Coverage-based Greybox Fuzzing as Markov Chain

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Abstract—Coverage-based Greybox Fuzzing (CGF) is a random testing approach that requires no program analysis. A new test is generated by slightly mutating a seed input. If the test exercises a new and interesting path, it is added to the set of seeds; otherwise, it is discarded. We observe that most tests exercise the same few "high-frequency" paths and develop strategies to explore significantly more paths with the same number of tests by gravitating towards low-frequency paths. We explain the challenges and opportunities of CGF using a Markov chain model which specifies the probability that fuzzing the seed that exercises path i generates an input that exercises path j. Each state (i.e., seed) has an energy that specifies the number of inputs to be generated from that seed. We show that CGF is considerably more efficient if energy is inversely proportional to the density of the stationary distribution and increases monotonically every time that seed is chosen. Energy is controlled with a power schedule. We implemented several schedules by extending AFL. In 24 hours, AFLFast exposes 3 previously unreported CVEs that are not exposed by AFL and exposes 6 previously unreported CVEs 7x faster than AFL. AFLFast produces at least an order of magnitude more unique crashes than AFL. We compared AFLFast to the symbolic executor Klee. In terms of vulnerability detection, AFLFast is significantly more effective than Klee on the same subject programs that were discussed in the original Klee paper. In terms of code coverage, AFLFast only slightly outperforms Klee while a combination of both tools achieves best results by mitigating the individual weaknesses.

Index Terms—vulnerability detection, fuzzing, path exploration, symbolic execution, automated testing

✦

1 INTRODUCTION

RECENTLY, there has been a controversial debate about the efficiency of symbolic execution-based whitebox fuzzers versus more lightweight greybox fuzzers [2], [3]. Symbolic execution is a systematic effort to stress different behaviors and thus considerably more effective. Yet, today most vulnerabilities were exposed by particularly lightweight fuzzers that do not leverage *any* program analysis.

It turns out that even the most effective technique is less efficient than blackbox fuzzing if the time spent generating a test case takes too long [4]. Symbolic execution is very effective because each new test exercises a different path in the program. However, this effectiveness comes at the cost of spending *significant time doing program analysis and constraint solving*. Blackbox fuzzing, on the other hand, does not require any program analysis and generates several orders of magnitude more tests in the same time.

Coverage-based Greybox Fuzzing (CGF) is an attempt to make fuzzing more effective at path exploration *without* sacrificing time for program analysis. CGF uses lightweight (binary) instrumentation to determine a unique identifier for the path that is exercised by an input. New tests are generated by slightly mutating the provided seed inputs (we also call the new tests as *fuzz*). If some fuzz exercises a new and interesting path, the fuzzer retains that input; otherwise, it discards that input. The provided and retained seeds are fuzzed in a continuous loop, contributing even more seeds.

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- An earlier version appeared at the 23rd ACM Conference on Computer and Communications Security (ACM CCS'16) [1].

Compared to symbolic execution, CGF does not require program analysis which brings several benefits. There is *no imprecision*, for instance, in the lifting of the control-flow graph from the program binary or the encoding of the path condition as SMT formula. CGF is more *scalable* because the time for one test depends on the program's execution time rather than its size or complexity. CGF is highly *parallelizable* because the retained seeds represent the only internal state. AFL implements the state-of-the-art of CGF, is behind hundreds of high-impact vulnerability discoveries [5], has been shown to generate valid image files (JPEGs) from an initial seed that is virtually empty [6], and has also been integrated with symbolic execution (which helps where AFL "gets stuck") [3]. Clearly, increasing the efficiency of fuzzers, like AFL, has a real and practical impact on vulnerability detection.

> *"Ultimately, the key to winning the hearts and minds of practitioners is very simple: you need to show them how the proposed approach finds new, interesting bugs in the software they care about."* – Michal Zalewski [2]

We discuss challenges of existing CGFs and opportunities to boost their efficiency by an order of magnitude. Our key observation is that *most fuzz exercises the same few paths*: Existing CGFs generate too many inputs which stress the same behavior. More efficient CGFs exercise more paths with the same amount of fuzz. For instance, suppose we want to expose vulnerabilities in `libpng`. Fuzzing a *valid* image file, there may be a 90% chance that a mutated variant exercises a path π which rejects invalid image files. Fuzzing an *invalid* image file, there may be a 99.999% chance that a mutated variant exercises the same path π. So, independent of the initial seed image files, an above-average amount of

fuzz is bound to exercise that path π which rejects invalid inputs. Informally, we call π a *high-frequency* path.

In this paper, we propose several strategies to systematically bias the fuzzer towards exercising low-frequency paths so as to explore more paths with the same amount of fuzz. The results are very encouraging. Our AFL extension AFLFAST discovered 9 vulnerabilities in GNU binutils which are now listed as CVEs in the US National Vulnerability Database. AFLFAST exposes 6 CVEs up to 14 times faster than AFL and exposes 3 CVEs that are not exposed by AFL in eight runs of 24 hours. AFLFAST reports an order of magnitude more unique crashes than AFL.[1] We will argue that our strategies have no detrimental impact on the effectiveness of AFL. So, given more than 24 hours, AFL is expected to report the same unique crashes and expose the three remaining CVEs.

To explain the remarkable performance gains of AFL-FAST, we model Coverage-based Greybox Fuzzing (CGF) as a Markov chain. The chain specifies the probability p_{ij} that fuzzing the seed exercising path i generates an input exercising path j. We let each state (i.e., seed) have an *energy* that specifies the amount of fuzz that is generated by fuzzing that seed when it is chosen next. For instance, the *minimum energy* required to discover a new and interesting path j by fuzzing the seed which exercises path i is expected to be p_{ij}^{-1}. Note, however, that in practice p_{ij} is clearly unknown. The energy of a state is controlled by a predefined *power schedule*.

AFL implements a power schedule that assigns an energy that is *constant* in the number of times $s(i)$ the seed has been chosen for fuzzing. Every time the seed is chosen, about the same number of inputs are generated. In some cases, AFL might assign significantly more than the minimum energy required to discover a new and interesting path; in other cases, AFL might assign not enough energy. In contrast, AFLFAST implements a power schedule that assigns an energy that is *exponential* in $s(i)$. When the seed is fuzzed for the first time, very low energy is assigned. Every time the seed is chosen thereafter, exponentially more inputs are generated up to a certain bound. This allows to rapidly approach the minimum energy required to discover a new path.

In fact, AFL implements a power schedule that assigns constantly *high energy*. Often, 80k inputs are generated for each seed which takes about one minute. This addresses the problem of *rapid mixing*: Independent of the initial seed inputs, after a (burn-in) time some paths will always be exercised by significantly more fuzz than others. Assigning a lot of energy to the inital seeds allows to discover many more "neighbors" that exercise *low*-frequency paths. For instance, it makes sense to fuzz a valid image file for the longest time with the objective to generate many more valid image files. It is also a good idea to assign a lot of energy to these neighbors and their neighbors. However, after some time, as more seeds are discovered, many seeds will start to exercise *high*-frequency paths and AFL ends up assigning way too much energy. The chance to generate a valid image file is significantly lower if the latest seed is an invalid file.

1. AFL reports an input that exercises a new and interesting path *and crashes the program* (i.e., which would otherwise be retained as new seed) as a *unique crash*.

In contrast, AFLFAST implements a power schedule that assigns energy that is *inversely proportional* to the density of the stationary distribution. In other words, it assigns low energy to seeds exercising high-frequency paths and high energy to seeds exercising low-frequency paths. To *estimate* the fuzzer's probability of exercising a path i, AFLFAST uses the maximum-likelihood estimator $\hat{p}_i = f(i)/n$ where $f(i)$ is the number of fuzz exercising i and n is the total number of fuzz generated throughout the fuzzing campaign.

AFL chooses seeds in the order they are added. Once all seeds have been fuzzed, AFL resumes with the first. A new cycle begins. AFLFAST effectuates a different *search strategy*. It chooses seeds in the order of their likely progressiveness (while choosing a seed only once per cycle). In the same cycle, AFLFAST chooses seeds earlier i) that exercise lower-frequency paths and ii) that have been chosen less often. The search strategy allows to fuzz the best seeds early on. However, independent of the search strategy and given the same power schedule, when a cycle is completed the same seeds will have been fuzzed.

We note that power schedules and search strategies merely impact AFL's *efficiency* (i.e., #paths explored per unit time), *not* its *effectiveness* (i.e., #paths explored on average). Since we do not modify the mutation operatorsthat are being used for fuzzing, the probability p_{ij} to discover path j by fuzzing the input exercising path i does not change from AFL to AFLFAST. In other words, AFLFAST effectively exposes exactly the same vulnerabilities as AFL – only significantly faster.

In summary, we argue that the effectivness of symbolic execution stems from the systematic enumeration of paths in the program. This allows to expose vulnerabilities that hide deep in the program. Unfortunately, most fuzzers trade this systematic path coverage for scalability. However, coverage-based greybox fuzzers maintain some of this effectiveness by retaining fuzz that exercises paths that have previously not been exercised. Each new seed results in progress towards generating even more seeds that exercise even "deeper" paths. Still, even coverage-based fuzzers tend to visit certain paths with high frequency, generating too much fuzz that exercises the same few paths.

To understand the difference in practice, we compared KLEE [7] and AFLFAST in terms of vulnerability detection and coverage achieved using the same subjects and settings that were used in the original KLEE-paper. KLEE exposes six of the nine KLEE-benchmark errors quicker than AFLFAST. However, AFLFAST discovered five new bugs that KLEE did not expose. This indicates that KLEE is able to detect certain types of errors quickly while it is unable to detect some other types of errors in the 1-hour time frame. Investigating the reason, we found that KLEE requires a constraint-based vulnerability detection mechanism and presumes the completeness of the constraint-encoding as well as the completeness of the environment modelling. In contrast, AFLFAST merely executes the program and reports any crashes, e.g., via runtime checking. In terms of code coverage, we found that AFLFAST performs slightly better than KLEE, covering an average of 82% of executable lines of code in 50 programs versus 78% for KLEE. However, we believe that a combination of both techniques is even more powerful, using their individual strengths to mitigate each others weaknesses.

Our main conceptual contribution is to smartly control the amount of fuzz generated from a seed, thereby veering the search towards paths that are exercised with low frequency, towards paths where vulnerabilities may lurk. Technically, we achieve this enhanced path coverage using power schedules and search strategies that do not require program analysis.

Specifically, our paper makes the following *contributions*:

- **Markov Chain Model**. We model coverage-based greybox fuzzing as a systematic exploration of the state space of a Markov chain. We provide insight about the machinery that drives AFL, which is arguably *the* most successful vulnerability detection tool to date. We utilize the model to explain the challenges of AFL and the remarkable performance gains of our tool AFLFAST.

- **Power Schedules**. We introduce and evaluate several strategies to control the number of inputs generated from a seed, with the objective to exercise a larger number of low-frequency paths in the same time.

- **Search Strategies**. We devise and evaluate several strategies to control the order in which seeds are chosen for fuzzing, with the same objective.

- **Comparison to Symbolic Execution**. We empirically compare the popular symbolic execution engine KLEE with our implementation of coverage-based greybox fuzzing, both in terms of vulnerability detection as well as in code coverage achieved.

- **Tool**. We published AFLFAST as a fork of AFL. Since the first release, AFLFAST has had considerable impact in software security practice, being featured in several blog posts and hundreds of tweets. AFLFAST was used by Team Codejitsu who came in 2nd *in terms of number of bugs found*[2] at the DARPA Cyber Grand Challenge: **https://github.com/mboehme/aflfast**

The remainder of this article is structured as follows. After the introduction in Section 1, we introduce some background in Section 2. The Markov chain model is introduced in Section 3 and used to discuss opportunities to boost the efficiency of CGF in Section 4. We compare our implementation of boosted CGF (i.e., AFLFAST) with vanilla CGF (i.e., AFL) Section 5 and with a symbolic execution engine (KLEE) in Section 6. After a discussion of related work in Section 8, we conclude in Section 9.

