Sapienza
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Fuzzing Symbolic Expressions

Emilio Coppa

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

Co-authors: Luca Borzacchiello and **Camil Demetrescu**

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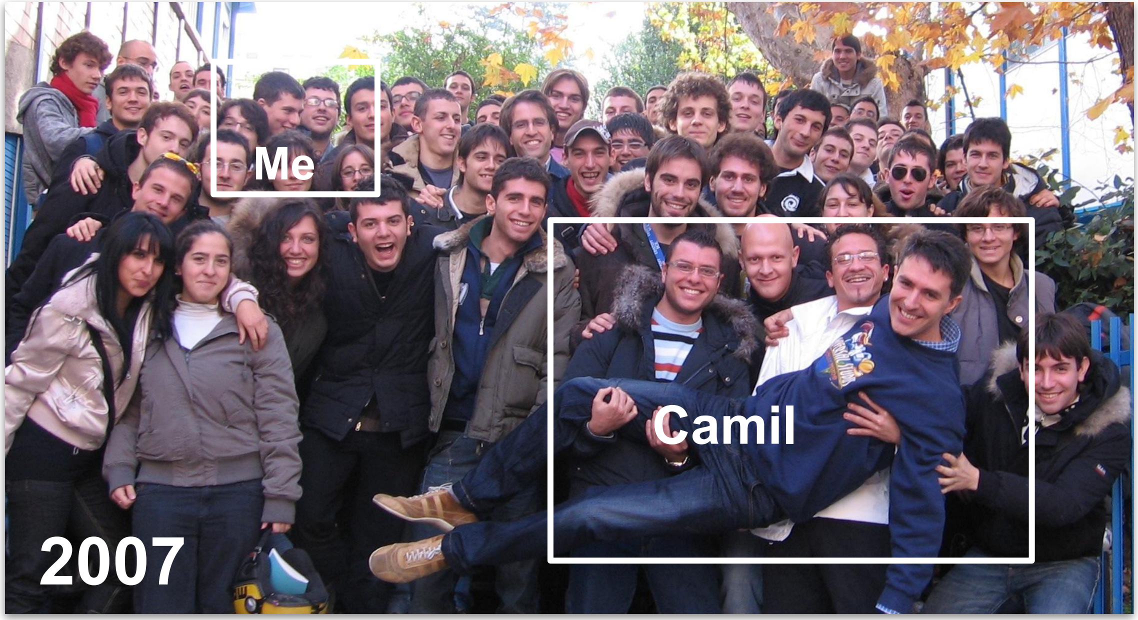
Unfortunately, Camil passed away in April 2022

- 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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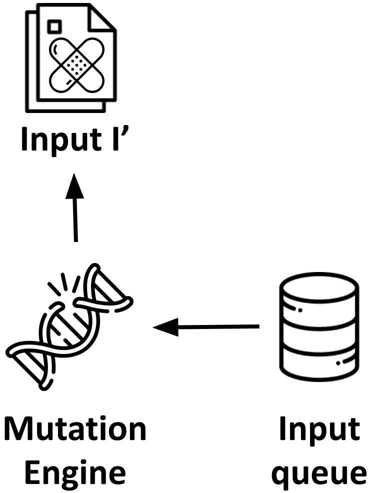
Coverage-guided Fuzzing

