Fuzzing Symbolic Expressions

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The work presented today appeared at ICSE 2021 (conference) and COSE 2021 (journal).

Co-authors: Luca Borzacchiello and Camil Demetrescu
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Unfortunately, Camil passed away in April 2022

- Full professor at Sapienza University of Rome
- A brilliant researcher (algorithms, program analyses)
- One of the best teachers. Students loved him.
He was my (best) teacher...
He was my thesis advisor (both BSc and MSc)…
He was my co-author for 10+ years and 20+ papers

PLDI 2012 @ China

[my first paper]
He was my friend…

It was an honour for me to work with Camil.
Symbolic execution is the coolest program analysis ever met! However:
- hard to implement
- …a lot of (non trivial) scalability issues!

When instead considering fuzzing:
- simple(r) to implement
- quite effective in practice
  (see OSS-Fuzz results)
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- quite effective in practice (see OSS-Fuzz results)

THAT IS SO UNFAIR
Coverage-guided Fuzzing

1. Pick an input from the queue

2. Mutate it:
   - random bit-flips
   - random substitutions
   - random… things
3. Run the program
   ○ Look for crashes
   ○ Track code coverage

4. If new coverage: keep mutating that input!

5. Repeat from (1) for a trillion of times
Can we reduce the number of (wasted) attempts?
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Some works have used taint analysis to understand which bytes to mutate.
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What if we build symbolic expressions to learn how to mutate the input?
Input I → Run → Program Execution → Trace → Symbolic Expressions

$\pi_1 \land \neg b_1$

$\pi_2 \land \neg b_2$

$\pi_3 \land \neg b_3$

→ Learn → Smart Mutations on Input I → Mutate → Input I'
Trace? Concolic Execution!

A dynamic twist of symbolic execution: execute the program over an input and build expressions along the path, negating branch conditions to generate new inputs.

Pros:
- driven by one input: no need for a solver to go on in the exploration
- exploit concrete state when hard to reason symbolically

Cons:
- for each input, rebuild expressions [recent works significantly reduced this cost, see, e.g., SymCC, Fuzzolic, SymQEMU, SymSan]
Observations

\[ \pi_i \land \neg b_i \]

1. \( \pi_i \) is satisfied by the input I that has induced the execution

2. to learn how to mutate input I, we should look at \( \neg b_i \)

3. if we change some bytes in input I, then \( \pi_i \) may become unsatisfied. Hence we should do it carefully… but fuzzing is often lucky… we may expect to be lucky as well.
Fuzzy-SAT: Learn and Mutate

Given a branch query $\neg b \land \pi$ and the input I, mutate the bytes of the input trying to solve $\neg b$ while keeping $\pi$ satisfiable.
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Given a branch query $\neg b \land \pi$ and the input $I$, mutate the bytes of the input trying to solve $\neg b$ while keeping $\pi$ satisfiable. Two stages:

- **Analysis**: learn from the symbolic expressions added to $\pi$
Fuzzy-SAT: Learn and Mutate

Given a branch query $\neg b \land \pi$ and the input $I$, mutate the bytes of the input trying to solve $\neg b$ while keeping $\pi$ satisfiable. Two stages:

- **Analysis**: learn from the symbolic expressions added to $\pi$
- **Reasoning**: use the acquired knowledge to apply simple but fast mutations to the input
Analysis Stage (simplified)

Learn from the constraints added to $\pi$

- Detect input groups
- Detect constants
- Detect ITS expressions
- Detect range constraints
Analysis Stage (simplified)

Learn from the constraints added to $\pi$

- Detect input groups
- Detect constants
- Detect ITS expressions
- Detect range constraints

**Input Group**: input symbols that are used together in the expression, and that never mix their bits

\[
i_0 + i_1 + 10 = 42
\]

\[
i_0 - i_1 = 0
\]
Analysis Stage (simplified)

Learn from the constraints added to $\pi$

- Detect input groups
- Detect constants
- Detect ITS expressions
- Detect range constraints

Collect the constants within the symbolic expression

\[ i_0 \cdot 10 = 30 \]
\[ i_0 + i_1 + 10 = 42 \]
Analysis Stage (simplified)

Learn from the constraints added to $\pi$

- Detect input groups
- Detect constants
- Detect ITS expressions
- Detect range constraints

Detect expressions that contains an input-to-state \[1\] relation, i.e., a comparison of an input group with raw bytes

$$(i_0 << 8) | i_1 = 42$$

$$i_0 + i_1 > 1$$

Analysis Stage (simplified)

Learn from the constraints added to $\pi$

- Detect input groups
- Detect constants
- Detect ITS expressions
- Detect range constraints

Detect patterns where a constraint sets an upper or lower bound to an input group:

$$(i_0 + i_1) + 0xAAAA <_{\text{unsigned}} 0xBBBB$$

$$i_0 + i_1 \in [0, 0x1110] \cup [0x5556, 0xFFFF]$$
Reasoning Stage (simplified)

*Mutate the bytes of the seed, trying to keep $\pi$ satisfiable*

- Mutation Engine
  - Input-to-State
  - Range brute-force
  - Gradient descent
  - AFL det. and non-det.
- Multi-Goal Engine
Reasoning Stage (simplified)

