Mutation Analysis: Answering the Fuzzing Challenge

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Abstract—Fuzzing is one of the fastest growing fields in software testing. The idea behind fuzzing is to check the behavior of software against a large number of randomly generated inputs, trying to cover all interesting parts of the input space, while observing the tested software for anomalous behavior. One of the biggest challenges facing fuzzers users is how to validate software behavior, and how to improve the quality of oracles used.

While mutation analysis is the premier technique for evaluating the quality of software test oracles, mutation score is rarely used as a metric for evaluating fuzzer quality. Unless mutation analysis researchers can solve multiple problems that make applying mutation analysis to fuzzing challenging, mutation analysis may be permanently sidelined in one of the most important areas of testing and security research.

This paper attempts to understand the main challenges in applying mutation analysis for evaluating fuzzers, so that researchers can focus on solving these challenges.

I. INTRODUCTION

In the new millennium, fuzz testing (fuzzing) has rapidly become one of the most popular techniques used in cybersecurity to test the robustness of programs [1]. It is used by industry giants such as Google [2], [3], Microsoft [4], Amazon [5], Meta [6] and others. Industry behemoths such as Microsoft now mandate fuzzing of every untrusted interface of every product [7]. Practitioners have used fuzzing to find thousands of vulnerabilities [7], [8] and other bugs in various applications. Indeed fuzzing has in effect democratized the field of software testing. Organizations such as small businesses can buy off-the-shelf fuzzers, or make use of online services [9], to evaluate their software, and have confidence that their applications are free of easily exploitable vulnerabilities.

While fuzzing has taken the world by storm, several challenges remain. The foremost among them is the question of oracles [10]. Traditional first generation fuzzers typically focused on finding inputs that made the program under evaluation crash. However, this is no longer sufficient. As Firefox fuzzing directions [11] note: Fuzzing is only effective if you are able to know when a problem has been found. That is, we need fuzzers to be able to identify more types of vulnerabilities. We need to find bugs that do not only manifest as a program crash. Going forward, we need to evaluate fuzzers not just on their ability to cover the program code, but also on their intelligence in detecting different kinds of incorrect behaviors.

Fuzzing research typically uses two metrics for evaluating fuzzer effectiveness: (1) various forms of coverage, with paths taken seen as the best measure [12] and branches taken being another common measure; and (2) artificial benchmarks with seeded bugs (Magma [13], LAVA-M [14], BugBench [15], CGC [16], Google FTS [17], FuzzBench [18], UNIFUZZ [19], Apocalypse [20], EvilCoder [21]) which are often considered the ground truth.

However, we know that coverage can often be quickly saturated [22], and that adequate coverage is a necessary, but not sufficient condition for all bugs to be detected. Indeed, fuzzing researchers are aware of the limitations of coverage as a proxy measure [23].

Regarding seeded bugs, the basic problem is that the distribution of such bugs is subject to human bias. That is, engineers who are tasked with inserting bugs may often be biased about what kind of bugs are possible and where they may be present. Hence, the distribution of such seeded bugs need not follow the actual real-world distribution. If one relies on automatic tools, the bug distribution may also be biased due to the capability of the tool in question. Indeed, as Bundt et al. [24] notes, these are limited by the the reachability of their analysis, limited bug types, and bug realism.

On the other hand, if one uses harvested bugs from existing programs [25], this too introduces a bias. The issue is that, the availability of bugs does not mean that the particular program elements contained more bugs. Rather, it only means that the bugs in those elements were more easily detected. That is, any tool that performs well in those benchmarks is likely to be better at finding bugs that we already know how to detect; such an approach may well penalize tools that are most suited for finding new kinds of bugs.

A related problem is that tools such as AFL are commonly used to find and remove bugs in programs before they become deployed or published. This means that the bugs found by such popular tools are likely to be found less and less in the bugs available for harvesting (e.g. in CVEs). This, in contrast, rewards tools that may be less able to detect bugs AFL finds easily, but are able to find bugs AFL cannot find easily.

A final issue in using such benchmarks is that fuzzers can become overfitted to finding bugs in such benchmarks [23], [24]. That is, we run the risk that our fuzzers become more and more efficient in exploring the bug-inducing statements in the benchmark, and more effective in triggering the bugs in the benchmark to the detriment of their real-world performance.
Various proposals for handling these problems have been posed; for instance Gavrilov et al. [26] propose using multiple versions of a program and detecting differences exposed by fuzzers as a richer evaluation measure (they also provide a more in-depth examination of the weakness of the coverage and seeded-bug measures discussed above). However, such an approach requires the availability of multiple versions of a program, and is not fundamentally tied to measuring bug detection (if outputs differ but are not flagged as faulty, this is seen as a difference in appeal, regardless of oracle strength).

Given the importance of oracles in fuzzing, one might expect mutation analysis to be actively used for fuzzer evaluation. Mutation analysis is free of all the above problems that we identified. For example, mutation analysis is much harder to saturate than code coverage [22], and is more robust than various forms of coverage as a proxy for the fault revealing power of the test suite.

