Systematic Assessment of Fuzzers using Mutation Analysis

Philipp Görz[1], Björn Mathis[1], Keno Hassler[1], Emre Güler[2],
Thorsten Holz[1], Andreas Zeller[1], and Rahul Gopinath[3]

[1]CISPA Helmholtz Center for Information Security, Germany
[2]Ruhr-Universität Bochum, Germany
[3]University of Sydney, Australia

Abstract

Fuzzing is an important method to discover vulnerabilities in programs. Despite considerable progress in this area in the past years, measuring and comparing the effectiveness of fuzzers is still an open research question. In software testing, the gold standard for evaluating test quality is *mutation analysis*, which evaluates a test's ability to detect synthetic bugs: If a set of tests fails to detect such mutations, it is expected to also fail to detect real bugs. Mutation analysis subsumes various coverage measures and provides a large and diverse set of faults that can be arbitrarily hard to trigger and detect, thus preventing the problems of saturation and overfitting. Unfortunately, the cost of traditional mutation analysis is exorbitant for fuzzing, as mutations need independent evaluation.

In this paper, we apply modern mutation analysis techniques that pool multiple mutations and allow us—for the first time—to *evaluate and compare fuzzers with mutation analysis*. We introduce an *evaluation bench* for fuzzers and apply it to a number of popular fuzzers and subjects. In a comprehensive evaluation, we show how we can use it to assess fuzzer performance and measure the impact of improved techniques. The required CPU time remains manageable: 4.09 CPU years are needed to analyze a fuzzer on seven subjects and a total of 141,278 mutations. We find that today's fuzzers can detect only a small percentage of mutations, which should be seen as a challenge for future research—notably in improving (1) detecting failures beyond generic crashes and (2) triggering mutations (and thus faults).

1 Introduction

Fuzzing is the key method to test the robustness of programs against malformed inputs. Since it reveals inputs that crash or hang programs, and as these failures can often be turned into actual exploits, fuzzing is also the prime method to discover security vulnerabilities. However, fuzzing is computationally expensive. Hence, researchers and practitioners must be able to determine which fuzzing tools and techniques are the most effective. In a recent survey, 63% of fuzzing practitioners [1] named *measures for fuzzer comparison* as one of the top three challenges that need to be solved.

Testing techniques, including fuzzers, are often assessed by obtained *code coverage* [2]. Code coverage refers to the number of program elements that were exercised by the fuzzer (we treat code coverage in detail in Section 2). This is reasonable because in order to find a bug at some location, the test must cover this very location in the first place. But code coverage alone is not sufficient to actually find bugs. Coverage on its own cannot evaluate the quality of sanitizers (used as bug oracles in fuzzing) or fuzzers set up to produce inputs specifically crafted to induce bugs [3, 4]. Furthermore, there is only a moderate association between bugs and coverage when using test generators: Previous research shows a correlation coefficient $R^2 = 0.72$ between Randoop generated test cases and mutation score [5]. Another alternative to evaluate fuzzers is to run them on a benchmark of programs with *known faults* and compare fuzzers by bugs found [2, 6, 7]. A general concern with such approaches is that the distribution of available faults may not be uniform or related to the actual possible fault distribution in the program [8]. Furthermore, when the faults are known in advance, we run the risk of fuzzer parameters or even the technique itself being fine-tuned to find these faults [9, 10, 11, 1].

In software testing, the technique of *mutation analysis* has established itself as the gold standard to evaluate tests and test generators [12]. In mutation analysis, *synthetic faults* (mutations) are injected into the program code by creating random variations (so-called *mutants*). The assumption is that a test set should be able to detect ("kill") these mutations, just as it should be able to detect real faults. As an example, Listing 1 shows a number of possible mutations for a C code fragment. We see that mutations such as changing the type of a variable (①) or manipulating a comparison (②, ③) may all impact the ability of a program to handle invalid inputs. A good test set should be able to trigger these faults; and the more mutants a test set detects ("kills"), the higher its quality.

```
1 ① unsigned int len = message_length(msg);
2 if (len ② < >= MAX_BUF_LEN ③ + 16) {
3     copy_message(msg);
4 } else {
5     // Invalid length, handle error
6 }
```

Listing 1: Mutations in C code. Mutation ① deletes `unsigned`; mutation ② replaces `<` with `>=`; mutation ③ adds `+16`.

In contrast to coverage metrics, mutation analysis also assesses the ability of the tests to *detect* the (injected) faults. Indeed, a test can have 100% coverage, but if it does not check any computation result, it will fail to detect errors. In a fuzzing context, mutation analysis thus also assesses whether the fuzzer can detect issues beyond generic errors. And in contrast to curated faults, tests cannot overfit, as the actual mutations being applied are many, diverse, and randomly distributed. This lack of *bias* in mutations (i.e., anything can happen, anywhere) is often touted as a big advantage of mutation analysis. However, while it may be tempting to model mutants after past fixes [13, 6], this biases test assessment towards past issues, which in turn puts less weight on the ability of tests to find yet *unknown* issues. (We are not aware how the Heartbleed [14], "goto fail;" [15], or log4shell [16] vulnerabilities could have been predicted from past issues.)

Several studies have confirmed the correlation between the ability to detect (mostly simple) mutations and the ability to detect (possibly complex) real faults [17, 18, 19]; and several works have explored how mutation analysis can be applied to security testing [20, 21, 22, 23, 24, 25]. Yet, mutation testing has a significant drawback: It is *expensive*. Every single mutation induces a code change that needs to be evaluated by an entire run of all tests to assess whether they detect the mutation—and this must be done for thousands of mutations. Multiplied with the dynamic tests produced by fuzzers, this makes mutation analysis *prohibitively expensive* for evaluating fuzzers. Furthermore, fuzzers can react to faults [4, 3, 26], limiting traditional avenues for optimizations in mutation analysis that assume static test suites. Recent advances in mutation analysis, however, can significantly reduce this complexity. Notably, the concept of a *supermutant* [27] enables us to evaluate multiple mutants together in a single test run. The idea is to group together mutations that are unlikely to interact and fuzz them in parallel. Also, we can proceed in multiple phases, first having the fuzzer quickly achieve maximum coverage, producing a seed corpus for the next phase. This seed corpus is then used as a static test suite to kill trivial mutants, leaving the few remaining ("stubborn") ones as potential fuzzing targets.

In this paper, we show that such optimizations actually allow us to apply *full mutation analysis to evaluate and compare fuzzers at scale,* using a myriad of *unbiased mutations* that assess the ability of a fuzzer to find any kind of bugs, including, but not limited to, software vulnerabilities. Our approach is implemented and available as a large-scale evaluation bench for fuzzers. We demonstrate the usefulness of the evaluation bench by applying it on a number of popular fuzzers (AFL, AFL++, libFuzzer, and Honggfuzz) and test subjects (`cares`, `vorbis`, `woff2_new`, `libevent`, `guetzli`, `re2`, and `curl`). We show that it is possible to conduct a full-scale evaluation and comparison of these fuzzers using 16.36 CPU years of computation time, just under a month with our available hardware—a nontrivial, yet affordable amount of resources and a first step toward making mutation analysis a feasible solution for comparing fuzzers. To the best of our knowledge, the present work thus

- is the first study to apply mutation analysis to fuzzers, using traditional mutation operators as well as operators from a security context (a total of 31 operators);
- identifies the limitations of traditional mutation analysis optimizations when used for fuzzer comparison;
- develops novel optimization strategies for mutation analysis when mutation analysis is used for fuzzer comparison (we show that these optimizations can make mutation analysis usable for fuzzer comparison);
- demonstrates that fuzzers indeed differ in their ability to detect mutations, and consequently, faults;
- shows that improvements in failure detection—notably the use of sanitizers—result in a better mutation detection.

These results demonstrate that our evaluation bench can be used to compare fuzzer performance and evaluate improvements of different tools.

In our study, we also found that only a small percentage of mutants is detected by at least one of the fuzzers. The best fuzzer in our evaluation, AFL++, covers 30.9% of all mutations and detects 28.3% of these covered mutants—that is, 8.8% of all mutations. These numbers may seem low on an *absolute* scale. However, note that mutation analysis produces *shallow mutants* that are easy to find, but also *deep mutants* that are very hard to trigger, as well as *subtle mutants* whose effects can be hard to detect. There even are mutants that, although altering the *syntax* of code or output, leave their *semantics* untouched, and hence cannot be detected by any approach in the first place. While a mutation detection rate of 100% is thus unlikely to ever be achieved, the detection rate is very useful as a *relative* measure to compare approaches and measure progress. In our study, for instance, using an enhanced oracle such as Address Sanitizer (ASAN) [28] results in a moderate improvement in detection to 34.2% of covered mutants (9.1% of total mutants).

We find that our results reveal important directions for research in fuzzing:

- First, *fuzzers can profit from better oracles*—that is, predicates that check for the presence of failures. Right now, fuzzers that use *generic oracles*, such as crashes or hangs, are quite limited because not every vulnerability (and

not every mutation) manifests itself this way. Our manual analysis shows that out of the mutants that were not detected, few could have been found by a crash oracle, see Section 5.2.1. However, a majority of these mutants would *still produce a behavioral divergence* from the original program and hence can represent a vulnerability in a security context.

- Second, *fuzzers can profit from more targeted intelligence*—that is, generating inputs based on possible bug locations. Out of all mutants killed by AFL++ (28.3% of covered mutants), 94.4% were found with inputs generated on an unmutated binary. That is, at most 5.6% of the mutants were killed because of targeted intelligence such as crafted inputs [3] or directing fuzzers towards potential problems [4, 26]. This is significant because, according to an analysis of our syntactic fault patterns, we find that 71 of 100 recent CVEs were *coupled* to a mutation. Hence, fuzzers could significantly benefit from better targeting.

In summary, mutation analysis provides *ambitious* and *unbiased* goals for fuzzing and testing that are not susceptible to saturation or potential overfitting—and thus pose great challenges for future research. Our optimizations of mutation analysis, as introduced in this paper, provide researchers and practitioners with the means to determine whether and which fuzzers meet these challenges. Our evaluation bench is available at `https://github.com/CISPA-SysSec/mua_fuzzer_bench` to help assess future progress in the field.

2 Technical Background

We use the IEEE 1044 [29] nomenclature: A *fault* is a code artifact causing a *failure*. A *failure* (aka *bug*) is an incorrect program behavior. An *error* is a human action that led to the fault. An *error model* defines the kinds of faults expected.

Given a limited computing budget, a fuzzing practitioner needs to choose a fuzzer that is most likely to find the most bugs, which is typically accomplished using *coverage criteria* or a set of curated bugs [8], which we discuss next.

2.1 Coverage Criteria for Fuzzer Comparison

Coverage, or code coverage, refers to the number of program elements in the program under test (PUT) that were exercised by the input or set of inputs. Some program elements typically considered are statements, basic blocks, branches, and unique acyclic paths through the program. The idea is that code coverage provides an indication of the amount of program code that was explored.