2 BACKGROUND

2.1 Coverage-based Greybox Fuzzing

FUZZ – an automated random testing tool was first developed by Miller et al. [8] in early 1990s to understand the reliability of UNIX tools. Since then, fuzzing has evolved substantially, becomes widely adopted into practice, and exposed serious vulnerabilities in many important software programs [9], [10], [11], [12]. There are three major categories depending on the degree of leverage of internal program structure: *black-box fuzzing* only requires the program to execute [9], [10], [13] while *white-box fuzzing* [7], [14], [15], [16] requires binary lifting and program analysis, for instance, to construct the control-flow graph. *Greybox fuzzing*

2. See red result bar for Galactica at http://bit.do/cgcresult.

is situated inbetween and uses only lightweight binary instrumentation to glean some program structure. Without program analysis, greybox fuzzing may be more efficient than whitebox fuzzing. With more information about internal structure, it may be more effective than blackbox fuzzing.

Coverage-based greybox fuzzers (CGF) [12] use lightweight instrumentation to gain coverage information. For instance, AFL's instrumentation captures basic block transitions, along with coarse branch-taken hit counts. A sketch of the code that is injected at each branch point in the program is shown in Figure 1.

```
cur_location = <COMPILE_TIME_RANDOM>;
shared_mem[cur_location ^ prev_location]++;
prev_location = cur_location >> 1;
```

Fig. 1. AFL's instrumentation.

The variable `cur_location` identifies the current basic block. Its random identifier is generated at compile time. Variable `shared_mem[]` is a 64 kB shared memory region. Every byte that is set in the array marks a hit for a particular tuple (A, B) in the instrumented code where basic block B is executed after basic block A. The shift operation in Line 3 preserves the directionality $[(A, B)$ versus $(B, A)]$. A hash over `shared_mem[]` is used as the path identifier.

Algorithm 1 Coverage-based Greybox Fuzzing

Input: Seed Inputs S
1: $T_\chi = \emptyset$
2: $T = S$
3: **if** $T = \emptyset$ **then**
4:     add empty file to T
5: **end if**
6: **repeat**
7:     $t = \text{CHOOSENEXT}(T)$
8:     $p = \text{ASSIGNENERGY}(t)$
9:     **for** i from 1 to p **do**
10:         $t' = \text{MUTATE\_INPUT}(t)$
11:         **if** t' crashes **then**
12:             add t' to T_χ
13:         **else if** ISINTERESTING(t') **then**
14:             add t' to T
15:         **end if**
16:     **end for**
17: **until** *timeout* reached or *abort*-signal

Output: Crashing Inputs T_χ

A CGF uses the coverage information to decide which generated inputs to retain for fuzzing, which input to fuzz next and for how long. Algorithm 1 and Figure 2 provides a general overview of the process and is illustrated in the following by means of AFL's implementation. If the CGF is provided with seeds S, they are added to the queue T; otherwise an empty file is generated as a starting point (lines 1–5). The seeds are choosen in a continuous loop until a timeout is reached or the fuzzing is aborted (line 7). AFL classifies a seed as a *favorite* if it is the fastest and smallest input for any of the control-flow edges it exercises. AFL's implementation of CHOOSENEXT mostly ignores non-favorite seeds.

For each seed input t, the CGF determines the number of inputs that are generated by fuzzing t (i.e., #fuzz for t; line 8). AFL's implementation of ASSIGNENERGY uses the execution time, block transition coverage, and creation time of t. Then, the fuzzer generates p new inputs by mutating t according to defined mutation operators (line 10). AFL's implementation of MUTATE_INPUT uses bit flips, simple arithmetics, boundary values, and block deletion and insertion strategies to generate new inputs.[3]
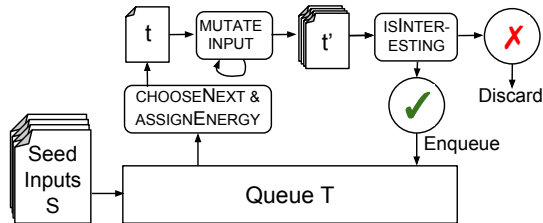

Fig. 2. Architecture of Coverage-based Greybox Fuzzing (CGF)

If the generated input t' is considered to be "interesting", it is added to the circular queue (line 14). AFL's implementation of ISINTERESTING returns true depending on the number of times the basic block transitions, that are executed by t', have been executed by other seeds in the queue. More specifically, t' *is interesting* if t' executes a path where transition b is exercised n times and for all other seeds $t'' \in T$ that exercise b for m times, we have that $\lfloor \log_2 n \rfloor \neq \lfloor \log_2 m \rfloor$ where $\lfloor \cdot \rfloor$ is the floor function. AFL uses this "bucketing" to address path explosion [3]. Intuitively, AFL retains inputs as new seeds that execute a new block transition or a path where a block transition is exercised twice when it is normally exercised only once. At the same time, AFL discards inputs that execute a path where some transition is exercised 102 times when it has previously been exercised 101 times. If the generated input t' crashes the program, it is added to the set T_{X} of crashing inputs (line 12). A crashing input that is also interesting is marked as *unique crash*.

Fuzzing stages. When new seeds are added, AFL runs a calibration and a deterministic stage. In the calibration stage, the new seed is executed multiple times to determine average execution time and whether the associated path identifier changes across executions. Normally, AFL would fuzz the seed by randomly choosing a sequence of mutation operators and apply them to random locations in the seed file. However, in the deterministic stage AFL applies a specific set of mutation operators to *each* input byte of the seed. We can say that AFL assigns very high energy to a seed that is chosen for the first time (Line 8).

Binary instrumentation. AFL supports both source code instrumentation and binary instrumentation via QEMU [17]. While QEMU does the instrumentation during interpretation at runtime, AFLDynInst [18] injects the instrumentation shown in Figure 1 directly into the binary.

Modifications. On this high level, our changes of AFL concern *only* the functions CHOOSENEXT which implements the search strategy and ASSIGNENERGY which implements the power schedules.

3. https://lcamtuf.blogspot.sg/2014/08/binary-fuzzing-strategies-what-works.html

2.2 Markov Chain

A Markov chain is a stochastic process that transitions from one state to another [19]. At any time, the chain can be in only one state. The set of all states is called the chain's *state space*. The process transitions from one state to another with a certain probability that is called the *transition probability*. This probability depends only upon the current state rather than upon the path to the present state.

More formally, a *Markov chain* is a sequence of random variables $\{X_0, X_1, \ldots, X_n\}$ where X_i describes the state of the process at time i. Given a set of states $S = \{1, 2, \ldots, N\}$ for some $N \in \mathbb{N}$, the value of the random variables X_i are taken from S. The probability that the Markov chain starts out in state i is given by the initial distribution $\mathbb{P}(X_0 = i)$.

The *probability matrix* $\boldsymbol{P} = (p_{ij})$ specifies the transition rules. If $|S| = N$, then $\boldsymbol{P}$ is a $N \times N$ stochastic matrix where each entry is non-negative and the sum of each row is 1. The conditional probability p_{ij} defines the probability that the chain transitions to state j at time $t + 1$, given that it is in state i at time t,

$$p_{ij} = \mathbb{P}(X_{t+1} = j \mid X_t = i)$$

A Markov chain is called *time-homogeneous* if the probability matrix (p_{ij}) does not depend on the time n. In other words, every time the chain is in state i, the probability of jumping to state j is the same.

If a Markov chain is time homogeneous, then the vector $\boldsymbol{\pi}$ is called a *stationary distribution* of the Markov chain if for all $j \in S$ it satisfies

$$0 \le \pi_j \le 1$$
$$1 = \sum_{i \in S} \pi_i$$
$$\pi_j = \sum_{i \in S} \pi_i p_{ij}$$

Informally, a Markov chain $\{X_0, X_1, \ldots, X_n\}$ is called *rapidly mixing* if X_n is "close" to the stationary distribution for a sufficiently low number of steps n. In other words, rapidly mixing chains approach the stationary distribution within reasonable time—independent of the initial state.

Random walkers sample the distribution that is described by a Markov chain. A walker starts at a state according to the initial distribution and transitions from one state to the next according to the transition probabilities. The state at which the walker arrives after n steps is considered a sample of the distribution. There may be an ensemble of walkers that move around randomly.

For instance, the crawling of web pages can be modelled as Markov chain. Pages are the states while the links are the transitions. Given page i with q_i links where one link goes to page j, the probability p_{ij} that a random surfer reaches j from i in one click is $p_{ij} = 1/q_i$. A crawler, like Google, seeks to index the important pages of the internet. Brin and Page [20] developed an algorithm, called PAGERANK that assigns an importance score to each page. Intuitively, the PAGERANK value of a page measures the chance that a random surfer will land on that page after a sequence of clicks. More formally, the PAGERANK approximates the *density of the stationary distribution* of the Markov chain where important pages are located in high-density regions.

3 MARKOV CHAIN MODEL

In this paper, we model the probability that fuzzing a seed which exercises program path i generates a seed which exercises path j as transition probability p_{ij} in a Markov chain. This allows us to discuss the *objective* of greybox fuzzing as the efficient exploration of the chain's state space and to explain the *challenges and opportunities* of CGF and of AFL specifically. We argue that a coverage-based greybox fuzzer exercises more distinct paths per unit time if it does focus on inputs in low-density regions of the Markov chain. Hence, we devise several strategies to bias the traversal towards visiting more states in low-density regions and less states in high-density regions of the stationary distribution. Before discussing these strategies, we introduce the Markov chain model.

3.1 Coverage-based Fuzzing as Markov Chain

Time-inhomogeneous model. Suppose, after providing the fuzzer with an initial seed input t_0 that exercises path 0, the fuzzer immediately explores path $i + 1$ by randomly mutating the previous input t_i which exercises path i. Every input that is generated is directly chosen as next seed. The sequence of paths that the fuzzer exercises is described by a Markov chain. The transition probability p_{ij} is defined as the probability to generate an input that exercises path j by randomly mutating the previous input t_i that exercises path i. Clearly, this Markov chain is not time-homogeneous. The transition probability p_{ij} depends on the path in the Markov chain by which the state i was reached. Say, a different input t_i' is fuzzed that also exercises path i, the probability p_{ij} to generate an input that exercises path j might be very different. While this is still a Markov chain, it is not time-homogeneous. The analysis is difficult and the existence of a stationary distribution is not guaranteed.

Time-homogeneous model. A stationary distribution does exist for the following model of coverage-based fuzzing. The *state space* of the Markov chain is defined by the discovered paths and their immediate neighbors. Given seeds T, let S^+ be the set of (discovered) paths that are exercised by T and $S^- \not\subseteq S^+$ be the set of (undiscovered) paths that are exercised by inputs generated by the fuzzer fuzzing any $t \in T$.[4] Then the set of states S of the Markov chain is given as

$$S = S^+ \cup S^-$$

The *probability matrix* $P = (p_{ij})$ of the Markov chain is defined as follows. If path i is a discovered path exercised by $t_i \in T$ (i.e., $i \in S^+$), then p_{ij} is the probability that randomly mutating seed t_i generates an input that exercises the path j. Else if path i is an undiscovered path that is not exercised by some $t \in T$ (i.e., $i \in S^-$), then $p_{ii} = 1 - \sum_{t_j \in T} p_{ji}$ and $p_{ij} = p_{ji}$ for all $t_j \in T$. In other words, we make the following two assumptions. We assume that generating an input that exercises path j from (undiscovered) seed t_i is as likely as generating from seed t_j an input that exercises (undiscovered) path i. We also assume that $i \in S^-$ has no other undiscovered neighbors.

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4. An input t_i is randomly mutated using `mutate_input` on t_i in Algorithm 1.

