Automatic Software Error Finding: Approaches and Tradeoffs

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PEOPLE AFFECTED (AT LEAST)

3,683,212,665

SOFTWARE FAIL WATCH

5TH EDITION

2017

LO$$E$

1,715,430,778,504

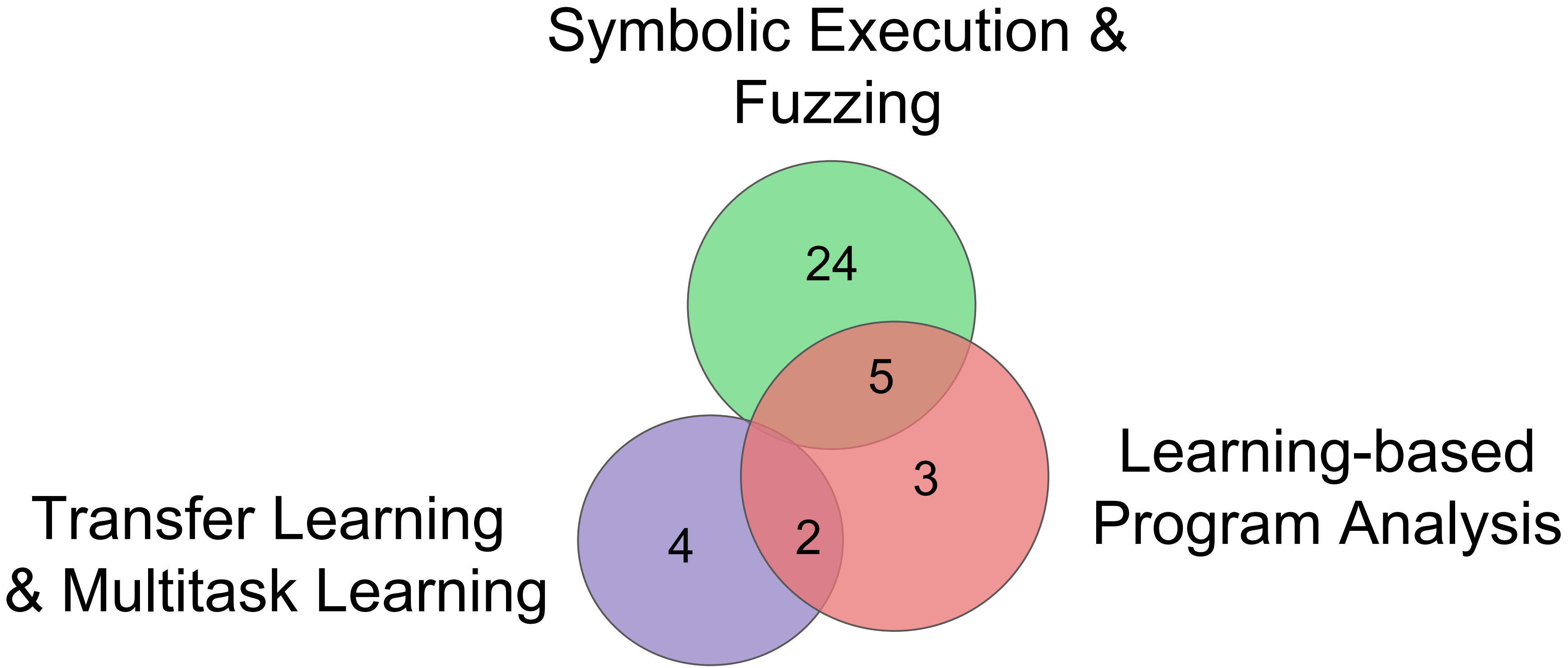
TRICENTIS

Software errors: Find them before they find you!

