Evaluating and Improving Neural Program-Smoothing-based Fuzzing

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ABSTRACT

Fuzzing nowadays has been commonly modeled as an optimization problem, e.g., maximizing code coverage under a given time budget via typical search-based solutions such as evolutionary algorithms. However, such solutions are widely argued to cause inefficient computing resource usage, i.e., inefficient mutations. To address this issue, two neural program-smoothing-based fuzzers, *Neuzz* and *MTFuzz*, have been recently proposed to approximate program branching behaviors via neural network models, which input byte sequences of a seed and output vectors representing program branching behaviors. Moreover, assuming that mutating the bytes with larger gradients can better explore branching behaviors, they develop strategies to mutate such bytes for generating new seeds as test cases. Meanwhile, although they have been shown to be effective in the original papers, they were only evaluated upon a limited dataset. In addition, it is still unclear how their key technical components and whether other factors can impact fuzzing performance. To further investigate neural program-smoothing-based fuzzing, we first construct a large-scale benchmark suite with a total of 28 popular open-source projects. Then, we extensively evaluate *Neuzz* and *MTFuzz* on such benchmarks. The evaluation results suggest that their edge coverage performance can be unstable. Moreover, neither neural network models nor mutation strategies can be consistently effective, and the power of their gradient-guidance mechanisms have been compromised. Inspired by such findings, we propose a simplistic technique, *PreFuzz*, which improves neural program-smoothing-based fuzzers with a *resource-efficient edge selection mechanism* to enhance their gradient guidance and a *probabilistic byte selection mechanism* to further boost mutation effectiveness. Our evaluation results indicate that *PreFuzz* can significantly increase the edge coverage of *Neuzz*/*MTFuzz*, and also reveal multiple practical guidelines to advance future research on neural program-smoothing-based fuzzing.

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1 INTRODUCTION

Fuzzing [44] nowadays has been widely adopted to detect software bugs or vulnerabilities via feeding invalid, unexpected, or random data as inputs for executing programs under test. To date, many existing approaches model fuzzing as an optimization problem and attempt to solve it by augmenting code coverage via mutating program seed inputs under a given time budget. Such *coverage-guided* fuzzing tasks can be typically resolved by applying search-based optimization algorithms such as evolutionary algorithms [13, 15, 42, 49, 51]. Specifically, test inputs are iteratively filtered, mutated, and executed such that the test results can approach the optimal solutions to satisfy the fitness functions of the adopted evolutionary algorithms, which are usually designed to maximize code coverage. However, evolutionary fuzzers have been argued that they fail to "leverage the structure (i.e., gradients or higher-order derivatives) of the underlying optimization problem" [41]. To address such issue, neural program-smoothing-based techniques, e.g., *Neuzz* [41] and *MTFuzz* [40], have been recently proposed to exploit the usage of gradients for fuzzing via neural network models. Specifically, they first adopt a neural network which, given the byte sequence of a seed as input, outputs a vector representing its associated program branching behaviors. Next, they compute the

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gradients of the collected output vectors with respect to the bytes of the given seed. Accordingly, they sort the resulting gradients and develop strategies to mutate the bytes with larger gradients more aggressively. Eventually, all the resulting mutants are used as test cases for fuzzing. Note that *MTFuzz* further attempts to outperform *Neuzz* by leveraging the power of multi-task learning and adopts a dynamic analysis module to augment the mutation strategy. In their original papers, *Neuzz* outperforms 10 existing coverage-guided fuzzers on 10 real-world projects by at least 3X more edge coverage over 24-hour runs and further detects 31 previously-unknown bugs. Compared to *Neuzz* and four other state-of-the-art fuzzers, *MTFuzz* achieves 2X to 3X edge coverage upon all the benchmark projects and exposes 11 previously-unknown bugs which cannot be detected by the other fuzzers.

Despite the effectiveness shown in their original papers, the evaluation on *Neuzz* and *MTFuzz* can be potentially biased due to their limited benchmark suite with only 10 projects. Moreover, *Neuzz* and *MTFuzz* adopt a different edge coverage metric from many existing fuzzers [4, 9, 27, 31, 51] that can potentially bias the performance comparison. Furthermore, the investigation on the factors that can impact their edge coverage performance is rather limited, i.e., they only simply presented the overall effectiveness of the techniques without investigating the contributions made by individual components, e.g., the model structure, the gradient guidance mechanism, and the mutation strategy.

In this paper, to enhance the understanding of the effectiveness and efficiency of program-smoothing-based fuzzing, we first construct a large-scale benchmark by retaining all the projects adopted in the original *Neuzz* and *MTFuzz* papers (except one that we fail to run) and adding 19 additional open-source projects that were frequently adopted in recent fuzzing research work. We then conduct an extensive evaluation for *Neuzz* and *MTFuzz* accordingly. The evaluation result suggests while *Neuzz* and *MTFuzz* can outperform AFL on all the studied benchmark projects by 10.5% and 8.9% on average in terms of edge coverage respectively, *MTFuzz* does not always outperform *Neuzz* and both their edge coverage performances are highly program-dependent. We also find neither their mutation strategies nor neural network models can be consistently effective. Meanwhile, although the gradient guidance mechanisms can be promising, their strengths have not been fully leveraged.

Inspired by the findings of our study, we propose an improved technique, namely *PreFuzz* [38], upon neural program-smoothing-based fuzzing. In particular, we develop a *resource-efficient edge selection mechanism* to facilitate the exploration on unexplored edges rather than the already covered edges. Moreover, we also apply a *probabilistic byte selection mechanism* guided by gradient information to *Neuzz* and *MTFuzz* to further boost edge exploration. Our evaluation results suggest that *PreFuzz* can significantly outperform *Neuzz* and *MTFuzz*, i.e., 43.1% more than *Neuzz* and 45.2% more than *MTFuzz* averagely in terms of edge coverage.

To conclude, this paper makes the following contributions:

- **Dataset.** A dataset including 28 real-world projects that can be used as the benchmarks for future research on fuzzing.
- **Study.** An extensive study of neural program-smoothing-based fuzzers on the large-scale benchmark suite, with detailed inspection of both their strengths and limitations.
- **Technical improvement.** A technique improving neural program-smoothing-based fuzzers by combining a *resource-efficient edge selection mechanism* and a *probabilistic byte selection mechanism.*
- **Practical guidelines.** Multiple practical guidelines for advancing future program-smoothing-based fuzzing research.

2 BACKGROUND

2.1 Coverage-guided Fuzzers

Coverage-guided fuzzers nowadays widely adopt evolutionary algorithms [49] for mutation strategies since they can be advanced in discovering program vulnerabilities without prior program knowledge. In this section, we first introduce the basic framework for evolutionary algorithms, and then illustrate how a typical coverage-guided fuzzer AFL integrates evolutionary algorithms.

2.1.1 *Evolutionary Algorithm.*

To solve an optimization problem, an evolutionary algorithm (EA) adopts operations such as mutating the existing solutions to generate new solutions. Among such generated solutions, an EA applies a fitness function to filter them based on their quality such that the remaining ones are retained as one population. Such process is iterated until hitting the preset time budget with the final population returned as the solutions for the optimization problem.

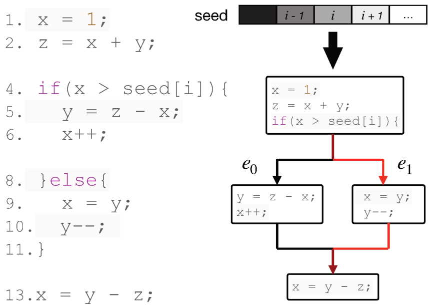
2.1.2 *Integrating fuzzing with EA.*

Coverage-guided fuzzers often use increased code coverage as the fitness functions. Specifically, they usually adopt edge coverage (where an *edge* refers to a basic-block-wise transition, e.g., a conditional jump in programs) to represent code coverage and retain only the seeds that can trigger new edge coverage for further mutations. For instance, American Fuzzy Lop (AFL) [51], a widely-used coverage-guided fuzzer, is launched by instrumenting programs such that it can acquire and store the edge coverage of each program seed input at runtime. Subsequently, AFL iterates and mutates each seed input according to its adopted evolutionary algorithm. Like most coverage-guided fuzzers [4, 9, 27, 31], when running a seed increases edge coverage, AFL identifies such seed as an "interesting" seed and retains it for further mutations. Note that the mutations in AFL consist of two stages: the deterministic stage ($AFL_{Deterministic}$) and the havoc stage (AFL_{Havoc}). In particular, $AFL_{Deterministic}$ applies a fixed set of mutators, e.g., the *bitflip*, *arithmetic*, and *interesting value* mutators, for respectively mutating the bits of each existing "interesting" seed deterministically. After $AFL_{Deterministic}$, all the collected "interesting" seeds are used to launch AFL_{Havoc} where random mutations, i.e., randomly chosen mutators, are iteratively applied to the randomly selected bits of the seed inputs.