The *stationary distribution* π of the Markov chain gives the probability that a random walker that takes N steps spends roughly $N\pi_i$ time periods in state i. In other words, the proportion of time spent in state i converges to π_i as N goes to infinity. We call a *high-density region* of π a neighborhood of paths I where $\mu_{i \in I}(\pi_i) > \mu_{t_j \in T}(\pi_j)$ and μ is the arithmetic mean. Similarly, we call a *low-density region* of π a neighborhood of paths I where $\mu_{i \in I}(\pi_i) < \mu_{t_j \in T}(\pi_j)$. Two paths i and j are in the same *neighborhood* if $p_{ij} + p_{ji} \geq \epsilon$ where ϵ is an arbitrary constant. It is not difficult to see that a greybox fuzzer is more likely to exercise paths in a high-density region of π than in a low-density region. Note that we get a new Markov chain once an undiscovered path $i \in S^-$ is discovered.

Sequence of chains. A fuzzing campaign is a sequence of Markov chains where a transition from one chain to the next occurs as a new and interesting path is discovered. However, we argue informally that *asymptotically* there is only one stationary distribution. First, we clarify what changes from one Markov chain to the next. Let T_n be a set of seeds, S_n^+ be the set of paths exercised by T_n, and t_i be a generated test input, such that t_i exercises a path $i \notin S_n^+$. Let $T_{n+1} = T_n \bigcup \{t_i\}$, S_{n+1}^+ be the set of paths exercised by T_{n+1}. Let $P_n = (p_{ij})$ be the probability matrix for the Markov chain specified by T_n and $P_{n+1} = (q_{ij})$ probability matrix for the Markov chain specified by T_{n+1}. For all $j, k \in S_n^+$ and for all $l \neq i$ s.t. $l \notin S_n^+$, we have that

$$(p_{jk} = q_{jk}) \wedge (p_{jl} = q_{jl}) \wedge (p_{lj} = q_{lj}) \wedge (p_{ji} = q_{ji}) \wedge (p_{ij} \neq q_{ij})$$

In other words, only the probability of generating an input exercising path $j \in S^+$ or $l \notin S^+$ changes when fuzzing the newly discovered seed t_i. The stationary distribution of the Markov chain specified by T_{n+1} is *not* very different from the stationary distribution of the chain specified by T_n. In fact, the *similarity increases over time*. As more test inputs are generated, less paths are considered as new and interesting. So, path discovery decelerates monotonically, approaching an asymptote. As the number of discovered paths approaches the asymptotic total number of paths, the stationary distribution of the current Markov chain approaches the stationary distribution of the Markov chain specified by the set of seeds exercising the asymptotic total number of paths.

Energy & power schedules. We let each state $s \in S^+$ have an energy. The *energy* of state i determines the number of inputs that should be generated by fuzzing the seed t_i when t_i is next chosen from the queue T. The energy of a state is controlled by a pre-defined *power schedule*. Note that energy is a local property specific to a state (unlike temperature in simmulated annealing). In Algorithm 1, the power schedule is implemented by the function ASSIGNENERGY.

Long tails. In our experiments, we observe several notable properties of the Markov chain model of coverage-based greybox fuzzing. For one, the stationary distribution has a large number of very-low-density regions and a small number of very-high-density regions. As shown in Figure 3, 30% of the paths are exercised by just a single generated test input while 10% of the paths are exercised by $1k$ to $100k$ generated test inputs. In other words, most inputs exercise a few high-frequency paths. Often, these inputs are invalid while the few inputs exercising the low-frequency paths
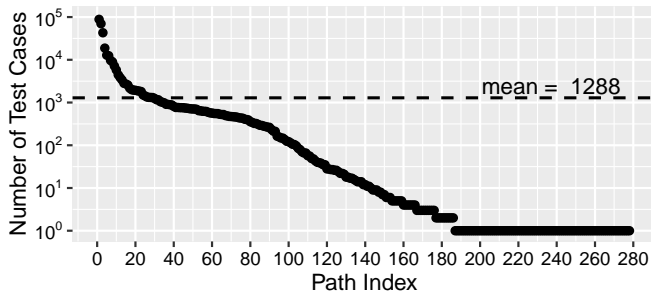
Fig. 3. #Fuzz exercising a path (on a log-scale) after running AFL for 10 minutes on the nm-tool.

are valid and interesting. Basically, almost each valid input would exercise different behavior. Hence, in this paper we devise strategies to explore such low-density regions more efficiently.

Rapid mixing. Moreover, such Markov chains are mostly rapidly mixing. Given our exploration objective, this is most unfortunate. It takes only a few transitions to "forget" the initial state and arrive in a high-density region that is visited by most walkers. After a few transitions, the probability that the current state corresponds to a *high*-frequency path is high, no matter whether the walker started with an initial seed that exercises a low-frequency path or not, or whether the walker started with a valid or an invalid input.

Benefits. The Markov chain model of coverage-based greybox fuzzing has several benefits. For example, it opens fuzzing for the efficient approximation of numerical program properties, such as the worst-case or average execution time or energy consumption. There exist several Markov Chain Monte Carlo (MCMC) methods, like Simulated Annealing [21] that offer guarantees on the convergence to the actual value. In the context of vulnerabilty research, the Markov chain model allows to explain the challenges and opportunities of existing coverage-based fuzzers, such as AFL.

3.2 Running Example

On a high level, we model the probability that fuzzing a test input $t \in T$ which exercises some path i generates an input which exercises path j as transition probabilities p_{ij} in a Markov chain. We illustrate this model using the simple program in Figure 4 which takes as input a 4-character word and crashes for the input "bad!".

```
void crashme (char* s) {
  if (s[0] == 'b')
    if (s[1] == 'a')
      if (s[2] == 'd')
        if (s[3] == '!')
          abort();
}
```

Fig. 4. Motivating example

The program has five execution paths. Path 0 (****) is executed by all strings that do not start with the letter 'b'. Path 1 (b***) is executed by all strings starting with "b" that do not continue with the letter 'a'. Path 2 (ba**) is executed by all strings starting with "ba" that do not continue with

the letter 'd'. Path 3 (bad*) is executed by all strings starting with "bad" that do not continue with the letter '!'. Finally, Path 4 is executed only by the input "bad!".

Now, let us specify the implementation of MU-TATE_INPUT (*MI*) in Algorithm 1 to modify a seed input $s = \langle c_0, c_1, c_2, c_3 \rangle$ to generate new inputs. *MI* chooses with equal probability a character c from s and substitutes it by a character that is randomly chosen from the set of 2^8 ASCII characters. For example, the word "bill" exercises Path 1. With probability $1/4$, *MI* chooses the second character c_1 and with probability $1/2^8$ it chooses the letter 'a' for the substitution. With a total probability of 2^{10}, *MI* generates the word "ball" from "bill" as the next test input which exercises Path 2.
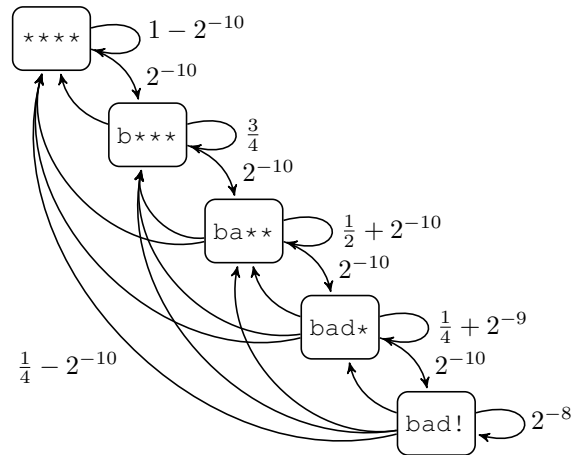

Fig. 5. Markov chain for motivating example

Figure 5 represents the simplified transition matrix p_{ij} as a state diagram.[5] For example, if the current input is the word "bill", the Markov Chain is in the state b***. The likelihood to transition to the state ba** is 2^{-10} as explained earlier. In other words, on average it takes $2^{10} = 1024$ executions of *MI* on the word "bill" to exercise Path 3 and reach state ba**. Given the word "bill", the likelihood to transition to the same state b*** is 0.75 because *MI* may choose the first letter and 'b' as substitute or the second letter and any letter except 'a' as substitute with a total probability of 0.25 and it may choose the third or fourth letter with a total probability of 0.5. The probability to transition to state **** is $\left(1/4 - 2^{-10}\right)$ because *MI* may choose the first of four letters and substitute it with any letter except 'b'.

Notice that there is a very high probability density in state ****. Most 4-character words do not start with 'b' such that the initial distribution is heavily biased towards that state. The random walker can transition to the next state only with probability 2^{-10}, stays in b*** with probability $3/4$ and comes back to the state **** with the approximate probability $1/4$. Many inputs will be generated until the walker reaches the state bad!.

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5. For simplicity, we ignore some low probability transitions, e.g., from state **** to state bad!.

3.3 Challenges of Coverage-based Fuzzers

A *coverage-based greybox fuzzer* is an ensemble of random walkers in the Markov chain. There is one walker for each seed $t \in T$. The *objective* is to discover an interesting path $s \in S^-$ that is not exercised by any $t \in T$ while generating a minimal number of inputs. Conceptually, all walkers can move simultaneously. Technically, resources are limited and we need to choose which walker can move and how often. In a sequential setting, the fuzzer chooses the next input to fuzz $t \in T$ according to CHOOSENEXT and generates as many inputs as determined by $p = $ ASSIGNENERGY(t) in Alg. 1. Usually, $p < M$ where $M \in \mathbb{N}$ gives an upper bound on the number of generated inputs. In AFL, $M \approx 160k$.

More Energy Than Needed. AFL implements a schedule that assigns energy that is *constant* in the number of times the corresponding seed has been chosen from the queue. Let i be a path such that $i \in S^+$ and let t_i be the seed input that execises i. Let X_{ij} be a random variable describing the number fuzz generated from t_i before discovering the path $j \in S^-$. We solve for the expected value of X_{ij} using a recursive argument: The probability of discovering j with the first fuzz that is generated from t_i is p_{ij}. The probability of not discovering j and requiring at least one more fuzz is $(1 - p_{ij})$. Formally,

$$\mathbb{E}[X_{ij}] = p_{ij} + (\mathbb{E}[X_{ij}] + 1)(1 - p_{ij})$$
$$= \frac{1}{p_{ij}}$$

In other words, in expectation the *minimum energy* that should be assigned to state $i \in S^+$ so that the fuzzer discovers the new state $j \in S^-$ is $1/p_{ij}$. Now, AFL's constant schedule might assign significantly more or significantly less energy than is actually required.

Example. Let AFL's power schedule assign an energy of $p(i) = 2^{16} = 64k$ to a state i every time t_i is chosen. Since most 4-character words do not start with 'b', the first input t_0 likely exercises Path 0. After 2^{16} inputs have been generated by fuzzing t_0, several inputs are expected to begin with the letter 'b'. One input that exercises Path 1 is retained as seed t_1. After another 2^{16} inputs have been generated by fuzzing t_1, at least one input is expected to exercise Path 2 and is retained as t_2. Figure 6 shows how the procedure continues. After a total of $256k$ inputs were generated from the four seeds that were retained for each path, the crashing input is found. A more efficient fuzzer would need to generate no more than $\mathbb{E}[X_{01}] + \mathbb{E}[X_{12}] + \mathbb{E}[X_{23}] + \mathbb{E}[X_{34}] = 4 \cdot 2^{10} = 4k$ inputs to expose the same vulnerability.

#Total Tests	State	Explored States
1	****	****
$2^{16}+1$	b***	****,b***
$2 \cdot 2^{16}+1$	ba**	****,b***,ba**
$3 \cdot 2^{16}+1$	bad*	****,b***,ba**,bad*
$4 \cdot 2^{16}+1$	bad!	****,b***,ba**,bad*,bad!

Fig. 6. The crash is found after $2^{18} = 256k$ inputs were generated by fuzzing when $p = 2^{16}$ is constant.