Similarly, the mutations produced by mutation analysis are based on a simple fault model that correspond fairly well to real-world [27] faults. That is, the simple faults produced by mutation analysis are free of influence from human biases. Further, given that the mutations produced are not based on any sort of harvested bugs, these are free of bias due to availability: mutation analysis will induce bugs that are both easy and hard for, e.g., AFL to detect.

Unfortunately, out of the numerous fuzzing evaluation research papers available [23], [19], [24], [28], [29], [30], [26] none recommends the use of mutation analysis for fuzzing. Indeed, none of the papers we examined [1], [31], [32], [33] actually used mutation score as a means of evaluation. To our knowledge, the only published paper that uses mutation to evaluate fuzzing is a Software Engineering in Practice short paper [34] discussing an effort to improve fuzzing for Bitcoin Core (suggesting that practitioners are interested in the possibility, even if researchers are not, yet). This is surprising because mutation analysis can actually answer many of the challenges posed by fuzzing researchers such as computing residual risk [10, C.7], and producing faults that are similar to real bugs [10, C.11, C.12]. Indeed, the theory of mutation analysis is well researched, and mature.

In this paper, we examine the reasons why mutation analysis has, so far, evaded the attention of security researchers. We identify a few likely reasons, propose mitigations, and identify areas of future research.

II. BACKGROUND

A. Fuzzing

Fuzzing is simple in concept. Given any application that accepts user specified inputs, the application is executed with inputs, generated by the fuzzer, that try to exercise as much of the application behaviour as possible. The program execution is monitored for crashes or other surprising behavior that can be detected by the available oracles [1].

Fuzzers, and test generators in general are typically evaluated based on the (1) speed of their turn around, their (2) speed of generation of inputs, and the (3) quality of their oracles. We define the following metrics for fuzzer evaluation.  

**Efficiency of the framework.** The turn-around time for the fuzzer. It is influenced by the speed of generation of inputs for execution, whether the fuzzer can be parallelized, the speed of execution of the program for a given input.

**Effectiveness of the generator.** The effectiveness of the tests generated in covering all features of the program, and the effectiveness of inputs for triggering failures.

**Efficacy of the oracle.** The capability of the fuzzer oracle to detect triggered changes in behavior, especially failures or vulnerabilities.

1) Input Generation Techniques: Fuzzers rely on being able to test the program under fuzzing a large number of times. They rely on raw computing power to accomplish this fast (that is, within a given time budget), and there is a lot of focus on improving the speed of execution of the input generator [35], [36] as well as fast execution of programs under test [37]. As to the intelligence used for generation of inputs, test generators in general are typically classified based on the assumptions they make about the program in question. These include:

**White-box generator.** White-box generators assume the availability of source code for both static as well as dynamic analysis. These generators are also called clear-box generators or structural test generators. The availability of source code has traditionally meant that the program input specification is also known. Sage [4] is a canonical example.

**Grey-box generator.** Grey-box generators are a spectrum of generators where deep program analysis may be impossible or prohibitive to perform. Instead, these generators assume that the program can be instrumented, and the feedback can be used to guide the program input generation. AFL [37] is a canonical feedback driven grey-box generator. A grey-box or white-box generator can be used even if the formal program interface is not known. Starting with an initial seed corpus, that may just be a single empty input, the generator mutates one input of the corpus, such as randomly changing a byte, and observing the resulting feedback. Interesting inputs are added to the corpus for further mutations, a typical evolutionary algorithm. The efficacy of this approach can be enhanced by a seed corpus that excercises larger parts of the target program, providing a larger frontier to find interesting inputs. Fuzzers that rely on mutation of a seed corpus

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1We note that there is no agreement on what these terms mean in fuzzing research. For example, Böhme et al. [10] defines efficiency as the rate at which vulnerabilities are discovered, and effectiveness as the total number of vulnerabilities that a fuzzer can discover in the limit (i.e. given infinite time). However, given that code coverage is used to measure effectiveness in a majority of papers [23], we believe that effectiveness as used by the fuzzing community relates to the quality of inputs rather than the oracle used. Hence, we use efficacy to denote the oracle quality here as it seems unused in fuzzing literature (and we could not find a corresponding term for oracle quality in fuzzing research). Finally, the speed at which vulnerabilities can be found seems to be related to the speed at which one can execute the tests (assuming a uniform distribution and difficulty of finding them). Hence, we use efficiency to denote the speed of execution.
for exploring the input space are called *mutation fuzzers*. AFL is again a canonical example. Both mutation and generation can also be combined as in AFLSmart [38].

**Black-box generator.** Black-box generators are used when the source code of the program under test is not available, and it is impossible to instrument the program for feedback. These generators typically assume that the program input specification is known [35] which is used for intelligent generation of inputs\(^2\). These kinds of fuzzers are also called *generational fuzzers* or *grammar fuzzers*.