2.2 Neural Program-smoothing-based Fuzzers

Program smoothing refers to setting up a smooth (i.e., differentiable) surrogate function to approximate program branching behaviors with respect to program inputs [41]. While traditional program smoothing techniques [7, 8] can incur substantial performance overheads due to heavyweight symbolic analysis, integrating such concept with neural network models can be rather powerful since they can be used to cope with high-dimensional optimization tasks, i.e., to resolve (approximate) complex and structured program behaviors. To this end, *Neuzz* [41] and *MTFuzz* [40] are proposed to smooth programs via neural network models and guide mutations by yielding the power of their gradients. Specifically, to formulate the optimization problem for fuzzing, the program branching behaviors are defined as a function $F(x)$, where x represents a seed input in terms of byte sequence and the solution is a vector representing its associated branching behaviors. For instance, a solution vector $[1, 0, 1, ...]$ indicates that the first and the third edges have been accessed/explored while the second one has not. Since $F(x)$ is typically discrete, smoothing programs, i.e., making $F(x)$ differentiable, is essential to cope with the usage of gradients.

We then illustrate the rationale behind *Neuzz* and *MTFuzz*. Note that a program execution path, i.e., a sequence of edges, can be determined by the byte sequence of a seed input. Accordingly, an edge can be accessed/explored when the value of its corresponding bytes satisfies its access condition. Otherwise, one of its "sibling" edges (i.e., edges under one shared prefix edge) can be alternatively accessed. For instance, in Figure 1, edge e_0 can be accessed when the value of $seed[i]$ satisfies the access condition for e_0, i.e., $seed[i] < 1$. Hence, mutating such $seed[i]$ can lead to exploring a new branching behavior, i.e., accessing e_0's "sibling" edge e_1 instead of e_0.

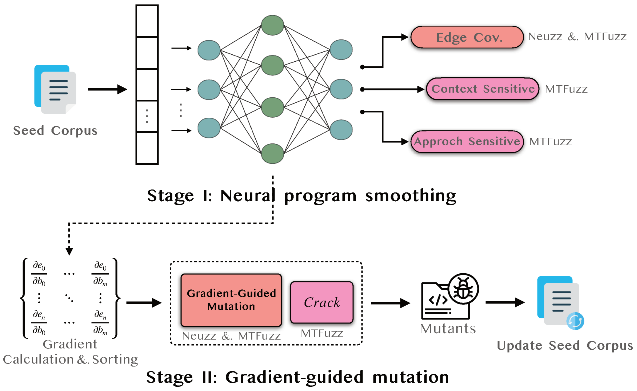


```
 x = 1;
 z = x + y;

 if(x > seed[i]){
    y = z - x;
    x++;

 }else{
    x = y;
    y--;
 }

x = y - z;
```

Figure 1: An example of neural program-smoothing rationale

Neuzz and *MTFuzz* assume that neural network models can identify the "promising" byte(s) (i.e., the byte(s) corresponding to the access condition) for a previously explored edge. Specifically, the gradient of such byte(s) (e.g., $seed[i]$ in Figure 1) to the explored edge is supposed to be larger than other bytes after training (illustrated in Section 2.2.1). Accordingly, mutating such byte(s) can indicate that the access condition of the corresponding edge may not be satisfied, i.e., potentially exploring new "sibling" edges. To summarize, *Neuzz* and *MTFuzz* learn to extract the existing branching behaviors to explore new edges rather than predicting "promising" bytes for unseen edges. In particular, their mechanisms commonly consist of two steps: neural program smoothing and gradient-guided mutations as shown in Figure 2.

2.2.1 Neural Program Smoothing. *Neuzz* and *MTFuzz* adopt an iterative training-and-mutation process. Under each iteration, they train neural network models using "interesting" seed inputs collected in real-time (out of the "Seed Corpus" in Figure 2). Note that Figure 2 also shows that *Neuzz* and *MTFuzz* adopt different neural network models which will be further illustrated in Section 2.2.3.



Seed Corpus
Edge Cov.
Neuzz &. MTFuzz
Context Sensitive
MTFuzz
Approch Sensitive
MTFuzz
Stage I: Neural program smoothing
$\frac{\partial e_0}{\partial b_0}$ ... $\frac{\partial e_0}{\partial b_m}$
$\frac{\partial e_n}{\partial b_0}$ ... $\frac{\partial e_n}{\partial b_m}$
Gradient
Calculation &. Sorting
Gradient-Guided Mutation
Neuzz &. MTFuzz
Crack
MTFuzz
Mutants
Update Seed Corpus
Stage II: Gradient-guided mutation

Figure 2: Framework of *Neuzz* and *MTFuzz*

2.2.2 Gradient-guided Mutations. After obtaining the neural network models, *Neuzz* and *MTFuzz* randomly select a deterministic number of the "interesting" seeds and the explored edges. For each selected seed, they calculate the gradients of the selected edges vectors with respect to all the bytes. Furthermore, all such bytes are sorted according to their corresponding gradient rankings and then aggregated as one vector for further mutations. In particular, *Neuzz* and *MTFuzz* segment each selected seed such that the bytes in the front segments have larger gradients than the bytes in the back segments and the front segments include fewer bytes than the back segments. Accordingly, the "promising" bytes are expected to be located in the front segments. For any segment *seg*, all its bytes are simultaneously mutated for 255 times. As a result, *Neuzz* and *MTFuzz* can explore more mutation space of the front segments than the back ones, i.e., mutating the more "promising" bytes more aggressively, for exploring new branching behaviors. Eventually, all the resulting seeds after the iterative training-and-mutation process are used as test cases for fuzzing.

2.2.3 MTFuzz vs. Neuzz. Figure 2 also demonstrates that *MTFuzz* differs from *Neuzz* by adopting multi-task learning technique and a dynamic analysis module to augment its mutation strategy.

In addition to the widely-used edge coverage, *MTFuzz* adopts two additional tasks—the approach-sensitive edge coverage, i.e., how far off an unexplored edge is from getting triggered, and the context-sensitive edge coverage, i.e., the context for an explored edge, to construct the multi-task neural network model for smoothing programs and further guiding fuzzing. Moreover, *MTFuzz* adopts an independent module, namely *Crack* in its implementation, which uses dynamic program analysis to explore new edges without gradient information. Specifically, *Crack* iterates each byte of the seed input and mutates it to observe whether the variables associated with an unexplored branch can be also changed. If so, such byte is identified as a "promising" byte to be mutated for 255 times.

3 EXTENSIVE STUDY

3.1 Benchmarks

Although *Neuzz* and *MTFuzz* have been shown to outperform the existing fuzzers in terms of the edge coverage in the original papers [40, 41], such results can be possibly biased by the used subject

Table 1: Statistics of the studied benchmarks

Benchmark	Class	LOC	Package
bison	LEX & YACC	18,701	3.7
xmlwf	XML	6,871	expat-2.2.9
mupdf	PDF	123,562	1.12.0
pngimage	PNG	11,373	libpng-1.6.36
pngfix	PNG	12,173	libpng-1.6.36
pngtest	PNG	11,323	libpng-1.6.36
tcpdump	PCAP	46,892	4.99.0
nasm	ASM	18,941	nasm-2.15.05
tiff2pdf	TIFF	17,272	libtiff-4.2.0
tiff2ps	TIFF	16,177	libtiff-4.2.0
tiffdump	TIFF	15,113	libtiff-4.2.0
tiffinfo	TIFF	15,014	libtiff-4.2.0
libxml	XML	73,239	2.9.7
listaction	SWF	6,278	libming-0.4.8
listaction_d	SWF	6,272	libming-0.4.8
libsass	SCSS	14,638	libsass-3.6.5
jhead	JPEG	1,886	3.04
readelf	ELF	72,111	Binutils 2.30
nm	ELF	55,212	Binutils 2.30
strip	ELF	65,683	Binutils 2.30
size	ELF	54,463	Binutils 2.30
objdump	ELF	74,710	Binutils 2.30
libjpeg	JPEG	8,856	9c
harfbuzz	TTF	9,853	1.7.6
base64	FILE	40,332	LAVA-M
md5sum	FILE	40,350	LAVA-M
uniq	FILE	40,286	LAVA-M
who	FILE	45,257	LAVA-M

projects. For example, 10 popular real-world projects are the main experimental subjects for both *Neuzz* and *MTFuzz*; however, it is not clear how such 10 projects are selected and whether the experimental findings can generalize to other real-world projects.