Numerous coverage criteria exist [5] that can be used for judging the effectiveness of test suites and test generators, such as fuzzers. Most feedback-driven fuzzers, such as AFL, use some form of code coverage for guidance. Hence, code coverage achieved in target programs can be seen as a reasonable criterion for comparing fuzzers. The main problem with using code coverage, however, is that it is insufficient on its own for evaluating fuzzers. In particular, code coverage is unable to judge the quality of oracles such as sanitizers. They make bugs detectable (e.g., ASAN detects many kinds of memory handling errors), which is critical to ensure effective fuzzing. Another limitation is coverage saturation. That is, once a program element is saturated, there is little extra information available [30]. Many fuzzers [4, 31, 3] include intelligence to craft inputs (e.g., calling an API with invalid values), which, while important, is invisible if coverage is used for fuzzer comparison.

2.2 Benchmarks Using Curated Faults

Fuzzers can be evaluated using curated fault benchmarks [2, 32, 7, 33]. However, such benchmarks are inherently limited to known faults. As specific benchmarks are used to measure the effectiveness of a technique, the published improvements in the technique can become influenced by the benchmark in non-obvious ways. For example, if faults are mined from existing ones, the result might be numerous faults or types of faults that are easy to detect. Further, if a given tool (such as AFL) was used to find and eliminate faults during development, these faults are no longer in the set mined from released versions—which does not mean that the effectiveness of the tool has reduced. For example, exchanging AFL for another tool that does well on such mined faults (but not necessarily on the faults already removed during development) may not produce the improvement a practitioner was hoping for.

That is, both bug-based and coverage-based techniques have inherent limitations. Next, we discuss how mutation analysis can overcome these.

2.3 Mutation Analysis

Mutation analysis is a key technique for evaluating the fault-revealing power of test suites on a given program. It is the premier method of test suite evaluation in both the industry [34, 35, 36] and the research community [12]. It is a white-box technique that can be used to evaluate test suites when the source code of the program under test is available.

For mutation analysis, we start with the following *error model*: Any token in a program is a possible location for a fault to exist, and faults are likely caused during transcription of the concept in the developer's mind to the code artifact. Further, we assume that the developer uses automatic tools such as compilers, which removes some categories of faults. This gives us a way to generate possible faults with minimal human bias[1]: Generate all instances of a fault type

[1] There remains an unavoidable human bias due to the selection of fault types. However, generating instances of a fault type avoids bias as it is done exhaustively.

We define the following mutation related terms that we use throughout this paper:

Mutation. A small syntactic change that can be induced in the program.

Mutation operator. Transformation pattern that describes how mutations are induced in the program. A mutation operator, when applied to a matching location in the program, will produce a *mutant*.

Mutant. A new program that contains differences (mutations) from the original. A *first order* mutant contains only a single mutation. A *higher order* mutant contains multiple mutations. A *supermutant* contains all possible mutations that can be applied at once.

Trivial mutants. Mutants that can be killed without targeted intelligence. That is, any input whose execution covers their location will kill them.

Stubborn mutants. Mutants that remain alive even after coverage reached their mutation locations.

Intelligent mutants. Mutants killed by fuzzers on individual evaluation (i.e., they are not killed simply by covering their location).

Equivalent mutants. An equivalent mutant is a mutant that, while different from the original program syntactically, has the same semantics.

Mutant kill matrix. A mutant kill matrix (and similarly mutant coverage matrix) is a matrix with test cases as columns and mutants as rows. A mutant that is killed by a test case is assigned `1` in the relevant cell (else `0`) [37].

Minimal test suite. A minimal test suite with respect to a given set of mutants and a given test suite containing simple test inputs is the smallest subset of test inputs that is required to kill the *exact same mutants* as the given test suite [37].

Minimal mutant set. A minimal mutant set with respect to a given set of mutants and a minimal test suite is the smallest subset of mutants that is required to maintain the minimal test suite [38].

for each source code element that will get past the compiler. However, many faults in the real world can be complex, containing multiple sub-faults. Modeling them with complex faults containing multiple sub-faults can lead to a combinatorial explosion, which can be avoided by depending on two well-studied axioms—the *finite neighborhood hypothesis* and the *coupling effect*. The *finite neighborhood hypothesis* (also called *competent-programmer hypothesis*) states that faults, if present in the program, are within a limited edit distance away from the correct formulation [39]. The *coupling effect* claims that simple faults are coupled to complex faults, such that tests capable of detecting failures due to simple faults will, with high probability, detect the failures due to complex faults. Hence, the probability of fault masking is very low [40]. Both axioms are well researched, with well-founded theory [41, 42, 43, 44], and confirmed in real-world software [45, 44, 46, 47]. With these two axioms, we can limit the faults we need to test. This allows us to focus on changes to the smallest program elements, such as tokens and statements, and still expect that the created mutations are representative of real bugs.

Given this error model, the idea of mutation analysis is to collect possible fault patterns (a single fault pattern is called a *mutation operator*), identify possible faults in the program (called *mutations*), generate corresponding faulty programs (called *mutants*) each containing a single *mutation*, and finally evaluate each *mutant* separately using each fuzzer and check whether the fuzzer is able to detect the changed behavior of the mutant (called *killing the mutant*).

In summary, we can use the huge body of work on mutation analysis as an effective method to compare fuzzers by using the number of mutants killed by each fuzzer as the criterion.

2.3.1 Computational Requirements

Cost is a major concern with mutation analysis, as each mutant needs independent evaluation. Furthermore, for fuzzing, we need to evaluate each produced input independently on each mutant. We cannot tell if a mutant will be killed by an input without executing the mutant on that input. Indeed, we cannot even assume that the fuzzer will produce the same input on both the original and the mutant because the fuzzer may detect the mutation in the program and take steps to induce failure on a perceived fault. That is, the number of program executions effectively increases quadratically with program size.

There are several traditional optimizations to make mutation analysis less costly. However, these techniques assume static test suites, which makes them inapplicable to fuzzers. For example, the most effective optimization is to find the statements in the program that are covered by the specific tests in the test suite, then only run tests against mutants they cover (or that lead to a state infection [48]). This technique is inapplicable to fuzzers because fuzzers are non-deterministic, and the possibility of introspection on the source code for input generation might result in different inputs for the original and the mutant (violating the clean program assumption [47]). The same problem affects usage of *weak mutations* [49], split stream execution [50, 51], equivalence modulo states [52], and function memoization [53]. Thus, these traditional optimization techniques do not work well for fuzzers. We describe in Section 3 how we still achieve a significant reduction of computation time by using supermutants [27].

2.3.2 Residual Defects

One of the main reasons for using mutation analysis is that it provides the best estimate for the number of *residual defects*. The residual defects are defects that remain in a program after testing is completed and all found defects have been fixed [54, 55]. Undetected faults that mirror a mutation (a single incorrect token) are accounted for with our approach, as all mutations are applied to a program exhaustively. The larger and more complex types of faults are also subsumed by these mutations due to the *coupling effect* hypothesis (see Section 2.3). That is, the number of mutants that remain undetected tracks the number of residual defects closely and can be considered a *true ordinal measure* [54, 56] of the number of residual defects in a program.

We also note that the residual defect density can be estimated from the number of mutants found using statistical estimation tools, such as *population estimation* [57] and *species richness* estimation as suggested by Böhme [58].

2.3.3 Design of Mutation Operators

Mutations are typically modeled on human errors such as exchanging a token in the source code for another or forgetting to add a statement. Some traditional mutation operators are carefully chosen so that a test suite capable of detecting the resulting mutants also satisfies statement, branch [59], data-flow [60, 61], and various logic criteria [62]. That is, the test objective represented by a given criterion can be satisfied by the detection of a subset of mutants [12]. In addition to the traditional operators, operators that reflect known fault patterns in specific domains [12] are also chosen.

2.3.4 Equivalent Mutants

One of the problems with traditional mutation analysis is equivalent mutants. These are mutants that are semantically the same as the original program. For example, in the following fragment,

```
1 if (cache.has(key)) return cache.get(key);
2 return compute(key);
```

removing the cache check need not induce a failure. Previous studies show that 10% to 23% of generated mutants could be equivalent [63, 64], which can limit the usefulness of the mutation score (the absolute number of mutants killed).

We do not expect equivalent mutants to be a concern (beyond computational expenditure) for the following reasons: (1) In fuzzer *comparison*, only the *relative mutant kills* matter. (2) We manually analyzed a random sample of 100 stubborn mutants and found only 11 equivalent mutants. This is also in line with the literature [63, 64]. Our analysis (in Section 5.2.1) provides statistical confidence ($89 \pm 6\%$ CI at 99% CL) that most of the generated mutants induced faults.

3 Approach

We now describe how to evaluate fuzzers using mutation analysis with security-relevant mutations. This requires answers to three questions: Which mutations to apply? How to detect if they are found? And, how to reduce the required computational effort?

3.1 Selecting Mutation Operators

As fuzzers are mainly used to detect security issues, we create mutations that focus on generating vulnerable code to compare different fuzzers. We started with the traditional mutation operators representing common programming errors as the baseline. Next, we went through the list of Common Weakness Enumerations (CWEs) for C [65] and C++ [66], creating mutations for interesting and feasible vulnerability types. Finally, we investigated recent CVEs for C and C++ projects and added unrepresented mutations modeling vulnerabilities that have been reported.

Our set of patterns can be grouped into seven types of mutations: *Compare patterns* (for example, increasing the right-hand side of a signed $<=$ comparison), *memory patterns* (modifying calls to allocation or de-allocation functions to trigger out-of-bounds, double free, or use-after-free issues), *control flow patterns* (deleting function calls or flipping branch conditions), *assignment patterns* (deleting variable assignments, changing comparisons into assignments, etc.), *library call patterns* (e.g., provoking a failure to test if return values are checked), *synchronization patterns* (removing locking operations or making atomics non-atomic), and *arithmetic patterns* (for example, turning a signed variable unsigned). The full list of currently supported mutation operators can be found in Table 10 in the Appendix.

3.2 Detecting Mutations

Another essential component is the detection of true mutant kills. To make this process robust against the possibility of targeted manipulation, it must be performed in a manner that makes it challenging for fuzzers to cheat. For instance, if we classify a mutant as killed when the fuzzer reports a crash, it would be trivial for a fuzzer to just report a crash in every run. Similarly, we cannot base this decision on a version of the subject that has been instrumented by a fuzzer, as the fuzzer could itself introduce a crashing change during the instrumentation process. Thus, to confirm any input that a fuzzer reports as crashing, the input is rerun on the non-instrumented version of the original as well as the mutant (see Section 4 for a detailed description). A mutation is killed if the original exits with a different exit code than the mutant does. We require the original to exit without an error signal to avoid the case that there is a crashing bug in the original.

3.3 Reducing Computational Requirements

We reduce the computational requirements by using two techniques: Split Analysis and Supermutants.

Split Analysis The analysis of fuzzer performance is split into two phases:

I. How much of the program is the fuzzer able to cover?

II. Does the fuzzer identify injected faults?

For Phase I, we are only interested in finding the maximum obtainable coverage, and for that, we use the fuzzer under test on the original program to generate a set of seed files that cover as much of the program as possible (called *coverage seeds* from now on). Since no known faults are present, the incentive for the fuzzer is purely to cover the maximum amount of source code. Next, we use the coverage seeds as a static test suite, where we can apply traditional mutation analysis optimizations and quickly remove any mutants that are killed by the coverage seed files. This allows us to eliminate trivial mutants (those that only need coverage to crash), which are a significant chunk of the total set of mutants, with limited computational overhead.