Excessive Energy for High-Density Regions. AFL's power schedule also assigns constantly *high energy*: Fuzzing a seed input often takes about a minute on our machine. This addresses the problem of *rapid mixing*. Initial seeds are

often provided such that they exercise interesting paths in a low-density region in the stationary distribution of the Markov chain. Assigning high energy to the inital seeds and the seeds in the immediate neighborhood allows to discover many more neighbors in the same low-density region. However, as the retained inputs exercise paths in high-density regions – and there is a natural tendency – too much energy is assigned to these states. By definition, the higher the density of the stationary distribution of the Markov chain for the given state i, the higher the proportion of inputs generated by fuzzing t_i that will exercise high-frequency paths.

	State	****	b***	ba**	bad*	bad!
1	ba**	$1 \cdot 2^7$	$1 \cdot 2^7$	$2 \cdot 2^7$	0	0
2	****	$5 \cdot 2^7$	$1 \cdot 2^7$	$2 \cdot 2^7$	0	0
3	b***	$6 \cdot 2^7$	$4 \cdot 2^7$	$2 \cdot 2^7$	0	0
4	ba**	$7 \cdot 2^7$	$5 \cdot 2^7$	$4 \cdot 2^7$	1	0
5	****	$11 \cdot 2^7$	$5 \cdot 2^7$	$4 \cdot 2^7$	1	0
6	b***	$12 \cdot 2^7$	$8 \cdot 2^7$	$4 \cdot 2^7$	1	0
7	bad*	$13 \cdot 2^7$	$9 \cdot 2^7$	$5 \cdot 2^7$	$1 \cdot 2^7$	0
8	ba**	$14 \cdot 2^7$	$10 \cdot 2^7$	$7 \cdot 2^7$	$1 \cdot 2^7$	0
9	****	$18 \cdot 2^7$	$10 \cdot 2^7$	$7 \cdot 2^7$	$1 \cdot 2^7$	0
10	b***	$19 \cdot 2^7$	$13 \cdot 2^7$	$7 \cdot 2^7$	$1 \cdot 2^7$	0
11	bad*	$20 \cdot 2^7$	$14 \cdot 2^7$	$8 \cdot 2^7$	$2 \cdot 2^7$	**1**

Fig. 7. Total #fuzz exercising the corresponding path when fuzzing the given state. Too much energy assigned to state **** and not enough to state bad* once it is discovered. Lines indicate new cycles.

Example. Let the initial seed input be the word ball and let AFL's power schedule assign an energy of $p(i) = 2^9 = 512$ to a state i every time t_i is chosen. This allows us to discuss the case where the next state is not found in a single fuzzing iteration and several cycles through the circular queue might be required. Recall that AFL chooses the seeds in the order they are added. Figure 7 elaborates the example. After fuzzing the initial seed input for 2^9 times, two new seeds are discovered. About one quarter of the fuzz (i.e., 2^7 inputs) exercises paths **** and b***, respectively (see Fig. 5 and Fig. 7, Row 1). Fuzzing the first discovered seed (Row 2), all fuzz exercises the same path. Fuzzing the second discovered seed (Row 3), a quarter of the fuzz exercises path **** and three quarters exercises path b***. Since no new seeds are discovered, a new cycle begins with the initial seed (Row 4). This procedure continues until the vulnerability is exposed (Row 11). In each row we see that most fuzz exercises path ****. Evidently, the fuzzer spends way too much time exercising this high-frequency path. The same time would be better spent fuzzing the seed exercising the low-frequency path bad*.

In summary, two *challenges* of existing coverage-based greybox fuzzers are: Their power schedules

1) may assign *more energy than is required* in expectation to discover a new and interesting path and

2) may assign *too much energy* to states in *high-density regions* of the chain's stationary distribution and not enough energy to states in low-density regions.

4 BOOSTING GREYBOX FUZZING

A more efficient coverage-based greybox fuzzer discovers an undiscovered state in a *low-density region* while assigning *the least amount of total energy*. More specifically,

1) **Search Strategy**. The fuzzer chooses $i \in S^+$ such that $\exists j \in S^-$ where π_j is low and $\mathbb{E}[X_{ij}]$ is minimal.

2) **Power Schedule**. The fuzzer assigns the energy $p(i) = \mathbb{E}[X_{ij}]$ to the chosen state i in order to limit the fuzzing time to the minimum that is required to be expected to discover a path in a low-density region.

In this paper, we propose *monotonous* power schedules that first assign low energy which monotonously increases every time the corresponding seed is chosen from the queue. This allows to rapidly approach $\mathbb{E}[X_{ij}]$. Moreover, our power schedules assign energy that is *inversely proportional* to the density of the stationary distribution of the Markov chain. Intuitively, as soon as a new path is discovered, we want to swiftly explore its general neighborhood expending only low energy. This allows us to get a first estimate of whether i lives in a high-density region. Every time i is chosen thereafter, it is assigned more energy. Intuitively, after the neighborhood is explored and it is established that i lives in a low-density region, the fuzzer can invest significantly more energy trying to find paths in the low-density neighborhood of i.

We also propose and evaluate search strategies that are aimed at the fuzzer expending most energy for paths in low-density regions. For instance, to establish whether a state is in a low-density region, we prioritize such $t \in T$ that have been chosen from the circular queue least often and such t that exercise paths that have least often been exercised by other generated test inputs.

4.1 Power Schedules

A power schedule regulates the energy $p(i)$ of a state. More specifically, a power schedule decides how many inputs are generated by fuzzing the seed $t_i \in T$ which exercises path i when t_i is selected next. In general, $p(i)$ is a function of a) the number of times $s(i)$ that t_i has previously been choosen from the queue T and b) the number of generated inputs $f(i)$ that exercise i. In fact, $f(i)/n$ is the maximum-likelihood estimator of the CGF's probability to generate an input that exercises i and thus approximates the distribution's density. We discuss and evaluate several power schedules.

The **exploitation-based constant schedule** (EXPLOIT) is implemented by most greybox fuzzers. After some burn-in, the assigned energy is fairly constant every time $s(i)$ that t_i is being chosen from the circular queue. The energy $p(i)$ for state i is computed as

$$p(i) = \alpha(i) \qquad \text{e.g., for AFL} \qquad (1)$$

where $\alpha(i)$ is the CGF's present implementation of `assignEnergy` in Algorithm 1 and remains constant as $s(i)$ or $f(i)$ varies. For instance, AFL computes $\alpha(i)$ depending on the <u>execution time, block transition coverage, and creation time of t_i</u>. The example in Figure 6 is derived using a constant schedule.

The **exploration-based constant schedule** (EXPLORE) is a schedule that assigns constant but also fairly low energy. The energy $p(i)$ for state i is computed as

$$p(i) = \frac{\alpha(i)}{\beta} \qquad (2)$$

where $\alpha(i)/\beta$ maintains the fuzzer's original judgement $\alpha(i)$ of the quality of t_i and where $\beta > 1$ is a constant.

Cut-Off Exponential (COE) is an exponential schedule that prevents high-frequency paths to be fuzzed until they become low-frequency paths. The COE increases the fuzzing time of t_i exponentially each time $s(i)$ that t_i is chosen from the circular queue. The energy $p(i)$ is computed as

$$p(i) = \begin{cases} 0 & \text{if } f(i) > \mu \\ \min\left(\frac{\alpha(i)}{\beta} \cdot 2^{s(i)}, M\right) & \text{otherwise.} \end{cases} \qquad (3)$$

where $\alpha(i)$ maintains the fuzzer's original judgement and $\beta > 1$ is a constant that puts the fuzzer in exploration mode for t_i that have only recently been discovered (i.e., $s(i)$ is low), and where μ is the mean number of fuzz exercising a discovered path

$$\mu = \frac{\sum_{i \in S^+} f(i)}{|S^+|}$$

where S^+ is the set of discovered paths. Intuitively, high-frequency paths where $f(i) > \mu$ that receive a lot of fuzz even from fuzzing other seeds are considered low-priority and not fuzzed at all until they are below the mean again. The constant M provides an upper bound on the number of inputs that are generated per fuzzing iteration.

#Tests	State	Explored States
1	****	****
2^{10}	b***	****,b***
$2 \cdot 2^{10}$	ba**	****,b***,ba**
$3 \cdot 2^{10}$	bad*	****,b***,ba**,bad*
$4 \cdot 2^{10}$	bad!	****,b***,ba**,bad*,bad!

Fig. 8. The crash is found after $2^{12} = 4k$ inputs were generated by fuzzing with a power schedule.

Example. Figure 8 depicts the states that a greybox fuzzer explores with the COE power schedule with $\alpha(i)/\beta = 1$. The first test input is chosen at random from the program's input space. Since most 4-character words do not start with 'b', the first input t_0 likely exercises path 0 which corresponds to state ****. The first time that t_0 is fuzzed, $s(0) = 0$ and $f(0) = \mu = 1$ so that $\alpha(0) = 2^0$. Next time, $s(0) = 1$ and $f(0) = \mu = 2$ so that $\alpha(0) = 2^1$. When $s(0) = 9$ and $\alpha(0) = 2^9$, 2^{10} test inputs will be generated so that one generated test input t_1 is expected to start with the letter 'b' and the state b*** is discovered (see Fig. 5). Now, the newly discovered state is assigned low energy $\alpha(1) = 2^0$. However, $f(0) > \mu$ so that soley t_1 will be fuzzed in a similar fashion as t_0 until $s(1) = 9$, $\alpha(1) = 2^9$ and 2^{10} test inputs have been generated by fuzzing t_1. Again, one test input is expected to start with "ba" and the state ba** is discovered. Figure 8 shows how the procedure continues. After $4k$ test inputs were generated from the four inputs that were retained for each path, the crashing input is found. The random generation of the same string would require *five orders of magnitude* more inputs on average ($4 \cdot 10^6 k$ random inputs) while the constant schedule in Figure 6 would require *one order of magnitude* more test inputs on average ($256k$).

The **exponential schedule** (FAST) is an extension of COE. Instead of not fuzzing t_i at all if $f(i) > \mu$, the power

schedule induces to fuzz t_i inversely proportional to the amount of fuzz $f(i)$ that exercises path i. The energy $p(i)$ that this schedule assigns to state i is computed as

$$p(i) = \min\left(\frac{\alpha(i)}{\beta} \cdot \frac{2^{s(i)}}{f(i)}, M\right) \tag{4}$$

Intuitively, $f(i)$ in the denominator allows to exploit t_i that have not received a high number of fuzz in the past and is thus more likely to be in a low-density region. The exponential increase with $s(i)$ allows more and more energy for paths were we are more and more confident that they live in a low-density region.

The **linear schedule** (LINEAR) increases the energy of a state i in a linear manner w.r.t. the number of times $s(i)$ that t_i has been chosen from T, yet is also inversely proportional to the amount of fuzz $f(i)$ that exercises path i.

$$p(i) = \min\left(\frac{\alpha(i)}{\beta} \cdot \frac{s(i)}{f(i)}, M\right) \tag{5}$$

The **quadratic schedule** (QUAD) increases the energy of a state i in a quadratic manner w.r.t. the number of times $s(i)$ that t_i has been chosen from T, yet is also proportional to the amount of fuzz $f(i)$ that exercises path i. The energy $p(i)$ for state i is computed as

$$p(i) = \min\left(\frac{\alpha(i)}{\beta} \cdot \frac{s(i)^2}{f(i)}, M\right) \tag{6}$$

4.2 Search Strategies

While a power schedule regulates the time spent fuzzing a seed, a search strategy decide which seed is chosen next. The decision is purely based on the number of times a seed has been fuzzed before and the amount of fuzz exercising the same path as the seed. An efficient coverage-based greybox fuzzer prioritizes inputs that have not been fuzzed very often and inputs that exercise low-frequency paths.

Prioritize small $s(i)$. This strategy chooses $t_i \in T$ such that the number of times $s(i)$ that t_i has been fuzzed is minimal. However, the fuzzer may still decide to skip the choosen test input, for instance if it is not a designated favourite. In that case, the search strategy is applied again until the fuzzer does not skip the input. Effectively, the queue is reordered using the search strategy. Intuitively, the fuzzer can establish early whether or not path i is a low-frequency path and whether it should invest more energy into fuzzing t_i.