To reduce such threat, we extend the benchmark for evaluating *Neuzz* and *MTFuzz*. In particular, in addition to retaining the adopted 9 projects in the original papers (we could not successfully run project `Zlib` out of the 10 original projects), we also adopt additional 19 projects for our extended evaluations. More specifically, to extend our benchmark projects, we first investigate all the fuzzing papers published in ICSE, ISSTA, FSE, ASE, S&P, CCS, USENIX Security, and NDSS in year 2020 and collect all their benchmark projects. Next, we sort the collected benchmark projects in terms of their usage in all the collected papers (presented in [38]). We then collect the top 30 most used benchmark projects and successfully run 19 of them which are eventually included in our extended benchmarks (the failed executions are mainly caused by environmental inconsistencies and unavailable dependencies). Table 1 presents the statistics of our adopted benchmarks. Specifically, we consider our benchmark to be sufficient and representative due to following reasons: (1) to the best of our knowledge, this is a rather large-scale benchmark suite compared with prior work; (2) the 28 collected benchmarks cover 12 different file formats for seed inputs, e.g., ELF, XML, and JPEG; and (3) the LoC of each program, ranging from 1,886 to over 120K, represents a wide range of program sizes.

3.2 Evaluation Setups

We conduct all our evaluations on Linux version 4.15.0-76-generic Ubuntu18.04 with RTX 2080ti. Following the evaluation setups of *Neuzz* and *MTFuzz*, for each selected benchmark project, we first run AFL-2.57b on a single CPU core for 1 hour to initialize our seed collection and then run *Neuzz*, *MTFuzz* and all their variants (introduced in later sections) upon the collected seeds with a time budget of 24 hours. Note that all the edges within the 1-hour initial seed collection are excluded from the evaluation results in the remaining sessions. Moreover, we run our experiments for 5 times for each fuzzer and present the average results with close performance under different runs. Note that we instrument all the benchmark projects with `afl-gcc` to acquire runtime edge coverage.

In addition to studying *Neuzz* and *MTFuzz*, we also include AFL as a baseline technique throughout our extensive evaluations because (1) AFL is widely adopted as baseline by many fuzzing approaches [3, 4, 28, 31, 50] and frequently upgraded for improving its performance; and (2) *Neuzz* adopts multiple concepts originated from AFL for its implementation [39].

3.3 Research Questions

We investigate the following research questions to extensively study neural program-smoothing-based fuzzing.

- **RQ1:** How do *Neuzz* and *MTFuzz* perform on a large-scale dataset? For this RQ, we investigate their effectiveness and efficiency of edge exploration under our large-scale benchmark suite.
- **RQ2:** How do the key components of *Neuzz* and *MTFuzz* affect edge exploration? For this RQ, we attempt to investigate how exactly their adopted gradient guidance mechanisms, neural network models, and mutation strategies can affect edge exploration.

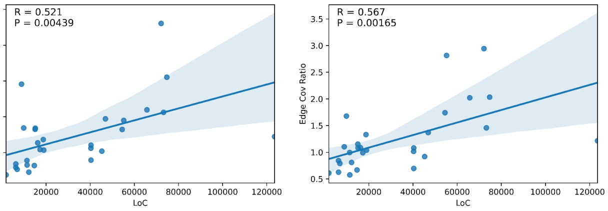
3.4 Results and Analysis

3.4.1 RQ1: performance of Neuzz and MTFuzz on a large-scale dataset. We first investigate the edge coverage performance of all the studied fuzzers. In this paper, following many existing coverage-guided fuzzers [4, 9, 27, 31, 51], we determine to adopt the number of the edges via `afl-showmap` as our default edge metric. Moreover, note that the edge metric of the original *Neuzz* and *MTFuzz* papers can be potentially biased since it counts the byte number of the `trace_bits` structure implemented by AFL and thus is inconsistent with the results provided by the guidance function (i.e., defining "interesting" seeds mentioned in Section 2.1.2) in their implementations. Nevertheless, as a comprehensive study, we also evaluate all the studied fuzzers in terms of the edge metric of the original *Neuzz* and *MTFuzz* papers.

Table 2 presents the edge coverage results of our extensive study for *Neuzz* and *MTFuzz* under both adopted metrics. For instance, for AFL under `bison`, 10,374 corresponds to our default edge metric and 308 corresponds to the original metric in the *Neuzz*/*MTFuzz* papers. For our default edge metric, we can observe that *Neuzz* significantly outperforms AFL by 10.5% (22,395 vs. 20,265 explored edges) in terms of edge coverage on average. Compared with the performance advantage claimed in its original paper (i.e., 2.7X), it is clearly degraded. We then investigate the performance difference among benchmark projects. Interestingly, we can observe that their performance advantage is rather inconsistent, i.e., ranging from -31.2% to 180.5%. Moreover, *Neuzz* only outperforms AFL upon 10 out of 19 extended projects. Such results suggest that *Neuzz* cannot

Table 2: Edge coverage results of all the studied approaches

Benchmarks	**AFL**	***Neuzz***	***Neuzz$_{Rev}$***	***MTFuzz***	***MTFuzz$_{Rev}$***	***MTFuzz$_{Off}$***	***Neuzz$_{CNN}$***	***Neuzz$_{RNN}$***	***Neuzz$_{BRNN}$***
bison	10,374 (308)	12,260 (432)	12,218 (264)	**13,812** (599)	12,799 (470)	12,801 (524)	12,375 (475)	12,592 (429)	12,444 (499)
xmlwf	**13,729** (3,272)	10,499 (2,200)	9,192 (1,644)	10,853 (509)	10,532 (457)	10,752 (476)	10,872 (2,794)	11,465 (2,891)	11,469 (2,831)
mupdf	13,665 (361)	16,705 (795)	**17,664** (654)	16,603 (328)	16,348 (237)	16,522 (334)	16,853 (796)	16,921 (792)	16,889 (804)
pngimage	**4,077** (201)	3,369 (324)	2,522 (199)	2,347 (200)	2,172 (198)	2,373 (194)	2,946 (241)	2,553 (197)	3,011 (323)
pngfix	**7,134** (135)	5,181 (85)	4,564 (71)	5,767 (80)	5,350 (71)	5,737 (73)	5,157 (74)	5,194 (74)	5,247 (76)
pngtest	3,185 (68)	2,828 (29)	2,933 (8)	3,166 (56)	2,719 (45)	3,016 (81)	3,074 (46)	**3,271** (58)	3,103 (42)
tcpdump	12,434 (3,525)	18,293 (4,310)	18,566 (5,005)	17,026 (5,512)	15,097 (3,715)	17,463 (4,621)	18,091 (4,495)	18,910 (4,635)	**19,411** (4,581)
nasm	33,633 (1,768)	34,788 (1,654)	33,838 (1,652)	34,958 (1,754)	34,451 (1,722)	33,907 (1,786)	**35,375** (1,791)	34,528 (1,695)	35,009 (1,899)
tiff2pdf	45,183 (4,844)	47,109 (4,365)	42,519 (3,993)	44,765 (4,355)	38,449 (3,676)	44,230 (4,044)	46,934 (3,971)	44,617 (3,765)	**50,347** (4,580)
tiff2ps	20,862 (3,621)	**23,705** (3,634)	21,063 (3,420)	22,671 (3,131)	16,700 (2,535)	21,817 (3,194)	23,931 (3,743)	21,322 (3,841)	23,160 (3,791)
tiffdump	2,416 (8)	**3,239** (52)	3,117 (52)	2,617 (64)	2,262 (38)	2,509 (61)	3,124 (46)	2,962 (47)	3,052 (43)
tiffinfo	11,964 (2,440)	**15,853** (2,618)	15,742 (2,407)	13,785 (2,799)	10,249 (1,431)	12,394 (1,904)	14,698 (2,788)	13,239 (2,649)	15,569 (2,379)
libxml	20,064 (541)	31,340 (1,553)	**32,075** (1,765)	29,236 (1,635)	29,162 (1,553)	27,902 (1,205)	31,421 (1,687)	31,774 (1,695)	31,731 (1,649)
listaction	**21,340** (3,151)	17,945 (2,893)	14,969 (2,328)	13,382 (622)	12,257 (559)	12,356 (591)	17,743 (2,791)	17,562 (2,822)	17,073 (2,770)
listaction_d	**31,617** (2,728)	25,006 (4,604)	18,643 (3,460)	26,629 (3,376)	21,644 (2,554)	23,619 (2,780)	25,869 (5,036)	28,436 (5,271)	23,622 (4,784)
libsass	**198,976** (10,385)	162,717 (8,492)	158,800 (8,438)	132,972 (7,373)	132,491 (7,232)	132,644 (7,106)	154,793 (8,742)	160,318 (8,902)	163,492 (8,527)
jhead	**2,082** (28)	1,433 (24)	1,566 (27)	1,268 (18)	1,215 (16)	1,273 (16)	1,327 (22)	1,560 (22)	1,502 (23)
readelf	14,329 (898)	40,186 (6,059)	34,994 (4,868)	42,173 (6,684)	35,178 (5,799)	40,005 (6,161)	42,889 (6,257)	**44,389** (6,159)	32,796 (5,314)
nm	11,154 (1,351)	16,159 (2,226)	13,505 (2,015)	**31,402** (3,707)	28,027 (3,128)	22,149 (3,045)	18,070 (2,312)	20,724 (3,132)	16,007 (4,099)
strip	20,536 (1,409)	32,791 (3,254)	31,604 (3,348)	**41,520** (5,172)	35,649 (5,699)	32,072 (3,674)	33,549 (3,649)	33,816 (3,916)	33,348 (3,753)
size	10,730 (1,188)	14,197 (2,450)	12,414 (2,036)	**18,675** (3,872)	16,525 (3,397)	12,623 (2,087)	14,488 (2,606)	14,254 (2,540)	12,284 (2,480)
objdump	15,492 (247)	31,808 (2,358)	28,617 (1,850)	31,507 (2,007)	27,227 (2,117)	30,074 (2,270)	31,176 (2,954)	33,165 (2,639)	**33,486** (3,062)
libjpeg	8,197 (266)	16,037 (1,600)	13,460 (1,566)	9,038 (876)	8,446 (797)	8,255 (487)	16,576 (1,729)	16,859 (1,713)	**17,566** (1,892)
harfbuzz	26,420 (3,107)	35,502 (5,982)	28,037 (5,606)	44,342 (6,268)	37,821 (4,930)	44,364 (6,155)	45,179 (7,542)	48,959 (7,656)	**50,911** (7,764)
base64	**1,344** (12)	1,202 (0)	987 (0)	935 (0)	912 (0)	819 (0)	1,247 (0)	1,226 (0)	1,243 (0)
md5sum	2,871 (33)	3,168 (131)	3,004 (37)	3,101 (35)	3,036 (35)	3,044 (35)	3,097 (33)	**3,241** (33)	3,163 (35)
uniq	713 (2)	**756** (2)	750 (2)	725 (0)	728 (0)	716 (0)	755 (2)	754 (2)	752 (2)
who	2,917 (14)	2,973 (17)	2,919 (17)	2,680 (15)	2,753 (17)	2,720 (17)	2,997 (17)	**3,031** (17)	3,026 (17)
Average	20,265 (1,640)	22,395 (2,219)	20,724 (2,026)	22,070 (2,180)	20,007 (1,872)	20,648 (1,890)	22,665 (2,380)	**23,130** (2,414)	22,883 (2,429)