*Mutate the bytes of the seed, trying to keep $\pi$ satisfiable*

- Mutation Engine
  - Input-to-State
    - Range brute-force
    - Gradient descent
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- Multi-Goal Engine

If the query has been tagged as input-to-state by the analysis stage, substitute the raw bytes in the input group

\[
(i_0 << 8)|i_1 = 42 \\
\downarrow \\
\begin{align*}
i_0 &\leftarrow 0 \\
i_1 &\leftarrow 42
\end{align*}
\]
Reasoning Stage (simplified)

*Mutate the bytes of the seed, trying to keep $\pi$ satisfiable*

- **Mutation Engine**
  - Input-to-State
  - Range brute-force
  - Gradient descent
  - AFL det. and non-det.
- **Multi-Goal Engine**

If an expression contains only one input group that has a small interval associated with it, brute force all the possible values.

\[ i_0 + i_1 \in [0, 9] \quad \text{Result of range analysis} \]

\[ i_0 + i_1 + 0xABAD = 0xCAFE \quad \text{Query} \]
Reasoning Stage (simplified)

*Mutate the bytes of the seed, trying to keep $\pi$ satisfiable*

- Mutation Engine
  - Input-to-State
  - Range brute-force
  - Gradient descent
  - AFL det. and non-det.
- Multi-Goal Engine

Reduce the query to a minimization problem, and use gradient descent to solve it

\[
(i_0 + i_1) - 10 > (i_2 + i_3) + 5
\]

\[
(i_2 + i_3) + 5 - ((i_0 + i_1) - 10) < 0
\]

\(^1\) The implementation also takes into account the wrap around!
Reasoning Stage (simplified)

*Mutate the bytes of the seed, trying to keep $\pi$ satisfiable*

- Mutation Engine
  - Input-to-State
  - Range brute-force
  - Gradient descent
  - AFL det. and non-det.
- Multi-Goal Engine

Apply deterministic and non-deterministic transformations inspired by two mutation stages of AFL:

- AFL transformations include bit-flips, addition and subtraction with small constants, etc.

- Differently from AFL:
  - our mutations are applied only to the bytes involved in the branch condition
  - multi-byte mutations are considered only in the presence of multi-byte input groups
Multi-Goal Engine (simplified)

Looking only at the branch condition is too restrictive:

```c
1. int f(char i1, char i2) {
2.     assert ( i1 == i2 );
3. if ( i2 == 1 ) input ← \{i_1 = 0, i_2 = 0\}
4.     return 0;
5. return 1;
6. }
```

\(\pi \leftarrow i_1 = i_2\)

\(\neg b \leftarrow i_2 = 1\)

\(\pi \land \neg b\) cannot be solved by mutating only \(i_2\)
Multi-Goal Engine (simplified)

Looking only at the branch condition is too restrictive:

```c
int f(char i1, char i2) {
    assert ( i1 == i2 );
    if ( i2 == 1 )
        return 0;
    return 1;
}
```

The multi-goal engine employs a greedy approach to solve this problem. Assuming that the reasoning engine solved $\neg b$:

- It checks whether $\neg b$ has conflicting constraints in $\pi$
- It tries to solve the conflicting constraints without modifying the bytes involved in $\neg b$
Implementation

Fuzzy-SAT:

- C library
- Operates on Z3 expressions
- Integration in:
  - QSYM
  - Fuzzolic
  - SymQEMU
  - SymCC

Fuzzy-SAT is available at
https://season-lab.github.io/fuzzolic/
Can Fuzzy-SAT actually solve queries generated by concolic executors?
Evaluation #1: Fuzzy-SAT vs Z3 vs JFS

Queries collected with QSYM using 12 real-world programs.

- **Fuzzy-SAT vs Z3**: Fuzzy-SAT may solve some queries that are not solved within the timeout by Z3. But is true also the opposite! Moreover, Fuzzy-SAT is designed to “fail fast” on too complex queries.

- **Fuzzy-SAT vs JFS**: Fuzzy-SAT may solve more queries than JFS likely due to the knowledge acquired during the analysis stage.

- Overall, Fuzzy-SAT was able to solve more queries than Z3/JFS, while also being faster.
Does Fuzzy-SAT only generate inputs that are already produced by traditional fuzzers? Does it actually make the difference?
Evaluation #2: Code Coverage

Fuzzolic (our concolic executor) with Fuzzy-SAT against:
- AFL++
- QSYM using Z3
- Eclipser

Concolic executors (Fuzzolic, QSYM) used in a hybrid fuzzing setup.

8H experiments, **Fuzzolic with Fuzzy-SAT** reached:
- an higher coverage in 7/12 programs
- a comparable coverage in 4/12 programs
- a lower coverage in 1/12 programs
Concluding remarks

Limitations (future directions?):
● It does not support the theory of arrays [ABV] and floating points.
● Not yet a clue on how to alternate effectively Fuzzy-SAT and Z3.

What we have learned:
● There are reasons why fuzzing is effective.
● Building symbolic expressions is expensive but we can learn a lot from them.
● JFS and Fuzzy-SAT are just first steps. Another recent step: JIGSAW @ IEEE SP 22

Thank you
I am open to research collaborations!
Let us have a chat if you wish :)