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Constraint-Based Testing for Floating-Point Code: Challenges and Opportunities

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Software Testing

- Software has bugs
- Many different bug finding tools exist
  - Regression suites, fuzzing, verification, static analysis, compiler sanitizers, …
- This talk: Tools using SMT constraints
  - Example: Symbolic Execution
- Floating point arithmetic is finicky...

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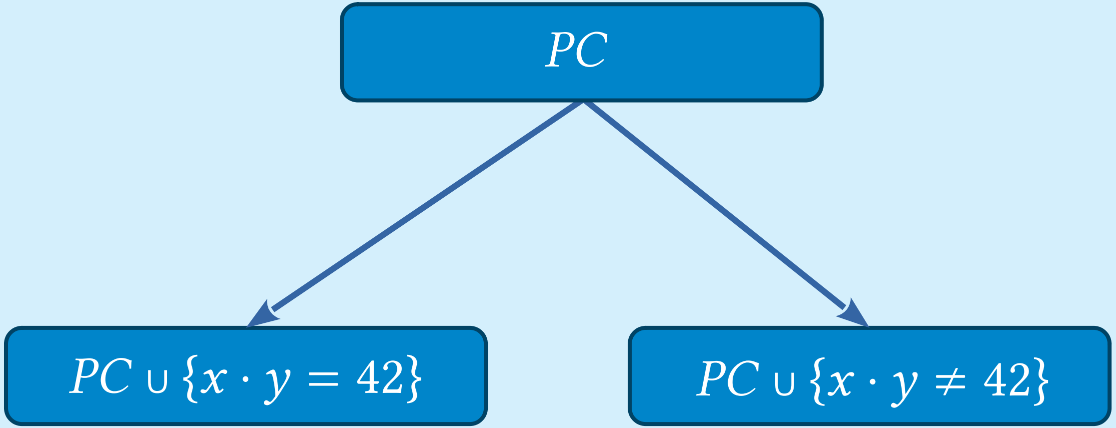
Very Quick: Symbolic Execution

```
if (x * y == 42) {
  printf("Welcome!\n");
} else {
  abort();
}
```



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Floating Point SMT Theory

- The obvious solution: Just use a floating point SMT theory!
  - E.g.: QF_ABVFP instead of QF_ABV
- Mapping from program to constraints similar as for bitvectors
- We implemented this approach for KLEE
  - Liew, Schemmel, Cadar, Donaldson, Zähl, Wehrle. Floating-point symbolic execution: A case study in N-version programming. ASE 2017.
- It is very slow

Floating Point SMT Theory Performance Experiment

- Three theories
  - Integers
  - Bitvectors equivalent to `int64_t`
  - Floating Point Numbers equivalent to `double`
- Three constraints for each theory
  - $x + y = z$
  - $x \cdot x = y$
  - $x \neq y$

Floating Point SMT Theory Performance Experiment

```
Benchmark 1: ./simple.py --mode int
  Time (mean ± σ):     146.2 ms ±   4.7 ms    [User: 124.3 ms, System: 21.1 ms]
  Range (min … max):   140.2 ms … 155.5 ms    19 runs

Benchmark 2: ./simple.py --mode bv64
  Time (mean ± σ):     189.8 ms ±   5.7 ms    [User: 161.2 ms, System: 27.7 ms]
  Range (min … max):   183.6 ms … 204.4 ms    14 runs

Benchmark 3: ./simple.py --mode fp64
  Time (mean ± σ):     714.7 ms ±   7.0 ms    [User: 676.5 ms, System: 35.7 ms]
  Range (min … max):   707.2 ms … 730.0 ms    10 runs
```

Floating Point SMT Theory Performance Experiment

- Let’s add just one more condition...
  - $x + y = z$
  - $x \cdot x = y$
  - $x \neq y$
  - $x > 1$

Floating Point SMT Theory Performance Experiment

```
Benchmark 1: ./still-simple.py --mode int
  Time (mean ± σ):     146.9 ms ±   3.6 ms    [User: 125.5 ms, System: 20.5 ms]
  Range (min … max):   139.8 ms … 153.9 ms    19 runs

Benchmark 2: ./still-simple.py --mode bv64
  Time (mean ± σ):     197.6 ms ±   6.5 ms    [User: 165.2 ms, System: 31.6 ms]
  Range (min … max):   190.4 ms … 210.3 ms    14 runs

Benchmark 3: ./still-simple.py --mode fp64
  Time (mean ± σ):      2.084 s ±  0.029 s    [User: 2.038 s, System: 0.039 s]
  Range (min … max):    2.044 s …  2.128 s    10 runs
```

Approximate Solutions

- Any technique is incomplete or imprecise for non-trivial programs
  - Symbolic execution, fuzzing: Path explosion
  - Model checking: State explosion
  - Static analysis: Imprecise (has false positives)
  - Verification: Writing proofs infeasible for arbitrary programs
- Maybe an approximate solution is good enough?

Fixed Point Approximation of Floating Point Numbers

- The floating point theory can be lowered to the bitvector theory
  - Softfloat libraries do the same thing in the concrete world
- Structurally simpler queries are usually easier to solve
- Use a simplified lowering not exactly capturing IEEE 754 semantics
- Many programs don’t really use the full range of a `double` anyway…
- Can we just use a fixed point number instead?

Fixed Point Performance Experiment

```
Benchmark 1: ./still-simple.py --mode int
  Time (mean ± σ):     146.9 ms ±   3.6 ms    [User: 125.5 ms, System: 20.5 ms]
  Range (min … max):   139.8 ms … 153.9 ms    19 runs

Benchmark 2: ./still-simple.py --mode bv64
  Time (mean ± σ):     197.6 ms ±   6.5 ms    [User: 165.2 ms, System: 31.6 ms]
  Range (min … max):   190.4 ms … 210.3 ms    14 runs

Benchmark 3: ./still-simple.py --mode fp64
  Time (mean ± σ):      2.084 s ±  0.029 s    [User: 2.038 s, System: 0.039 s]
  Range (min … max):    2.044 s …  2.128 s    10 runs

Benchmark 4: ./still-simple.py --mode fix64
  Time (mean ± σ):     504.7 ms ±   5.9 ms    [User: 459.2 ms, System: 43.7 ms]
  Range (min … max):   498.2 ms … 513.7 ms    10 runs
```

Fixed Point Approximation of Floating Point Numbers

- Advantages:
  - Can grant massive speedups
- Challenges:
  - Simplifying too far gives bogus results (basically degrades to a slow fuzzer)
  - Applicability in the real world
- Ongoing work – input appreciated!
  - How many bits for fixed point representation?
  - Overflow or wraparound behavior?

Summary

- Floating point arithmatic is a problem for constraint-based approaches
- SMT solving is very slow
- Fuzzing can quickly generate satisfying assignments
- Using simpler, approximate number representations can potentially speed up analysis at the cost of precision