(a) ***Neuzz*/AFL** (b) ***MTFuzz*/AFL**

Figure 3: Edge coverage advantage of the fuzzers over AFL

always outperform AFL and the performance advantage of *Neuzz* over AFL can be program-dependent.

We also observe that *Neuzz* outperforms *MTFuzz* by 1.5% (22,395 vs. 22,070 explored edges) averagely in terms of edge coverage on all benchmark projects. While on 11 of 28 total projects, *MTFuzz* outperforms *Neuzz* by 20.8% averagely, *Neuzz* outperforms *MTFuzz* by 17.7% on the other 17 projects. Furthermore, even AFL outperforms *MTFuzz* by 33.6% averagely on a total of 11 projects. Such results indicate that similar to *Neuzz*, *MTFuzz* cannot perform consistently either.

We then attempt to reveal the characteristics of how the edge coverage performance varies among the studied projects. To this end, we delineate the correlation between the edge coverage advantage of the studied fuzzers compared with AFL and the size of their studied projects via the Pearson Correlation Coefficient analysis [1]. Figure 3 presents such results of *Neuzz* and *MTFuzz*. In each subfigure, the horizontal axis denotes the LoC of each project and the vertical axis denotes the ratio as dividing the edge coverage result of each studied approach by the edge coverage result of AFL. We can observe that overall, the correlation is rather strong (at the significance level of 0.05), i.e., all the studied approaches can result in larger edge coverage improvement over AFL upon larger projects than smaller ones. Such results clearly demonstrate that program size can significantly impact the edge coverage performance of neural program-smoothing-based fuzzers.

We observe similar data trends in terms of the edge metric in the original *Neuzz*/*MTFuzz* papers. In particular, *Neuzz* can outperform AFL by 35.3% (2,219 vs. 1,640 explored edges) and can outperform *MTFuzz* by 1.8% (2,219 vs. 2,180 explored edges). Note that under such measure, for certain projects, e.g., base64, *Neuzz* and *MTFuzz* explore zero edges after excluding the edges from 1-hour initial seed collection. Such results could be misleading that the studied fuzzers perform equally poor in base64, while such performance gaps can be clearly presented by our default edge metric.

> *Finding 1: The performance of Neuzz and MTFuzz can be largely program-dependent. Interestingly, such program-smoothing-based fuzzers tend to perform better on larger programs.*

Note that randomness is injected to many existing fuzzers [4, 27, 31, 50] for selecting bytes to guide mutations, e.g., *AFL$_{Havoc}$*. However, *Neuzz* and *MTFuzz* utilize only deterministic mutation strategies, i.e., adopting no randomness for selecting bytes which can be deterministically identified based on their corresponding gradient ranking. Therefore, we further investigate the edge exploration efficiency of random byte selection to infer whether including them in *Neuzz* and *MTFuzz* can be potentially beneficial. Specifically, we involve AFL in a fine-grained manner, i.e., its deterministic stage *AFL$_{Deterministic}$* and the havoc stage *AFL$_{Havoc}$* (i.e., essentially the random byte selection mechanism) both of which enable non-deterministic execution time, for performance comparison with *Neuzz* and *MTFuzz*.

Figure 4 presents our evaluation results in terms of the explored edge number per second, namely *Edge Discovery Rate* (EDR) in this paper, of *Neuzz*, *MTFuzz*, AFL, $AFL_{Deterministic}$ and AFL_{Havoc}. We can observe that overall, *Neuzz* and *MTFuzz* can outperform AFL by 10.2% and 8.5% respectively. Interestingly, AFL_{Havoc} achieves the highest EDR, i.e., 21.8X larger than $AFL_{Deterministic}$, 7.7X larger than *Neuzz*, and 7.8X larger than *MTFuzz* averagely on all the benchmarks. Accordingly, we can derive that AFL_{Havoc} can significantly augment edge exploration, i.e., it promptly explores edges upon the limited seed inputs provided by $AFL_{Deterministic}$. Such result is enlightening that applying random byte selection mechanism to neural program-smoothing fuzzers can potentially boost edge exploration.

> *Finding 2: AFL_{Havoc} dominates the efficiency of edge exploration, indicating that it is promising to augment edge exploration by adopting random byte selection mechanism.*

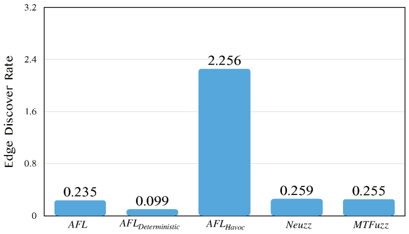


Figure 4: EDR of the studied approaches

3.4.2 *RQ2: Effectiveness of the key components.*

Gradient guidance. The inconsistencies between our finding and the declared results in the original papers (i.e., finding 1) inspire us to further investigate the performance impact of the adopted mechanisms of *Neuzz* and *MTFuzz*. To this end, we determine to first investigate the effectiveness of their dominating factor, i.e., the gradient guidance mechanism. In particular, since such mechanism is proposed to facilitate the mutations on the "promising" bytes for edge exploration via gradient computation, our purpose is to investigate whether their derived gradients can locate such bytes. More specifically, we propose an intuitive gradient guidance mechanism—instead of aggressively mutating the bytes with larger gradients in the original *Neuzz* and *MTFuzz*, we aggressively mutate the bytes with smaller gradients. Such mechanism is injected to *Neuzz* and *MTFuzz* to form their variants $Neuzz_{Rev}$ and $MTFuzz_{Rev}$. We thus evaluate $Neuzz_{Rev}$ and $MTFuzz_{Rev}$ to observe their performance difference from the original *Neuzz* and *MTFuzz* to investigate the effect of the gradient guidance mechanisms.