1. Pick an input from the queue

2. Mutate it:
   - random bit-flips
   - random substitutions
   - random… things

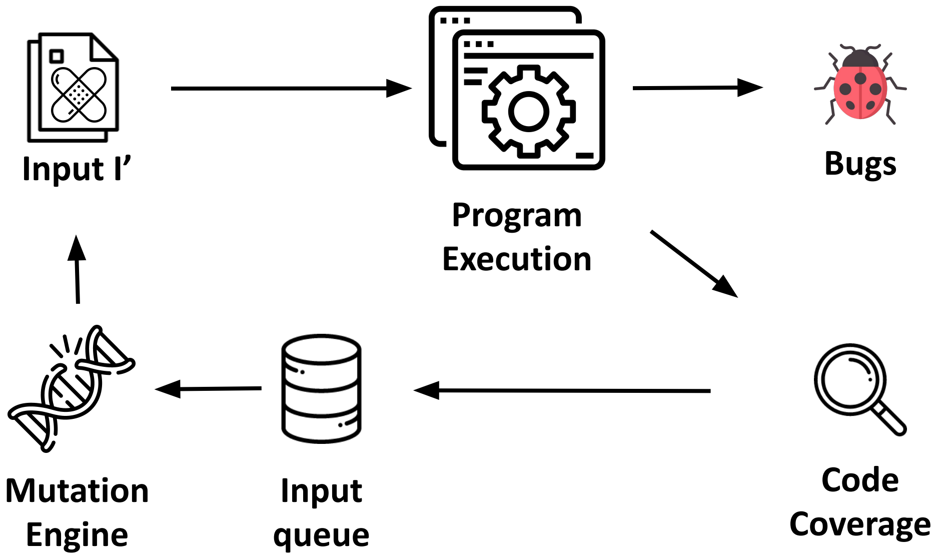


Coverage-guided Fuzzing (2)

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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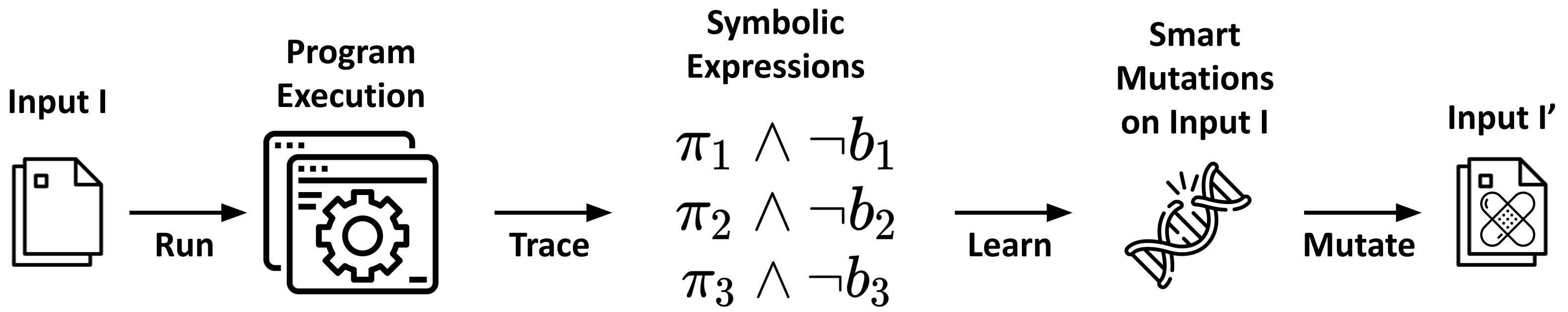
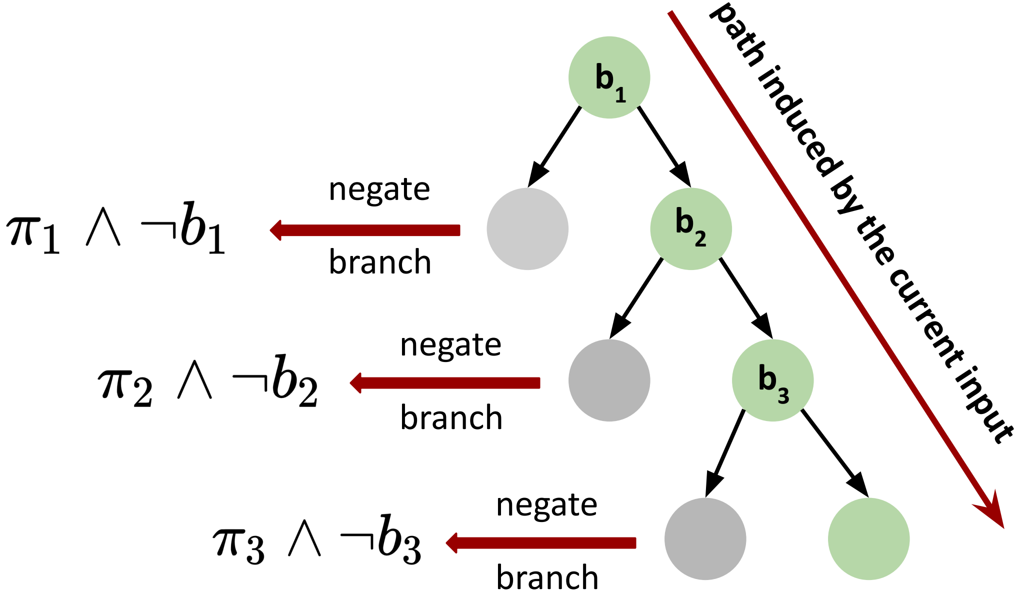
What if we build symbolic expressions to **learn** how to **mutate** the **input**?