Prioritize small $f(i)$. This strategy chooses $t_i \in T$ such that the number $f(i)$ of generated inputs that exercise path i is minimal. The fuzzer may skip the chosen test input, for instance if it is not a designated favourite, until finally an input is chosen according to the search strategy and accepted for fuzzing. Intuitively, fuzzing an input that exercises a low-frequency path might generate more inputs exercising low-frequency paths.

5 EVALUATION: VANILLA VERSUS BOOSTED CGF

We compare AFLFAST our implementation of the presented monotonous power schedules with AFL 1.94b the baseline implementation featuring a constant schedule.

5.1 Implementation: AFLFAST 1.94b

AFL is a coverage-based greybox fuzzer that collects information on the basic block transitions that are exercised by an input. AFL's binary instrumentation is discussed in Section 2.1. In our experiments, we extended version 1.94b. AFL implements certain strategies to select "interesting" inputs from the fuzz to add to the queue. We did not change this functionality. AFL addresses path explosion by "bucketing" – the grouping of paths according to the number of times all executed basic block transitions are exercised. We did not change this functionality either. All changes were made to ASSIGNENERGY and CHOOSENEXT in Algorithm 1.

Changes for Power Schedule. We changed the computation of the amount of fuzz $p(i)$ that is generated for an input t_i. Firstly, AFL computes $p(i)$ depending on execution time, transition coverage, and creation time of t_i. Essentially, if it executes more quickly, covers more, and is generated later, then the number of fuzz is greater. We maintain this evaluation in the various power schedules discussed above. Secondly, AFL executes the deterministic stage the first time t_i is fuzzed. Since our power schedules assign significantly less energy for the first stage, our extension executes the deterministic stage later when the assigned energy is equal to the energy spent by deterministic fuzzing. Lastly, AFL might initially compute a low value for $p(i)$ and then dynamically increase $p(i)$ in the same run if "interesting" inputs are generated. Since our implementation controls $p(i)$ via a power schedule, we disabled this dynamic increase.

Changes for Search Strategy. We changed the order in which AFL chooses the inputs from the queue and how AFL designates "favourite" inputs that are effectively exclusively chosen from the queue. Firstly, for all executed basic block transitions b, AFL chooses as favourite the fastest and smallest inputs executing b. AFLFAST first chooses the input exercising b with the smallest number of time $s(i)$ that it has been chosen from the queue, and if there are several, then the input that exercises a path exercised by the least amount of fuzz $f(i)$, and if there are still several, then the fastest and smallest input. Secondly, AFL chooses the next favourite input which follows the current input in the queue. AFLFAST chooses the next favourite input with the smallest number of time $s(i)$ that it has been chosen from the queue and if there are several, it chooses that which exercises a path exercised by the least amount of fuzz $f(i)$.

While AFLFAST has since been improved, the version we used for the experiments is still available at https://github.com/mboehme/aflfast/tree/AFLFast.old.

5.2 Vulnerabilities

We chose GNU binutils v2.26 as subject because it is non-trivial and widely used for the analysis of program binaries. It consists of several tools including `nm`, `objdump`, `strings`, `size`, and `c++filt`. We zoom into some results by discussing the results for `nm` in more detail. Binutils is a difficult subject because the fuzzer needs to generate some approximation of a program binary in order to exercise interesting behaviors of the programs. We found a large number of serious vulnerabilities and several bugs (listed in Table 1).

TABLE 1
CVE-IDs and Exploitation Type

Vulnerability	Type
CVE-2016-2226	Exploitable Buffer Overflow
CVE-2016-4487	Invalid Write due to a Use-After-Free
CVE-2016-4488	Invalid Write due to a Use-After-Free
CVE-2016-4489	Invalid Write due to Integer Overflow
CVE-2016-4490	Write Access Violation
CVE-2016-4491	Various Stack Corruptions
CVE-2016-4492	Write Access Violation
CVE-2016-4493	Write Access Violation
CVE-2016-6131	Stack Corruption
Bug 1	Buffer Overflow (Invalid Read)
Bug 2	Buffer Overflow (Invalid Read)
Bug 3	Buffer Overflow (Invalid Read)

All vulnerabilities were previously unreported and rated as medium security risk. We informed the maintainers, submitted patches, and informed the security community via the *ossecurity* mailing list.[6] Mitre assigned *nine (9) CVEs*. At the time of writing, all patches have been accepted. These vulnerabilities affect most available binary analysis tools including valgrind, gdb, binutils, gcov and other libbfd-based tools. An attacker might modify a program binary such that it executes malicious code upon *analysis*, e.g., an analysis to identify whether the binary is malicious in the first place or when trying to reverse-engineer the binary.

TABLE 2
Subjects from Binutils

Utility	Parameters	File Size
c++filt	@@	27kB
nm	-C @@	41kB
objdump	-d @@	36kB
readelf	-a @@	49kB
size	@@	32kB
strings	@@	28kB

Subjects. The specific utilities and command line parameters are shown in Table 2. The parameter @@ is a placeholder for the file that the fuzzer generates as input.

Measure of #paths. AFL maintains a unique path indentifier cksum for each input in the queue that is computed as a hash over the shared memory region that has a bit set for each basic block transition that is exercised by t. We implemented a map $\{(\text{cksum}(i), f(i)) \mid t_i \in T\}$ that keeps track of the number of generated (and potentially discarded) inputs for each exercised path.

Measure of #crashes. AFL defines *unique crash* as follows. If two crashing inputs exercise a path in the same "bucket", then both inputs effectively expose the same unique crash.

Experimental Infrastructure. We ran our experiments on a 64-bit machine with 40 cores (2.6 GHz Intel® Xeon® E5-2600), 64GB of main memory, and Ubuntu 14.04 as host OS. We ran each experiment eight times for six hours, except for nm which was run eight times for 24 hours. We ran 40 experiments simultaneously, that is, one experiment was run on one core. All 40 experiments were also started and stopped simultaneously. So, there is no advantage for experiments that run longer. For each experiment, only one seed input is provided — the empty file. Time is measured using unix time stamps.

6. http://www.openwall.com/lists/oss-security/2016/05/05/3
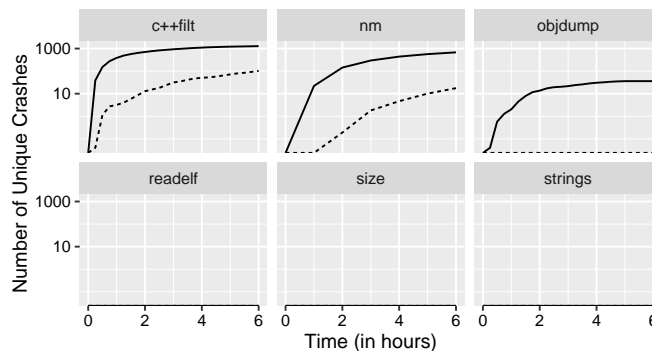
5.3 General Results

Fig. 9. Average #crashes over time (on a log-scale) for AFLFAST (solid line) vs. AFL (dashed line) computed as mean over all runs in five minute intervals.

Crashes over time. After 6h, AFLFAST found one and two *orders of magnitude* more unique crashes than AFL in c++filt and nm, respectively.[7] AFLFAST found 30 unique crashes in objdump where AFL found no crash at all. None of the fuzzers found a crashing input for the remaining three studied tools in any of eight runs of six hours. For each tool, the number of crashes found over time is shown in Figure 9. In what follows, we investigate the unique crashes generated for nm with a 24 hour budget in more details.

TABLE 3
Time to expose the vulnerability.

Vulnerability	AFL	*AFL-Fast*	Factor
CVE-2016-2226	> 24.00 h	3.85 h	N/A
CVE-2016-4487	2.63 h	0.46 h	5.8
CVE-2016-4488	6.92 h	0.98 h	7.0
CVE-2016-4489	10.68 h	2.78 h	3.8
CVE-2016-4490	3.68 h	0.41 h	9.1
CVE-2016-4491	> 24.00 h	4.74 h	N/A
CVE-2016-4492	12.18 h	0.87 h	14.1
CVE-2016-4493	4.48 h	1.00 h	4.5
CVE-2016-6131	> 24.00 h	5.48 h	N/A
Bug 1	20.43 h	3.38 h	6.0
Bug 2	20.91 h	2.89 h	7.2
Bug 3	> 24.00 h	5.07 h	N/A

Vulnerabilities in nm. On average, AFLFAST exposes the CVEs seven (7) times faster than AFL and exposes three (3) CVEs that are not exposed by AFL in any of eight runs in 24 hours. AFLFAST exposes all found vulnerabilities in 2h17m, on average while AFL would require more than 12h30m. The first three rows of Figure 10 show the results for the vulnerabilities in the nm tool in more details. Each facet compares AFLFAST on the left hand-side and AFL on the right hand side using a box plot with a jitter overlay. In all of eight runs, AFLFAST consistently and significantly outperforms classic AFL. The average time to first exposure is shown in Table 3. All vulnerabilities are exposed within the first six hours. The exponential power schedule and improved search strategies clearly boost the efficiency of the state-of-the-art coverage-based greybox fuzzer.

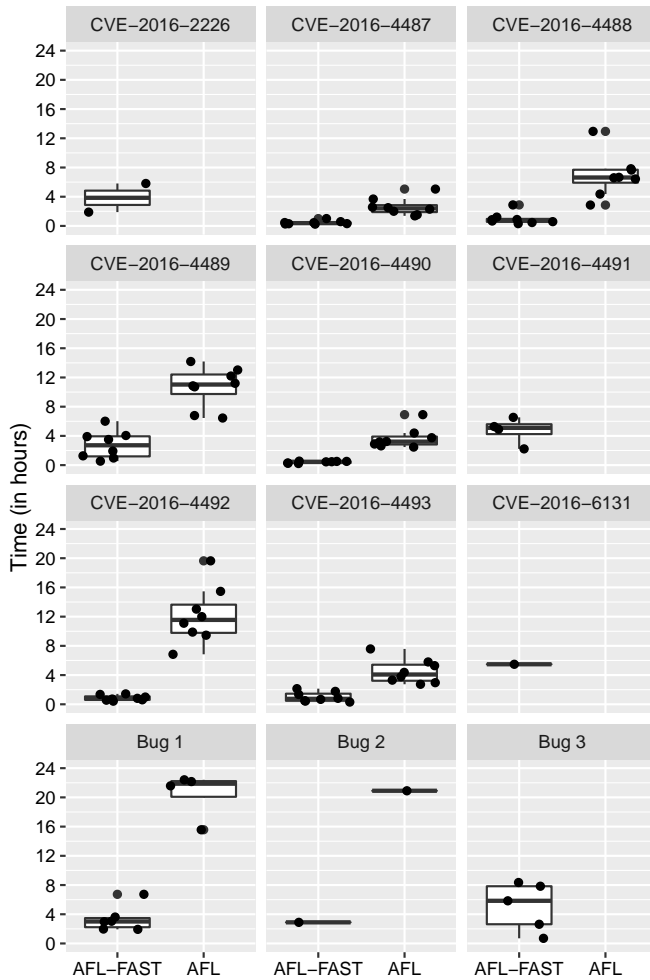7. Notice the logarithmic scale in Figure 9.

Fig. 10. Time to expose the vulnerability.

Fig. 11. #Fuzz exercising a path (on a log-scale) after running AFL for 10 minutes on the `nm`-tool.

frequency paths that are exercised by most fuzz anyways. Finally, it allows the coverage-based greybox fuzzer to efficiently discover more paths per generated input. As we can see in Figure 11, indeed our heuristics generate more fuzz for low-frequency paths and less fuzz for high-frequency paths. In 10 minutes, AFLFAST discovered twice as many paths as AFL. For AFLFAST only 10% of the discovered (low-frequency) paths are exercised by just one input while for AFL, 30% are exercised by just one input. The mean amount of generated test inputs per path is about three times higher for AFLFAST. This clearly demonstrates the effectiveness of our heuristics in exploring a maximal number of (low-frequency) paths while expending minimum energy.