In Phase II, we use the coverage seeds as the starting point to fuzz the remaining stubborn mutants. This ensures that if the fuzzer contains "intelligence" to recognize and target the inserted fault, it can use that intelligence to find and kill the mutation. This method accounts for fuzzers that go beyond coverage and use advanced code analysis to guide fuzzing.

Supermutants. We use an approach based on supermutants [27] to evaluate mutants with fewer computational resources than traditional analysis. The basic idea is to identify independent mutations and combine them into supermutants to allow a sound evaluation of multiple mutations without fault interactions for the compute cost of a single mutant.

We identify two mutations as independent if no seed input covers both mutations during execution (for more context, see Section 4). Depending on whether mutations were covered in Phase I, we create supermutants as follows: Covered mutations are combined into supermutants if they are mutually independent. Non-covered mutations form supermutants by randomly choosing 100 mutations. In both cases, a function contains at most one mutation (due to a technical limitation of our mutation engine).

If during Phase II, we find that a supermutant cannot be killed, we mark all mutations in this supermutant as alive. Otherwise, we identify the particular input or test case that killed it. If more than one of the included mutants was covered, indicating a derivation from the initial identification, we split up the supermutant and re-run the crashing input on the resulting mutants. The fuzzing process is restarted for any surviving mutants, which removes the possibility of multiple mutations interfering with each other.

4 Implementation

Our chosen subjects are C and C++ projects to cover programs that are affected by memory corruption vulnerabilities. We implemented an LLVM pass to find mutation locations (*mutation finder*) and another pass to do the actual code changes (*mutator*). See Figure 1a for an overview of the compilation process. The mutation finder identifies all mutation locations and possible mutations and assigns an ID to each of them. It also produces an executable (location executable) with logging code in place of the actual mutation that can be used to check which mutations are covered for a given input. One comparison executable without any mutations is compiled using the base compiler. Given mutation ID(s), the mutator produces the corresponding supermutant bitcode file. The bitcode file is then compiled with a base compiler to create a mutated executable for comparison, and each fuzzer compiles its own instrumented version. To decide which mutations can be put together into one supermutant, we run all seed inputs on the executable produced by the mutation finder.

To evaluate a mutation, we need to know if the mutation has been covered and whether it has been killed. An overview of this process is shown in Figure 1b. During fuzzing, we check if a mutation is covered using the mutated executables. To decide if a mutation has been killed, we rerun inputs that a fuzzer reports as crashing on the unmutated and mutated executables.

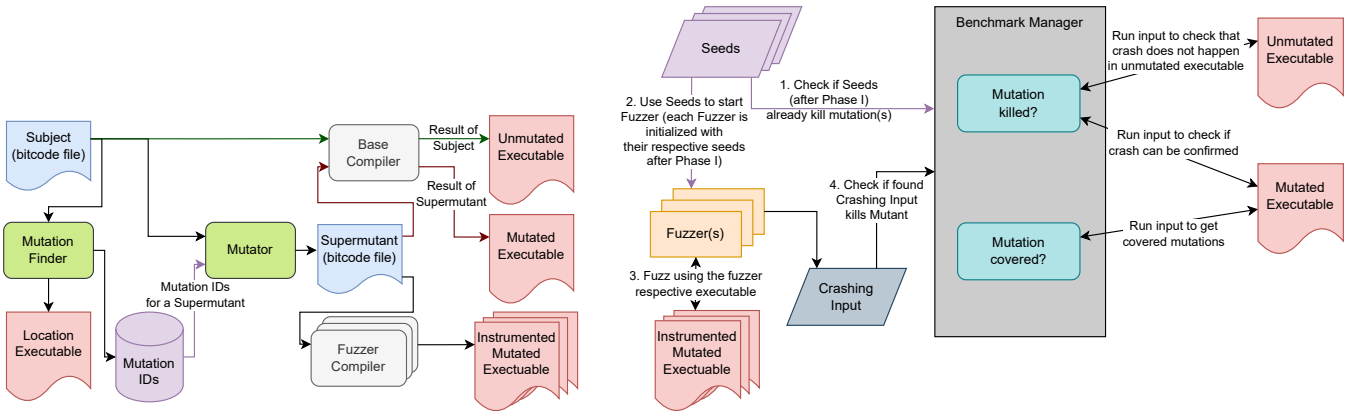
5 Evaluation

Our evaluation seeks to answer the central question: *How well can fuzzers be compared using Mutation Analysis?* We evaluate four research questions to study mutation analysis as a comparative metric for fuzzer evaluation.

RQ1. *How do different fuzzers compare in killing mutants?* The question has three parts: (1) what percentage of mutants were killed in Phase I, (2) what percentage of the remaining mutants were killed in Phase II, and (3) how do the killed mutant sets intersect between different fuzzers?

RQ2. *How much can sanitizers improve the results?* Inputs generated by a fuzzer account for only a part of the toolchain. Detecting bugs requires some kind of oracle, ranging from simple crash feedback to more sophisticated sanitizers. With this question we want to assess if we can measure sanitizer influence.

RQ3. *How many real vulnerabilities are coupled to mutations?* For mutation analysis to be useful, the mutations it produces should be semantically coupled to some real faults. That is, for any real fault, there should exist a mutation such that detecting the mutation guarantees detecting the real fault [45]. Hence, this question seeks



(a) The different executables created from a single subject.

(b) Steps taken to evaluate mutations.

Figure 1: Schematic overview of the compilation and evaluation process.

Table 1: Overview of the subjects used for evaluation. LOC as counted by cloc [68], taking the sum of C/C++ lines.

Subject	Description	Version	LOC
`cares_name`	DNS query creation	809d5e84	62,749
`cares_parse_reply`	DNS reply parsing	809d5e84	62,749
`woff2_new`	Font Format	4721483a	39,373
`libevent`	Event Notification	5df3037d	56,881
`guetzli`	JPEG Encoder	214f2bb4	8,029
`re2`	Regular Expressions	58141dc9	27,545
`curl`	Data Transfer	curl-7_83_1	151,413

to understand whether we have succeeded in capturing the characteristics of real-world vulnerabilities with our mutation operators.

5.1 Setup

We describe our experimental setup next.

Subjects. For our experiments, we looked for robust subjects with no known faults. We selected OSS-Fuzz [67] subjects (see Table 1) that were compilable with gllvm and do not crash when fuzzed for 48 hours.

Fuzzers. We chose fuzzers that are general purpose, support in-process fuzzing, offer a compiler-wrapper and ASAN support, resulting in AFL, AFL++, libFuzzer, and Honggfuzz for evaluation (see Table 2). We follow generally recommended flags and use forking mode for libFuzzer to avoid early stopping. If dictionaries are available for subjects, they are provided to the fuzzers.

Hardware. We used four servers providing an Intel Xeon Gold 6230R CPU, each with 52 cores and 188 GB RAM. The computation times for all experiments are shown in Table 3.

Table 2: Overview of the fuzzers used for evaluation. The arguments under Dictionary are additionally provided if there is a dictionary available.

Fuzzer	Arguments	Dictionary	Version
AFL	`-d`	`-x`	2.57b
AFL++	`-d -c cmplog`	`-x`	3.14c
Honggfuzz	`-n 1`	`--dict`	2.4
libFuzzer	`-fork=1`	`-dict`	11.1

Table 3: Actual computation times for all experiments. Experiments were run on four servers, each with 52 cores. Note that evaluating a single fuzzer takes 4.09 CPU years ("Seed + Default" / #Fuzzers) with our chosen subjects.

	CPU (Years)	4 Servers (Days)
Seed Collection	1.99	3.50
Default	14.37	25.22
Seed + Default	16.36	28.72
ASAN	15.16	26.61
24 Hours Runs	7.42	13.02
Sum	38.95	68.34

Runtime. As the required CPU time is a central concern, we employ two approaches to reduce the required CPU time, which are described in Section 3.3. One is the application of supermutants which, for our evaluation, results in a reduction of required runs by between 1.76× and 19.95× (a mean reduction of 3.8×), as shown in Table 4. Note that this ignores supermutants that are not independent—see Table 8 for details.

The other approach is splitting the benchmark into a coverage phase (I) and a fault-detection phase (II). A speedup is achieved by using a long individual runtime for phase I (for

Table 4: Computational Reduction by Using Supermutants

Subject	#Mutants	#Supermutants	Factor
`curl`	29,118	5,804	5.02
`guetzli`	22,961	13,040	1.76
`woff2_new`	40,914	5,930	6.90
`cares_name`	4,822	550	8.77
`cares_parse_reply`	4,822	1,288	3.74
`libevent`	17,234	864	19.95
`re2`	21,407	9,670	2.21
Sum	141,278	37,146	**3.80**

our evaluation, 13 repetitions of 48 hours each) to allow a shorter runtime for phase II (1 hour per supermutant). The real speedup is highly dependent on the chosen runtimes and can be calculated by the following formula: $\frac{M \times R}{R_I \times S + M \times R_{II}}$; where M is the number of supermutants, R is the normal runtime, R_I is the runtime of phase I, R_{II} is the runtime of phase II, and S is the number of repetitions for coverage seed gathering. For our evaluation, this results in a speedup of 25×.

5.2 RQ1: How do different fuzzers compare?

Seed inputs are first created for each fuzzer and subject pair. These are either extracted from subject repositories if available or created manually. Each fuzzer is run on the unmutated base executable of the subject to fuzz for coverage for 48 hours (13 instances per fuzzer). The resulting inputs are then minimized by the tools provided by the respective fuzzer. Of the 13 instances for each fuzzer, the median run based on covered mutations is selected as the coverage seed corpus. The median run is used to avoid outliers in performance, as is recommended by previous research [2].

Next, we create supermutants (Section 3.3) and evaluate each on the coverage seeds from Phase I. In Phase II, each fuzzer is run for an hour on each supermutant.

Results. The results of this experiment are provided in Table 5. The column *#Mutations* represents the number of produced mutations. *Fuzzer* represents the used fuzzer. *Phase I Covered* represents the number of mutations covered by the seeds. *Phase I Killed* represents the number of mutations killed by the seeds. *Phase II Covered* represents the number of mutations that were covered in the Phase II beyond Phase I. *Phase II Killed* represents the number of mutations that were killed in Phase II beyond Phase I. *Total Covered* represents the number of mutants that were covered in total, and *Total Killed* represents the number of mutants that were killed in total. Summing up all subjects, we see that AFL++ kills 8.8% of all mutants, closely followed by Honggfuzz with 8.7% and AFL with 8.4%. libFuzzer lags behind at only 7.5%. In terms of covered mutations, AFL++ (30.9%) is again narrowly in front of Honggfuzz (30.4%), followed after a large gap by libFuzzer (25.9%) and AFL (24.6%). We find that coverage alone accounts for most of the killed mutants. The ensemble of all fuzzers in our evaluation (*combined* rows in Table 5) gets 99.95% of its coverage and 97.5% of its kills in Phase I. Indeed, none of the evaluated fuzzers employ bug-targeted feedback instrumentation, hence, this is expected.