**Hidden-box generator.** Traditionally called dumb generators, these are generators that make the least amount of assumptions about the program in question. They assume *nothing* about what kind of inputs are accepted by the program, but rely on the fact that program crashes are undesirable. Pure random fuzzers [39] are the best known, but not the only kind of hidden-box generator. Other examples include Anti-random [40] and failure-feedback [41] generators.

2) **Type of Oracles:** Different fuzzers can also be distinguished by their oracle efficacy, as follows.

**Explicit oracles.** These are contracts that are explicitly specified by the practitioner [42]. These are also called *specification based* oracles [43]. An example of an explicit contract is that the output should conform to, say, a given XML schema, or that the output should be a valid JSON file. Property based testers such as QuickCheck [44] can make use of sufficiently detailed contracts for strong oracles.

**Implicit oracles.** Implicit oracles are oracles that describe the general valid state of the program. These are the typical oracles used in general fuzzers [42]. Tools such as DeepState [45] make it possible to use QuickCheck-style property-based specifications with off-the-shelf fuzzers like AFL. Sanitizers are one of the most common types of *implicit oracles* used for fuzzing. A number of sanitizers exist that can be used with general fuzzers [46]. The most popular ones [47] are memory (MSAN) sanitisers which detects uses of uninitialized memory, address (ASAN) sanitizer which targets use-after-free buffer-overflows and memory leaks, thread sanitizer (TSAN) which detects data races and deadlocks, floating-point sanitizer (NSAN), and undefined behaviour sanitizer (UB-San) [46], [48].

**Differential oracles.** These are also called pseudo oracles [49], [50], [51]. If there exists a different program that implements the same specification, then one can make use of a differential oracle. The idea is to generate inputs and compare the behavior of different programs. If there is a difference between the two implementations, at least one of them is wrong. Common examples include parsers for common file formats, virtual machines such as CLR, WASM, and JVM, and protocol implementations such as FTP and HTTP. A common variant of this idea is the regression oracle [52]. In this case, a different version of the same program is used to verify that only expected features differ. Finally, tools such as Evosuite [53] that make use of mutants for generating test cases also use the same idea.

**Metamorphic oracles.** These are oracles that rely on metamorphic relations between inputs [54], [55], [56], [57]. An important category of metamorphic oracles are cross-checking oracles [58], which use redundant operations in software APIs as a way of constructing possibly equivalent API call test sequences and assertions.

**Dynamic invariants.** The final approach involves monitoring the invariants between program variables during execution, and tries to identify outlying executions. These are exemplified by Daikon [59].

**B. Mutation Analysis**

Mutation analysis is a technique for evaluating the fault revealing power of test suites on a given program. We define the following mutation related terms:

**Mutation.** A mutation is a small syntactic change that can be induced in the program, that will likely lead to a semantic difference.

**Mutation operator.** Mutation operators are replacement patterns that describe 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 mutant is 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.

**Trivial mutants.** These are mutants that can be killed (detected as failure inducing) without targeted intelligence. That is, an input that covers the mutation location in the program already killed them, such as a fuzzer’s seed input.

**Redundant mutants.** A mutant A is redundant with respect to another mutant B if any test that can kill mutant B is guaranteed to kill A.

**Duplicate mutants.** A mutant A is duplicate of another mutant B if any test that kills A will kill B and vice versa.

**Stubborn Mutants.** These are mutants that remained alive even after coverage reached their mutation locations.

**Intelligent mutants.** These are mutants that were killed by fuzzers on individual evaluation (i.e., they required intelligence to kill).

**Immortal mutants.** Mutants that can’t be killed by any weak oracles such as crash oracles in the current program.

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

1) **Error Model:** For mutation analysis, we start with the following error model: Any token\(^3\) 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.

\(^2\)Black-box testing is also called specification-based testing.

\(^3\)A token is the smallest syntactical element in the program.
to the code artifact. Further, we assume that the developer uses automatic tools such as compilers which can identify and remove a limited category of faults. This gives us a way to generate possible faults without human bias: Simply generate all possible instances of faults for each source code element that will get past the compiler. Unfortunately, this can lead to a combinatorial explosion. Hence, we rely on a few axioms to limit the number of faults generated. The finite neighborhood hypothesis and the coupling effect.

2) Fundamental Axioms: The finite neighborhood hypothesis states that faults, if present in the program, are within a limited edit distance away from the correct formulation [27]. 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 [60]. Both these axioms are well researched, with well-founded theory [61], [62], [63], [64], and confirmed in large number of real world software [65], [64], [66], [67]. With these two axioms, we can limit the faults that we need to test. Allowing us to focus only 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 simply 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 software verifier (test suites, static analyzers), static test generators, and fuzzers) and check whether the verifier is able to detect the changed behavior of the mutant (called killing the mutant). The idea is that the number of mutants thus killed by each verifier provides a simple and effective criteria to compare verifiers.