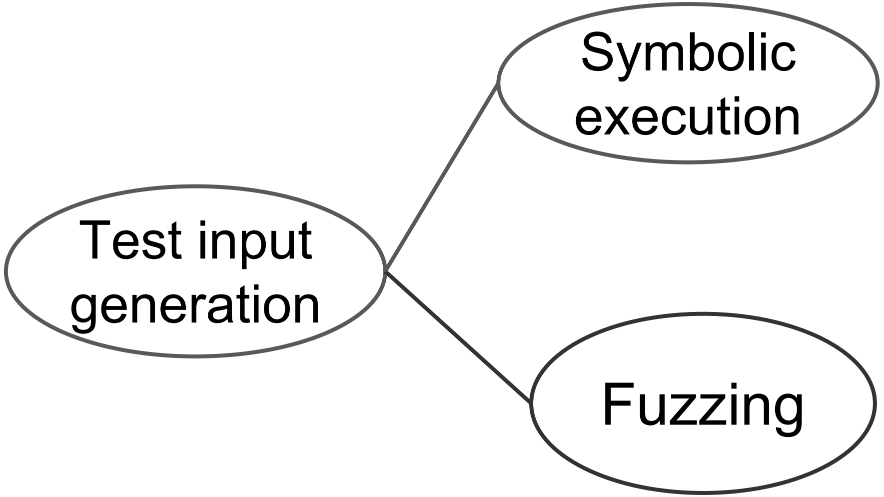
Reviewed approaches

- Test input generation
- Statistical error detection

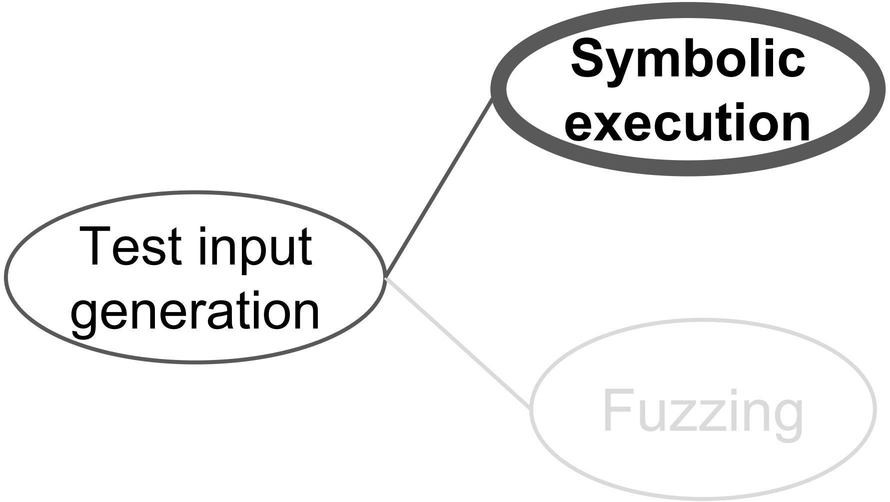
Papers from three areas



Symbolic execution & fuzzing



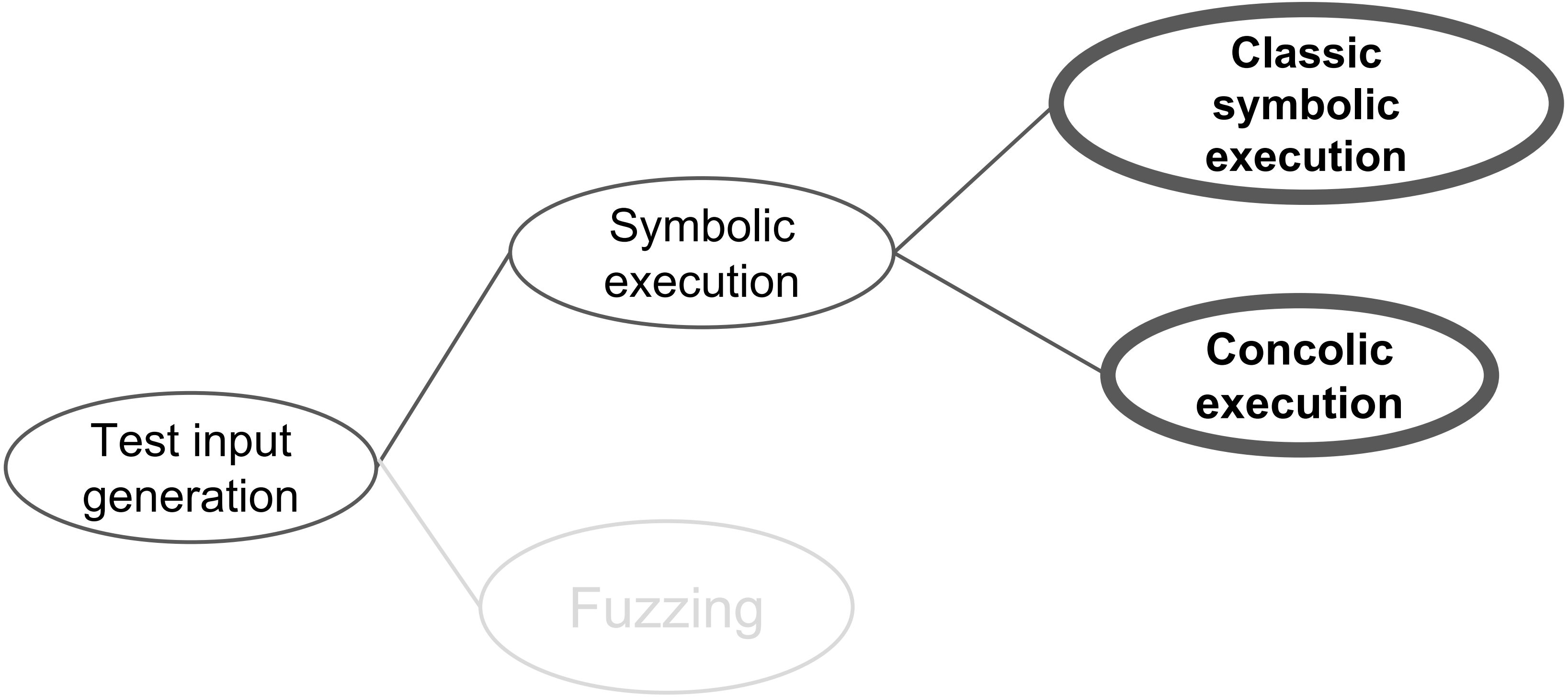
Symbolic execution 101



Introduced in EFFIGY[1](1976)

- Execute on symbolic inputs
- Summarize classes of inputs

Classic symbolic vs concolic execution



Classic symbolic vs concolic execution

Classic symbolic execution

- Maintain symbolic state
- Fork symbolic execution on branches
- Use solver
    - Branch feasibility

➢ Implemented in EXE [2](2006)

Concolic execution

- Maintain **conc**rete & symb**olic** state
- Run concrete execution on taken branches
- Use solver
    - Cover not-taken branches

➢ Implemented in DART [12](2005)

Example

```
void test_me(int x, int y){
    //naughty programmer
    z = x*x*x;

  if (z == y + 1)
        abort();
  else
        exit(0);
}
```

Symbolic state	Path constraint	Concrete state
Create symbolic variables: x=a, y=b		Random concrete values: x=1, y=1
z=a*a*a		z=1
	a*a*a != b + 1	

Example

```
void test_me(int x, int y){
    //naughty programmer
    z = x*x*x;

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Symbolic state	Path constraint	Concrete state
Create symbolic variables: x=a, y=b		Random concrete values: x=1, y=1
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Path constraint: (a*a*a != b + 1)

Cannot solve

Example

```
void test_me(int x, int y){
    //naughty programmer
    z = x*x*x;

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Symbolic state	Path constraint	Concrete state
Create symbolic variables: x=a, y=b		Random concrete values: x=1, y=1
z=a*a*a		z=1

Path constraint: (a*a*a != b + 1)

Cannot solve

Simplify: a = 1 ↔ 1 != b + 1

Example

```
void test_me(int x, int y){
    //naughty programmer
    z = x*x*x;

  if (z == y + 1)
        abort();
  else
        exit(0);
}
```

Symbolic state	Path constraint	Concrete state
Create symbolic variables: x=a, y=b		**New concrete values: x=1, y=0**
z=a*a*a		z=1

Path constraint: (a*a*a != b + 1)

Cannot solve

Simplify: a = 1 ↔ 1 != b + 1

Negate & solve: b = 0

Example

```
void test_me(int x, int y){
    //naughty programmer
    z = x*x*x;

  if (z == y + 1)
          abort();
  else
          exit(0);
}
```

Symbolic state	Path constraint	Concrete state
Create symbolic variables: x=a, y=b		New concrete variables: x=1, y=0
z=a*a*a		z=1
	a*a*a == b + 1	

Example

```
void test_me(int x, int y){
    //naughty programmer
    z = syscall(x)

   if (z == y + 1)
         abort();
   else
         exit(0);
}
```

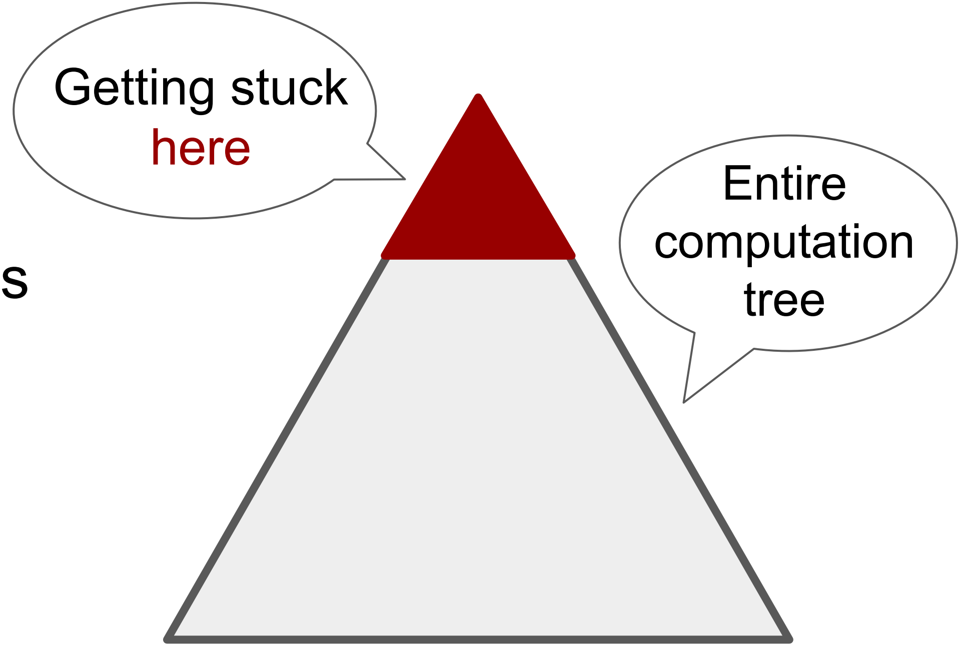
Symbolic state	Path constraint	Concrete state
Create symbolic variables: x=a, y=b		New concrete variables: x=1, y=0
z=a*a*a		z=1
	a*a*a == b + 1	