5.4 Comparison of Power Schedules

Earlier, we introduced two constant and four monotonous power schedules. AFL adopts a constant power schedule and assigns a fairly high amount of energy. Basically, the same input will get the same performance score the next time it is fuzzed. This is the exploitation-based constant schedule (exploit). To understand the impact of our choice to start with a reduced fuzzing time per input, we also investigate an exploration-based constant schedule (explore) that assigns a fairly low and constant amount of energy. The monotonous schedules increase the fuzzing time in a linear, quadratic, or exponential manner. Specifically, AFLFAST implements an exponential schedule.

Bugs in `nm`. AFLFAST finds two buffer overflows seven (7) times faster than AFL. AFLFAST also exposes a third bug which is not exposed by AFL at all. The three overflows are invalid reads and unlikely to be exploitable. The last row of Table 1 shows more details. Again, our extension consistently outperforms the classic version of AFL.

Independent Evaluation. We note that our collaborators, Team Codejitsu at DARPA Cyber Grand Challenge (CGC), evaluated both AFL and AFLFAST on all 150 benchmark programs that are provided as part of the CGC. On these binaries, AFLFAST exposes errors 19x faster than AFL, on average. In one run, AFL exposed four errors that are not exposed by our extension. However, AFLFAST exposed seven errors that are not exposed by AFL. Team Codejitsu integrated AFLFAST in their bot Galactica to prove vulnerabilities in the other teams' binaries. Galactica went on to take 2nd place in the CGC finals *in terms of number of bugs found*. A thorough discussion and reflection of the CGC experience will not be covered in this article. However, we think that Codejitsu's success demonstrates the potential of AFLFAST.

Low-frequency Paths. In this paper, we argue that the fuzzing time is better spent exploring low-frequency paths. Firstly, we believe that low-frequency paths are more likely to be exercised by valid inputs that stress different behaviors of the program. Secondly, less time is wasted fuzzing high-
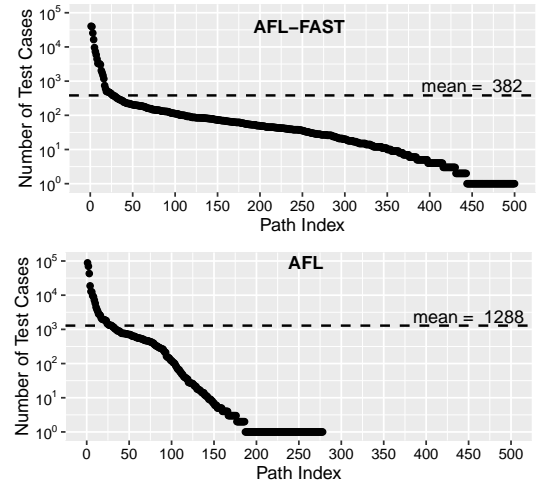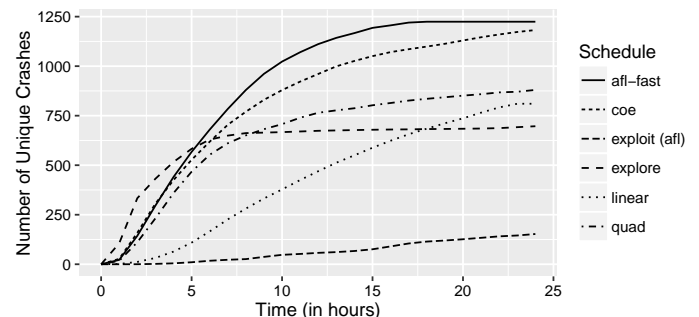

Fig. 12. #Crashes over Time (Schedules).

Results. The exponential schedule that is implemented in AFLFAST outperforms all other schedules. The cut-off exponential schedule (coe) performs only slightly worse than AFLFAST. After 24 hours, both schedules (fast and coe) exposed 50% more unique crashes than the other three (linear, quad, and explore). Interestingly, the exploration-based constant schedule (explore) starts off by discovering a larger number of crashes than any of the other schedules; it fuzzes each input quickly and swiftly moves on to the next. However, this strategy does not pay off in the longer run. After 24 hours, it performs worse than any of the other schedules (except AFL's exploitation-based constant schedule). The quadratic schedule (quad) starts off revealing a similar number of unique crashes as AFLFAST but at the end of the 24 hour budget it performs comparably to the other two (linear and explore).

5.5 Comparison of Search Strategies

Our search strategies prioritize inputs that have not been fuzzed very often (small $s(i)$) and inputs that exercise low-frequency paths (small $f(i)$). In the following, we investigate two strategies targeting the implementation of AS-SIGNENERGY and CHOOSENEXT in Algorithm 1. *Strategy 1* designates as favourites $t_i \in T$ where $s(i)$ and $f(i)$ are small, and then where execution time, transition coverage, and creation time are minimal.[8] Without Strategy 1, AFLFAST (like AFL) designates as favorites $t_i \in T$ where execution time, transition coverage, and creation time are minimal. *Strategy 2* chooses the next input t_i from the queue where $s(i)$ and $f(i)$ are minimal and t_i is a favourite. Without Strategy 2 AFLFAST (like AFL) chooses the next input from the queue that is marked as favourite. All strategies are run with the exponential power schedule.
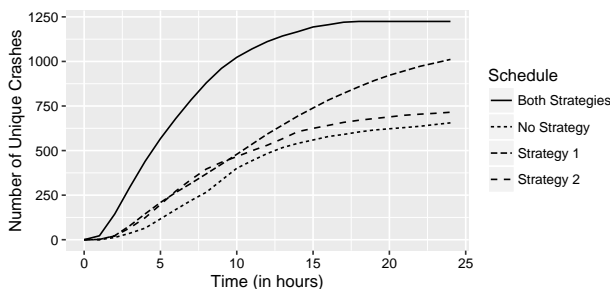

Fig. 13. #Crashes over Time (Search Strategies).

Results. The combination of both strategies is significantly more effective than any of the strategies individually. Until about 12 hours the other strategies perform very similarly. After 24 hours as individual strategy, strategy 1 which changes how AFL designates the favourite is more effective than strategy 2 and no strategy in the long run. As individual strategy, the strategy 2 which changes the order in which test inputs are chosen from the queue seems to be not effective at all. It performs similarly compared to running AFLFAST without any strategies (comparable to AFL but with exponential power schedule). However, after 24 hours, AFLFAST with both strategies exposes almost twice as many unique crashes as AFLFAST with no strategy or with only strategy 1.

8. For more details see Section 5.1.

5.6 Result Summary

We evaluated AFLFAST and several schedules plus search strategies on the GNU binutils v2.26. The exponential schedule outperforms all other schedules while our search strategies turn out to be effective. In eight runs of six hours, AFLFAST with an exponential schedule found an average of more than one order of magnitude more unique crashes than AFL for the tools `nm` and `c++filt`; it found crashing inputs for `objdump` where AFL did not expose any crashes at all. In eight runs of 24 hours, AFLFAST found 6 vulnerabilities in `nm` 7x faster than AFL and exposed 3 vulnerabilities that were not exposed by AFL. AFLFAST also exposes two bugs in `nm` (that are unlikely exploitable) about seven times faster than AFL and exposed one bug that is not exposed by AFL. An independent evaluation of Team Codejitsu on all 150 binaries that are provided in the benchmark for the Cyber Grand Challenge establishes similar results. On average, AFLFAST exposes an error 19 times faster than AFL and also exposes 7 errors that are not found by AFL, at all.

6 SYMBOLIC-EXECUTION-BASED WHITEBOX FUZZING VS COVERAGE-BASED GREYBOX FUZZING

We compare AFLFAST our boosted coverage-based greybox fuzzer implementing the exponential schedule with the most recent version of KLEE `v1.2-094a2183` [7] a widely-used state-of-the-art symbolic-execution-based whitebox fuzzer—both in terms of vulnerability detection and in terms of code coverage. For the comparison in terms of *vulnerability detection*, we use the same subjects as the authors of KLEE when it was originally introduced, GNU Coreutils `v6.10-1440ca24`. Having exposed previously unreported errors that still existed in the most recent version, we were motivated to repeat this experiment on the most recent version, Coreutils `v8.25-f1799198`. For the comparison in terms of *code coverage*, we use the most recent version of Coreutils `v8.25-f1799198`.

6.1 Conceptual Comparison

Symbolic execution is designed for efficient *path exploration*, the systematic enumeration of the paths in a program. For each path in the control-flow graph of a program, the symbolic execution engine can construct a *path constraint*, a quantifier-free first-order logic formula that is satisfied by all inputs exercising this path. The path constraint is constructed as the conjunction of branch constraints. One *branch constraint* is added to the path constraint for each conditional instruction along the control-flow-path, deciding whether the true or false branch should be exercised next. The resulting path constraint is passed to a *Satisifiability Modulo Theorem* (SMT) solver to provide an input that satisfies the path constraint and thus exercises the path. KLEE [7] is a symbolic-execution engine that implements several search heuristics to explore paths particularly that yield a high degree of code coverage quickly.

In contrast, blackbox fuzzers are not at all designed for path exploration. They treat the program as a blackbox whence there is no notion of program path. However, blackbox fuzzers can generate an enourmous amount of inputs in

a very short time. In earlier work, we showed that even the most effective fuzzer is less efficient than blackbox fuzzing if generating a test input takes relatively too long [4]. Since the blackbox fuzzer generates so many inputs (compared to a symbolic execution engine), many paths will be explored quickly in a collateral, incidental manner. However, the blackbox fuzzer's ability to discover new paths quickly decelarates while the symbolic execution engine keeps on discovering new paths steadily. So, the symbolic execution engine outperforms the blackbox fuzzer when more time is available.

Now, a coverage-based greybox fuzzer (CGF) is much better at path exploration than a blackbox fuzzer. The objective of a CGF is explicitly to discover as many new and interesting paths as possible. A CGF leverages lightweight instrumentation to identify which path is exercised by an input. It uses the inputs that were retained because they exercised new and interesting paths to explore their neighborhood and discover further new and interesting paths that were otherwise difficult to reach from the original seed inputs. While symbolic execution uses program analysis, tainting, and constraint solving, a CGF still uses only random mutations of the seed inputs, retaining much of the efficiency of blackbox fuzzers. Our power schedules improve on the capability to explore a maximal number of paths per unit time.

Hence, we compare KLEE and AFLFAST head to head to determine which one is better at path exploration, code coverage, and exposing errors. We leverage the same benchmarks as the original KLEE paper. However, we note that such tool comparisons should always be taken with a grain of salt. An empirical evaluation is always comparing only the implementations of two concepts rather than the concepts themselves. Improving the efficiency or extending the search space may only be engineering effort unrelated to the concept [22]. We make a conscious effort to explain the observed phenomena and distinguish conceptual from technical origins.

### 6.2 Fuzzing Command Line Utilities using AFLARGV

The GNU Coreutils [23] is a collection of more than 50 widely used command-line tools, including `cp` to copy files and `mkdir` to create new directories. An overview of the utilities for a more recent version is shown in Table 4. Most utilities have mandatory and optional command line parameters and process one or more files. Given lower and upper bounds on the number and size of options and files, KLEE is able to synthesis both options and files during the symbolic execution. However, AFLFAST (just like AFL) can only generate a single file as program input.