Input I
Run
Program Execution
Trace
Symbolic Expressions
$\pi_1 \wedge \neg b_1$
$\pi_2 \wedge \neg b_2$
$\pi_3 \wedge \neg b_3$
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

$$\pi_i \wedge \neg b_i$$

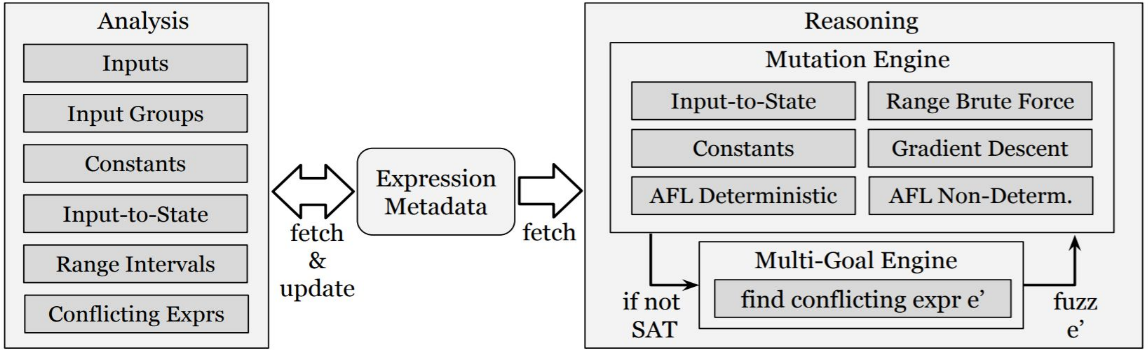
1. π_i is satisfied by the input I that has induced the execution

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 π_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 $\neg b \wedge \pi$ and the input I, mutate the bytes of the input trying to solve $\neg b$ while keeping π satisfiable.



Fuzzy-SAT Architecture

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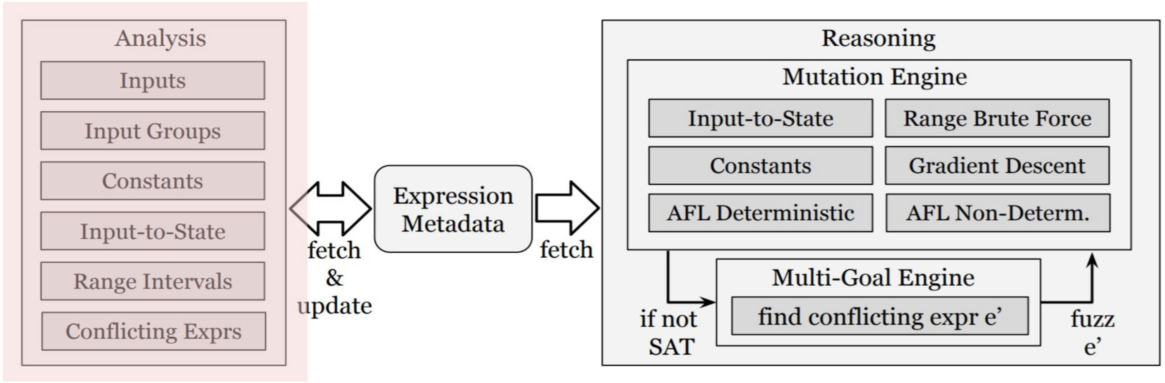
- **Analysis**: learn from the symbolic expressions added to π