We can observe from Table 2 that *Neuzz* can explore 8.1% (1,671) more edges than $Neuzz_{Rev}$ and *MTFuzz* can explore 10.3% (2,063) more edges than $MTFuzz_{Rev}$ on average. Such consistent results suggest that larger gradients can be a better indicator to promising bytes, i.e., the derived gradients can reflect promising bytes.

Interestingly, $Neuzz_{Rev}$ can outperform *Neuzz* on 5 out of 28 projects, i.e., `libxml`, `mupdf`, `jhead`, `tcpdump` and `pngtest`. Meanwhile, $MTFuzz_{Rev}$ can outperform *MTFuzz* under `uniq` and `who`. Such results also indicate that the power of the gradient guidance in *Neuzz* and *MTFuzz* has not been completely leveraged.

> *Finding 3: Although the gradient guidance mechanisms adopted by Neuzz and MTFuzz are overall effective for identifying the promising bytes, their performance can be rather unstable on some programs.*

DNN models. Now that the gradients derived by *Neuzz* and *MTFuzz* can be proven to be effective in reflecting promising bytes for mutations, we further investigate how their corresponding neural network models impact edge exploration. Specifically, since compared to *Neuzz*, *MTFuzz* enables the independent dynamic analysis module *Crack* to augment their mutation strategy, we turn it off and form its variant $MTFuzz_{Off}$, i.e., applying the mutation strategy of *Neuzz* in *MTFuzz*, such that they only differ in the adopted neural network models. Moreover, we also include the Convolutional Neural Network (CNN) [26] model and two commonly-used Recursive Neural Network (RNN) [14] models, i.e., LSTM [24] and Bi-LSTM [22], and adopt them in the original *Neuzz* to form its variants $Neuzz_{CNN}$, $Neuzz_{RNN}$, and $Neuzz_{BRNN}$. Note that we investigate more RNN-based models since they are typically used in learning the distribution over a sequence to predict the future symbol sequence [10] (e.g., for speech recognition) and expected to better match the program input features than CNN-based models. Eventually, we determine to evaluate *Neuzz* and all the variant techniques to detect how multiple neural network models impact the edge exploration of program-smoothing-based fuzzers. Note that their hyper-parameter setups are introduced in our GitHub page [38].

We can observe from Table 2 that overall, all our studied approaches perform similarly in terms of edge coverage. Specifically, *Neuzz* slightly outperforms $MTFuzz_{Off}$ by 8.5% (22,395 vs 20,648 explored edges), underperforms $Neuzz_{CNN}$ by 1.2% (22,395 vs. 22,665 explored edges), $Neuzz_{RNN}$ by 3.3% (22,395 vs. 23,130 explored edges) and $Neuzz_{BRNN}$ by 2.2% (22,395 vs. 22,883 explored edges). Meanwhile, we can also observe that none of the studied approaches can dominate on top of all the studied projects, i.e., *Neuzz* dominates 7, $MTFuzz_{Off}$ dominates 2, $Neuzz_{CNN}$ dominates 4, $Neuzz_{RNN}$ dominates 9, and $Neuzz_{BRNN}$ dominates 6. Therefore, we derive that upgrading neural network models cannot significantly impact the performance of edge exploration.

> *Finding 4: Different neural network models have limited impact on the effectiveness of program-smoothing-based fuzzing.*

Mutation Strategies. We then investigate the impact from the mutation strategy of the neural program-smoothing-based fuzzers. Specifically, since *MTFuzz* differs from *Neuzz* mainly by enabling *Crack* for mutations and their respective neural network models do not significantly impact the edge exploration (reflected by Finding 4), we concentrate our investigation on the impact from *Crack*. To this end, we evaluate *MTFuzz* and $MTFuzz_{Off}$. Table 2 demonstrates that overall, *MTFuzz* can outperform $MTFuzz_{Off}$ by 6.9% (22,070 vs. 20,648 explored edges). However, such advantage can be rather inconsistent, ranging from -2.5% to 47.9% upon individual projects. On the other hand, applying *Crack* can be potentially cost-ineffective since it is quite heavyweight. Therefore, it is essential to consider whether it is worthwhile in applying such technique for neural program-smoothing-based fuzzing.

> *Finding 5: The dynamic analysis module Crack adopted by MTFuzz can be cost-ineffective.*

3.5 Discussion

We first discuss why neural network models do not significantly impact the edge coverage performance. To this end, we ought to understand the effect of the adopted neural network models of *Neuzz* and *MTFuzz*. In particular, note that neural networks are usually used for data prediction, i.e., learning and generalizing historical data to predict unseen data. Accordingly, researchers have developed many neural network models to strengthen their generalization and prediction capabilities. Therefore, one may misunderstand that *Neuzz* and *MTFuzz* attempt to use neural network models to predict the bytes corresponding to unexplored edges. Instead, as a matter of fact, *Neuzz* and *MTFuzz* leverage neural network models which compute the gradients to reflect the relations between explored edges and seed inputs, i.e., mutating the byte corresponding to a larger gradient can be more likely to explore a new edge other than the existing edge under one shared prefix edge. As a result, any neural network model can be applied as long as it can successfully deliver gradients to reflect such *explored edge—seed input* relations, i.e., how its generalization or prediction capability does not quite matter under such scenarios. Therefore, it is quite likely that a simplistic model (e.g., feed-forwarded network model adopted by *Neuzz*) can perform similarly as fine-grained models (e.g., multi-task learning model adopted by *MTFuzz* and the RNN models adopted by the studied *Neuzz* variants).

We then attempt to illustrate why *Neuzz* and *MTFuzz* cannot always be effective. Note that even though *Neuzz* and *MTFuzz* enable gradient guidance mechanisms to explore new edges, their iterative training-and-mutation strategy via randomly selecting edges and seeds in the beginning can nevertheless select existing edges other than unexplored edges to compute gradients (illustrated in Section 2.2.2), i.e., they still allow inefficient mutations. Specifically for the smaller programs where *Neuzz* and *MTFuzz* cannot outperform AFL, their edge exploration converges faster than larger programs due to the limited number of edges, i.e., they have a higher chance to select an existing edge whose “sibling” edges have already been explored by other seeds for gradient computation. Thus, it can be difficult to mutate its “promising” bytes for exploring new edges.

4 *PREFUZZ*

Our findings reveal that we can possibly leverage the power of the gradient guidance mechanism to enhance the edge exploration of neural program-smoothing-based fuzzers. To this end, we propose *PreFuzz* (**P**robabilistic **re**source-efficient program-smoothing-based **Fuzz**ing). Figure 5 presents the workflow of *PreFuzz*. *PreFuzz* first trains a neural network model by applying all the existing seeds as the training set. Next, *PreFuzz* adopts a *resource-efficient edge selection mechanism* to select edges for gradient computation. Then, the gradient information is utilized to generate mutants for fuzzing. Note that a mutant which explores new edges can be used as a seed for further edge exploration. Meanwhile, *PreFuzz* adopts *probabilistic byte selection mechanism* (*PBS* in Figure 5) to facilitate mutations.

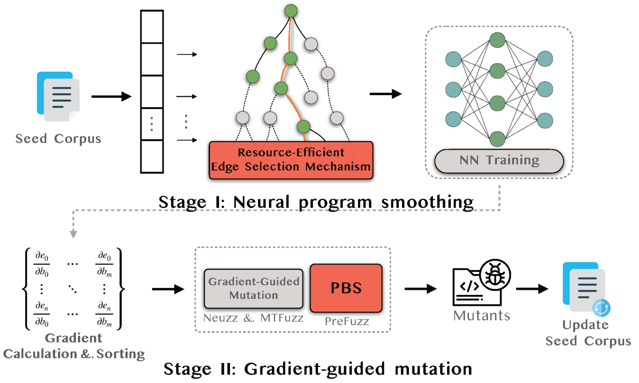
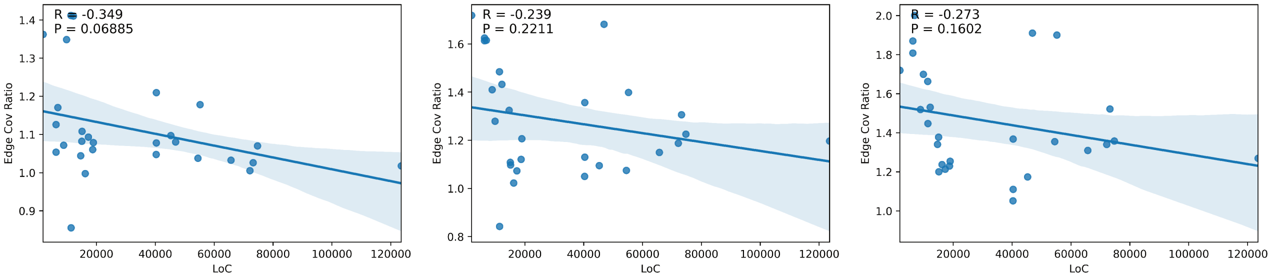