> *Coverage accounts for most mutants (97.5%) detected in our evaluation.*

We found two anomalous results regarding AFL: For `guetzli`, the median run covers only around 7,000 mutations, which is caused by wildly inconsistent runs covering from 2,500 to 12,000 mutations, a disadvantage from which AFL recovers surprisingly well in Phase II. Additionally, for `re2`, AFL crashes for most mutations.

How do these fuzzers relate to each other? See Figure 3 for a Venn diagram of killed mutants per fuzzer. The fuzzers have a large intersection of killed mutations (78.6%). Consider AFL++: It finds 94.9% of all killed mutants. Adding a second fuzzer provides only a marginal improvement: Honggfuzz (+3.2%), AFL (+2.3%) or libFuzzer (+1.3%). For further details, a comparison per mutation type is available in Figure 2.

Is an extra hour of fuzzing beyond 24 hours of fuzzing for coverage sufficient for targeted fuzzing? To examine this question, we sampled up to 104 (to keep a multiple of CPU count) stubborn mutants for each subject and fuzzed them for 24 hours on every fuzzer. Note that, as we do not use supermutants for this experiment (i.e., we use only one mutation per mutant), this also serves as a test if supermutants introduce inconsistencies. As only *three* of the total of 690 mutants are killed, we believe that one hour runs are indeed sufficient for Phase II. Additionally, we feel that this result confirms our choice of using supermutants. The detailed results can be found in Table 7.

5.2.1 Manual Analysis of Mutations

To assess whether mutations that we introduce result in a semantic change, we manually examine 100 randomly selected mutations that were not found during the 24-hour runs. Of these, we identify 11 mutations as equivalent, 5 as potentially leading to crashes, and the remaining 84 as introducing a semantic change, but unlikely to be detected by a simple crash oracle.

5.3 RQ2: Evaluating the sanitizer contribution

To answer this question, we re-run the previous experiment with ASAN. To analyze the results of this experiment, we

Table 5: Results of the full benchmark run. The *#Mutations* column contains the number of mutations available. *Phase I* represents 24-hour runs, *Phase II* represents the one-hour runs, and *Total* represents both combined. *Covered* represents the number of covered mutants, while *Killed* represents the number of killed mutants. The **combined** rows show the total number of mutants that were killed by *any* fuzzer.

Program	#Mutations	Fuzzer	Phase I Covered	Phase I Killed	Phase II Covered	Phase II Killed	Total Covered	Total Killed
cares_name	4822	afl	88	17	0	3	88	20
		aflpp	88	18	0	2	88	20
		honggfuzz	88	17	0	1	88	18
		libfuzzer	86	17	0	0	86	17
		combined	88	18			88	20
cares_parse_reply	4822	afl	937	292	0	29	937	321
		aflpp	941	289	0	26	941	315
		honggfuzz	940	290	1	23	941	313
		libfuzzer	932	292	0	5	932	297
		combined	941	305			941	324
curl	29118	afl	9,935	2,328	89	68	10,024	2,396
		aflpp	11,713	2,593	69	82	11,782	2,675
		honggfuzz	10,195	2,299	506	150	10,701	2,449
		libfuzzer	8,895	2,099	120	39	9,015	2,138
		combined	12,459	2,807			12,477	2,857
guetzli	22961	afl	6,943	1,691	6,189	1,827	13,132	3,518
		aflpp	12,564	3,205	685	378	13,249	3,583
		honggfuzz	13,586	3,698	0	72	13,586	3,770
		libfuzzer	9,923	2,816	32	26	9,955	2,842
		combined	13,610	3,810			13,610	3,912
libevent	17234	afl	425	75	0	6	425	81
		aflpp	427	78	0	3	427	81
		honggfuzz	421	77	1	3	422	80
		libfuzzer	417	77	0	2	417	79
		combined	427	80			427	81
re2	21407	afl	4,825	4,461	0	1	4,825	4,462
		aflpp	11,563	4,457	65	134	11,628	4,591
		honggfuzz	11,636	4,431	0	97	11,636	4,528
		libfuzzer	11,164	4,328	0	20	11,164	4,348
		combined	11,639	4,571			11,639	4,627
woff2_new	40914	afl	5,386	955	2	70	5,388	1,025
		aflpp	5,578	1,044	1	69	5,579	1,113
		honggfuzz	5,555	1,018	1	111	5,556	1,129
		libfuzzer	5,018	896	2	20	5,020	916
		combined	5,631	1,139			5,634	1,232

compare the percentage of killed mutants out of all covered mutations. This is visualized for AFL++, Honggfuzz and libFuzzer in Figure 4, omitting AFL due to its inconsistencies between both oracles. The full results can be seen in Table 6. We see a clear increase of the number of killed mutants when using ASAN. Interestingly, enabling ASAN also results in some crashes in the original no longer being reported, which indicates a surprising effect of ASAN instrumentation in some cases. Overall, with ASAN, AFL++ found 9.1% (+0.3%) of mutations, Honggfuzz found 9.0% (+0.3%), AFL found 8.5% (+0.1%), and libFuzzer found 7.9% (+0.4%).

ASAN moderately increases the number of killed mutants.

5.4 RQ3: Mutant and Vulnerability Coupling

We analyzed the 100 most recent[2] CVEs referencing GitHub commits that patch `.c`, `.cc`, `.cpp` or `.h` files. A mutation is identified as *coupled* to a vulnerability if this mutation reintroduces the vulnerability into the patched program. We will provide detailed results and justifications for this manual analysis along with our code.

For the evaluated CVEs, the way our mutations reintroduce bugs can be classified broadly as: (1) The program behavior is modified such that the bug is reintroduced without side effects. (2) The mutation reintroduces the bug, but also breaks some functionality. (3) No mutation that reintroduces the bug can be found.

```
1 - if (instr[y].size < 29)
2 + if (instr[y].size >= 4 && instr[y].size < 29)
```

Listing 2: Patch for CVE-2022-34927.

An example patch for the first category can be seen in Listing 2. The added check for `size >=4` can be reversed by an UNSIGNED GREATER THAN EQUALTO mutation, which will change the right-hand constant to `0` here, effectively re-introducing the original bug without side effects.

```
1 + if (nft_chain_is_bound(chain))
2 +     return -EINVAL;
```

Listing 3: Patch for CVE-2022-39190.

A very common pattern among the studied patches is the introduction of a new branch checking an error condition.

[2] as of September 5th, 2022

Table 6: Results of the benchmark run *when ASAN is enabled*. The *#Mutations* column contains the number of mutations available. *Phase I* represents 24-hour seed gathering, *Phase II* represents the one-hour runs, and *Total* represents both combined. The *Covered* represents the number of mutants covered, while *Killed* represents the number of mutants killed. The **combined** rows show the total number of mutants killed by *any* fuzzer.

Program	#Mutations	Fuzzer	Phase I Covered	Phase I Killed	Phase II Covered	Phase II Killed	Total Covered	Total Killed
cares_name	4822	afl	88	21	0	0	88	21
		aflpp	88	22	0	0	88	22
		honggfuzz	88	21	0	1	88	22
		libfuzzer	87	21	0	1	87	22
		combined	88	22			88	22
cares_parse_reply	4822	afl	938	429	0	1	938	430
		aflpp	941	418	0	17	941	435
		honggfuzz	940	427	1	7	941	434
		libfuzzer	906	427	0	2	906	429
		combined	941	432			941	438
curl	28779	afl	9,981	3,068	87	38	10,068	3,106
		aflpp	11,680	3,458	68	73	11,748	3,531
		honggfuzz	10,155	3,057	481	162	10,636	3,219
		libfuzzer	8,833	2,728	130	80	8,963	2,808
		combined	12,349	3,729			12,387	3,774
guetzli	22961	afl	3,713	1,019	3,187	903	6,900	1,922
		aflpp	6,704	1,903	340	212	7,044	2,115
		honggfuzz	7,253	2,273	0	52	7,253	2,325
		libfuzzer	5,213	1,706	15	15	5,228	1,721
		combined	7,261	2,330			7,263	2,363
libevent	17234	afl	423	117	0	7	423	124
		aflpp	427	119	0	5	427	124
		honggfuzz	421	116	1	7	422	123
		libfuzzer	418	122	0	3	418	125
		combined	427	124			427	126
re2	21407	afl	11,492	5,193	18	115	11,510	5,308
		aflpp	11,485	5,209	68	183	11,553	5,392
		honggfuzz	11,577	5,171	3	167	11,580	5,338
		libfuzzer	11,003	5,009	4	81	11,007	5,090
		combined	11,586	5,347			11,586	5,438
woff2_new	40914	afl	5,395	1,047	1	53	5,396	1,100
		aflpp	5,574	1,113	2	47	5,576	1,160
		honggfuzz	5,555	1,082	5	75	5,560	1,157
		libfuzzer	4,958	990	1	19	4,959	1,009
		combined	5,631	1,193			5,637	1,247

Table 7: Mutants killed during 24 hour runs on 104 stubborn mutants for each subject (using ASAN).

Prog	Total	afl	aflpp	libfuzzer	honggfuzz
re2	104	0	0	0	0
cares_parse_reply	104	0	0	0	0
woff2_new	104	0	0	0	1
curl	104	0	0	1	0
guetzli	104	0	0	0	1
libevent	104	0	0	0	0
cares_name	66	0	0	0	0

These mostly fall into the second category because the buggy behavior can be triggered by inverting the branch condition (REDIRECT BRANCH), although this will result in the rejection of valid inputs. Listing 3 shows an example for this situation: After applying the mutation, only invalid `chains` are accepted, and valid input is discarded.

```
1 - length = dir->length;
2 + length += dir->length;
```

Listing 4: Patch for CVE-2022-29379.

Patches in the third category sometimes require a more specialized mutation, such as the replacement of `+=` with `=` for the code in Listing 4. In other cases, patches may be impossible to revert due to information being lost (e.g., a deleted function call cannot be re-inserted).

For this analysis, we count vulnerabilities in categories (1) and (2) as coupled to a mutation, as per definition, the vulnerability is reintroduced. As a result, 71 out of 100 analyzed CVEs are covered by our mutations.

> *The mutations induced by our mutation operators are coupled to real faults.*

6 Discussion

Our paper demonstrates how to perform a principled, yet practical comparison of two fuzzers to determine whether (1) using one is better than using the other or (2) using both combined is better than using each in isolation (Figure 3). Furthermore, we can measure the improvement in a fuzzer compared to an older version without biasing the results on previously discovered faults. Additionally, our approach can account for sanitizers and other strong oracles, enabling a more principled comparison of oracles. In summary, with this paper, we hope to encourage fuzzing researchers to develop better fuzzers without being unduly influenced by benchmarks.