Classic symbolic execution

General limitations

- Handling complex constraints
- Environment problem

➢ Path explosion

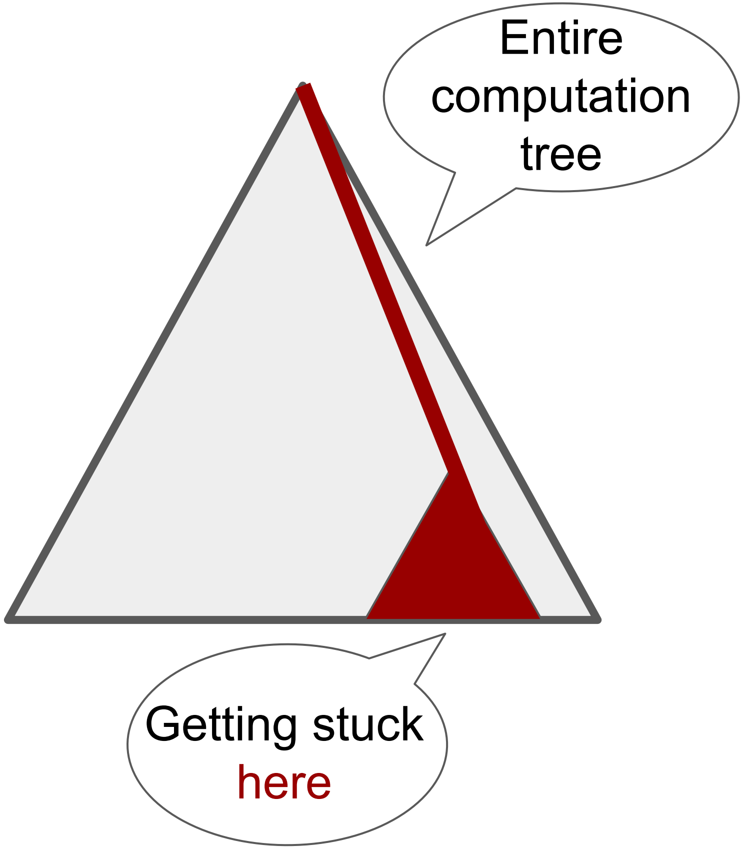


Concolic execution

What do we gain?

- Executions run to completion

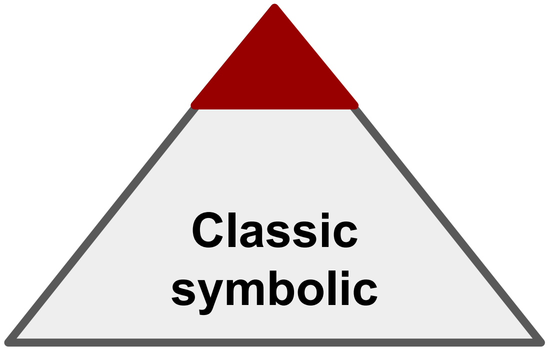
➢ Path explosion still a problem



Entire computation tree

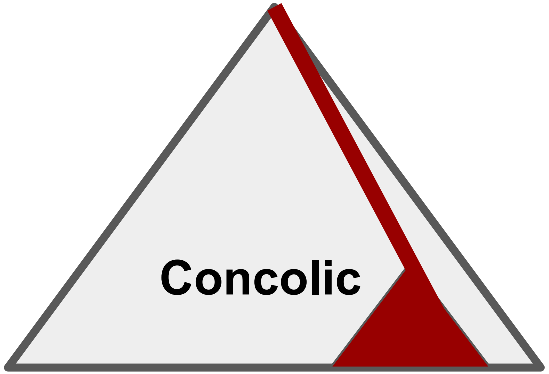
Getting stuck here

Comparative view



Coverage	Number of COREUTILS tools	Avg. #ELOC
100%	16	3307
90-100%	38	3958
80-90%	22	5013

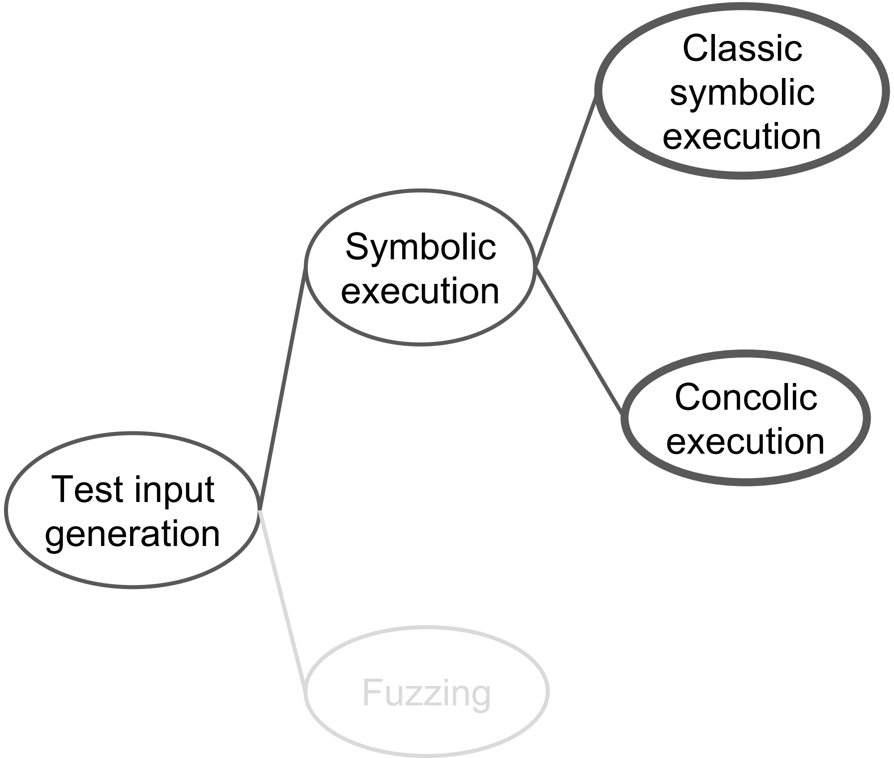
COREUTILS tools statement coverage KLEE [3]