Seed Corpus
Resource-Efficient
Edge Selection Mechanism
NN Training
Stage I: Neural program smoothing
$\frac{\partial e_0}{\partial b_0}$ ... $\frac{\partial e_0}{\partial b_m}$
$\frac{\partial e_n}{\partial b_0}$ ... $\frac{\partial e_n}{\partial b_m}$
Gradient
Calculation &. Sorting
Gradient-Guided
Mutation
Neuzz &. MTFuzz
PBS
PreFuzz
Mutants
Update
Seed Corpus
Stage II: Gradient-guided mutation

Figure 5: Framework of *PreFuzz*

4.1 The Details

4.1.1 Resource-Efficient Edge Selection Mechanism. The purpose of the *resource-efficient edge selection mechanism* is to prevent exploring the existing branching behaviors (i.e., edges). To this end, our mechanism is designed to identify the edge worthy being explored for later selecting and mutating its corresponding byte. Intuitively, when one edge can identify the number of its “sibling” edges (as defined in Section 2.2), such edge number can be a potential indicator whether the given edge should be included for further gradient computation. More specifically, the more “sibling” edges have been explored, the less likely new “sibling” edges can be explored via the gradient computation for the given edge.

Algorithm 1 presents the details of the *resource-efficient edge selection mechanism*. First, it is quite essential to acquire the runtime edge exploration states, e.g., the number of “sibling” edges of a given edge and how many have been explored (lines 2 to 3). To this end, we decompile the assembly-level programs, parse them to the instructions via AFL-specific instrumentation, and construct the edge exploration states via statically analyzing the parsed instructions. Next, given one edge, we derive the ratio of its explored “sibling” edge number over its total “sibling” number (lines 5 to 9). If such ratio is lower than a preset threshold, we retain the given edge and stores it in a *Candidate Edge Set* where we later randomly select such edges for further gradient computation (lines 10 to 12). We use Figure 1 to further illustrate such algorithm. Assuming that e_0 can be explored given the “seed” in Figure 1, mutating the byte of the given seed corresponding to the access condition of e_0 can explore its “sibling” edge e_1. While *Neuzz* and *MTFuzz* are designed to perform such mutation for edge exploration, e_1 could have nevertheless been explored already due to the randomness injected to their mechanisms (illustrated in Section 2.2.2). Thus, the effectiveness of the gradient guidance mechanism may be compromised. However, our *resource-efficient edge selection mechanism* can collect the exploration information of the “sibling” edge of e_0, i.e., e_1, before computing the gradient for e_0. If it finds out that e_1 has already been explored, it would not select e_0 for gradient computation in the first place to save the computing resource.



(a) ***Neuzz$_{EdgeSelection}$/Neuzz***

(b) ***Neuzz$_{Prob}$/Neuzz***

(c) ***PreFuzz/Neuzz***

Figure 6: Edge coverage ratio upon *Neuzz*

Algorithm 1 Candidate Edge Set Construction

```
Input : threshold, exploredEdge
Output:selectedEdges
function CONSTRUCT_CANDIDATE_EDGE_SET
    candidate ⟵ set()
    correspRelation ⟵ getEdgeRelation()
    for edge in exploredEdge do
        explored ⟵ 0
        siblings ⟵ |correspRelation[edge]|
        for neighbour in correspRelation[edge] do
            if neighbour in exploredEdge then
                explored ⟵ explored + 1
        if explored/siblings < threshold then
            candidate.add(edge)
    selectedEdges ⟵ randomlySelectFromSet(candidate)
    return selectedEdges
```

Table 3: Edge coverage results of *PreFuzz*

Benchmarks	AFL	*Neuzz*	*MTFuzz*	*Neuzz$_{EdgeSelection}$*	*Neuzz$_{Prob}$*	*PreFuzz*
bison	10,374	12,260	13,812	13,003	13,744	**15,078**
xmlwf	13,729	10,499	10,853	12,290	16,960	**21,009**
mupdf	13,665	16,705	16,603	17,002	19,995	**21,203**
pngimage	4,077	3,369	2,347	2,883	2,838	**4,876**
pngfix	7,134	5,181	5,767	7,307	7,422	**7,930**
pngtest	3,185	2,828	3,166	3,993	4,199	**4,703**
tcpdump	12,434	18,293	17,026	19,764	30,767	**34,947**
nasm	33,633	34,788	34,958	37,534	41,973	**43,628**
tiff2pdf	45,183	47,109	44,765	51,506	50,555	**57,172**
tiff2ps	20,862	23,705	22,671	23,649	24,247	**29,332**
tiffdump	2,416	3,239	2,617	3,590	3,554	**3,888**
tiffinfo	11,964	15,853	13,785	17,157	17,572	**21,839**
libxml	20,064	31,340	29,236	32,161	40,935	**47,689**
listaction	21,340	17,945	13,382	20,208	29,161	**32,447**
listaction_d	31,617	25,006	26,629	26,351	40,355	**46,762**
libsass	198,976	162,717	132,972	169,936	215,510	**218,130**
jhead	2,082	1,433	1,268	1,952	2,463	**2,464**
readelf	14,329	40,186	42,173	40,396	47,727	**53,859**
nm	11,154	16,159	**31,402**	19,040	22,605	30,709
strip	20,536	32,791	41,520	33,864	37,705	**42,943**
size	10,730	14,197	18,675	14,734	15,261	**19,231**
objdump	15,492	31,808	31,507	34,036	38,983	**43,195**
libjpeg	8,197	16,037	9,038	17,192	22,615	**24,365**
harfbuzz	26,420	35,502	44,342	47,877	45,412	**60,333**
base64	1,344	1,202	935	1,454	1,631	**1,644**
md5sum	2,871	3,168	3,101	3,415	**3,580**	3,518
uniq	713	756	725	792	794	**795**
who	2,917	2,973	2,680	3,262	3,255	**3,491**
Average	20,265	22,395	22,070	24,155	28,636	**32,042**

4.1.2 Probabilistic Byte Selection Mechanism. Inspired by Finding 2, we further inject an additional nondeterministic stage to neural program-smoothing fuzzers. To this end, we develop a *Probabilistic Byte Selection Mechanism* and append it to *Neuzz* to expand edge exploration. Note that the *probabilistic byte selection mechanism* utilizes the gradient information generated by the *resource-efficient edge selection mechanism*, and gets activated after the mutation stage inherited from *Neuzz*. This stage contains three steps: (1) dividing each seed input into segments, (2) selecting segments by gradient-based probability distribution, and (3) randomly selecting bytes from the selected segment for mutation via AFL_{Havoc} mutators.

Unlike AFL_{Havoc} which randomly selects bytes from the whole seed, we first divide a seed into a constant number (8 by default in our paper) of equal-length segments. We then select seed segments based on their probabilities. Note that while intuitively leveraging byte-wise probability distribution for byte selection is more natural, this is essentially deterministic and excludes the benefits of randomness (as in Finding 2). Therefore, our probability distribution is established upon seed segments rather than individual bytes so as to leverage the power of randomness and AFL_{Havoc}.

Next, we calculate the fitness score for each segment, presented in Equation 1, where $\sum_{j=1}^{seg_i} grad_j$ denotes the gradient sum for all the bytes within a given segment seg_i, $length(seg_i)$ denotes its byte number, and the fitness score for a given segment seg_i is computed as the average gradient of all the bytes within seg_i.

$$fitness_{seg_i} = \frac{\sum_{j=1}^{seg_i} grad_j}{length(seg_i)} \tag{1}$$

Accordingly, the probability $Prob_{seg_i}$ for selecting a segment seg_i for mutation is presented in Equation 2, i.e., the ratio of the fitness score of seg_i over the total fitness scores of all the segments.

$$Prob_{seg_i} = \frac{fitness_{seg_i}}{\sum_{j=1}^{total} fitness_{seg_j}} \tag{2}$$

Finally, we apply AFL_{Havoc} to mutate the selected segments. In particular, AFL_{Havoc} randomly selects a byte from the segment for mutation based on its mechanism. Note that if the mutants are also "interesting", they are retained for further gradient computation and the *probabilistic byte selection mechanism*. Such process is iterated until hitting the time budget.