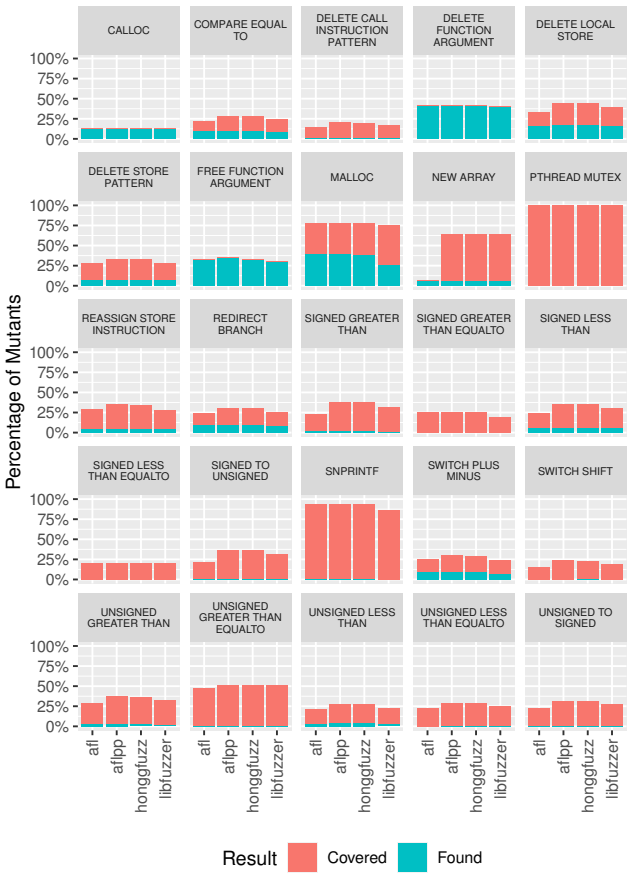


Figure 2: Percentage of covered and found mutants per mutation type and fuzzer (all found mutations are inherently covered). AFL underperforms for some mutation types due to crashes caused by instrumentation bugs. This can also be seen in Table 5 and Table 6.

Mutation analysis is the gold standard of measuring test suite effectiveness in software testing and comes with solid theory and empirical support. The only restriction in using it for fuzzing so far has been the computational cost associated with it. We have taken the first step in solving this issue, making mutation analysis practical for fuzzing. As proof that our approach indeed works in the real world, we have compared four popular fuzzers on seven programs provided by the OSS-Fuzz benchmark, the results of which we now present.

Our experiments largely confirm the fuzzer ranking established in previous literature [7, 33, 6]. AFL++ leads the board, clearly outperforming AFL and libFuzzer (Honggfuzz was not part of the evaluation in [6]). Furthermore, our evaluation shows again that the fuzzers are very similar and either AFL++ or Honggfuzz represent a solid choice. As expected, the fuzzers in our evaluation have very limited targeted bug finding capabilities, since there is nearly no improvement in

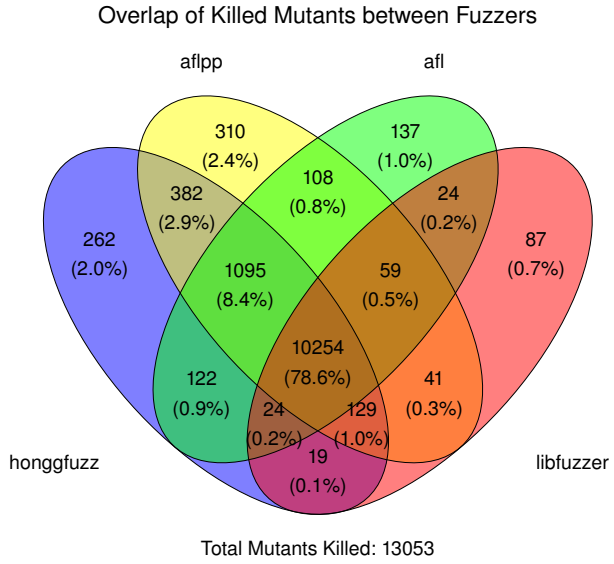


Figure 3: Venn diagram of killed mutants for each fuzzer.

the second phase. The re-evaluation with ASAN demonstrates the importance of improved oracles, as the number of killed mutants increases. It also shows that our approach is indeed capable of evaluating the complete tool chain.

Implications. Why should we trust mutation analysis any more than the numerous metrics out there, such as coverage measures [69], defect-based benchmarks[7, 32], etc.?

As discussed in Section 2.3.2, mutants that remain alive represent possible undetected faults in the program, and with the detection of each new mutant, that possibility decreases monotonically. That is, unlike coverage, alive mutations are a good proxy measure for residual defects in a program. Compared to defect-based benchmarks, mutation analysis minimizes bias and manual effort. Finally, the mutations themselves can be studied to provide examples to improve fuzzers, without the limitations of coverage or the bias of defect-based benchmarks.

Our results call for a reorientation of priorities in security testing. We have focused mostly on improving coverage during fuzzing. However, it seems that there is a lot more to be gained by improving oracles instead. This is not simple, however, and is known as the *oracle problem* in software testing [70]. The difficulty is that there is no general way to identify and extract the *intended logic* of a given program. Some promising approaches exist that can help: (1) metamorphic relations [71, 72] and equivalence modulo inputs [73]; (2) differential oracles [74, 75]; and (3) invariants such as those mined by Daikon [76] and the like. We believe that future research should also be spent on improving the effectiveness of these techniques rather than just pursuing the ever shrinking returns on improving coverage.

Figure 4: Percentage of covered mutants (in both experiments) that are killed with and without ASAN. "Both" shows mutations killed with or without ASAN, "default" those only found without ASAN, and "asan" shows kills only found using ASAN.

7 Limitations and Future Work

Our work is subject to the following important limitations.

Missing patterns and faults. We rely on a set of mutation operators that we mined from real faults, which are unlikely to be exhaustive. This can be mitigated by future adaption of the supported mutations.

Cost of mutation analysis. While we reduced the cost of applying mutation analysis to fuzzers, a further reduction would still improve the practicality of this approach. One such approach could involve sampling mutations, reducing computation time at the cost of accuracy.

Coupling effect. We rely on the *coupling effect* hypothesis in mutation analysis to ensure that the mutants we generate are similar to real faults. The coupling effect is well attested in literature [44, 45]. However, relying on the coupling effect ignores subtle faults due to fault-interactions (between faults). While there is some evidence that such interactions are rare [77], they are still important to address. One direction is exploring a larger neighborhood, with multiple mutations in a mutant. Unlike supermutants, however, we need mutations that interact, and *callability* that we used for supermutants can provide a first level approximation. Indeed, given that mutation analysis is a form of fuzz-testing the software test suite, the fuzzing community may be able to make better progress here.

Allocated Time for Phases. Some fuzzers may not attempt to expand the coverage front and instead scan for possible vulnerability patterns, using static analysis. In such a case, the time provided for developing the coverage seed may not be useful to the fuzzer and may lead to unfair comparison. How to fairly compare such fuzzers without the overhead of full mutation analysis is an open question. (We note that while the coverage optimization may not work, the supermutant optimization will work even in such cases.) A possible solution is to use the state-of-the-art coverage maximizing fuzzer on the original program and extract the coverage mutants from the given program. Next, use random sampling [78] to identify a small set of coverage mutants, which when combined with the (complete set of) stubborn and other live mutants can serve to limit the overhead of full mutation analysis. Another option is to use the state-of-the-art coverage maximizing fuzzer and extract a mutant kill matrix. Then, identify the minimal test suite and the corresponding minimal mutant set, and use that minimal mutant set for evaluation of coverage mutants. We note that the relative merits of random sampling and minimal mutant set still needs to be calibrated [78, 79]. For random sampling, we note that a smaller sample size may suffice in theory [80]. However, the actual practical reduction in mutants is yet to be established (it is likely to be program-specific).

Supermutants. We use supermutants to check whether any

fuzzer can find mutations that were not covered in the initial seed files. In doing this, we run the risk of fault masking. Hence, future work is to investigate the prevalence of fault masking and techniques to avoid fault masking. We, however, note that fault masking is likely to be rare. For one fault (say A) to mask the other (say B), the following conditions have to be fulfilled: (1) there should be no input that covers both in the coverage-maximizing phase, (2) fault A should never cause a crash independently (if it does, fault A would be removed and the remaining faults would be fuzzed separately), (3) there should be some inputs that cover both fault A and fault B, and on these inputs, fault A should induce just sufficient behavioral change such that, while the input may have caused a crash without fault A, the crash is removed when both are present. We believe that these constraints make fault masking due to supermutants rare.

Comparing Fuzzers without Sanitizers. We find that sanitizers can significantly improve the effectiveness of fuzzers. However, mutation analysis can allow us to go beyond merely accounting for the impact of sanitizers. We can compare the behavior (even coverage) of a mutant against the original using *differential fuzzing* and identify whether a fuzzer was able to induce a change in behavior compared to the original even in the absence of a suitable sanitizer. This will allow us to develop effective fuzzers that focus on input generation independent of sanitizer development. Indeed, differential fuzzing by keeping track of coverage or behavior divergence between original and mutants can provide strong hints on which inputs hold promise in fuzzer guidance [81, 82].

8 Related Work

The comparison and evaluation of fuzzers is an important foundation for meaningfully improving fuzzers. Several fuzzing platforms exist [32, 7, 33] that seek to provide a way to compare fuzzers under a common framework.

One such approach is LAVA [32], a tool to inject crash bugs that can be triggered by finding specific values in unused parts of user-controlled input. Later analysis showed that the introduced bugs are dissimilar to real-world vulnerabilities [2], are not coupled to real faults (reported CVEs) [11], tend to overfit [9], and are "solved" by modern fuzzers [83]. In comparison, bugs from mutation analysis are not guaranteed to be triggerable. However, this is a trade-off making it possible to create a comprehensive set of bugs, spanning from trivially detectable to subtle and hard-to-detect ones. A similar approach that can insert bugs into subjects is Evil Coder [84]. Potentially vulnerable source code locations are detected using data flow analysis, focusing on user-controlled inputs that lead to sensitive functions. A bug is introduced by removing security-relevant checks, such as input sanitization. While our approach is not as targeted, mutation testing will not only generate similar bugs but also a wider range of bugs.

The challenge binaries of the Cyber Grand Challenge (CGC) [85] are also sometimes used for comparison of fuzzers [2]. The binaries were especially created for the CGC. Hence, challenge binaries necessarily have a bias to be used in the CGC and consist mostly of command line tools.

A recent benchmarking approach is Magma [7]. It uses real-world vulnerabilities and re-inserts them into newer versions of the projects. Additionally, it provides an assertion that tests if an input results in a state that would trigger the bug. This assertion is used to measure bug detection capability. As in other benchmarks, the number of bugs is limited because of the manual effort to port them to the current version and has a necessary bias towards bugs that can be re-inserted.

Another project is Fuzzbench [33], using Google infrastructure. Fuzzbench already provides coverage-based benchmarks and is working on supporting bug-based benchmarks [86].

FIXREVERTER [6] mines a restricted set of syntactic patterns from bug fixes that were associated with vulnerabilities and injects these bugs where the bug inducibility can be guaranteed, but has several limitations. First, the researchers could identify only three general patterns accounting for 170 CVEs from a study of 814 CVEs (20.9%). Second, using patterns with semantic analysis to guarantee bug inducibility restricts the number of fixes that can be reverted. Such a guarantee also limits what kinds of bugs can be simulated, as the specific bug patterns and corresponding bug semantics that were mined represent only a small fraction of the possible bugs that can be present in a given program (in contrast to mutation analysis). This might also open the door to fine-tuning fuzzers for specifically identifying such behavior. These drawbacks reduce the diversity of bugs and thus the effectiveness of the benchmark [78, 79]. Finally, FIXREVERTER does not address the issue of fault-interactions and fault-masking.