To facilitate the proper testing of the Coreutils command-line utilities, we implemented AFLARGV a simple tool that takes (i) lower and upper bounds on the number and size of command-line options and files and (ii) an input file, and *disassambles* the given file into command-line options and the required number of files. AFLARGV allows to specify the upper and lower bounds using the same format as KLEE.[9] The AFLARGV arguments `-sym-args` `<MIN>` `<MAX>` `<N>` would specify between *MIN* and *MAX*

number of command-line options of maximum length N characters. The AFLARGV arguments `-sym-files <MIN>` `<MAX>` `<N>` would specify between *MIN* and *MAX* number of files of maximum N bytes. There can be one argument `-file` that specifies a file of arbitrary length. For instance, to use AFLFAST with AFLARGV to fuzz the utility `md5sum` with up to one argument of maximum length four and a file of arbitrary length, we would execute:

```
$ afl-fuzz -i in -o out \
        aflargv -sym-args 0 1 4 -file md5sum
```

The *file format* leverages fixed-length data chunks to accomodate the actual values and size for the specified options and files. For instance, AFLFAST generates the following fuzz as input to AFLARGV:

A file is a sequence of bytes split into chunks.
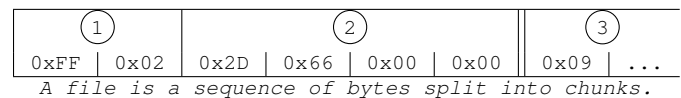
Via the AFLARGV arguments, we specified up to one command-line option of maximum four characters. The first two bytes ① specify that this optional parameter is indeed used and that the parameter is two characters long. The following four bytes ② specify the ASCII code of the actual argument. Only two bytes are interpreted ('`0x2D 0x66`' is ASCII code for "`-f`"). The remaining two bytes are ignored. Via the AFLARGV arguments, we specified a file of arbitrary length. Hence, everything beyond the sixth byte ③ is interpreted as file content.

AFLFAST is oblivious to AFLARGV. As far as the fuzzer is concerned, it generates inputs with the objective to discover a maximum number of paths per unit time. Given the generated fuzz, AFLARGV synthesizes the files and passes the corresponding command-line parameters to the tool under test which (as per normal) provides feedback on the discovered paths. In our example, AFLARGV generates a file t1.txt and calls `md5sum -f t1.txt`.

6.3 Experimental Setup

We used the same subjects and experimental parameters[10] as provided in the original KLEE paper [7] in order to mitigate experimenter bias and allow for a fair comparison. We run each fuzzing campaign for *one (1) hour* using the same experimental infrastructure that was discussed earlier (Sec. 5.2). We start KLEE and AFLFAST with the following command-line options (as provided by the authors):

```
-sym-args 0 1 10 -sym-args 0 2 2 -sym-files 1 8
```

We start AFLFAST with no options and an empty file. Technically, we assembled a single, "empty" seed file representing the minimum number of options, all of length zero characters, and the minimum number of files, all of size zero bytes. AFLARGV also allows to assemble such a file from a provided set of arguments and files according to the required file format. This would be important when we needed to seed the fuzzer using test cases from an existing regression test suite. However, we do not actually utilize that functionality in our experiments.

We measure effectiveness by executing the generated inputs on the utilities compiled with AddressSanitizer [24].

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9. https://klee.github.io/docs/options/#klee-usage

10. Tutorial at https://klee.github.io/tutorials/testing-coreutils.

6.4 Vulnerability Detection

In this experiment, we compare the symbolic execution-based whitebox fuzzer KLEE and our boosted greybox fuzzer AFLFAST in terms of vulnerability detection. We use the KLEE *benchmark*, a collection of bugs that were reported in the original KLEE paper [7].

First, we measure the time it takes to expose these errors (*efficiency*). Second, we discuss bugs found only by AFLFAST but not by KLEE (*effectiveness*). Finally, encouraged by our findings, we conducted an experiment using the most recent version of Coreutils where we compare AFLFAST and KLEE in terms of previously unreported bugs found (*effectiveness*).

```
KLEE    AFLFAST          How to Reproduce
09:48   > 1h  md5sum -c t1.txt
18:49   00:20 mkdir -Z a b
09:30   00:20 mkfifo -Z a b
00:02   00:24 mknod -Z a b p
00:16   01:53 paste -d\\ abcdefghijklmnopqrstuvwxyz
16:17   21:56 pr -e t2.txt
00:04   07:14 ptx -F\\ abcdefghijklmnopqrstuvwxyz
00:03   01:31 seq -f %0 1
 > 1h   05:00 tac -r t3.txt t3.txt
where files  t1.txt: "\t \tMD5 ("
             t2.txt: "\b\b\b\b\b\b\t"
             t3.txt: "\n"
```

Fig. 14. Time to expose the KLEE benchmark bugs. KLEE is fairly deterministic. So, we report the results for one run (as min:sec). AFLFAST is a random approach. Hence, we report the mean over ten runs.

Results (Efficiency). *On the* KLEE *benchmark,* KLEE *is more efficient than* AFLFAST *for six out of nine bugs (Figure 14).* However, on average AFLFAST requires much less time to expose an error than KLEE. Specifically, the mean time-to-exposure is 4:49 for AFLFAST and 6:51 for KLEE. Moreover, we note that the KLEE benchmark consists of bugs that were explicitly discovered and reported by the authors of KLEE, which introduces a *selection bias*: KLEE might be best in discovering those errors that it *did* discover (but not in discovering those that it did *not* discover).

> KLEE outperforms AFLFAST in terms of efficiency on the KLEE benchmark bugs.

How to reproduce	Crash Location	Symptom
pr -l55555555 -5	pr.c:1918	Memory exhausted
echo ""| ptx -W^.* -O	regexec.c:2354	Buf. Overflow (W)
echo ""| ptx -fW ^	regex_internal.c:940	Buf. Overflow (R)
echo ""| ptx -W.++* A	regexec.c:3780	Buf. Overflow (R)
echo ""| ptx "-W\\\|" A	regexec.c:2312	Buf. Overflow (R)
where file A: "\n"		

Fig. 15. Bugs found only by AFLFAST in the same subjects using in [7] for Coreutils v6.10. These bugs are not fixed in v6.11. The bug in Row 1 is an integer overflow that leads to memory exhaustion and still exists in the most recent version (v8.25-f1799198). The remaining bugs are heap-based buffer overflows in the regular expression component of GNULIB that is used by Coreutils.

Results (Effectiveness). *On the benchmark,* AFLFAST *and* KLEE *fail to discover one bug in the* KLEE *benchmark. Moreover,* AFLFAST *discovered five bugs that* KLEE *did not find, one of which still existed in the most recent version of Coreutils (Figure 15).* The four buffer overflows in ptx that only AFLFAST could detect should be within the search space of KLEE. However, we are unsure whether KLEE has even the capability to detect that pr tries to allocate a negative

amount of memory, which together with an integer overflow leads to memory exhaustion. We investigated the failure to detect the bugs within the one hour time budget. For KLEE, we attribute the failure to discover the bug in tac to recent changes in KLEE. For AFLFAST, we attribute the failure to discover the bug in md5sum to the difficulty to synthesize the specific sequence of characters required to expose the bug (see Figure 14). AFLFAST must generate a file containing a *specific* sequence of eight bytes and the option -c to expose the bug. We note, however, that AFLFAST *can* detect the bug with a two hour time budget.

> AFLFAST outperforms KLEE in terms of effectiveness within the 1-hour time frame.

AFLFAST	KLEE	How to reproduce / *Error type*	Bug Report
		pr -l55555555 -5	
✔	✘	*Allocating negative #memory*	http://bugs.gnu.org/24996
		split -n2/3 /dev/null	
✔	✘	*Buffer Underflow (Heap, Write)*	http://bugs.gnu.org/25003
		printf "abcde\x00\x00\x0a " \\| od -tazfL -	
✔	✘	*Segmentation Fault*	http://bugs.gnu.org/25004
		echo a > $PWD/a; ptx -w1 -A $PWD/a	
✔	✘	*Buffer Overflow (Heap, Read)*	http://bugs.gnu.org/25011
		echo a > a; pr "-S$(printf "\t\t\t")" a -m a	
✔	✘	*Buffer Overflow (Global, Read)*	http://bugs.gnu.org/25023
		echo 0>a; printf "%0.s0" 1..58 >> a; sort -R a	
✔	✘	*Misaligned Address*	http://bugs.gnu.org/25024
		tail -f <&-	
✔	✘	*Use-After-Free*	http://bugs.gnu.org/25041
		tac - - <&-	
✔	✔	*Loading-of-Invalid-Value*	http://bugs.gnu.org/25041

Fig. 16. Bugs found in the recent version v8.25-f1799198 of Coreutils.

Results (Coreutils v8.25). *On Coreutils v8.25,* AFLFAST *discovers eight previously unreported bugs while* KLEE *discovers only one (Figure 16).* We attribute much of this advantage to AFLFAST's *runtime checking* while KLEE requires a *constraint-based error detection* mechanism. KLEE symbolically executes (i.e., interprets) the program's LLVM intermediate representation and uses constraint solving to determine whether an error could have occured. Most symbolic-execution-based whitebox fuzzers integrate the error detection directly into the constraint solving process. This embedding restricts the detection to such errors that can be encoded as constraint violations. For instance, it might be difficult to encode (and thus detect) the misaligned address bug that AFLFAST could find. The error detection is further impaired by the incompleteness of the *environment model* that underlies the symbolic interpreter. In contrast, AFLFAST as greybox fuzzer executes the compiled binary concretely and reports any generated input that *crashes*. Runtime checkers, such as ASAN [24], crash the program for executions where the program would not normally crash.

> To detect vulnerabilities, KLEE requires a constraint-based vulnerability detection mechanism and presumes completeness of constraint encoding and environment modelling while AFLFAST merely executes the program reporting any crashes, e.g., using runtime checking.

TABLE 4
Statement coverage achieved in Coreutils v8.25-f1799198 of Coreutils and Executable Lines of Code (ELOC) for each subject.

Utility	ELOC	AFLFast	Klee	Utility	ELOC	AFLFast	Klee	Utility	ELOC	AFLFast	Klee	Utility	ELOC	AFLFast	Klee	Utility	ELOC	AFLFast	Klee
base64	104	90.0	92.0	echo	97	64.0	81.0	logname	25	96.0	96.0	pwd	129	33.0	33.0	tty	32	96.0	100.0
basename	55	100.0	100.0	expand	72	94.0	94.0	ls	1547	61.7	33.0	seq	282	89.6	71.0	uname	85	82.0	91.0
cat	219	83.8	78.0	expr	334	76.0	70.0	md5sum	297	53.4	69.0	shuf	223	86.0	60.0	unexpand	104	93.9	92.0
cksum	61	86.0	91.0	factor	510	52.8	23.0	nl	194	84.6	94.0	sort	1702	68.1	48.0	uniq	195	89.6	89.0
comm	146	95.0	94.0	fmt	315	90.0	88.0	od	637	89.1	87.0	split	641	76.3	30.0	uptime	70	92.0	92.0
csplit	521	79.3	77.0	fold	104	94.0	96.0	paste	189	91.0	93.0	stat	555	68.1	61.0	users	53	97.1	90.0
cut	188	87.3	93.0	head	382	68.0	70.0	pr	854	95.0	67.0	tac	238	70.1	71.0	wc	308	72.9	76.0
df	664	74.3	49.0	hostid	23	100.0	100.0	printenv	41	100.0	100.0	tail	841	55.1	52.0	who	279	83.0	86.0
dirname	35	100.0	100.0	id	160	85.0	83.0	printf	224	88.7	95.0	tr	620	74.8	75.0	whoami	28	96.0	96.0
du	347	65.3	68.0	join	430	90.5	85.0	ptx	657	93.6	64.0	tsort	193	69.3	96.0	**Average**	**327**	**82.1**	**78.3**

6.5 Code Coverage

We compare KLEE and AFLFAST in terms of coverage achieved. Leveraging our earlier experimental infrastructure, we choose the most recent version of GNU Coreutils (v8.25-f1799198) as subjects. The experimental setup as discussed in Section 6.3 remains. We measure *statement coverage* achieved after one hour of fuzzing by re-executing the generated inputs on the utilities compiled for GCOV.

Results. *On average*, AFLFAST *achieves slightly more code coverage than* KLEE (Table 4). While KLEE covers circa 78% of executable lines of code in the average utility, AFLFAST covers about 82%. In total, there are 16k executable statements, out of which AFLFAST covers slightly more than 12k (76%) and KLEE slightly more than 10k (64%). This means that AFLFAST *scales better* than KLEE and is more effective when covering statements in the larger utilities. However, in our experience (i.e., by checking the statements in some utilities that were covered by one fuzzer or the other) KLEE and AFLFAST have individual strengths and perform best in different circumstances. For instance, KLEE could easily synthesize complex command-line options (e.g., `--help`) that would be out of reach for AFLFAST running without a dictionary. The results might have looked very different if the majority of options were not just two characters long (e.g., `-h`).