App	Mean number of instructions	#Test cases
Media	54M	2,266
Office	923M	3,008

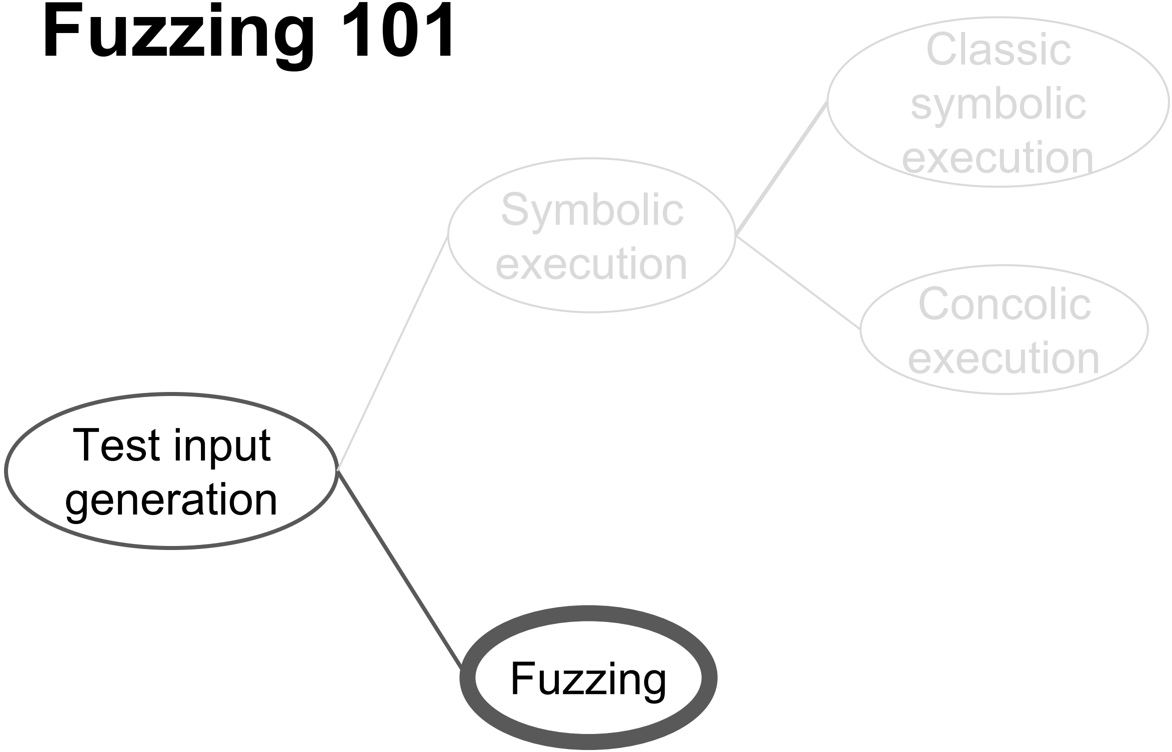
Statistics from SAGE[19]

Classic symbolic vs concolic execution

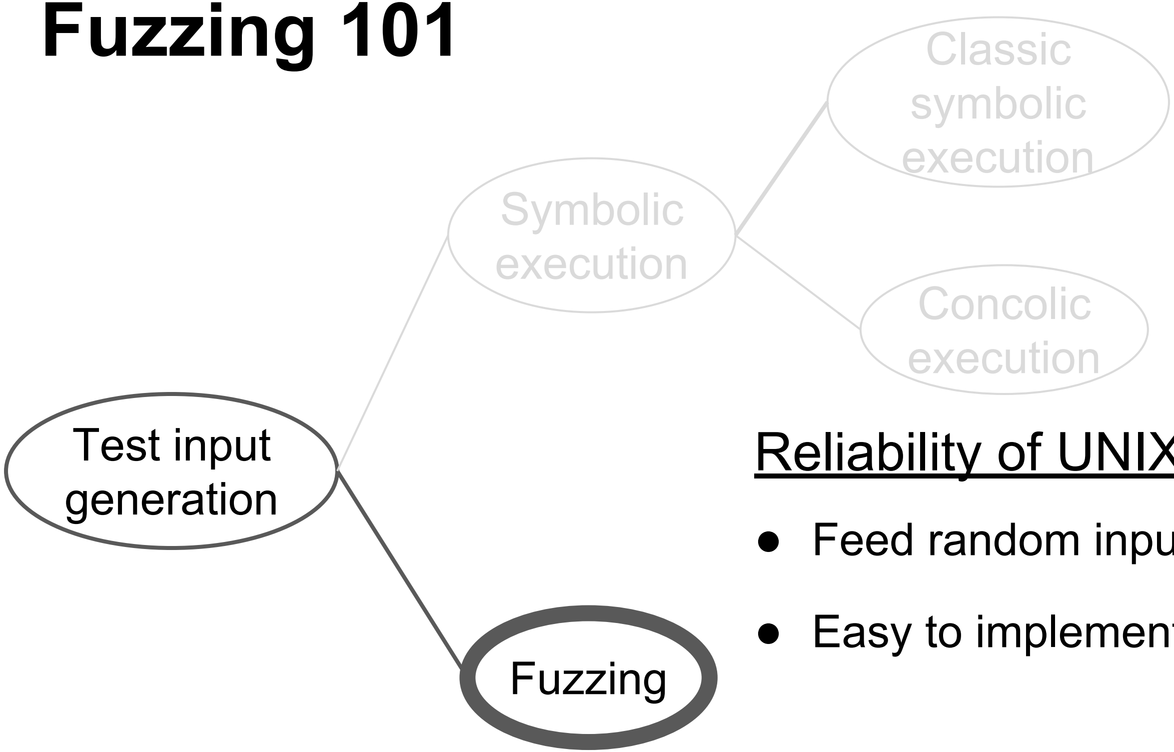


System	Type	What's new?
EXE[2]	Symbolic	Pioneer symbolic execution engine
KLEE[3]	Symbolic	Models environment
UC-KLEE[9]	Symbolic	Checks individual functions
CLOUD9[7]	Symbolic	Parallelization of symbolic execution
DART[12]	Concolic	Pioneer concolic execution engine
CUTE[13]	Concolic	Adds symbolic with pointers
PEX[5]	Concolic	Concolic execution in .NET
SAGE[19]	Concolic	Generational search on deep paths
CREST[15]	Hybrid	Concolic exec. & random testing
VERISOFT[8]	Hybrid	Concolic exec. & state merging
S2E[6]	Hybrid	Symbolic exec. w/ virtualization

Fuzzing 101


Test input generation
Symbolic execution
Classic symbolic execution
Concolic execution
Fuzzing