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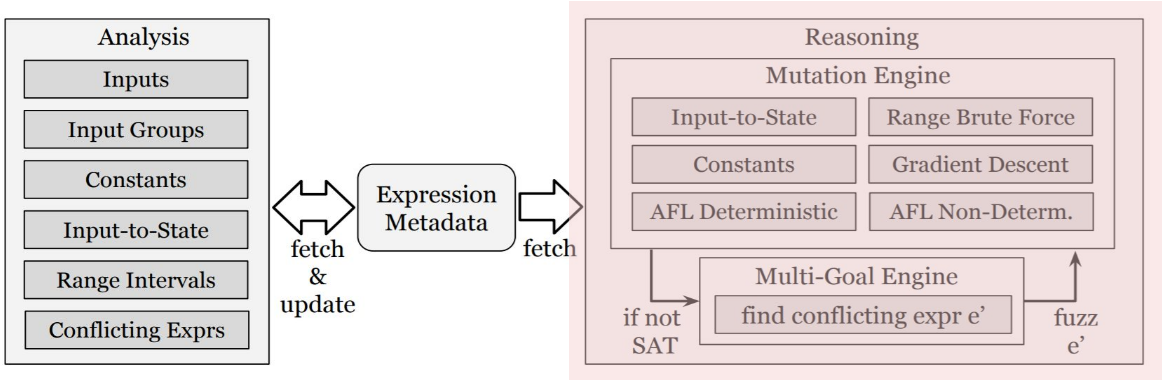
Fuzzy-SAT: Learn and Mutate

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

- **Analysis**: learn from the symbolic expressions added to π
- **Reasoning**: use the acquired knowledge to apply simple but fast mutations to the input



Fuzzy-SAT Architecture

Analysis Stage (simplified)

Learn from the constraints added to π

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

Analysis Stage (simplified)

Learn from the constraints added to π

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

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

$$\boxed{i_0 \mathbin{+\!\!+} i_1} + 10 = 42$$

$$\boxed{i_0} - \boxed{i_1} = 0$$

Analysis Stage (simplified)

Learn from the constraints added to π

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

Collect the constants within the symbolic expression

$$i_0 \cdot \boxed{10} = \boxed{30}$$

$$i_0 \mathbin{+\!\!+} i_1 + \boxed{10} = \boxed{42}$$

Analysis Stage (simplified)

Learn from the constraints added to π

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

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

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

$$i_0 + i_1 > 1$$

[1] C. Aschermann et al. "*REDQUEEN: fuzzing with input-to-state correspondence*". NDSS 2019

Analysis Stage (simplified)

Learn from the constraints added to π

- 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:

$$(i_0 \mathbin{+\!\!+} i_1) + 0\mathrm{xAAAA} <_{unsigned} 0\mathrm{xBBBB}$$

$$\downarrow$$

$$i_0 \mathbin{+\!\!+} i_1 \in [0, 0\mathrm{x}1110] \cup [0\mathrm{x}5556, 0\mathrm{xFFFF}]$$

Reasoning Stage (simplified)

Mutate the bytes of the seed, trying to keep π *satisfiable*

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

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

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

$$\downarrow$$

$$i_0 \leftarrow 0$$
$$i_1 \leftarrow 42$$

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

$i_0 \mathbin{+\!\!\!+} i_1 \in [0, 9]$ Result of *range analysis*

$i_0 \mathbin{+\!\!\!+} i_1 + 0\mathrm{xABAD} = 0\mathrm{xCAFE}$ Query

Reasoning Stage (simplified)

Mutate the bytes of the seed, trying to keep π *satisfiable*

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

$$(i_0 + i_1) - 10 > (i_2 + i_3) + 5$$

$$\Big\downarrow{}^{1}$$

$$(i_2 + i_3) + 5 - ((i_0 + i_1) - 10) < 0$$

[1] The implementation also takes into account the wrap around!

