SLOPT: Bandit Optimization Framework for Mutation-Based Fuzzing

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Fuzzing has become a widespread method to find bugs

Thanks to its automaticity, fuzzers are

- easy-to-use in CI/CD.
- highly scalable.

These characteristics made fuzzing in popular use.

As of July 2022, OSS-Fuzz has found over 40,500 bugs in 650 open source projects.

As of May 2022, ClusterFuzz has found 25,000+ bugs in Google (e.g. Chrome).
Mutation-based fuzzing

1. Seed Scheduler selects a seed to be mutated
2. Mutator selects mutation operators and applies it to the seed
3. Executor evaluates the input by running a program with it
   - program
   - bif flip
   - string insertion
4. Save the new input to the queue if it was valuable (= found new code blocks)
Mutation operators

Arith Little End

Insert/Delete

+15

BitFlip
Fuzzer performance improves when tuned for specific programs.

E.g.

- Structure-aware fuzzing
  - considers file format during mutation not to create unfruitful invalid inputs.
- Human-in-the-loop fuzzing
  - Human analyst adds special annotations by hand to boost fuzzing.

But such performance tunings can spoil generality and scalability.

- Employing them may narrow the range of applicable target softwares.
- It is unrealistic for us to take time to tune fuzzers for each of thousands of open source projects.
Performance tuning (specialization) vs. generality

Fuzzer performance improves when tuned for specific programs. E.g.

- **Structure-aware fuzzing**
  - considers file format during mutation not to create unfruitful invalid inputs.

- **Human-in-the-loop fuzzing**
  - Human analyst adds special annotations by hand to boost fuzzing.

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- Employing them may narrow the range of applicable target softwares.
- It is unrealistic for us to take time to tune fuzzers for each of thousands of open source projects.
Related work: online optimization for mutation

There are studies employed online optimization in mutation to boost fuzzing performance while keeping the generality.

- Some of them found that effective mutation operators are different depending on programs.
  - This fact serves as the foundation of these studies.
- Most related existing studies:
  - with bandit: Karamcheti et al., CMFuzz, HavocMAB
  - with heuristics: MOPT

From "MOPT: Optimized Mutation Scheduling for Fuzzers." Chenyang et al. 2019. In Proceedings of the 28th USENIX Security Symposium (Security’19).
Bandit problem

Basic definition of bandit problem:

- There is the predetermined set of choices.
- Once picked, each choice returns some rewards with an unknown probability.
- A player needs to pick one choice in each round and maximize the total rewards earned over T rounds.

Bandit algorithms efficiently maximize rewards.
In fuzzing, choice is mutation operator and reward is whether input is valuable.
Our motivation is also improving fuzzer performance with generality. We use bandit algorithms to this end because optimizing mutation can be naturally interpreted as bandit problem.

To fully draw the power of bandit algorithms, we made three observations before incorporating bandit algorithms into fuzzers.
While the previous studies observed that mutation operators have different efficiency, they apply multiple different operators to a single input in mutation. This makes it difficult to analyze which operator was actually effective later.

Observations#1: mutation scheme

The new input was valuable. But which was contributed?

```
Algorithm 1 Conventional Random Mutation Scheme

Input: seed – a test case to be mutated
Output: input – a new input to be tested

function RANDOM_MUTATION(seed)
    input ← COPYBYTESFROMSEED(seed)
    batch_size ← DECIDE_BATCH_SIZE()
    for i ← 1 to batch_size do
        mutation ← SELECT_OPERATOR()
        pos ← SELECT_POSITION(input)
        input ← APPLY_OPERATOR(mutation, input, pos)
    end for
    return input
end function
```
Observations#1: mutation scheme

We modified the mutation scheme so that only one type of mutation operator is applied to a single input.

Empirical experiments revealed this modification does not seriously affect the performance. Thus, there is no need to mix different mutation operators.

Algorithm 2 Our Random Mutation Scheme

| Input: seed – a test case to be mutated  |
|----------------------------------------|
| Output: input – a new input to be tested |

function RANDOM_MUTATION(seed)
  input ← COPY_BYTES_FROM_SEED(seed)
  batch_size ← DECIDE_BATCH_SIZE()
  mutation ← SELECT_OPERATOR()
  for i ← 1 to batch_size do
    pos ← SELECT_POSITION(input)
    input ← APPLY_OPERATOR(mutation, input, pos)
  end for
  return input
end function
Observations#2: batch size

Batch size is a parameter meaning how many operators applied to one input. We ran AFL++ to see which batch size tended to produce valuable inputs. We found:

- distributions of effective batch size are different depending on programs.
- It also depends on seed size.
  - This means optimization should be done independently for different seed sizes.