4.2 Performance Evaluation

We attempt to evaluate the performance of *PreFuzz* and its technical components respectively. To evaluate the usage of the *resource-efficient edge selection mechanism* and the *probabilistic byte selection mechanism*, we form two *Neuzz* variants, i.e., *Neuzz$_{EdgeSelection}$*

which injects *resource-efficient edge selection mechanism* to *Neuzz* and $Neuzz_{Prob}$ which appends the *probabilistic byte selection mechanism* to *Neuzz*. Note that we retain *Neuzz*, *MTFuzz*, and AFL as our baselines for performance comparison. The experimental setups in this section follow the same settings in Section 3.2. The `threshold` for Algorithm 1 is set to 0.4[1].

4.2.1 Edge exploration effectiveness. Table 3 presents the experimental results of edge exploration effectiveness. We can find that overall, *PreFuzz* outperforms all the existing baselines in terms of edge coverage averagely, e.g., *PreFuzz* can outperform AFL by 58.1% (32,042 vs. 20,265 explored edges) and *Neuzz* by 43.1% (32,042 vs. 22,395 explored edges). Note that under the originally adopted metric of edge coverage, *PreFuzz* also outperforms *Neuzz* and *MTFuzz* by 34.3% and 36.7%. Such results suggest that combining the *resource-efficient edge selection mechanism* and the *probabilistic byte selection mechanism* for *Neuzz* can be rather powerful. Moreover, $Neuzz_{EdgeSelection}$ outperforms *Neuzz* by 7.9% (24,155 vs. 22,395 explored edges) and *MTFuzz* by 9.4% (24,155 vs. 22,070 explored edges). Specifically, *Neuzz* obtains 271 more edges averagely than $Neuzz_{EdgeSelection}$ on 2 projects while $Neuzz_{EdgeSelection}$ obtains 1,917 more edges averagely than *Neuzz* on the rest 26 projects. Such results indicate that the *resource-efficient edge selection mechanism* can enhance the overall effectiveness of *Neuzz*. In addition, $Neuzz_{Prob}$ also outperforms *Neuzz* by 27.9% (28,636 vs. 22,395 explored edges) and *MTFuzz* by 29.8% (28,636 vs. 22,070 explored edges). Such results demonstrate that introducing randomness can also significantly increase the edge coverage of the neural program-smoothing-based fuzzers.

Figure 6 presents the correlation between the edge coverage advantage of $Neuzz_{EdgeSelection}$, $Neuzz_{Prob}$, *PreFuzz* over *Neuzz* by dividing their corresponding edge coverage results and the LoC of the studied benchmark projects. Interestingly, we can observe that the correlation is rather weak, i.e., all presented p values (0.0688, 0.2211 and 0.1602) fail to reach the significance level of 0.05. It indicates that the edge coverage advantage over the original *Neuzz* is not affected by the program size. Moreover, such advantage is rather consistent. Specifically, we determine to use Coefficient of Variation (CV) [5], a widely-used metric for measuring the dispersion of a probability distribution [35, 37, 48], to measure the consistency of their performance improvement. Note that a lower CV indicates a more consistent performance improvement. As a result, *PreFuzz*, $Neuzz_{EdgeSelection}$, and $Neuzz_{Prob}$ can achieve 19.6%, 11.5%, and 17.4% of CV for their performance improvement over *Neuzz*, which are all significantly reduced compared with the CV of *Neuzz* (37.6%) for its improvement over AFL. Therefore, we summarize that our proposed mechanisms can significantly and consistently strengthen the neural program-smoothing-based fuzzers. Note that we find under the edge coverage metric adopted in the original *Neuzz*/*MTFuzz* papers, the performance gain of *PreFuzz* over *Neuzz* is 34.3% (2,981 vs. 2,219 explored edges) which is also rather significant.

Figure 7 presents the average time trend of edge coverage within 24 hours for AFL, *MTFuzz*, *Neuzz* and *PreFuzz* among all the benchmark projects. We can observe that at any time being, *PreFuzz* can outperform other fuzzers significantly in terms of edge coverage.

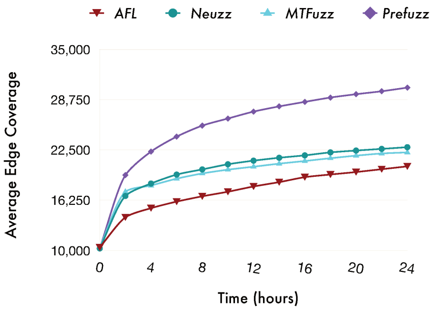


Figure 7: Edge coverage of *PreFuzz* in terms of time

4.2.2 In-depth Ablation Study. In this section, we further perform in-depth ablation studies to investigate the efficacy of our *resource-efficient edge selection mechanism* and *probabilistic byte selection mechanism* respectively. Specifically for the *resource-efficient edge selection mechanism*, we find that overall, 24.0% edges do not need to be explored by applying $Neuzz_{EdgeSelection}$ under each iteration averagely (1,230 vs. 935 edges). Moreover, the *probabilistic byte selection mechanism* in *PreFuzz* is more efficient when combining with the *resource-efficient edge selection mechanism* since *PreFuzz* explores averagely 11.9% more edges than $Neuzz_{Prob}$ (32,042 vs. 28,636 explored edges in Table 3). Such results indicate that applying the *resource-efficient edge selection mechanism* can significantly save the effort on exploring the edges which cannot contribute to increasing edge coverage.

We further investigate the *probabilistic byte selection mechanism* in terms of *Edge Discovery Rate*. To this end, we also include AFL_{Havoc}, $Neuzz_{EdgeSelection}$, the gradient-guided mutation stage of *PreFuzz*, and the probabilistic byte selection stage of *PreFuzz* (represented as $PreFuzz_{Gradient}$ and $PreFuzz_{Prob}$, respectively) for performance comparison. Note that $PreFuzz_{Gradient}$ and $PreFuzz_{Prob}$ results are extracted from the two stages of a complete *PreFuzz* run, e.g., $PreFuzz_{Prob}$ utilizes the *resource-efficient edge selection mechanism* to select edges for computing their gradients while $Neuzz_{Prob}$ randomly selects explored edges for gradient computation. Figure 8 presents our evaluation results. We can observe that overall, $PreFuzz_{Prob}$ can significantly outperform all the other studied approaches on top of all the studied benchmarks, e.g., $PreFuzz_{Prob}$ can be 62.0% more efficient than AFL_{Havoc} (3.656 vs. 2.256 EDR). Accordingly, we can infer that the gradient guidance adopted by *PreFuzz* can provide more "high-quality" seeds and more efficient guidance (i.e., gradients) for launching its *probabilistic byte selection mechanism* to explore more new edges than AFL_{Havoc}. Furthermore, we can observe that the EDR of $PreFuzz_{Gradient}$ can also outperform the original $Neuzz_{EdgeSelection}$ by 91.4%. Therefore, we also infer that $PreFuzz_{Prob}$ can advance the edge exploration efficiency of $PreFuzz_{Gradient}$. To summarize, combining the two improvements can mutually advance their edge exploration.

4.2.3 Crashes. Table 4 presents the unique crashes exposed by *Neuzz*, *MTFuzz* and *PreFuzz* in the studied benchmarks. Overall, *PreFuzz* explores the most unique crashes by outperforming *Neuzz* by 62% (149 vs. 92), and *MTFuzz* by 80% (149 vs. 83). In addition, *PreFuzz* dominates the number of the exposed unique crashes in each benchmark. Furthermore, the crashes exposed by *Neuzz* and

[1] We also evaluate more threshold setups and present the results in our GitHub link [38] which indicate that changing threshold setups incurs limited performance impact.

Table 4: Unique crashes found by *Neuzz*, *MTFuzz* and *PreFuzz*

Benchmarks	*Neuzz*	*MTFuzz*	*PreFuzz*
size	5	9	7
readelf	15	7	37
libjpeg	2	0	5
objdump	0	0	1
who	2	0	4
bison	15	18	20
jhead	8	7	12
listaction	25	16	31
listaction_d	7	8	17
nm	3	3	3
strip	10	15	12
Total	92	83	149

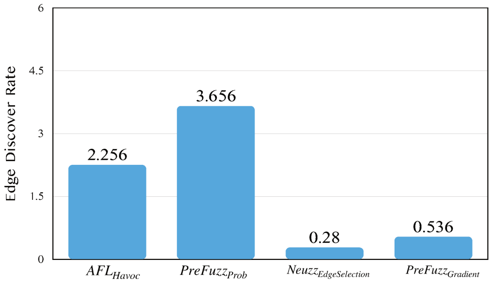


Figure 8: *Edge Discovery Rate* of different *PreFuzz* stages

MTFuzz are also detected by *PreFuzz* in our evaluation. Such results suggest that *PreFuzz* can also be more effective than *Neuzz* and *MTFuzz* in terms of exposing potential vulnerabilities.