Böhme et al. suggest that coverage-based benchmarking can be unreliable based on a comparison with curated bugs [8]. The paper illustrates the difficulty we face when we rely on an external source of bugs. In particular, because the bugs that the researchers rely on are external, the distribution of such bugs is not related to the actual possibility of bugs in the tested program. To illustrate this, consider the following thought experiment: Given a benchmark program that accepts inputs as JSON and a black-box random fuzzer. The fuzzer will find lots of crashing bugs in the JSON parser itself but few in the program logic. Any ranking using this source of bugs will favor fuzzers that find bugs in the JSON parser when compared to, say, a grammar fuzzer that reaches the program internals. Hence, the ranking based on finding such bugs is not a reliable indicator of fuzzer quality. This is precisely what (unbiased) mutation analysis aims to correct.

Beyond Fuzzing. Mutation analysis can also be applied for software verification tasks beyond fuzzing. It can be used

to evaluate the quality of static analysis tools [87], of type systems [88] (good type systems can make whole classes of errors non-representable), contracts [89], and even the effectiveness of program proofs [90].

9 Conclusion

As fuzzing budget is limited, it is important to use fuzzers that are better at finding faults. The available benchmarks are, however, limited or biased towards known bugs and are susceptible to overfitting and fine-tuning.

This paper demonstrates how the gold standard for measuring test suite quality—mutation analysis—can be adapted for fuzzing. We show that two techniques, eliminating coverage mutants using static seed files and using supermutants for the remaining evaluation, can significantly reduce the computational expenditure necessary for mutation analysis and can make mutation analysis feasible for fuzzing. We investigated security faults and converted the identified patterns into security-specific mutation operators, which were used for evaluation. Using mutation analysis, practitioners are no longer limited to specific curated benchmarks. Instead, practitioners can evaluate fuzzers on the programs from a specific domain before allocating resources for fuzzing.

Our evaluation demonstrates that with our technique, mutation analysis can now be used for comparing fuzzers in real-world programs. Using mutation analysis ensures that the practitioners can rely on the solid theory and decades of empirical research, leading to better fuzzers and sanitizers. The fine-grained results from mutation analysis can directly help fuzzing practitioners to understand the deficiencies in current approaches and take steps to correct them.

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References

[1] Marcel Böhme, Cristian Cadar, and Abhik Roychoudhury. "Fuzzing: Challenges and Reflections". *IEEE Software* 38 (2021).

[2] George Klees et al. "Evaluating Fuzz Testing". *ACM Conference on Computer and Communications Security (CCS)*. 2018.

[3] Tielei Wang et al. "TaintScope: A Checksum-Aware Directed Fuzzing Tool for Automatic Software Vulnerability Detection". *IEEE Symposium on Security and Privacy (S&P)*. 2010.

[4] Sebastian Österlund et al. "ParmeSan: Sanitizer-guided Greybox Fuzzing". *USENIX Security Symposium*. 2020.

[5] Rahul Gopinath, Carlos Jensen, and Alex Groce. "Code coverage for suite evaluation by developers". *International Conference on Software Engineering (ICSE)*. 2014.

[6] Zenong Zhang et al. "FIXREVERTER: A Realistic Bug Injection Methodology for Benchmarking Fuzz Testing". *USENIX Security Symposium*. 2022.

[7] Ahmad Hazimeh, Adrian Herrera, and Mathias Payer. "Magma: A Ground-Truth Fuzzing Benchmark". *Proceedings of the ACM on Measurement and Analysis of Computing Systems* 4 (2020).

[8] Marcel Böhme, László Szekeres, and Jonathan Metzman. "On the Reliability of Coverage-Based Fuzzer Benchmarking". *International Conference on Software Engineering (ICSE)*. 2022.

[9] Andreas Zeller, Sascha Just, and Kai Greshake. *When Results Are All That Matters: The Case of the Angora Fuzzer*. 2019. URL: https://andreas-zeller.info/2019/10/10/when-results-are-all-that-matters-case.html (visited on 10/12/2022).

[10] Andreas Zeller, Sascha Just, and Kai Greshake. *When Results Are All That Matters: Consequences*. 2019. URL: https://andreas-zeller.info/2019/10/17/when-results-are-all-that-matters.html (visited on 10/12/2022).

[11] Joshua Bundt et al. "Evaluating Synthetic Bugs". *ACM Symposium on Information, Computer and Communications Security (ASIACCS)*. 2021.

[12] Mike Papadakis et al. "Mutation Testing Advances: An Analysis and Survey". *Advances in Computers*. Ed. by Atif M. Memon. Vol. 112. Elsevier, 2019.

[13] Michele Tufano et al. "Learning How to Mutate Source Code from Bug-Fixes". *IEEE International Conference on Software Maintenance and Evolution (ICSME)*. 2019.

[14] Zakir Durumeric et al. "The Matter of Heartbleed". *Internet Measurement Conference (IMC)*. 2014.

[15] Synopsis Editorial Team. *Understanding the Apple 'goto fail;' vulnerability*. 2014. URL: https://www.synopsys.com/blogs/software-security/understanding-apple-goto-fail-vulnerability-2/ (visited on 10/12/2022).

[16] Tatum Hunter and Gerrit De Vynck. "The 'most serious' security breach ever is unfolding right now. Here's what you need to know." *The Washington Post* (2021). URL: https://www.washingtonpost.com/technology/2021/12/20/log4j-hack-vulnerability-java/ (visited on 10/12/2022).

[17] J. H. Andrews, L. C. Briand, and Y. Labiche. "Is mutation an appropriate tool for testing experiments?" *International Conference on Software Engineering (ICSE)*. 2005.

[18] René Just et al. "Are mutants a valid substitute for real faults in software testing?" *ACM SIGSOFT International Symposium on Foundations of Software Engineering (FSE)*. 2014.

[19] Mike Papadakis et al. "Are mutation scores correlated with real fault detection?: a large scale empirical study on the relationship between mutants and real faults". *International Conference on Software Engineering (ICSE)*. 2018.

[20] Tejeddine Mouelhi, Yves Le Traon, and Benoit Baudry. "Mutation Analysis for Security Tests Qualification". *Testing: Academic and Industrial Conference Practice and Research Techniques - MUTATION (TAICPART-MUTATION)*. 2007.

[21] Frédéric Dadeau, Pierre-Cyrille Héam, and Rafik Kheddam. "Mutation-Based Test Generation from Security Protocols in HLPSL". *IEEE International Conference on Software Testing, Verification and Validation (ICST)*. 2011.

[22] Daniel Woodraska, Michael Sanford, and Dianxiang Xu. "Security mutation testing of the FileZilla FTP server". *ACM Symposium on Applied Computing (SAC)*. 2011.

[23] Yves Le Traon, Tejeddine Mouelhi, and Benoit Baudry. "Testing Security Policies: Going Beyond Functional Testing". *IEEE International Symposium on Software Reliability Engineering (ISSRE)*. 2007.

[24] Thomas Loise et al. "Towards Security-Aware Mutation Testing". *IEEE International Conference on Software Testing, Verification and Validation Workshops (ICSTW)*. 2017.

[25] Amit Seal Ami et al. "μSE: Mutation-Based Evaluation of Security-Focused Static Analysis Tools for Android". *International Conference on Software Engineering: Companion (ICSE-Companion)*. 2021.

[26] Lu Yu et al. "Vulnerability-oriented directed fuzzing for binary programs". *Scientific Reports* 12 (2022).

[27] Rahul Gopinath, Bjorn Mathis, and Andreas Zeller. "If You Can't Kill a Supermutant, You Have a Problem". *IEEE International Conference on Software Testing, Verification and Validation Workshops (ICSTW)*. 2018.

[28] Konstantin Serebryany et al. "AddressSanitizer: A Fast Address Sanity Checker". *USENIX Annual Technical Conference*. 2012.

[29] IEEE. "IEEE Standard Classification for Software Anomalies". *IEEE Std 1044-2009 (Revision of IEEE Std 1044-1993)* 0 (2010).

[30] Yiqun T. Chen et al. "Revisiting the relationship between fault detection, test adequacy criteria, and test set size". *IEEE/ACM International Conference on Automated Software Engineering (ASE)*. 2020.

[31] Alessandro Mantovani, Andrea Fioraldi, and Davide Balzarotti. "Fuzzing with Data Dependency Information". *IEEE European Symposium on Security and Privacy (EuroS&P)*. 2022.

[32] Brendan Dolan-Gavitt et al. "LAVA: Large-Scale Automated Vulnerability Addition". *IEEE Symposium on Security and Privacy (S&P)*. 2016.

[33] Jonathan Metzman et al. "FuzzBench: an open fuzzer benchmarking platform and service". *European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*. 2021.

[34] Goran Petrović and Marko Ivanković. "State of mutation testing at google". *Proceedings of the 40th international conference on software engineering: Software engineering in practice*. 2018.

[35] Moritz Beller et al. "What it would take to use mutation testing in industry—a study at facebook". *2021 IEEE/ACM 43rd International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*. 2021.

[36] Goran Petrovic et al. "An industrial application of mutation testing: Lessons, challenges, and research directions". *2018 IEEE International Conference on Software Testing, Verification and Validation Workshops (ICSTW)*. 2018.

[37] Paul Ammann, Marcio Eduardo Delamaro, and Jeff Offutt. "Establishing theoretical minimal sets of mutants". *2014 IEEE seventh international conference on software testing, verification and validation*. 2014.

[38] Rahul Gopinath et al. "Measuring effectiveness of mutant sets". *2016 IEEE Ninth International Conference on Software Testing, Verification and Validation Workshops (ICSTW)*. 2016.

[39] Rahul Gopinath, Carlos Jensen, and Alex Groce. "Mutations: How Close are they to Real Faults?" *IEEE International Symposium on Software Reliability Engineering (ISSRE)*. 2014.

[40] A. Jefferson Offutt. "Investigations of the software testing coupling effect". *ACM Transactions on Software Engineering and Methodology* 1 (1992).

[41] K. S. How Tai Wah. "A theoretical study of fault coupling". *Software Testing, Verification and Reliability* 10 (2000).

[42] K. S. How Tai Wah. "Theoretical Insights into the Coupling Effect". *Mutation Testing for the New Century*. Ed. by W. Eric Wong. Springer US, 2001.

[43] K. S. How Tai Wah. "An analysis of the coupling effect I: single test data". *Science of Computer Programming* 48 (2003).

[44] Rahul Gopinath, Carlos Jensen, and Alex Groce. "The Theory of Composite Faults". *IEEE International Conference on Software Testing, Verification and Validation (ICST)*. 2017.

[45] René Just et al. "Are mutants a valid substitute for real faults in software testing?" *ACM SIGSOFT International Symposium on Foundations of Software Engineering (FSE)*. 2014.

[46] Goran Petrovic et al. "Does Mutation Testing Improve Testing Practices?" *International Conference on Software Engineering (ICSE)*. 2021.