Thus, batch size also should be an optimization target.

```
function RANDOM_MUTATION(seed)
    input ← CoreBugsFromSeed(seed)
    batch_size ← DECIDE_BATCH_SIZE()
    for i ← 1 to batch_size do
        mutation ← SELECT_OPERATOR()
        pos ← SELECT_POSITION(input)
        input ← APPLY_OPERATOR(mutation, input, pos)
    end for
    return input
end function
```
Our proposed algorithm: SLOPT

1. Select mutation operator.

2. Select batch size.

3. Mutate seed with selected parameters.

4. Check if new input was valuable and update problem instances.

instance of batch size used if operator == bitflip and len(seed) ∈ [100, 1000)
The aforementioned existing methods use different optimization algorithms such as KL-UCB and Thompson Sampling. Whether adopting other algorithms affects the performance was not mentioned.

We had a preliminary experiment of optimizing AFL++ with different algorithms. It showed the difference of algorithms somewhat affects the performance.

### Table 2: Ranks and scores averaged over 10 PUTs of AFL++ and 8 versions of SLOPT-AFL++ after 24 h.

|           | AFL++ | UCB1 | KL-UCB | TS | dTS |
|-----------|-------|------|--------|----|-----|
| Rank Avg  | 7.9   | 5.5  | 3.5    | 3.9| 3.0 |
| Score Avg | 89.44 | 93.83| 96.58  | 98.81| 97.85|

|           | dBE   | ADS-TS | EXP3-IX | EXP3++ |
|-----------|-------|--------|---------|--------|
| Rank Avg  | 4.9   | 2.6    | 6.5     | 6.9    |
| Score Avg | 95.57 | 97.39  | 94.11   | 93.56  |
Proof of concept and result

We incorporated SLOPT and the aforementioned existing methods into AFL++ to compare the performance improvement (of code coverage).

The reasons we chose AFL++ as baseline

● It exactly has the mutation scheme we mentioned.
● It produces good results on various benchmarks such as FuzzBench.
● It is one of the fuzzers used in OSS-Fuzz

○ Our performance improvement can be immediately available in OSS-Fuzz.

Our result

● the best in the same metrics as FuzzBench (average score and rank),
● also better in statistical significance and effect size for each program.

| PUT      | AFL++ [21] | MOpt [40] | CMFuzz [64] | Karamcheti [35] | HavocMAB [66] | SLOPT |
|----------|------------|-----------|-------------|------------------|---------------|-------|
|          |            |           |             |                  |               |       |
|          |            |           |             |                  |               | 1.6   |
| Rank Avg | 4.4        | 5.1       | 3.9         | 2.7              | 3.0           |       |
| Score Avg| 92.81      | 92.13     | 96.37       | 97.59            | 95.69         | 99.28 |

...
Limitation and future work

SLOPT did not outperform the others in every program.

**Estimated Cause**
Considering that SLOPT uses a sole operator while the others mix operators, it may imply mixing them is fruitful sometimes.

**Difficulty we faced in analysis**
A lot of experiments would be needed to reveal when exactly the "sometimes" is. Repeating experiments was very hard due to an enormous amount of required computing resources (more than thousands CPU days).

**Possible future direction**
Investigating the cause may produce a more efficient hybrid optimization method of mixing and not mixing operators.
To boost the performance of mutation-based fuzzer while keeping its generality, we proposed SLOPT, a general optimization framework employing bandit algorithm. Although some existing methods share the same motivation and direction as ours, we made three observations they unconsidered and utilized the findings in ours. The evaluation result showed SLOPT showed the best performance (code coverage) reliably on average. However, considering it was not the best always, there is still room for further investigation and improvement.
Thank you!

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Git Repo: https://github.com/RICSecLab/SLOPTAFLpp
The followings are Omitted pages
Some studies employed online optimization in mutation to boost fuzzing performance while keeping the generality.

Some existing methods employ bandit algorithms because optimizing mutation can be naturally interpreted as bandit problem.

- Karamcheti et al. used Thompson Sampling (a bandit algorithm) to optimize operators with the same motivation as MOPT.
- CMFuzz extended the algorithm of Karamcheti et al. with LinUCB (a contextual bandit algorithm).
- HavocMAB finally suggested online optimization with KL-UCB (a bandit algorithm) through experiments similar to MOPT.
Batch size is a parameter controlling how many operators applied to one input. We ran AFL++ and recorded batch size for each valuable input. Then, we found

- Batch size affects the number of valuable inputs produced.
- Which batch size is the most effective depends on programs.

Thus, batch size also should be an optimization target.
While HavocMAB previously found this finding with a different observation, our observation also found another phenomenon:

- Distributions of effective batch size are different depending on seed size.
- This means optimization should be done independently for different seed sizes.