III. MUTATION ANALYSIS FOR FUZZING – ADVANTAGES

Böhme et al. [12] identified the following questions as the current challenges in fuzzing. We mark each question that mutation analysis or mutation analysis research can potentially answer (✓), help answer (✓), evaluate (✓), or provide insights on(✓).

C.1. How to fuzz more types of software. ✓
C.2. How to identify more types of vulnerabilities. ✓
C.3. How to find more deep bugs. ✓
C.4. What kind of vulnerabilities are not found by fuzzing. ✓
C.5. How to leverage the auditor.
C.6. How to improve the usability of fuzzing tools.
C.7. How to assess the residual security risk. ✓
C.8. What are the limitations of fuzzing.
C.9. How to evaluate more specialized fuzzers. ✓
C.10. How to prevent overfitting to a specific benchmark? ✓
C.11. Are synthetic bugs representative? ✓
C.12. Are bugs discovered by fuzzers, representative? ✓
C.13. Is coverage a good measure for fuzzer effectiveness? ✓
C.14. What is a fair time budget? ✓

C.15. How to evaluate techniques instead of implementations.

Mutation analysis can help in overcoming 10 out of 15 challenges in fuzzing. Next we discuss how and why this is the case for each challenge in more detail.

C.2. How to identify more types of vulnerabilities: This is a major limitation in current fuzzing benchmarks [24]. As discussed in the introduction, this is the most obvious way mutation analysis can aid fuzzing research. Research currently uses either structural coverage (which almost always provides no insight into oracles and vulnerability types) or seeded/harvested bugs, where adding new categories of bug is labor-intensive and prone to either human or tool bias.

Mutation analysis has a lot to offer here. In particular, mutation analysis is fault-based, which means that it explicitly evaluates the oracular strength. Something structural coverage metrics are not able to do, additionally, mutation analysis does not get saturated as fast as coverage does.

Indeed, mutation analysis is one of the best fault based evaluation techniques we have, as it is based on a well founded theory, and was created with the explicit purpose of avoiding the pitfalls of fault seeding (i.e. benchmarks).

Mutation analysis avoids pitfalls of fault seeding benchmarks, and can induce a much larger variety of bugs that match the real world bugs in behavioral variety and difficulty.

Mutation analysis exhausts seeds the program with first order variations. As a consequence, there is no bias in the kinds of bugs that are seeded, avoiding the possibility of fuzzers overfitting. All in all, mutation analysis can adequately answer the challenge posed by Böhme [10, C.2].

C.3. How to find more deep bugs: Solving this challenge can likely be achieved by improving the quality of input generators. However, inducing subtle faults into predicates as T-Fuzz [69] does can help. However, the induced faults need to be small enough so as to affect the validity of the input execution minimally. Mutation analysis research can help here [70]; in work-in-progress (citation blinded for review), we have used mutation to generate program variants to explore deep behavior. Furthermore, unlike traditional fault-injection techniques such as LAVA-M [14], faults injected by mutation analysis is not limited to a limited reachable subset of the program as it faithfully recreates possible errors by the programmer anywhere in the program. Hence, bugs induced by mutation analysis can distinguish the capability of fuzzers to detect deep bugs.

The faults injected by mutation analysis is not limited by any analysis.

C.4. What is the nature of vulnerabilities that are not found?: This challenge is about identifying the nature of bugs that evaded detection after long fuzzing campaigns. While empirical studies are certainly helpful here, mutation analysis has something to offer as well. In particular, mutation analysis is a mature field with well established research on the nature of bugs [71], [65].
Second, mutation analysis has a well founded theory based on exhaustively seeding first order faults. The first order faults serve as the base case and the coupling effect hypothesis which serves as the induction to ensure that a large majority (> 99% [64]) of the higher order faults are found by test suites adequate to detect these first order mutants. Further, for those rare faults that slip through, mutation analysis can be easily extended with new operators that need not be first order [72], [73].

The mutants that remain after a fuzzing campaign indicates the kinds of bugs a fuzzing campaign missed.

What about failures that require interaction between multiple faults? Such faults are impossible to find by first order mutation. However, there are two mitigations here. The first is that surprisingly small number of faults are sufficient for a majority of FTFI (failure-triggering fault interactions) found [74], [64], with more than 90% of the failures observed involving just one or two faults. Indeed, most failures were triggered by a single erroneous parameter to a function, and almost all could be induced by fewer than 4 faults. Second, one may induce subtle mutations using higher order mutation [72] which can adequately represent such rare faults.