[47] Thierry Titcheu Chekam et al. "An Empirical Study on Mutation, Statement and Branch Coverage Fault Revelation That Avoids the Unreliable Clean Program Assumption". *International Conference on Software Engineering (ICSE)*. 2017.

[48] René Just, Michael D. Ernst, and Gordon Fraser. "Efficient mutation analysis by propagating and partitioning infected execution states". *International Symposium on Software Testing and Analysis (ISSTA)*. 2014.

[49] W.E. Howden. "Weak Mutation Testing and Completeness of Test Sets". *IEEE Transactions on Software Engineering* 8 (1982).

[50] Susumu Tokumoto et al. "MuVM: Higher Order Mutation Analysis Virtual Machine for C". *IEEE International Conference on Software Testing, Verification and Validation (ICST)*. 2016.

[51] Rahul Gopinath, Carlos Jensen, and Alex Groce. "Topsy-Turvy: a smarter and faster parallelization of mutation analysis". *International Conference on Software Engineering (ICSE)*. 2016.

[52] Bo Wang et al. "Faster mutation analysis via equivalence modulo states". *International Symposium on Software Testing and Analysis (ISSTA)*. 2017.

[53] Ali Ghanbari and Andrian Marcus. "Toward Speeding up Mutation Analysis by Memoizing Expensive Methods". *International Conference on Software Engineering: New Ideas and Emerging Results (ICSE-NIER)*. 2021.

[54] Rahul Gopinath, Philipp Görz, and Alex Groce. *Mutation Analysis: Answering the Fuzzing Challenge*. 2022. arXiv: 2201.11303[cs].

[55] Iftekhar Ahmed et al. "Can testedness be effectively measured?" *ACM SIGSOFT International Symposium on Foundations of Software Engineering (FSE)*. 2016.

[56] Terence Tao. *An introduction to measure theory*. Vol. 126. American Mathematical Society Providence, RI, 2011.

[57] Mauro Pezze and Michal Young. *Software testing and analysis: process, principles, and techniques*. John Wiley & Sons, 2008.

[58] Marcel Böhme. "Assurances in Software Testing: A Roadmap". *International Conference on Software Engineering: New Ideas and Emerging Results (ICSE-NIER)*. 2019.

[59] Nan Li, Upsorn Praphamontripong, and Jeff Offutt. "An experimental comparison of four unit test criteria: Mutation, edge-pair, all-uses and prime path coverage". *IEEE International Conference on Software Testing, Verification and Validation (ICST)*. 2009.

[60] Phyllis G. Frankl, Stewart N. Weiss, and Cang Hu. "All-uses vs mutation testing: An experimental comparison of effectiveness". *Journal of Systems and Software* 38 (1997).

[61] Sahitya Kakarla, Selina Momotaz, and Akbar Siami Namin. "An evaluation of mutation and data-flow testing: A meta-analysis". *IEEE International Conference on Software Testing, Verification and Validation (ICST)*. 2011.

[62] Gary Kaminski, Paul Ammann, and Jeff Offutt. "Improving logic-based testing". *Journal of Systems and Software* 86 (2013).

[63] Yue Jia and Mark Harman. "An Analysis and Survey of the Development of Mutation Testing". *IEEE Transactions on Software Engineering* 37 (2011).

[64] Xiangjuan Yao, Mark Harman, and Yue Jia. "A study of equivalent and stubborn mutation operators using human analysis of equivalence". *International Conference on Software Engineering (ICSE)*. 2014.

[65] *CWE VIEW: Weaknesses in Software Written in C*. 2021. URL: https://cwe.mitre.org/data/definitions/658.html (visited on 10/12/2021).

[66] *CWE VIEW: Weaknesses in Software Written in C++*. 2021. URL: https://cwe.mitre.org/data/definitions/659.html (visited on 10/12/2021).

[67] *OSS-Fuzz*. 2021. URL: https://google.github.io/oss-fuzz/ (visited on 10/12/2022).

[68] *cloc*. 2023. URL: https://github.com/AlDanial/cloc (visited on 02/10/2023).

[69] Alex Groce, Mohammad Amin Alipour, and Rahul Gopinath. "Coverage and Its Discontents". *Conference on Systems, Programming, and Applications: Software for Humanity (SPLASH)*. 2014.

[70] Earl T. Barr et al. "The Oracle Problem in Software Testing: A Survey". *IEEE Transactions on Software Engineering* 41 (2015).

[71] Sergio Segura et al. "A Survey on Metamorphic Testing". *IEEE Transactions on Software Engineering* 42 (2016).

[72] Tsong Yueh Chen et al. "Metamorphic Testing for Cybersecurity". *Computer* 49 (2016).

[73] Vu Le, Mehrdad Afshari, and Zhendong Su. "Compiler validation via equivalence modulo inputs". *ACM SIGPLAN Notices* 49 (2014).

[74] William M McKeeman. "Differential testing for software". *Digital Technical Journal* 10 (1998).

[75] Muhammad Ali Gulzar, Yongkang Zhu, and Xiaofeng Han. "Perception and Practices of Differential Testing". *International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*. 2019.

[76] Michael D. Ernst et al. "The Daikon system for dynamic detection of likely invariants". *Science of Computer Programming* 69 (2007).

[77] D.R. Kuhn, D.R. Wallace, and A.M. Gallo. "Software fault interactions and implications for software testing". *IEEE Transactions on Software Engineering* 30 (2004).

[78] Rahul Gopinath et al. "On the limits of mutation reduction strategies". *International Conference on Software Engineering (ICSE)*. 2016.

[79] Rahul Gopinath et al. "Mutation Reduction Strategies Considered Harmful". *IEEE Transactions on Reliability* 66 (2017).

[80] R. Gopinath et al. "How hard does mutation analysis have to be anyway?" *Software Reliability Engineering (ISSRE), 2014 IEEE 26th International Symposium on*. 2015.

[81] Alex Groce et al. "Registered report: First, fuzz the mutants". *International Fuzzing Workshop, ser. FUZZING*. Vol. 22. 2022.

[82] Vasudev Vikram et al. "Guiding Greybox Fuzzing with Mutation Testing". *International Symposium on Software Testing and Analysis (ISSTA)*. 2023.

[83] Cornelius Aschermann et al. "REDQUEEN: Fuzzing with Input-to-State Correspondence". *Symposium on Network and Distributed System Security (NDSS)*. 2019.

[84] Jannik Pewny and Thorsten Holz. "EvilCoder: Automated Bug Insertion". *Annual Computer Security Applications Conference (ACSAC)*. 2016.

[85] DARPA. *Cyber Grand Challenge*. 2016. URL: https://www.ll.mit.edu/research-and-development/cyber-security-and-information-sciences/cyber-grand-challenge (visited on 10/12/2022).

[86] Various Authors. "Use bugs to measure fuzzer performance". *github.com/google/fuzzbench* (2023). URL: https://github.com/google/fuzzbench/issues/165 (visited on 02/10/2023).

[87] Sajeda Parveen and Manar H Alalfi. "A mutation framework for evaluating security analysis tools in IoT applications". *2020 IEEE 27th International Conference on Software Analysis, Evolution and Reengineering (SANER)*. 2020.

[88] Rahul Gopinath and Eric Walkingshaw. "How Good Are Your Types? Using Mutation Analysis to Evaluate the Effectiveness of Type Annotations". *IEEE International Conference on Software Testing, Verification and Validation Workshops (ICSTW)*. 2017.

[89] Alexander Knüppel, Leon Schaer, and Ina Schaefer. "How much specification is enough? Mutation analysis for software contracts". *2021 IEEE/ACM 9th International Conference on Formal Methods in Software Engineering (FormaliSE)*. 2021.

[90] Kush Jain et al. "mCoq: mutation analysis for Coq verification projects". *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering: Companion Proceedings*. 2020.

A Appendix

A.1 Supplements for Evaluation

Additional results as mentioned in the Section 5.

Table 8: Number of mutants that were covered together with other mutants (i.e., mutants wrongly thought independent).

Program	afl	aflpp	honggfuzz	libfuzzer
cares_name	4	0	0	0
cares_parse_reply	2	4	4	0
curl	4,850	5,836	4,851	3,852
guetzli	10	24	16	0
libevent	0	2	0	0
re2	39	66	37	47
woff2_new	26	46	56	48

Supplementary Information for Table 8 Any non-independent mutants recorded during Phase II are given in Table 8. We find that except for `curl`, the number of multi-covered mutants is minimal. For `curl` the interaction between mutations is caused by mutations that result in an error when handling http, these are then retried with the http2 protocol, covering functions and mutations there. This kind of interactions can also occur in utility functions.

Table 9: The number of mutants **Cov**ered or **Kill**ed for **Def**ault and **ASAN** experiments, for each mutation type and fuzzer.

