-ares-CVE-2016-5180 and guetzli-2017-3177, which cannot be exposed by original AFL in 6 hours.

Zeror shows better performances compared with other fuzzing speed-up techniques. Compared with INSTRIM, Zeror is averagely 50.70% faster for each execution, covers 6.82% more branches and spends less time on bugs exposure. Compared with Untracer, Zeror covers 20.84% more branches averagely and spends less time on bugs exposure. Because of the real-time scheduling, Zeror is averagely 0.46% slower than Untracer, which is almost negligible.

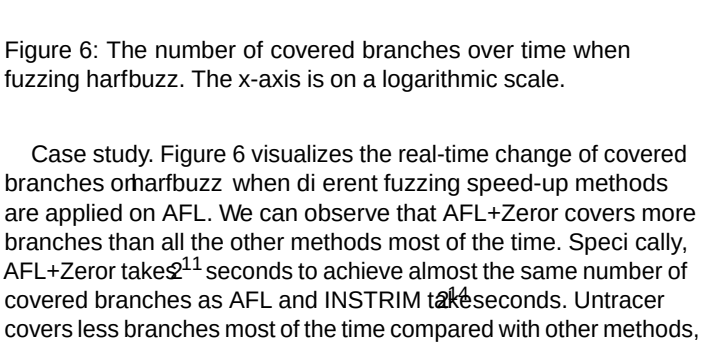

Figure 6: The number of covered branches over time when fuzzing harfbuzz. The x-axis is on a logarithmic scale.

Case study. Figure 6 visualizes the real-time change of covered branches on harfbuzz when different fuzzing speed-up methods are applied on AFL. We can observe that AFL+Zeror covers more branches than all the other methods most of the time. Specifically, AFL+Zeror takes 2^{11} seconds to achieve almost the same number of covered branches as AFL and INSTRIM take 2^{14} seconds. Untracer covers less branches most of the time compared with other methods, even compared to the original AFL. As demonstrated in Table 2, Untracer is the fastest for test case execution, but when it deletes almost all the instrumentation points, it will also lose the fine-grained coverage information such as hit count of branches for fuzzing guidance, and will greatly reduce the number of covered branches. INSTRIM makes AFL faster, but not as fast as Untracer and Zeror, and it reconstructs the coverage information for guidance with instrumenting a part of basic blocks, to partially maintain the ability to cover more branches.

From the above statistics, it is reasonable to draw the conclusion that: with the aid of Zeror, fuzzers are able to gain higher speedup, covers more branches, and exposes bugs faster. In addition, Zeror shows better performance of coverage increase and vulnerability discovery compared with other fuzzing speed-up techniques.

5.3 Scalability of Zeror

In addition to AFL, we also generalize our experiments to another state-of-the-art fuzzer, MOPT [36], to study the scalability of Zeror. MOPT is a fuzzer that improves fuzzing performance by optimizing the efficiency of mutation strategy. We applied Zeror to MOPT (namely MOPT+Zeror) in the same way as AFL+Zeror and evaluated it on all the 24 programs of Google fuzzer-test-suite. The results are shown in Figure 7 and Table 4. From Figure 7 we can observe that MOPT+Zeror improves the number of covered branches in 17 out of 24 projects and averagely increases the number of covered branches by 6.91% compared with the original MOPT. Specifically, MOPT+Zeror improves the number by 64.95% on proj4 and 40.45% on libarchive. Table 4 shows the time taken by MOPT and MOPT+Zeror to expose known bugs, those projects whose bugs cannot be triggered by them in 6 hours are removed from the table. From Table 4 we can observe that with the aid of Zeror, MOPT exposes known bugs faster. Specially, Zeror improves the speed of bug exposure by 2.39x on llvm-libcxxabi, 2.01x on pcre2.