C.7. How to assess the residual security risk?: One of the main reasons for using mutation analysis is that it provides the best estimate for residual defects in a program, the number of defects that remain in a program after testing is completed\(^4\). Assume for a moment that the fault was small enough to be a mutation, and one of our mutants reverses this fault. If so, (assuming sound testers), a testing professional would never have written a test to kill the mutant. Rather, it would have been flagged a defect, and fixed. If, on the other hand, the difference between the corrected version and the faulty version was bigger than any mutant, by the coupling effect hypothesis, there must still exist multiple mutants that correspond to different parts of the failure behavior (not necessarily representing the correct behavior). If so, for a tester to kill such mutants, the tester has to assert the correct behavior for that mutant, and given that the failure behavior is different from the correct behavior, this would again have been flagged as a fault and fixed. This is true for assertions from any oracle, so long as the oracle is sound. We note that mutation relies on weak crash oracles that are sound but not complete. Hence, as the number of mutants that remain undetected decreases, the number of defects that remain undetected also decreases monotonically. Hence, the number of mutants that remain alive is a true ordinal measure\(^5\) for the residual defects in the program.

Mutation analysis can comprehensively answer the question of residual risk after fuzzing.

\(^4\)At this point, we assume that no detected faults remain in the program. Any that were found were fixed.

\(^5\)By true ordinal measure, we simply mean a measure that corresponds to the definitions from measure theory [75]. That is, it follows monotonicity of the measured quantity, and additivity of measures between independent subsets. That is, it is different from mere correlation.

C.9. How to evaluate more specialized fuzzers?: This question is about the challenge of evaluating fuzzers that are focused on specific kinds of bugs, or specific kinds of programs. For example, one may be out of luck if one is looking for parser bugs, or specifically binary parser bugs because the baselines may not contain such parsers. As Böhme notes [10], current benchmarks are often not designed for such tasks, and he advocates for suitable programs and baselines for comparison. The trouble is that, adding new programs to your benchmark is only postponing the problem. Say you have — after many months of manual effort — added a few parsers and corresponding harvested bugs to your benchmark. A new language feature, or a new kind of parsing such as combinatorial parsing can make such benchmarks inadequate to deal with the new kinds of bugs introduced, while removing the bugs that are evaluated in your benchmark. Hence, improving the benchmark is not a solution here.

However, mutation analysis has a simple solution here. If a particular kind of program is not present in the benchmark, simply add the program, and let mutation analysis generate the bugs to be evaluated. This removes the manual effort present in keeping the benchmark up to date.

C.10. How to prevent overfitting to a specific benchmark?: In this question, Böhme points out that fuzzers can become overfitted to a specific benchmark irrespective of the superiority of a benchmark. Böhme proposes various solutions involving collecting even more benchmarks. The trouble here is again that for fault-seeding, one needs not only programs, but also harvested or seeded bugs on these programs. This is a labour intensive task.

As before, the mutation analysis solution is simple. Collect as many programs as are possible. So long as you are able to run it, mutation analysis will take care of seeding the right bugs for you. Indeed, if you are a user of specific kinds of programs such as the military or government, with the traditional approach of fault seeding, it is nearly impossible to find preexisting benchmarks that suit your purpose. With mutation analysis, you can make your own benchmark, and evaluate fuzzers on it without much manual effort.

Further, one can extend mutation analysis with new kinds of mutation operators as well as higher order mutants [72], [73] deriving more value out of an existing benchmark.

Similarly, if you are working on a new or less popular language, you are again out of luck with the traditional fault-seeding benchmarks. With mutation analysis, you can simply collect programs, and mutation analysis to seed bugs, given the existence of universal mutation tools that apply to essentially any program language [76].

Using mutation analysis fuzzing researchers can avoid overfitting to benchmarks.

C.11. Are synthetic bugs representative?: This question is about whether the seeded bugs designed by engineers or by artificial injectors such as LAVA-M [14] are representative of the real bugs [24]. If not, what can we do to make them
so? This is a question that was comprehensively answered by mutation analysis research. Indeed, we know that the faults seeded by mutation analysis are representative of real world bugs both in terms of syntax [27] as well as semantics [77], [78], and having a higher mutation score means lesser number of found bugs in the future [79], [80], and thus mutants are valid substitutes for real faults [65]. That is, if one is to rely on bugs induced by mutation analysis, one can have high confidence that the bugs induced are representative of the real world.

The bugs induced by mutation analysis can match the realism of real world bugs.

C.12. Are bugs discovered previously by fuzzers, representative?: This question is about bugs collected through harvesting preexisting bugs for benchmarks. As we discussed in C.11, the faults induced by mutation analysis are indeed representative of real world. Further, new fault patterns can be easily mined and added if necessary.

C.13. Is coverage a good measure for fuzzer effectiveness?: The problem with coverage is that it is a necessary but not sufficient condition for detecting faults. In particular, covering a fault is a necessary but not a sufficient precondition for triggering that failure, and even if the failure is triggered, we need adequate oracles that can detect the failure. Coverage does not measure the quality of oracles available. Secondly, coverage is often easily saturated [22]. Once coverage is saturated, there is little feedback available for further fuzzing.