> AFLFAST performs slightly better than KLEE in terms of code coverage. However, a combination might be even more powerful, using their strengths to mitigate each other's weaknesses.

7 DEPLOYMENT IN AFL 2.33B

Together with the publication of the shorter version of this paper [1], we made AFLFAST available to the public at

https://github.com/mboehme/aflfast

The release of AFLFAST as Github repository created considerable interest among practicing cyber-security researchers. Links to the paper as well as to the repository were shared and re-tweeted hundreds of times on Twitter. Members of the security community downloaded our tool and evaluated it on their own, finding a large number of bugs that were previously out of reach. The blogposts they wrote were featured for several hours as TOP-1 entry on Hackernews, a popular forum for tech-savvy readers. Google security awarded USD 2,000 in bug bounties for the bugs found by AFLFAST (and reported in this paper).

Only eight months after its release, the Github repository of AFLFAST received 172 stars and was forked 89 times. Even though the changes to the source code were relatively small, the impact on the security community was immense.

Michał Zalewski, the main developer of AFL, read our paper, studied our implementation, improved AFL according to several observations, and conducted experiments of his own.[11] We report on his observations about AFLFAST, the resulting improvements to AFL and the outcome of his experiments. Zalewski observed the following about our implementation

1) Rather than spending time in the deterministic stage, AFLFAST spends a greater proportion of time on "non-deterministic" fuzzing early in the campaign. In other words, AFLFAST assigns substantially less energy in the beginning of the fuzzing campaign.
2) Most of the cycles that AFLFAST carries out, are in fact very short. This causes the queue to be cycled very rapidly, which in turn causes new retained inputs to be fuzzed almost immediately. In other words, because AFLFAST assigns less energy, it can process the complete queue substantially faster. We say it starts by exploration rather than by exploitation.

Based on these observations, Zalewski implemented into mainline AFL what we call the *explore*-schedule. Concretely, he reduced the time a seed is being fuzzed by a factor of 20. For the experiments, he calls this new version *FidgetyAFL* (version 2.33b) – not to be confused with the older versions which implement the *exploit*-schedule (up to version 2.32b). For the experiments, Zalewski compared AFL, FidgetyAFL, and AFLFAST on four subjects. Instead of the number of paths or number of crashes, Zalewski measures the map density. The *map density* correlates with the number of edges that have been exercised in the subject's control-flow graph. All fuzzers are started with the same parameters.

- **libpng** (*2 runs of 6h*). AFL was consistently but slightly ahead of AFLFAST (~1%). FidgetyAFL outperformed both AFL and AFLFAST by about 10% at the one (1) hour mark but slightly trailed behind at the six (6) hour mark. This is consistent with our observation that the *explore*-schedule is quite efficient only for the first few hours—but is later outperformed by other schedules (see Figure 12).
- **libjpeg-turbo** (*2 runs of 6h*). AFLFAST outperformed AFL by 15% at the one hour mark and by 5% at the

11. The discussion can be found here: https://groups.google.com/forum/#!topic/afl-users/fOPeb62FZUg

six hour mark. FidgetyAFL outperformed AFL by 13% at the one hour mark and by 4% at the six hour mark.

- **zlib** (*3 runs of 1h*). AFLFAST and AFL perform similarly in the beginning but AFLFAST takes a solid lead of 20% later on. FidgetyAFL and AFLFAST perform similarly throughout.
- **patch** (*3 runs of 1h*). AFLFAST outperforms AFL very decisively by 50% while FidgetyAFL and AFLFAST perform similarly.

We note that the experiments may not be statistically sound (i.e., only results for two to three fuzzing campaigns of relatively short time are reported). Specifically, it may take some more time for the *exponential schedule* implemented in AFLFAST to gain traction and outperform the *explore schedule* implemented in FidgetyAFL (see Figure 12).

Since version 2.33b, AFL implements the explore-schedule. This does not require to record the number of fuzz exercising a certain path, and in our experiments the explore-schedule outperforms all other schedules for the first few hours (see Figure 12). This revised version of AFL was shown to be significantly more efficient than its predecessors. While AFLFAST still compares favourably against the improved version of AFL, the performance difference to AFL 2.33b and newer versions is smaller than we have shown in our experiments.
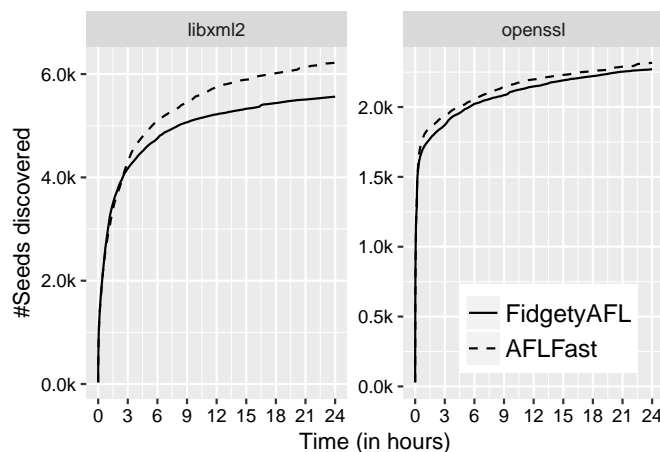

Fig. 17. Average #paths discovered in LibXML2 and OpenSSL in 10 runs of 24 hours using FidgetyAFL and AFLFAST.

We also conducted a small experiment where we compared FidgetyAFL and AFLFAST in terms of number of paths discovered on two security-critical programs: Openssl [25], a library for secure communication over the internet and LibXML2 [26], a popular XML parser library for C. For OpenSSL, we fuzzed the `asn1` utility and for LibXML2 the `xmllint` utility. Both were fuzzed without additional command line parameters, for 24 hours, and using only the empty file as initial seed. We conducted ten runs for FidgetyAFL and 10 runs for AFLFAST.

The results are shown in Figure 17. Overall, AFLFAST is more efficient than FidgetyAFL. For LibXML2, FidgetyAFL takes 24 hours to discover the same number of paths that AFLFAST discovers in 9 hours (i.e., about $3\times$ longer). For OpenSSL, FidgetyAFL takes 24 hours to discover the same number of paths that AFLFAST discovers in 19.5 hours.

8　RELATED WORK

Several techniques [12], [27], [28], [29] have been proposed to increase the efficiency of fuzzing. An important optimization pertains to selecting the seed inputs wisely from a wealth of inputs [28]. Our work makes no assumptions about the existance seed inputs; we seeded our experiments with the empty file. However, Coverage-based Greybox Fuzzing (CGF) would clearly benefit from a smart seed selection if many seed files are available. Others suggest to use program analysis to detect dependencies among the bit positions of an input [29]. For instance, the image width occupies four bytes in the PNG image file format which are best modified together. The dependency analysis allows to fuzz such dependent bytes as a group. In our work, we do not change the mutation operators or ratio. Woo et al. [27] recognize the exploration-exploitation trade-off between fuzzing an input for a shorter versus a longer amount of time. They proceed to model blackbox fuzzing as a multi-armed bandit problem where the seed's "energy" is computed based on whether or not it has exposed a (unique) crash in any previous fuzzing iteration. So, the fuzzer is biased towards generating more crashing inputs for already known errors. In our work, there is no such bias. Instead, we direct the search towards low-frequency paths in order to stress more of the program's behavior in the same time.

Symbolic execution-based fuzzers can generate files that stress low-frequency paths. Probabilistic symbolic execution [30] uses model counting to compute the probability that a random input exercises a given path. Symbolic execution is very effective because it enumerates paths essentially independent of their "frequency" and because it can be directed towards "dangerous" program locations [7], [14], [15], [31]. It can generate the specific values that are needed in order to negate an if-condition and exercise the alternative branch. Taint-based fuzzing [16], [32] is a directed whitebox fuzzing technique. It exploits classical taint analysis to localize parts of the input which should be marked symbolic. For instance, it marks portions of the input file as symbolic that control arguments of executed and critical system calls. Model-based Whitebox Fuzzing [33] leverages an input model to synthesize and "transplant" complete data chunks to exercise so called *critical* branches that are only exercised if a certain chunk is present in the input file. However, symbolic execution-based techniques rely on program analysis and constraint solving which hampers their scalability. Imprecisions during lifting of the program binary and during the encoding of the path constraints hamper their applicability. In contrast, CGF completely relinquishes program analysis for the sake of scalability with tremendous success in the vulnerability detection practice [2].

Colleagues have combined lightweight black- or greybox fuzzers with symbolic execution-based whitebox fuzzers to get the best of both worlds [3], [34]. For instance, Hybrid-Fuzz [34] first runs symbolic execution to generate inputs leading to "frontier nodes" and then passes these inputs to a blackbox fuzzer. In contrast, Driller [3] begins with AFL and seeks help from symbolic execution when it "gets stuck", for instance, to generate a magic number. Our monotonous power schedules allow to employ expensive symbolic execution for seeds/states with a sufficiently high energy.

Markov chains can model a variety of random processes in fuzz testing. Markov Chain Monte Carlo Random Testing (MCMC-RT) uses a Markov Chain Monte Carlo (MCMC) method to leverage knowledge about an input's probability to reveal an error. However, MCMC-RT is not entirely scalable because it maintains this probability for *every* input in the program's input space. While CGF can be well explained as Markov chain, it does not actually maintain the chain or any probabilities in-memory. While MCMC-RT is biased towards revealing suspected or known errors, CGF can expose unknown errors that hide deep in the program. The bias of boosted CGF is towards low-frequency paths. Chen et al. [35] utilize MCMC to leverage knowledge about a mutation operator's effectiveness. Operators that have been shown to be more effective in previous fuzzing iterations are chosen with greater probability during fuzzing. Sparks et al. [36] model program control-flow as Markov chain to prioritize seeds that exercise less explored paths. In contrast, we use Markov chains to *explain* why it is more efficient to smartly control the time spent fuzzing a seed and which seed to fuzz next *without* program analysis.

Markov chains are often used by meta-heuristic search algorithms to solve optimization problems. A demonstration of the utility of the Markov chain model of CGF is our recent work. *Directed greybox fuzzing* [37] uses a novel set of power schedules that implement the Simulated Annealing meta-heuristic to minimize the distance to a given set of target locations in the program. This is important for patch testing or directed vulnerability detection where dangerous locations are known. These power schedules assign more energy to seeds that are "closer" to the targets. At compile-time, the control-flow graph is analyzed and the program instrumented, such that at runtime the seed distance can be efficiently computed. Using the Markov chain model of CGF, we cast the reaching of target locations as optimization problem. Other fuzzing objectives may also be encoded.

9 CONCLUSION

While symbolic execution-based techniques have gained prominence, their scalability has not approached those of blackbox or greybox fuzzers. While blackbox and greybox techniques have shown effectiveness, the limited semantic oversight of these techniques do not allow us to explain the working of these techniques even when they are effective.

In this work, we took a state-of-the-art greybox fuzzer AFL which keeps track of path identifiers. We enhanced the effectiveness and efficiency of AFL in producing crashes, as evidenced by our experiments and those of our collaborators. AFLFAST, our extension of AFL exposes an order of magnitude more unique crashes than AFL in the same time budget. Moreover, AFLFAST can expose several bugs and vulnerabilities that AFL cannot find. Other vulnerabilities AFLFAST exposes substantially earlier than AFL.

More importantly, we provide an explanation of the enhanced effectiveness by visualizing CGF as the exploration of the state space of a Markov chain. We observe that existing CGF tools much too often visit states in high-density regions. We have devised and investigated several strategies to force the CGF tool to visit more states that are otherwise hidden in a low-density region and to generate less inputs for states in a high-density region.

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