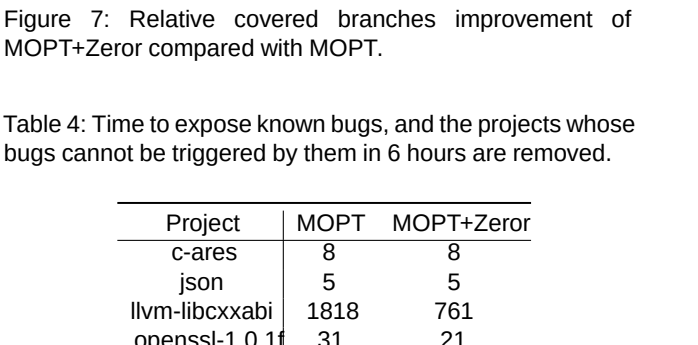

Figure 7: Relative covered branches improvement of MOPT+Zeror compared with MOPT.

Table 4: Time to expose known bugs, and the projects whose bugs cannot be triggered by them in 6 hours are removed.

Project	MOPT	MOPT+Zeror
c-ares	8	8
json	5	5
llvm-libcxxabi	1818	761
openssl-1.0.1f	31	21
openssl-1.0.2d	1633	1320
pcre2	1944	968
wo 2	3767	3196

In summary, Zeror is applicable to other fuzzing optimizations like MOPT, and more importantly, Zeror can further improve fuzzing vulnerability discovery performance on top of them. Although we only use MOPT for illustration in the experiment, it can be easily applied to other fuzzers such as AFLFast [5] and FairFuzz [28].

5.4 Evaluation of Individual Components

Zeror consists of two main mechanisms: self-modifying tracing and real-time scheduling. To analyze the effects of each individual mechanism, we configure two variants of our framework:

Zeror-represents the fuzzer which adopts AFL as seeds generator and only integrates self-modifying tracing mechanism.

Zeror represents the fuzzer which adopts AFL as seeds generator. Besides, it integrates self-modifying tracing and AFL's instrumentation to collect coverage, and dynamically switches between the two instrumented binaries during fuzzing process based on real-time scheduling mechanism.

Evaluation of self-modifying tracing . Since Untracer [39] shares the similar idea with our self-modifying tracing component, we evaluate our tracing by comparison with Untracer, using 19 projects of fuzzer-test-suite (Untracer is incompatible to the rest 5 projects). For speed improvement, both methods eliminate the coverage-collecting time of non-coverage-increasing test cases by erasing visited instrumentation points, but with di erent approaches. Figure 8a shows that, when considering erasing instrumentation points, self-modifying tracing saves much more time than Untracer on the average time consumed. Averagely, self-modifying tracing is 13.74x faster than Untracer when erasing instrumentation points. The saved coverage tracing time can be used for e cient binary-switch scheduling. Additionally, self-modifying tracing is edge-aware while Untracer is basic-block-aware. Figure 8b shows the relative covered branches improvement of self-modifying tracing, from which we can conclude that self-modifying tracing mechanism helps fuzzer cover more branches compared with Untracer. Speci cally, self-modifying tracing improves the branch coverage by 56.92% on proj4 , 48.43% on libarchive , 43.80% on lcms, 42.90% on freetype2 .

(a) Average time taken for di erent methods to erase instrumentation points (lower is better).

(b) Relative covered branches improvement of Zeror- compared with Untracer.

Figure 8: Comparison between Zeror- and Untracer.

Evaluation of real-time scheduling . Our scheduling mechanism integrates two binaries: the zero-overhead binary instrumented by self-modifying tracing and the original binary instrumented by the integrated fuzzer, and then dynamically switches between them. To study the e ectiveness of the scheduler, we compare Zeror with Zeror- and AFL. The overall result is consistent to Table 2, and for page limitation, we only visualize 2 projects to demonstrate the coverage increase process of di erent con gurations in Figure 9. Both Zeror- and Zeror cover more branches than AFL, and Zeror outperforms Zeror-. The visualization indicates that integrating two di erent instrumented binaries with the real-time scheduling helps fuzzers achieve better performance.

(a) libjpeg (b) harfbuzz

Figure 9: Branches covered over time with di erent con gurations. The x-axis is on a logarithmic scale.

5.5 Discussion

Although binary-switching scheduler is able to integrate multiple diversely-instrumented binaries, we applied Zeror to fuzzers by switching only between original instrumented binary and self-modifying tracing instrumented binary in our evaluation, which could not fully excavate Zeror's potentiality, but already demonstrates the e ectiveness of tracing and scheduling. Furthermore, even with the scheduling of two binaries, it improves both speed and coverage. Recently, Dines [12] proposed a novel approach of instrumentation, we plan to integrate it in the future.