Mutation Type	Fuzzer	Cov Def	Cov Asan	Kill Def	Kill Asan	Mutation Type	Fuzzer	Cov Def	Cov Asan	Kill Def	Kill Asan
MALLOC	afl	41	34	21	21	SIGNED LESS THAN	afl	447	543	104	95
	aflpp	41	34	21	21		aflpp	670	556	116	103
	honggfuzz	41	34	20	21		honggfuzz	672	555	111	100
	libfuzzer	40	34	14	21		libfuzzer	571	471	100	91
SIGNED GREATER THAN	afl	434	590	33	34	SIGNED LESS THAN EQUALTO	afl	2	2	0	0
	aflpp	719	603	38	36		aflpp	2	2	0	0
	honggfuzz	725	604	42	35		honggfuzz	2	2	0	0
	libfuzzer	614	526	28	29		libfuzzer	2	2	0	0
SIGNED GREATER THAN EQUALTO	afl	4	4	0	0	FREE FUNCTION ARGUMENT	afl	923	887	918	879
	aflpp	4	4	0	0		aflpp	981	945	976	939
	honggfuzz	4	4	0	0		honggfuzz	944	909	940	905
	libfuzzer	3	3	0	0		libfuzzer	876	843	870	837
PTHREAD MUTEX	afl	3	3	0	0	SIGNED TO UNSIGNED	afl	825	1,172	32	30
	aflpp	3	3	0	0		aflpp	1,393	1,197	38	35
	honggfuzz	3	3	0	0		honggfuzz	1,407	1,209	35	34
	libfuzzer	3	2	0	0		libfuzzer	1,201	1,060	32	29
UNSIGNED TO SIGNED	afl	1,470	1,617	46	49	SWITCH SHIFT	afl	568	692	6	9
	aflpp	1,984	1,682	53	51		aflpp	903	785	5	13
	honggfuzz	1,981	1,666	52	55		honggfuzz	825	711	2	9
	libfuzzer	1,736	1,489	40	48		libfuzzer	718	635	3	9
CALLOC	afl	1	1	1	1	DELETE LOCAL STORE	afl	203	236	96	89
	aflpp	1	1	1	1		aflpp	277	254	108	98
	honggfuzz	1	1	1	1		honggfuzz	273	252	107	96
	libfuzzer	1	1	1	1		libfuzzer	244	227	100	89
UNSIGNED LESS THAN	afl	885	940	167	140	UNSIGNED GREATER THAN	afl	625	664	71	76
	aflpp	1,121	970	182	145		aflpp	825	686	68	79
	honggfuzz	1,125	968	180	148		honggfuzz	819	679	77	86
	libfuzzer	960	829	145	117		libfuzzer	728	600	54	56
UNSIGNED LESS THAN EQUALTO	afl	12	11	0	0	UNSIGNED GREATER THAN EQUALTO	afl	23	17	0	0
	aflpp	15	13	0	0		aflpp	25	17	0	0
	honggfuzz	15	13	0	0		honggfuzz	25	17	0	0
	libfuzzer	13	11	0	0		libfuzzer	25	17	0	0
COMPARE EQUAL TO	afl	2,367	2,643	1,055	1,164	SNPRINTF	afl	14	9	0	0
	aflpp	3,060	2,816	1,103	1,243		aflpp	14	9	0	0
	honggfuzz	2,992	2,741	1,074	1,209		honggfuzz	14	9	0	0
	libfuzzer	2,620	2,390	974	1,088		libfuzzer	13	9	0	0
NEW ARRAY	afl	2	21	2	13	SWITCH PLUS MINUS	afl	5,001	4,089	1,845	1,484
	aflpp	21	21	2	13		aflpp	5,928	4,489	1,884	1,543
	honggfuzz	21	21	2	13		honggfuzz	5,692	4,240	1,916	1,589
	libfuzzer	21	21	2	13		libfuzzer	4,716	3,544	1,495	1,321
REDIRECT BRANCH	afl	8,120	8,539	3,192	3,233	DELETE FUNCTION ARGUMENT	afl	466	433	465	432
	aflpp	10,061	8,967	3,335	3,472		aflpp	469	436	468	435
	honggfuzz	9,963	8,806	3,311	3,432		honggfuzz	469	436	468	435
	libfuzzer	8,534	7,578	2,819	3,038		libfuzzer	447	415	445	414
DELETE STORE PATTERN	afl	6,935	7,006	1,885	2,003	DELETE CALL INSTRUCTION PATTERN	afl	1,545	1,607	184	741
	aflpp	8,560	7,381	1,995	2,117		aflpp	2,122	1,757	193	838
	honggfuzz	8,471	7,256	2,002	2,088		honggfuzz	2,022	1,666	192	800
	libfuzzer	7,060	6,253	1,752	1,881		libfuzzer	1,699	1,436	166	708
REASSIGN STORE INSTRUCTION	afl	2,421	2,241	368	372						
	aflpp	2,878	2,354	400	388						
	honggfuzz	2,854	2,331	404	395						
	libfuzzer	2,300	1,940	354	345						

A.2 Supplements for Approach

The full list of mutation operators as mentioned in Section 3.

Table 10: List of all mutations used in our study.

Pattern Name	Description	Procedure
MALLOC	Mutating all malloc calls to achieve buffer overflow/out of bounds errors.	We decrease allocated memory byte_size in the malloc call by 16.
FGETS MATCH BUFFER SIZE	Mutating all fgets calls to achieve buffer overflow errors.	We increase the size (n) parameter in the fgets call by increasing the value by 1 and then multiplying it by 5. E.g. 4->5->25.
SIGNED LESS THAN	Mutating all '<' comparisons either between two integer pointers or between 1 signed integer variable and an integer to achieve overflow errors.	For pointer comparison, 8*4=32 is added to the right hand side pointer in the comparison. For integer comparison, the integer on the right hand side is squared if larger than 1024 or smaller than 2, else 32 is added.
SIGNED GREATER THAN	Mutating all '>' comparisons either between two integer pointers or between 1 signed integer variable and an integer to achieve underflow errors.	For pointer comparison, 8*4=32 is subtracted from the right hand side pointer in the comparison. For integer comparison, either the sqrt is taken for integers > 1024*1024, halved for integers > 1024 and either 0 is returned or 32 is substracted, whatever gives the largest result.
SIGNED LESS THAN EQUALTO	Mutating all '<=' comparisons either between two integer pointers or between 1 signed integer variable and an integer to achieve overflow errors.	For pointer comparison, 8*4=32 is added to the right hand side pointer in the comparison. For integer comparison, the integer on the right hand side is squared if larger than 1024 or smaller than 2, else 32 is added.
SIGNED GREATER THAN EQUALTO	Mutating all '>=' comparisons either between two integer pointers or between 1 signed integer variable and an integer to achieve underflow errors.	For pointer comparison, 8*4=32 is subtracted from the right hand side pointer in the comparison. For integer comparison, either the sqrt is taken for integers > 1024*1024, halved for integers > 1024 and either 0 is returned or 32 is substracted, whatever gives the largest result.
FREE FUNCTION ARGUMENT	Mutating all functions that receive a pointer type function argument to achieve double free and possibly illegal memory access errors.	We check for functions that receive a pointer type argument. Before returning at the end of the function, one argument per mutant is freed.
PTHREAD MUTEX	Mutating all pthread_lock and pthread_unlock calls to achieve data races errors.	We remove all pthread_lock and pthread_unlock calls in a function per mutant.
ATOMIC CMP XCHG	Mutating all atomic compare exchanges to achieve data races.	If we have at least one atomic cmpxchg instruction, we replace all atomic cmpxchg return success values (the element with index 1 in the result array) by 1 per function.
ATOMICRMW REPLACE	Mutating all atomicrmw instructions to achieve data races.	Takes the given atomic instruction and replaces it with its non-atomic counterpart for the following instructions: ADD, SUB, AND, OR, XOR, FADD, FSUB. For other operators no mutation is done, the mutant is equivalent.
SIGNED TO UNSIGNED	Mutating all signed integer comparisons to achieve overflow and out of bound errors.	Each of the four integer comparison predicates - ICMP_SGT, ICMP_SGE, ICMP_SLT, ICMP_SLE are transformed into the corresponding unsigned predicates - ICMP_UGT, ICMP_UGE, ICMP_ULT, ICMP_ULE respectively.
UNSIGNED TO SIGNED	Mutating all unsigned integer comparisons to achieve overflow and out of bounds errors.	Each of the four integer comparison predicates - ICMP_UGT, ICMP_UGE, ICMP_ULT, ICMP_ULE are transformed into the corresponding unsigned predicates - ICMP_SGT, ICMP_SGE, ICMP_SLT, ICMP_SLE respectively.
SWITCH SHIFT	Mutating all shift calls to achieve overflow and out of bounds errors.	Replaces an arithmetic shift with a logical shift and vice versa.
CALLOC	Mutating all calloc calls to achieve overflow and out of bounds errors.	The size parameter's value is decreased by 16.
DELETE LOCAL STORE	Mutating all stores on a local variable in one function to achieve uninitialization errors.	The store call is removed.
UNSIGNED LESS THAN	Mutating all '<' comparisons either between two integer pointers or between 1 unsigned integer variable and an integer to achieve overflow errors.	For pointer comparison, 8*4=32 is added to the right hand side pointer in the comparison. For integer comparison, the integer on the right hand side is squared if larger than 1024 or smaller than 2, else 32 is added.
UNSIGNED GREATER THAN	Mutating all '>' comparisons either between two integer pointers or between 1 unsigned integer variable and an integer to achieve underflow errors.	For pointer comparison, 8*4=32 is subtracted from the right hand side pointer in the comparison. For integer comparison, either the sqrt is taken for integers > 1024*1024, halved for integers > 1024 and either 0 is returned or 32 is substracted, whatever gives the largest result.
UNSIGNED LESS THAN EQUALTO	Mutating all '<=' comparisons either between two integer pointers or between 1 unsigned integer variable and an integer to achieve overflow errors.	For pointer comparison, 8*4=32 is added to the right hand side pointer in the comparison. For integer comparison, the integer on the right hand side is squared if larger than 1024 or smaller than 2, else 32 is added.
UNSIGNED GREATER THAN EQUALTO	Mutating all '>=' comparisons either between two integer pointers or between 1 unsigned integer variable and an integer to achieve underflow errors.	For pointer comparison, 8*4=32 is subtracted from the right hand side pointer in the comparison. For integer comparison, either the sqrt is taken for integers > 1024*1024, halved for integers > 1024 and either 0 is returned or 32 is substracted, whatever gives the largest result.
INET ADDR FAIL WITHOUTCHECK	Mutating all calls to the libc function inet_addr to achieve unhandled non-established connection errors.	Replaces all uses of the function return value to the failure value. Also removes the function call from the corpus as a fail of the function call should be simulated. Furthermore, the comparison instructions are flipped, s.t. on failure the 'correct' path is taken, i.e. we simulate a missing check for the error return value.
COMPARE EQUAL TO	Mutating all '==' comparisons between two integers to '='.	The value of integer on the right hand side is assigned to the variable on the left. The condition passes and the inside block is executed as long as the value on the RHS is not equal to 0.
PRINTF	Mutating printf such that the format string gets already filled and then plainly printed.	Mutating printf such that the format string is already filled on printing, so instead of calling printf('%d %s', 10, string); we simulate the call printf('10 <string-value>');. This might cause illegal memory accesses and printing of secrets if the string argument is user controlled.
SPRINTF	Mutating sprintf such that the format string gets already filled and then plainly printed.	Mutating sprintf such that the format string is already filled on printing, so instead of calling sprintf('%d %s', buffer, 10, string); we simulate the call sprintf('10 <string-value>', buffer);. This might cause illegal memory accesses and printing of secrets if the string argument is user controlled.
SNPRINTF	Mutating snprintf such that the format string gets already filled and then plainly printed.	Mutating snprintf such that the format string is already filled on printing, so instead of calling snprintf('%d %s', size, buffer, 10, string); we simulate the call snprintf('10 <string-value>', size, buffer);. This might cause illegal memory accesses and printing of secrets if the string argument is user controlled.
NEW ARRAY	Mutating new[] in (only) cpp files such that the array is allocated lesser memory	We decrease allocated memory size in the 'new' call by 5 units.
SWITCH PLUS MINUS	Changing a '+' operator to a '-' operator and vice versa.	Changing a '+' operator to a '-' operator regardless for integer and floating point numbers.
REDIRECT BRANCH	Negate the result of the branching condition before branching.	Redirecting the control flow by negating the result of the condition before branching.
DELETE FUNCTION ARGUMENT	Mutating all functions in (only) cpp files that receive a pointer type function argument to achieve double delete and possibly illegal memory access errors. N.B. - Can possibly lead to a memory leak when delete is called for arrays instantiated with new[]	We check for functions that receive a pointer type argument. Before returning at the end of the function, one argument per mutant is deleted.
DELETE STORE PATTERN	Deletes all store instructions one by one to simulate a forgotten variable assignment.	Find a store instruction and delete it. As there are no further dependencies on the store, there is nothing else to do.
DELETE CALL INSTRUCTION PATTERN	Deletes all call instructions without return value assignment one by one to simulate a forgotten call to a function.	Find a call instruction without return value assignment and delete it. As there are no further dependencies on the call instruction, there is nothing else to do.
REASSIGN STORE INSTRUCTION	Reassigns the value of a previous store with the same type in this store.	Checks if in this basic block is another store with the same types used and assigns the first operand of the previous store to the memory location denoted by the second operand of the store we are currently at.