Fuzzing 101



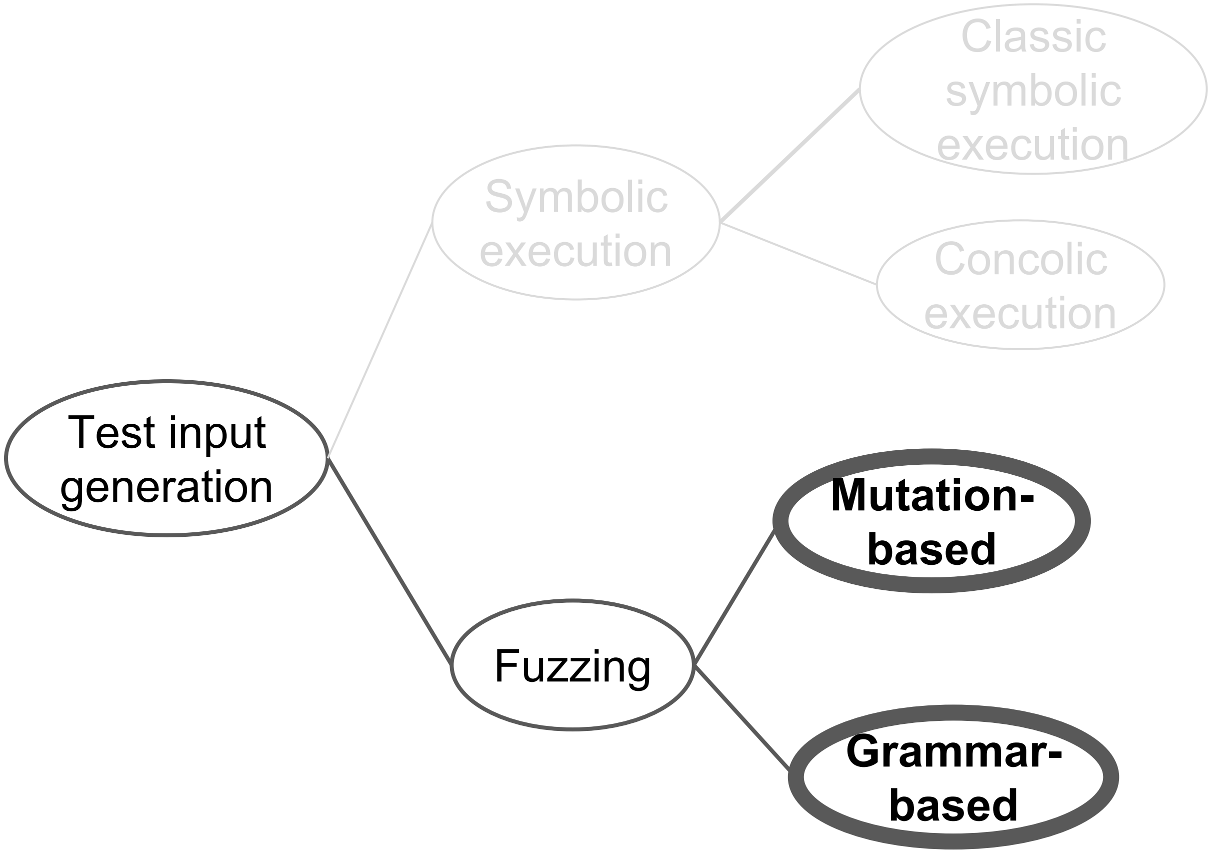
Reliability of UNIX utilities[18](1990)

- Feed random inputs and monitor for errors
- Easy to implement:

```
$> while true; \
  > do head -n 10 /dev/urandom | a.out; \
  > done
```

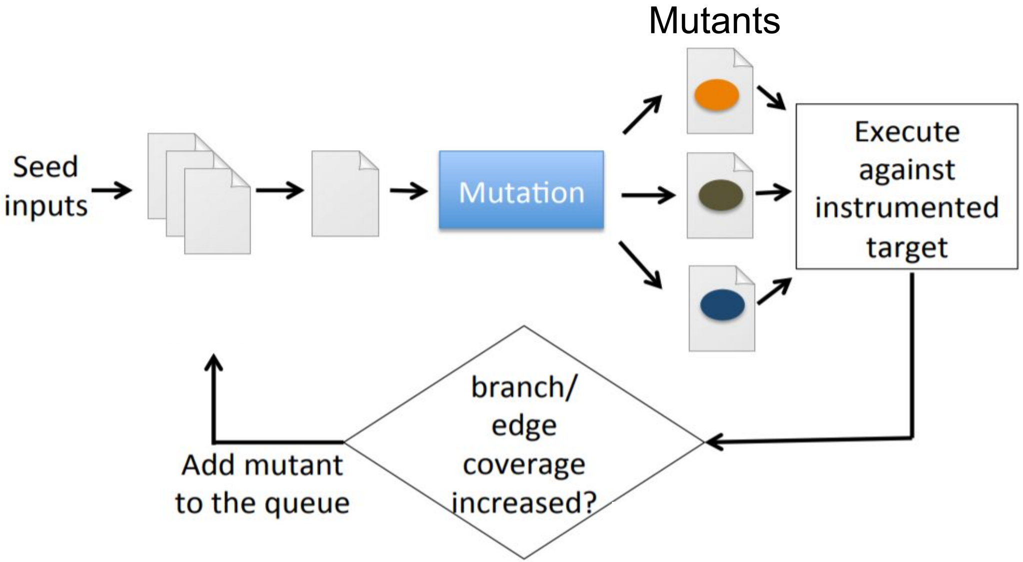
- Inputs that trigger incorrect behaviour are small fraction

Fuzzing: mutation-based vs grammar-based



Mutation-based fuzzing

- ➢ American Fuzzy Lop (AFL)[23]



Key points

- Coverage-guided search
- No assumptions for particular input format
- Hard branches (e.g., magic numbers)

Grammar-based fuzzing

➢ SPIKE grammar-based fuzzer [24]

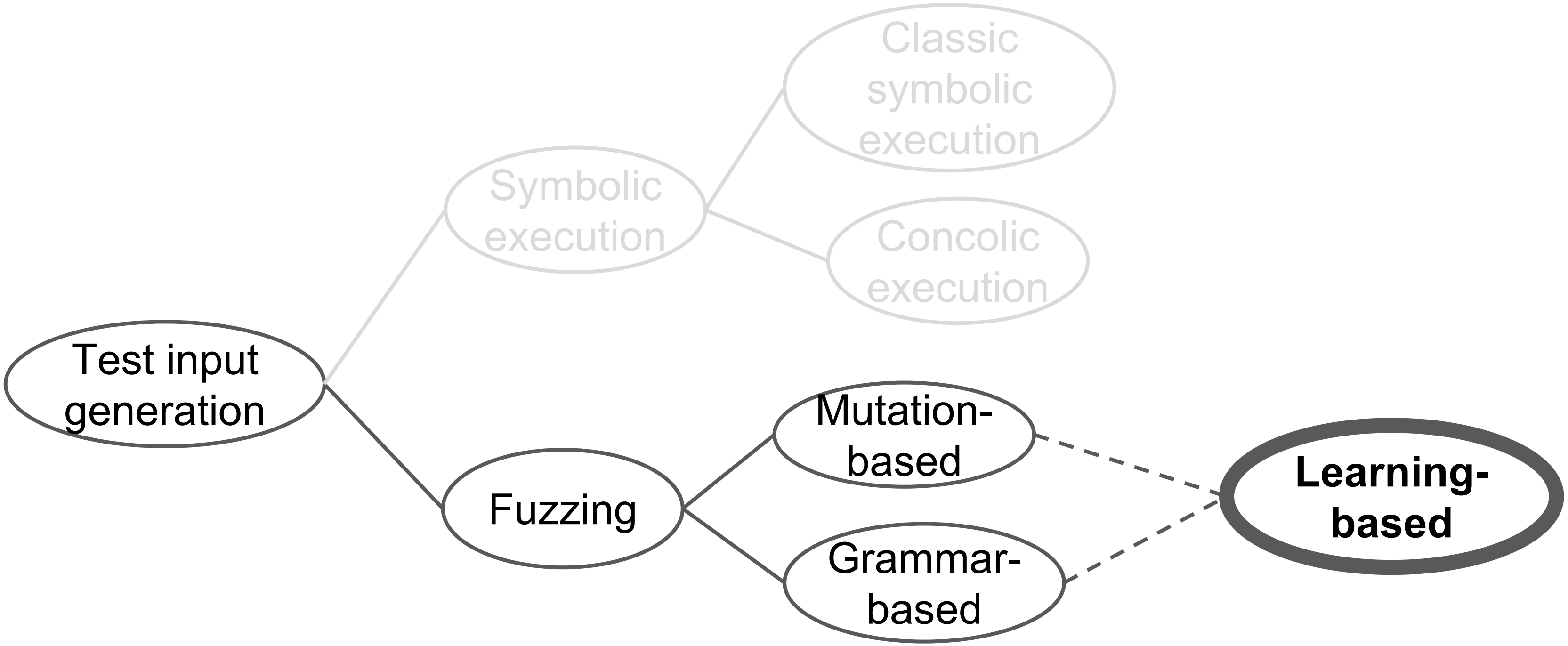
```
// Magic number -- don’t fuzz
static("89504E470D0A1A0A");
…
// Fuzz next bytes
block_start("Header");
fuzzable_byte(1);  // Width
...
block_end("Header”);
...
```