(a) Number of covered branches over time. (b) Chosen probabilities of different binaries over time.

Figure 10: Case study on sqlite of AFL- Zeror .

Another potential concern is whether the scheduling mechanism can help fuzzer shift into proper binary. Figure 10 is the real-time visualization of covered branches and the chosen probabilities of diversely-instrumented binaries when AFL+Zeror is applied to test sqlite . We can observe that the chosen probability of the binary instrumented by AFL is in decline when the number of covered branches reaches the plateau at the time of 30min-60min, Zeror has high probability to shift into the faster binary (instrumented by self-modifying tracing) when the AFL-instrumented binary cannot make any process. The observation indicates that the scheduling scheme do help fuzzer properly choose binary for execution. However, the scheduling scheme only collects execution statistical data, which may not be su cient enough to fully display its e ciency. It could be further improved by gaining more information from data- ow analysis and control- ow analysis.

6 RELATED WORKS

Optimize fuzzing strategies . Existing optimizations of fuzzing reside in di erent stages. For the preparation stage, CollAFL [14] provides a solution to collect coverage feedback without bitmap collision, DeepFuzzer [32] leverages symbolic execution to generate quali ed initial seeds. For the seed selection stage, AFLFast [5] gives more mutation times to valuable seeds which exercise low-frequency paths, Cerebro [29] prioritizes seeds in corpus on the basis of static analysis and dynamic scoring. For the seed mutation stage, FairFuzz [28] mutates input seeds in a restricted way so that they are more likely to still explore the rarest branch, MOPT [36] nds the optimal selection probability distribution of operators with respect to fuzzing e ectiveness. Specially, a number of seed mutation optimizations leverage taint analysis such as REDQUEEN [2], Angora [7] and Matryoshka [8]. REDQUEEN [2] uses a lightweight input-to-state correspondence mechanisms as an alternative to data- ow analysis, Angora [7] adopts byte-level taint analysis and a gradient-descent algorithm for constraint penetration, Matryoshka [8] identi es nesting conditional statements by control ow and taint ow and proposed three strategies for mutating the input to solve path constraints.

Boost fuzzing speed. Xu et al [51] design three new operating primitives to solve the performance bottlenecks of parallel fuzzing on multi-core machines. INSTRIM [22] reduces instrumentation cost by selectively instrumenting a part of basic blocks and reconstructing coverage information. Untracer [39] avoids tracing coverage of non-coverage-increasing test cases by removing visited instrumentation points.

Main di erences . Optimizations of fuzzing strategies are orthogonal to Zeror , and most of them could also bene t from Zeror . For example, the experiment results show that, with the aid of Zeror , MOPT achieves better performance of coverage exploration and vulnerability discovery. Di erent from INSTRIM and Untracer, our study aims to boost fuzzing speed while preserve ne-grained coverage collection. Although Untracer has a similar idea with our self-modifying tracing component, rather than static binary rewriting, our tracing relies on self-modifying code to erase visited instrumentation points, which barely introduces new overheads and provides more ne-grained coverage collection. With the novel binary-switching scheduler, more improvements can be achieved.

7 CONCLUSION

In this paper, we propose a coverage-sensitive fuzzing framework Zeror , which integrates diversely-instrumented binaries to boost fuzzing speed and further improve the vulnerability discovery. Zeror is mainly made up of two parts: (1) a self-modifying tracing mechanism to provide a zero-overhead instrumentation for coverage collection; and (2) a real-time scheduling mechanism to select the proper instrumented binary for fuzzing on the basis of empirical Bayesian inference. In the experiments of fuzzing projects from Google fuzzer-test-suite, results show that with the aid of Zeror , fuzzers are able to gain higher speedup, cover more branches, and more importantly, expose bugs faster than the existing speed-up techniques. It can be applied to most of the existing fuzzers. In our future work, we plan to complement Zeror with other orthogonal fuzzing optimizations.

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