C.14. What is a fair time budget?: In this question Böhme points out that there may be a difference between fuzzers in terms of the number of vulnerabilities that they can detect in the limit (given infinite time). However, even a hidden-box fuzzer assuming nothing about the program in question can, in the limit, generate any input. Any fuzzer that doesn’t can be trivially extended with a hidden-box fuzzer to be maximally effective in terms of its inputs. However, the idea here seems to have been about distinguishing between fuzzers in terms of the trade-off between efficiency and effectiveness in terms of the curve of discovery. We note that the complexity of a program is related to the number of mutants it can have [81]. Hence, any fair budget should correspond to the number of mutants produced. We discuss how to measure this curve in more detail in Section IV-B2.

IV. MUTATION ANALYSIS FOR FUZZING – CHALLENGES

Mutation score and structural coverage metrics are typically used for two different but related purposes in the software-engineering world.

(1) The first, and traditional, use is by a practitioner to evaluate the adequacy of a test suite. That is, if one considers statement coverage, a coverage result of 100% means that all statements in the program were executed at least once. That is, the test suite is coverage adequate.

(2) The second common use of mutation score and other coverage metrics is as a means of comparing between two test suites.

The adequacy of a test suite was often the most important factor when considering static test suites. The reason is that, in traditional testing scenario, one rarely needed to compare different ways of creating test cases, because there was often only one kind – developer written test cases. However, with the advent of test generators such as Evosuite [53], Randoop [82], and different fuzzers, the situation has changed. Most of these fuzzers and other test generators can make use of any and all computational resources as you can provide them. There is no fixed point at which they stop. Unfortunately, there is an exponential increase in difficulty in finding the next bug [12]. Hence, we need to decide how to allocate limited testing budget, and for that we need to find the best test generator.

A. Computational Expense

The main problem with mutation analysis is its computational requirements. The number of mutants that have to be evaluated increases with the size of the program. Further, for fuzzing we need to evaluate each input produced independently on each mutant. That is, we can’t tell if a mutant will be killed by an input without executing the mutant on that input. We can’t even assume that the fuzzer will produce the same input on the original as well as the mutant because the fuzzer may find the mutation in the program using static analysis, and take steps to reach it or to induce failure on a perceived fault. Further, most feedback driven fuzzers (e.g., AFL) will modify their next input correspondingly to take advantage of any new coverage found, which may be induced by the mutation. Hence, it is highly likely that the fuzzer generated inputs are different for the original code and various mutants. This means that there is a quadratic increase in the number of program executions required with program size.

There are a number of traditional optimizations to make mutation analysis less computationally demanding. However, most of these techniques assume static test suites, which makes them inapplicable to fuzzers. For example, two algorithms try to reduce the number of mutants to be evaluated by identifying which tests are applicable to which mutants. The first, called lazy mutation analysis, by Fleishgakker [83] uses weak mutation kills to identify which tests to run on which mutants. A less complex approach is to use code coverage for the same purpose [84], [85]. The idea 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. Unfortunately, these techniques are inapplicable to fuzzers because fuzzers may not use the same input sequences on all mutants, as we mentioned above.

That is, a fuzzer may analyze the source code statically and modify its behavior correspondingly resulting in different fuzzer behaviors for the original program and the mutant
Another optimization is to use weak mutations [86] which only check whether an input would have resulted in a different state in the mutant when compared to the original. This again assumes that the test suite will not change when a mutation is present. Partitioning infected states [87], split stream execution [88], [89] and equivalence modulo states [90] assume again that the same inputs are used for both mutant and original program. A recent optimization technique is to memorize expensive with non-determinism is also that the results achieved depend on the initial random seed, and also on the seed corpus. Indeed, even the relatively harm less schema based mutation execution optimization [92], [93], [94] can induce changes in the fuzzer behavior, as the fuzzer can wastefull try to generate inputs in an attempt to reach the disabled mutations when another mutation is enabled.

Techniques such as test selection [95], [96] can’t be used for fuzzing because they rely on a static test suite.

Thus, these traditional optimization techniques do not work well for fuzzers.

**Challenge 1:** Find optimizations that do not rely on static test suites.

### B. Comparing Test Generators

1) **Non-determinism**:

One of the challenges in evaluating test generators is that many of these are dependent on non-deterministic execution for their effectiveness. The problem with non-determinism is also that the results achieved depend on the initial random seed, and also on the seed corpus [23]. Hence, one evaluation alone is insufficient for statistical confidence in the evaluation rankings [23].

Unlike coverage techniques which impose very little overhead over the program, mutation analysis can be costly. Hence, running mutation analysis multiple times for statistical certainty can be prohibitive.

2) **Distribution**:

The second challenge in evaluating test generators is that there is no single point at which a test generator stops. Secondly, the speed of analysis and execution plays a large role in how effective a fuzzer is. For example, a naive fuzzer [39] or a simple grammar fuzzer [35] can run circles around a more intelligent symbolic execution based fuzzer in the initial stages [4] because program analysis and symbolic execution can take time. However, beyond the easily explorable program paths, the symbolic fuzzer can leverage information about the predicates guarding program paths, and make better use of the computational resources at a later stage [23]. Finally, any fuzzer can (or can be trivially extended with a hidden-box fuzzer to) find all bugs that its oracle can detect, in the limit. This is because, in the limit, all inputs will be tried at some point.