Key points

- Use grammar to describe input formats
- Good for structured input formats

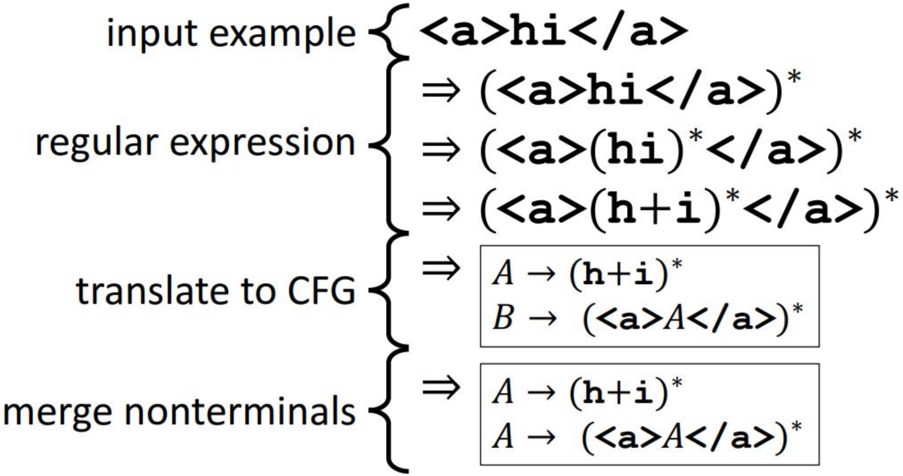
➢ Writing grammar is labour-intensive, manual process

Learning-based fuzzing



Learning-based fuzzing

➢ GLADE: Synthesizing program input grammars [25](2017)



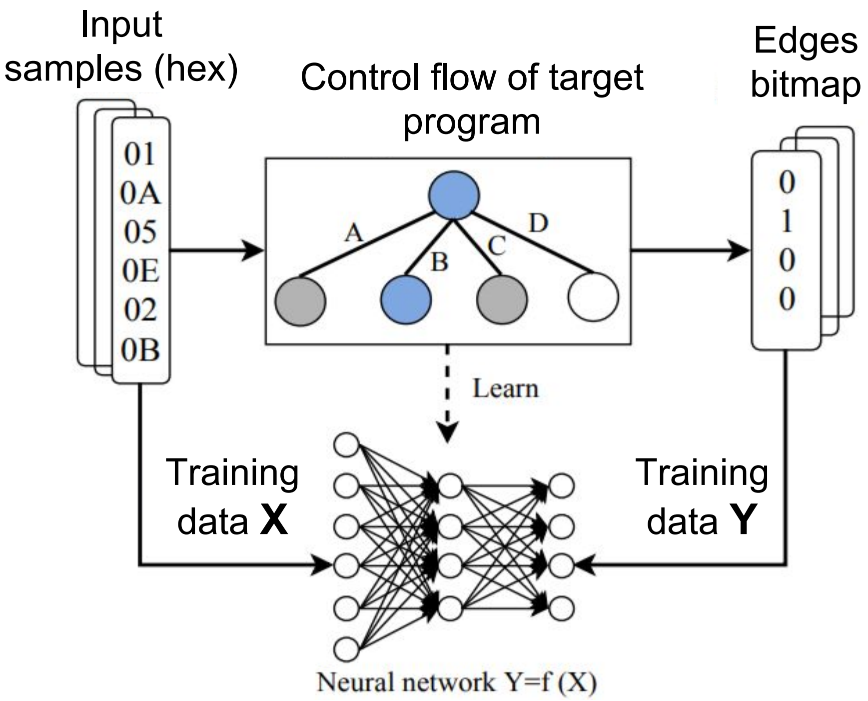
Key points

- Start with an input sample
- Construct increasingly general regular expressions
- Translate to Context Free Grammar

➢ Learning is slow

Learning-based fuzzing

➢ NEUZZ: Fuzzing with Neural Program Learning [29](2018)



Key points

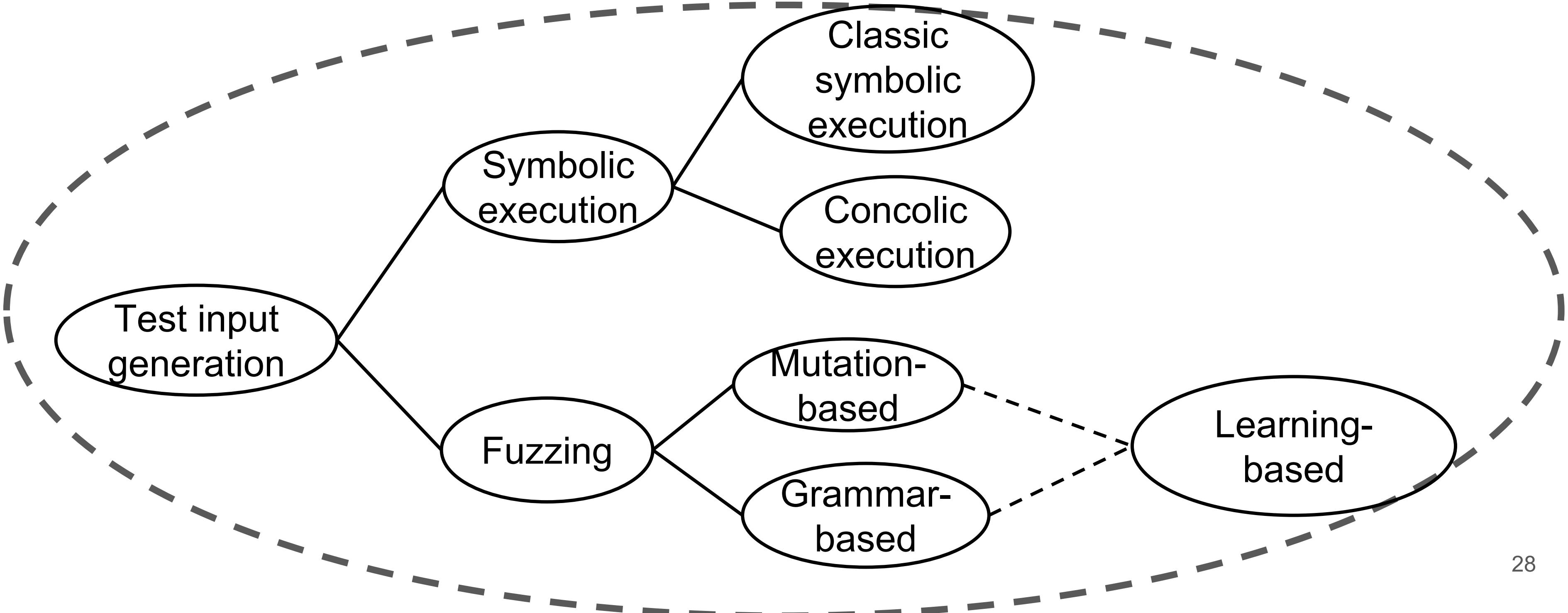
- Feed input samples and monitor taken/non-taken branches
- Use training data X,Y learn model for branching behavior
- Use model to perform gradient-guided mutations