Reasoning Stage (simplified)

Mutate the bytes of the seed, trying to keep π *satisfiable*

- Mutation Engine
  - Input-to-State
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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
int f(char i1, char i2) {
  assert ( i1 == i2 );
  if ( i2 == 1 )
    return 0;
  return 1;
}
```

$\text{input} \leftarrow \{i_1 = 0, i_2 = 0\}$

$\pi \leftarrow i_1 = i_2$

$\neg b \leftarrow i_2 = 1$

$\pi \wedge \neg b$ *cannot* be solved by mutating only i_2

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$$\pi \leftarrow i_1 = I_2$$
$$\neg b \leftarrow i_2 = 1$$

$\pi \wedge \neg b$ *cannot* be solved by mutating only i_2

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 π
- It tries to *solve* the conflicting constraints without modifying the bytes involved in $\neg b$

Implementation

Fuzzy-SAT:

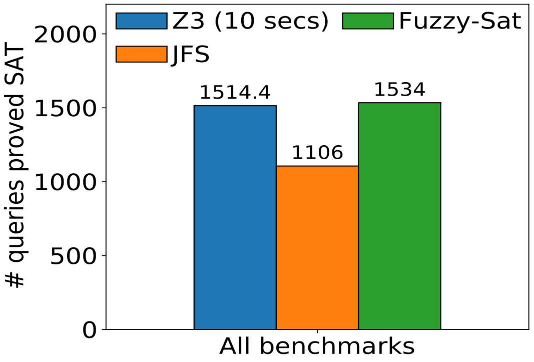
- C library
- Operates on Z3 expressions
- Integration in:
  - QSYM
  - Fuzzolic
  - SymQEMU
  - SymCC

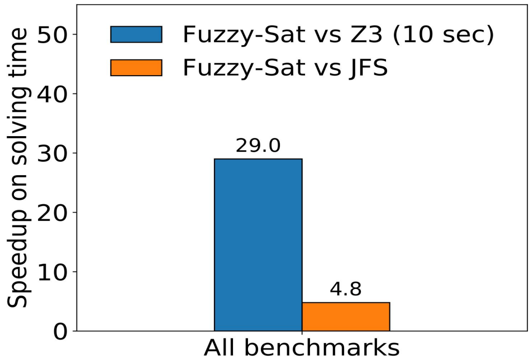
Fuzzy-SAT is available at
https://season-lab.github.io/fuzzolic/

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

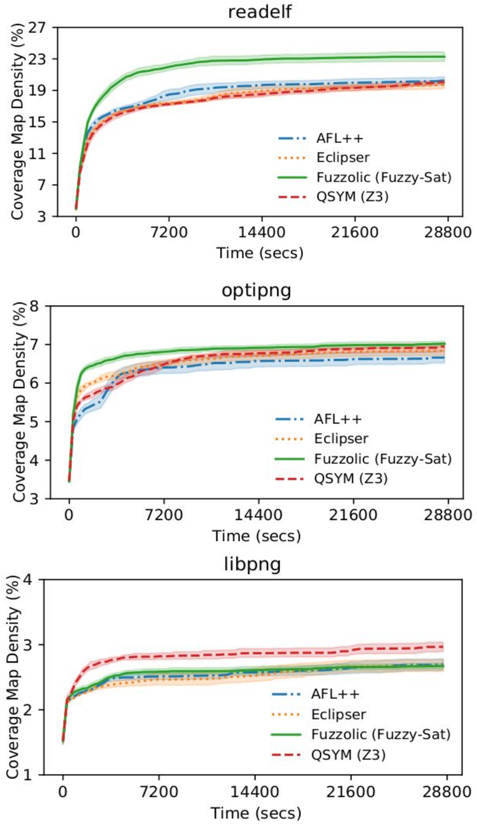
Fuzzolic (our concolic executor) with Fuzzy-SAT against:

- 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 :)