Hence, we need to identify the fault revealing curve of a test generator for adequate comparison, which should be provided to the practitioners. A single score will no longer cut it.

### C. Problems with Redundancy

One of the problems with mutation analysis is that the mutants produced may be redundant or there may even be true duplicate mutants. The problem with such mutants is that they can affect the correlation of mutation score to the real fault detection. That is, say you have N duplicate mutants. If we have an input that kills these N mutants, it is only worth one mutant, but will be counted as N in the mutation score. On the other hand, if these mutants remain undetected, the number of mutants yet to be killed is inflated. Hence, redundant and duplicate mutants are undesirable. The traditional approach to eliminating them has been to compute the full mutation matrix of tests x mutants result, and compute the minimal mutant set. However, with fuzzing this is not possible for two reasons: (1) there is no end point for fuzzing. Hence, the size of test suite is limited only by the available time and (2) the test suites may differ between each mutant. That is, we have no simple way to compute duplicate and redundant mutants during fuzzing.

**Challenge 2:** Find ways to incorporate statistical and time based distribution of mutant kills cost-effectively.

### D. Equivalent Mutants

A somewhat similar problems with mutation analysis is equivalent mutants. These are mutants that are semantically the same as the original program. For example, a cache

```java
if (cache.containsKey(key))
    return cache.get(key);
return compute(key);
```

removing the cache check need not induce a failure. The problem with equivalent mutants is that they make the final mutation score unreliable. That is, we do not know for sure if the live mutants remaining are actually killable or not. Indeed, anywhere from 10% to 40% of generated mutants could be equivalent [97], [98]. However, the actual percentages are very program dependent.

One of the promising approaches toward estimation of equivalent mutants is using species richness estimation as proposed by Böhme. [100]. The idea is to use the frequency of counts of mutants that are found by different test cases to estimate the number of mutants that are yet to be found. This can provide us with an estimate of the total killable mutants if one is given the full kill matrix that describes which mutants...

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*Later analysis suggests a more refined figure of 23% [99].*
are killed by which tests \((M \times T)\). Unfortunately, given that the test cases are not static between different mutants, this method can’t be used for estimation of equivalent mutants during fuzzing.

While equivalent mutants are troublesome for interpretation of mutation score, such equivalent mutants are less of a concern for fuzzer comparison, because, for comparison, the only concern is the number of relative mutant kills between fuzzers.

**Challenge 4:** Determine how to account for equivalent mutants in fuzzer evaluation.

**E. Lack of mutation analysis Frameworks that Focus on Fuzzers**

One of the difficulties encountered when trying to use mutation analysis with fuzzers is that there are no mutation frameworks that are capable of running fuzzers on mutants efficiently. Fuzzers typically rely on framework support for coverage feedback. Further, many fuzzers also rely on starting seeds. Accounting for, and managing such seeds while also parallelizing mutation analysis is not yet available in mutation frameworks.

**Challenge 5:** Build mutation analysis frameworks that are fully capable of fuzzer evaluation.

**F. Lack of Awareness Among Researchers**

While we have identified possible technical reasons for the dismal popularity of mutation analysis among security researchers, lack of awareness may also be an equally important reason. Indeed, none of the fuzzing review papers we examined contained any reference to mutation analysis.

**Challenge 6:** Improve visibility of mutation analysis among fuzzing researchers.

**V. Promising Directions for Research**

**A. Computational Expense**

Computational expense in running mutation analysis is one of the major impediments for the use of mutation analysis to evaluate fuzzers. We discuss a few possibilities to mitigate this problem.

1) **Mutant reduction:** One of the possible ways to reduce the cost of mutation analysis without assuming anything about the test suite is to reduce the number of mutants evaluated. Indeed, this is one of the traditional techniques for reducing the cost of mutation analysis. However, one needs to be careful how the number of mutants is reduced. In particular, mutation operator selection techniques can have unexpected disadvantages [101]. The best reduction can be achieved using random sampling or various forms of strata sampling techniques with different strata such as program elements or operators.

Sampling may not sound promising because it comes with associated non-determinism and loss of distinguishing power for mutation analysis (when we sample, we are essentially accepting a more limited accuracy for the metric).

2) **Splitting the evaluation:** However, there may be a better way out. It may be observed that during fuzzing, one needs both effectiveness as well as efficacy. That is, one needs to generate inputs that can cover all possible input features. Further, we need oracles that can validate these inputs. Given that coverage is good in the first part, and mutation analysis is good at the second part, why not split them?