➢ Unclear generalization to “never-taken” paths

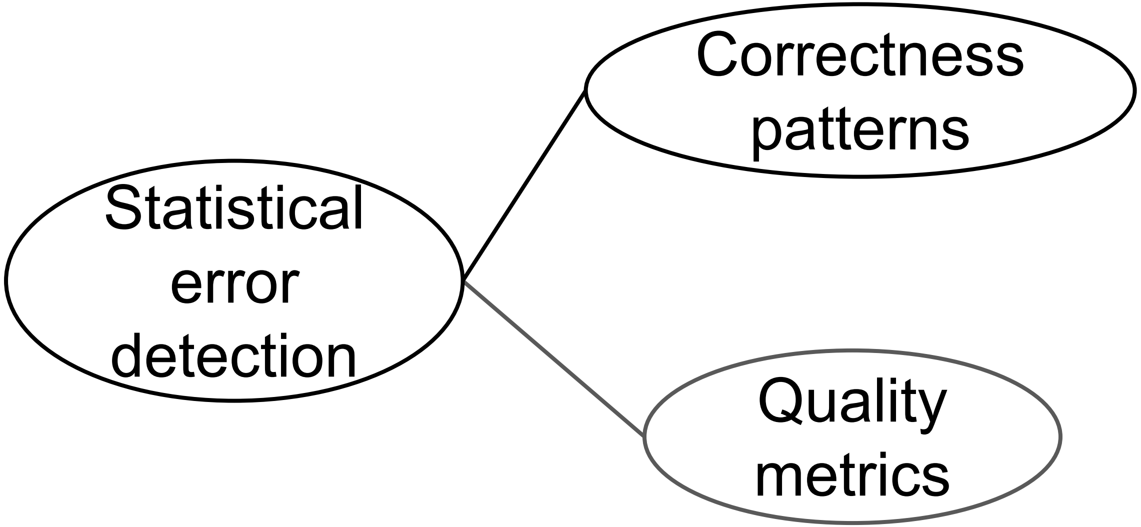
Learning-based fuzzing

Characteristics	**GLADE [25]**	**NEUZZ [29]**	**SKYFIRE [27]**	**RL Fuzzing [28]**	**Learn & Fuzz [26]**
Learns to model	Valid input format	Taken/non-taken branches	Valid input format	High reward mutation policy	Valid input format
Mutations	Use grammar	Use model's gradients	Use grammar and AFL	Use learnt policy	Use model's predictions
Strength	Fully blackbox	Gradient-guided mutations	Semantic validity of test cases	End-to-end RL formulation	Location-specific mutation probabilities
Weakness	Learning realistic grammars slow	Unclear generalization to unseen behaviors	Used a huge collection of input samples	Unclear quality of RL policy	Unclear benefit (production-optimized initial seeds)

Dynamic program analysis



Statistical error detection

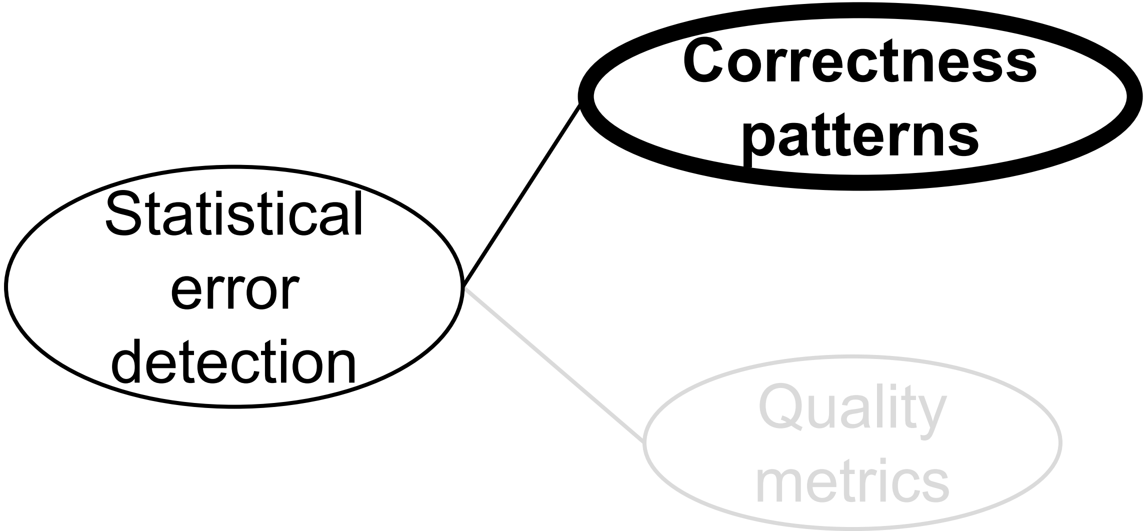


Statistical error detection

Correctness patterns

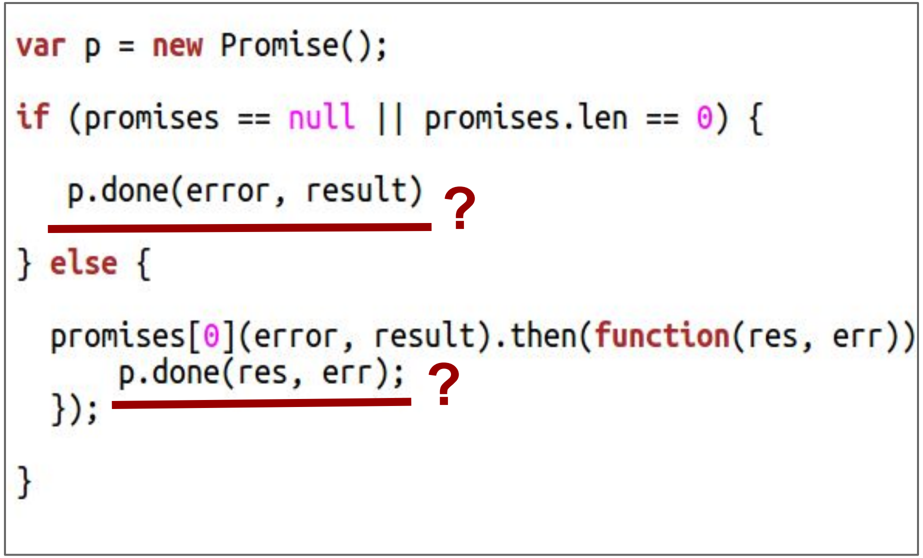
Quality metrics

Correctness patterns



Correctness patterns

- ➢ DeepBugs [31](2017)