4.3 Implications

Based on our findings in this paper, we propose the following implications for advancing the future research on fuzzing.

Simplistic neural network models may suffice. Our study results reveal that the edge coverage performance can be essentially impacted by how the resulting gradients of the adopted neural network models reflect the relations between explored edges and seed inputs rather than their generalization or prediction capabilities. That said, simplistic neural network models may already suffice for program-smoothing-based fuzzing.

Think twice before applying dynamic analysis. Our evaluations indicate that the dynamic analysis module adopted in *MTFuzz* can be quite effective on large programs. However, executing such module can be rather heavyweight, similar as many other program analysis techniques [6, 12, 19]. Therefore, we recommend to think carefully before adopting dynamic analysis techniques to enhance neural program-smoothing-based fuzzing.

Edge selection? Yes! Gradient computation? Maybe. Our evaluations reveal that selecting "promising" edges for mutations can be quite effective in increasing the edge coverage performance on programs of varying sizes. Meanwhile, one question can be asked: is it necessary to bind such powerful mechanism with gradient guidance? Especially when we realize that the power of neural networks can be argued to be "underused" (i.e., their generalization and prediction capabilities are underused), such question can then be transformed as — is it necessary to use neural networks for computing gradients to represent the relations between explored edges and seed inputs? To answer such question, it is worthwhile to attempt other lightweight alternatives to represent such relations as potential future research directions.

Probabilistic search helps. Our study results indicate that the edge coverage performance of the neural program-smoothing-based fuzzers can be significantly enhanced by appending the *probabilistic byte selection mechanism*. Intuitively, we suggest the users to design such probabilistic search strategy with more guidance to any of their adopted fuzzers when possible. Accordingly, one possible research direction can be how to integrate such probabilistic search strategy with diverse fuzzers for optimizing the edge coverage performance.

5 THREATS TO VALIDITY

Threats to internal validity. The threat to internal validity lies in the implementation of the studied fuzzing approaches in the experimental study. To reduce this threat, we reused the source code of *Neuzz* and *MTFuzz* when we implemented *PreFuzz*. Meanwhile, to implement the *probabilistic byte selection mechanism*, we also reused such code from the original AFL for the *PreFuzz* implementation. Moreover, all the student authors manually reviewed *PreFuzz* code carefully to ensure its correctness and consistency.

Threats to external validity. The threat to external validity mainly lies in the benchmarks used. To reduce this threat, we adopt the original benchmarks used by *Neuzz* and *MTFuzz*, and add 19 more projects widely used for the evaluations in many popular fuzzers [3, 4, 28, 31, 50] published recently.

Threats to construct validity. The threat to construct validity mainly lies in the metrics used. While the edge coverage metrics adopted by *Neuzz* and *MTFuzz* are not widely used by the existing fuzzers and can be arguably limited to reflect edge coverage, to reduce this threat, we determine to follow the majority by using the AFL built-in tool *afl-showmap* for measuring edge coverage while also presenting partial results in the original measure as well. Notably while under our metric, the performance advantages of *Neuzz* and *MTFuzz* are reduced, our *PreFuzz* can incur quite strong performance gain under both metrics.

6 RELATED WORK

As this work mainly studies deep learning-based fuzzing approaches, we are going to discuss closely related work in the following three dimensions: the existing fuzzing approaches (Section 6.1), the deep learning-based fuzzing techniques (Section 6.2), and the existing studies on fuzzing (Section 6.3).

6.1 Fuzzing

To date, various fuzzing techniques have adopted evolutionary algorithms to improve the performance of fuzz testing. Böhme et al. [4] proposed *AFLFast* which designs a seed selection strategy to weigh seeds via Markov Chain on top of the original AFL [51]. They also proposed *AFLGo* [3] to take advantages in weighting seeds based on edge structures to explore the target point specified by users. Lemieux et al. [27] proposed *FairFuzz* to increase greybox fuzz testing coverage by fuzzing rare branches of program. Manès et al. [32] proposed *Ankou*, a grey-box fuzzing solution based on different combinations of execution information. Fioraldi et al. [16] introduced *WEIZZ* to automatically generate and mutate inputs for unknown chunk-based binary formats. Similar to our *PreFuzz*, many works also utilized light-weight program analysis to facilitate fuzzing efficacy. Rawat et al. [36] proposed *VUzzer* to leverage control- and data-flow features based on static and dynamic analysis to infer fundamental properties of the application without any prior knowledge or input format. Mathis et al. [33] presented a technique to learn program tokens by tainting for fuzzing. Padhye et al. [34] automatically guided QuickCheck-like random input generators to semantically analyze test programs for generating test-oriented Java bytecode. Chen et al. [9] introduced *Angora*, a mutation-based fuzzer that solves path constraint without symbolic execution by taint checking and searching. Furthermore, new guidance other than code coverage are proposed to fuzz specific software systems. Wu et al. [46] proposed *Simulee* to parse constraints of inputs from a given GPU kernel function and mutate the inputs guided by memory access conflict to fuzz CUDA programs. Accordingly, they further proposed *AuCS* [47] to repair the detected synchronization bugs. Wen et al. [43] proposed a memory-usage-guided fuzzer to generate excessive memory consumption inputs and trigger uncontrolled memory consumption bugs. Zhao et al. [53] synthesized programs for testing JVMs based on the ingredients extracted from JVM historical bug-revealing tests.

6.2 Deep Learning on Fuzzing

She et al. proposed *Neuzz* [41], the first neural program-smoothing-based fuzzer using neural network models to discover "promising" bytes for a previously explored edge. They [40] also proposed *MTFuzz* to fuzz a system more efficiently via a multi-task neural network. Meanwhile, deep learning is also used in evolution-based fuzzing. Zong et al. [55] proposed *FuzzGuard*, a deep-learning-based approach to help evolution-based fuzzers predict the reachability of inputs before executing programs. Moreover, researchers have also utilized deep learning to learn how to generate valid inputs for deeply fuzzing a system. Lyu et al. [30] introduced *SmartSeed* which used Generative Adversarial Networks [21] to generate seeds from learning the patterns of valuable existing seeds. Liu et al. [29] proposed *DeepFuzz* to automatically and continuously generate C programs by a generative Sequence-to-Sequence model [11]. Godefroid et al. [20] divided fuzzing tasks into two categories, i.e., learning input format to fuzz deeper and breaking input format to trigger defects. Zhang et al. [52] proposed *DeepRoad* to automatically generate driving scenes to fuzz image-based autonomous driving systems. Zhou et al. [54] further generated realistic and continuous physical-world images to fuzz such systems. In this paper, we propose *PreFuzz* with the *resource-efficient edge selection mechanism* and the *probabilistic byte selection mechanism* to improve the performance of neural program-smoothing-based fuzzers.

6.3 Studies on Fuzzing

The empirical studies on fuzzing give many implications for further research. Klees et al. [25] provided guidelines on evaluating the effectiveness of fuzzers by assessing the experimental evaluations carried out by different fuzzers. Gavrilov et al. [17] proposed a new metric consistently with bug-based metrics by conducting a program behavior study during fuzzing. Böhme et al. [2] summarized the challenges and opportunities for fuzzing by studying existing popular fuzzers. Geng et al. [18] performed an empirical study on multiple artificial vulnerability benchmarks to understand how close these benchmarks reflect reality. Herrera et al. [23] investigated and evaluated how seed selection affects a fuzzer's ability to find bugs in real-world software. Wu et al. [45] studied the features of the havoc mechanism adopted by many fuzzers including AFL and found it is already a powerful fuzzer which outperforms many existing ones. In this paper, we conduct an empirical study to investigate the power and limitation of neural program-smoothing-based fuzzing and reveal various findings/guidelines for future learning-based fuzzing research.

7 CONCLUSION

In this paper, we investigated the strengths and limitations of neural program-smoothing-based fuzzing approaches, e.g., *MTFuzz* and *Neuzz*. We first extended our benchmark suite by including additional projects that were widely adopted in the existing fuzzing evaluations. Next, we evaluated *Neuzz* and *MTFuzz* on the extensive benchmark suite to study their effectiveness and efficiency. Inspired by our study findings, we proposed *PreFuzz* combining two technical improvements, i.e., the *resource-efficient edge selection mechanism* and the *probabilistic byte selection mechanism*. The evaluation results demonstrate that *PreFuzz* can significantly outperform *Neuzz* and *MTFuzz* in terms of edge coverage. Furthermore, our results also reveal various findings/guidelines for advancing future fuzzing research.

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