The idea is to use coverage as the evaluator for fuzzers until coverage is saturated. We use the standard 24 hours timeout for fuzzing [23]. Once coverage is saturated for all fuzzers, we collect any and all inputs that are required to cover the program maximally, and minimize them to produce a minimal test suite with the same coverage. Let us call this the coverage seed. Next, we use this test suite as a static test suite, and run mutation analysis with it, removing any mutant that is killed using this set of inputs. At this point, all traditional optimizations of mutation analysis can be applied. This allows us to remove trivial mutants cheaply. We then run mutation analysis for each fuzzer starting with the minimal test suite as the seed corpus for each. With this technique, we only evaluate intelligently selected mutants with fuzzing runs.

3) **Supermutants:** A third way out is to evaluate multiple mutants at once. The idea is to produce higher order mutants where the individual mutations are independent of each other in terms of semantics [102] and fuzz the higher order mutant. The idea is to produce higher order mutants such that any input will cover at most one simple mutation in the higher order mutant. Count any crash as killing the mutant corresponding to the mutation that was covered by the crash inducing input. The higher order mutant is completely killed when all corresponding simple mutants are killed. This can reduce the number of mutants to be independently evaluated.

**B. Comparing Test Generators**

For comparing test generators, we need the curve of discovery as we discussed in Section IV-B2. However, if we split the evaluation into a coverage part and a mutation analysis part as discussed in Section V-A2, then we can reduce the computational requirements for computing the curve as follows. For every chosen mutant, we keep track of the time at which it was killed. We also have the coverage curve which is comparatively easy to obtain, and the corresponding lines of code that were covered.

Now, for computing the mutation curve, the idea is as follows. For any trivial mutant, the time taken for detection is the time taken for covering the corresponding program element. For any chosen mutant, the time taken for killing is the time taken for covering its corresponding mutation along with the time taken to kill it. Once we compute the time to kill for each mutant, it can be plotted, and the curve of mutant detection can be obtained for any time period.

**C. Redundancy**

For evaluating the redundancy of mutants, we propose the following solution. For any mutant, identify the input that kills it during fuzzing. This may be from the coverage seed
collection or during later fuzzing. Next, use this final set of inputs as a static test suite (let us call this the final static test suite), and run full matrix mutation analysis using the traditional optimizations. This will allow us to compute the minimal set of mutants using the traditional minimal mutant computation.

D. Equivalent Mutants

Once we have the final static test suite, we propose to use the final static test suite along with species richness estimation by Böhme [100] for evaluating the range of equivalent mutants. However, we note that this is yet to be validated even for traditional mutation analysis. A second possibility is to sample from the remaining mutants to evaluate whether the sampled mutant is killable. We note that detecting equivalent mutants will be no different for fuzzers than in traditional mutation analysis.

VI. RELATED WORK

The latest research in mutation analysis is discussed by Papadakis et al. [103] who also discuss numerous techniques to reduce the computational expenditure involved in traditional mutation analysis.

The survey paper by Pizzoleto et al. [104] focuses on cost reduction of mutation analysis and suggests that one of the main areas of research in this direction recently has been in trying to reduce the number of mutants executed. Other options include various forms of selective mutation, statistical sampling of mutants, clustering and then sampling mutants, finding subsuming mutants, and so forth. Researchers have also explored various strategies for cost reduction including higher order mutation, weak and firm mutation [105], [86], [106], [107], [108]. Finally, another possibility is to use a proxy for mutation score such as checked coverage [109].

Lima et al. [110] examines different strategies including different higher order mutants for reducing the cost of execution of mutants. They found each-choice strategy was the best in this regard.

There have been numerous ideas focused on improving the efficiency of evaluation. Some of the work in this area involves parallelization of mutation analysis using MIMD [111] and SIMD [112] machines, in HPC systems [113], and using Hadoop [114].

VII. CONCLUSION

Mutation analysis has been relegated to the sidelines in fuzzing research. However, we find that two thirds of the key challenges identified in fuzzing research can potentially be addressed using mutation analysis.

At the same time, we find that mutation analysis still requires solutions to some significant challenges before it can be used for fuzzing. Of particular importance is the computational cost. Mutation analysis is a costly technique even in traditional settings with static test suites. When used for fuzzing, most of the traditional optimization techniques can’t be used because they assume static test suites. Further, the fuzzing itself is computationally costly, with fuzzing campaigns on programs typically recommended to run for at least 24 hours. Finally, the requirement of statistical confidence because of non-determinism in fuzzing adds even more computational requirement for successful use of mutation analysis in fuzzing.

Lack of frameworks that can do both mutation analysis and fuzzing is another problem that discourages use of mutation analysis in fuzzing. Finally, lack of awareness of mutation analysis may also be a factor in cybersecurity researchers ignoring mutation analysis for fuzzer evaluation.

In this paper, we document the ways in which mutation analysis can potentially help fuzzing research, or help the fuzzing practitioner, identify the challenges ahead before mutation analysis can be considered a viable alternative to bug benchmarks and coverage for fuzzer evaluation, and propose a few possible mitigation strategies.

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