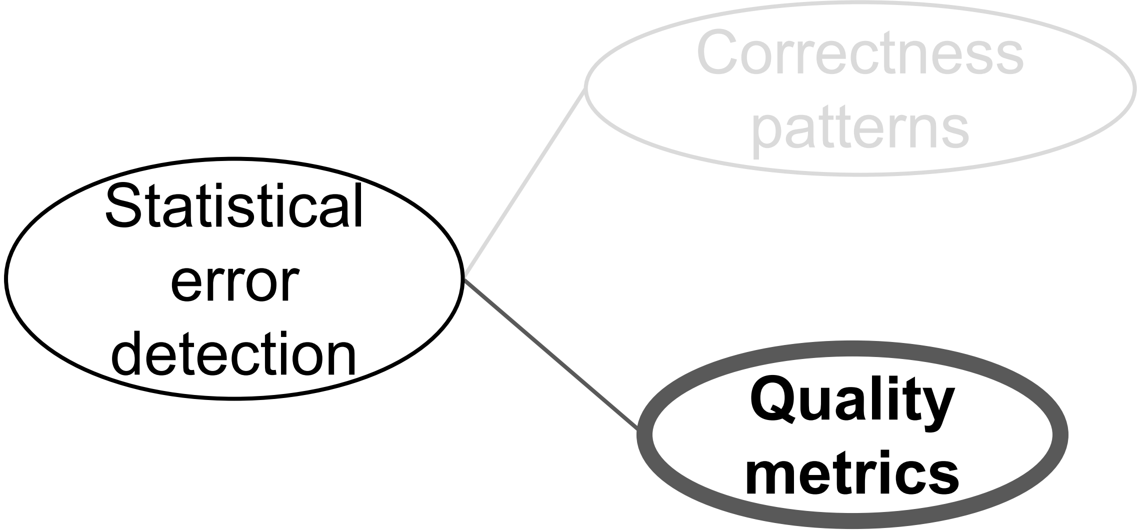
```
var p = new Promise();

if (promises == null || promises.len == 0) {

  p.done(error, result)

} else {

  promises[0](error, result).then(function(res, err))
      p.done(res, err);
  });

}
```

Key points

- Inconsistent but...which is correct?
- Most code is (hopefully) correct
- Perform transformations to create incorrect samples

➢ Need to come up with language-specific checkers

Quality metrics



Correctness patterns

Statistical error detection

Quality metrics

Quality metrics

- ➢ Transfer Defect Learning [34](2013)

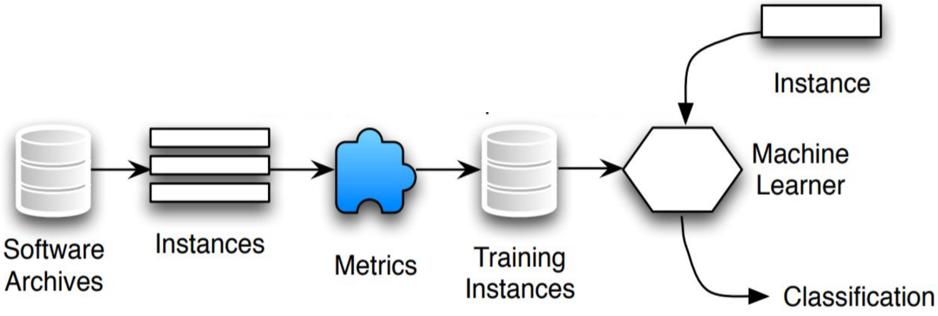


Fig. 1: Defect Prediction Process

Key points

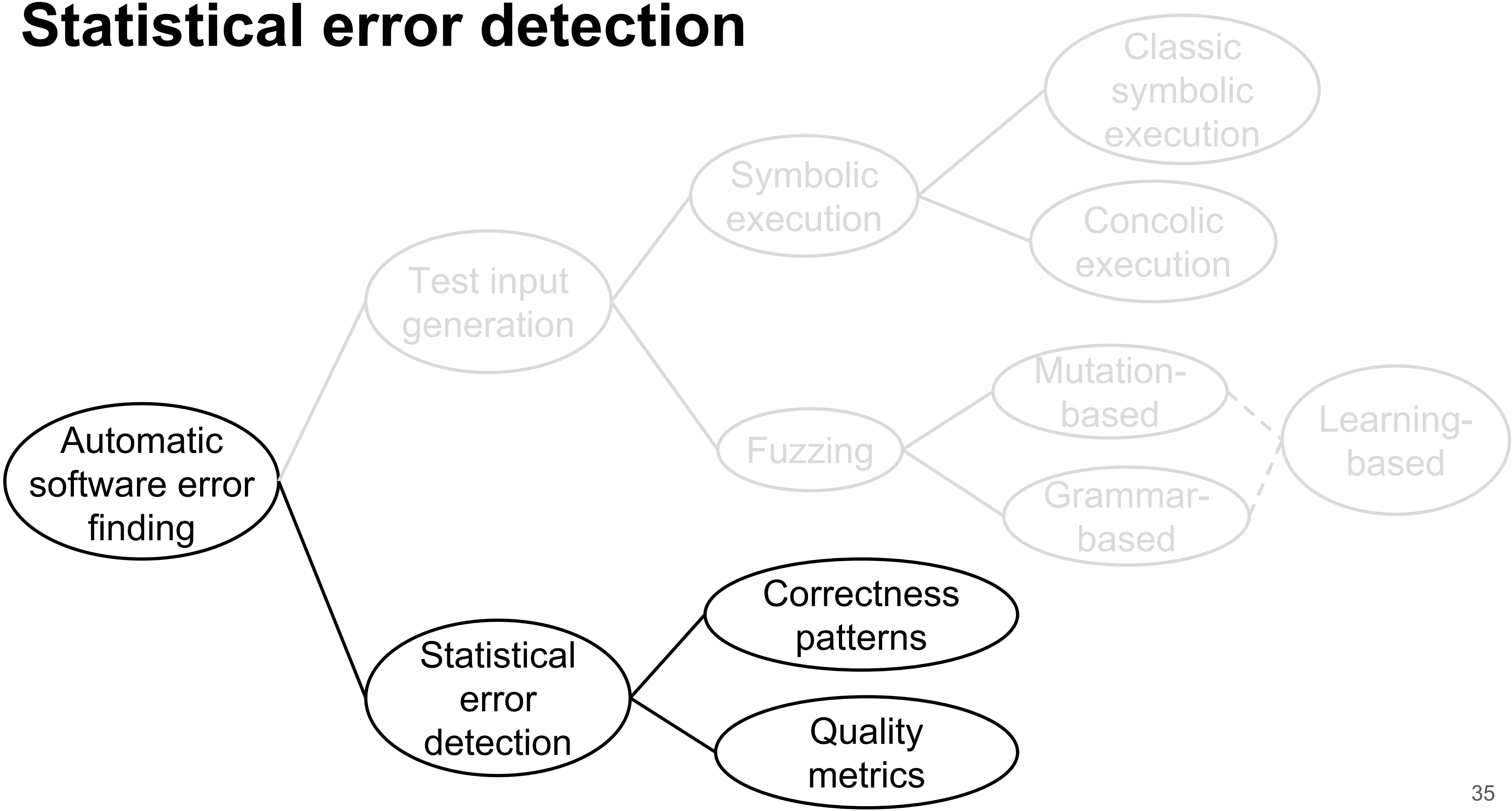
- Code quality metrics of known defects
- Predict if new files look defective
- General metrics ↔ reusable across new targets

➢ File-level reports

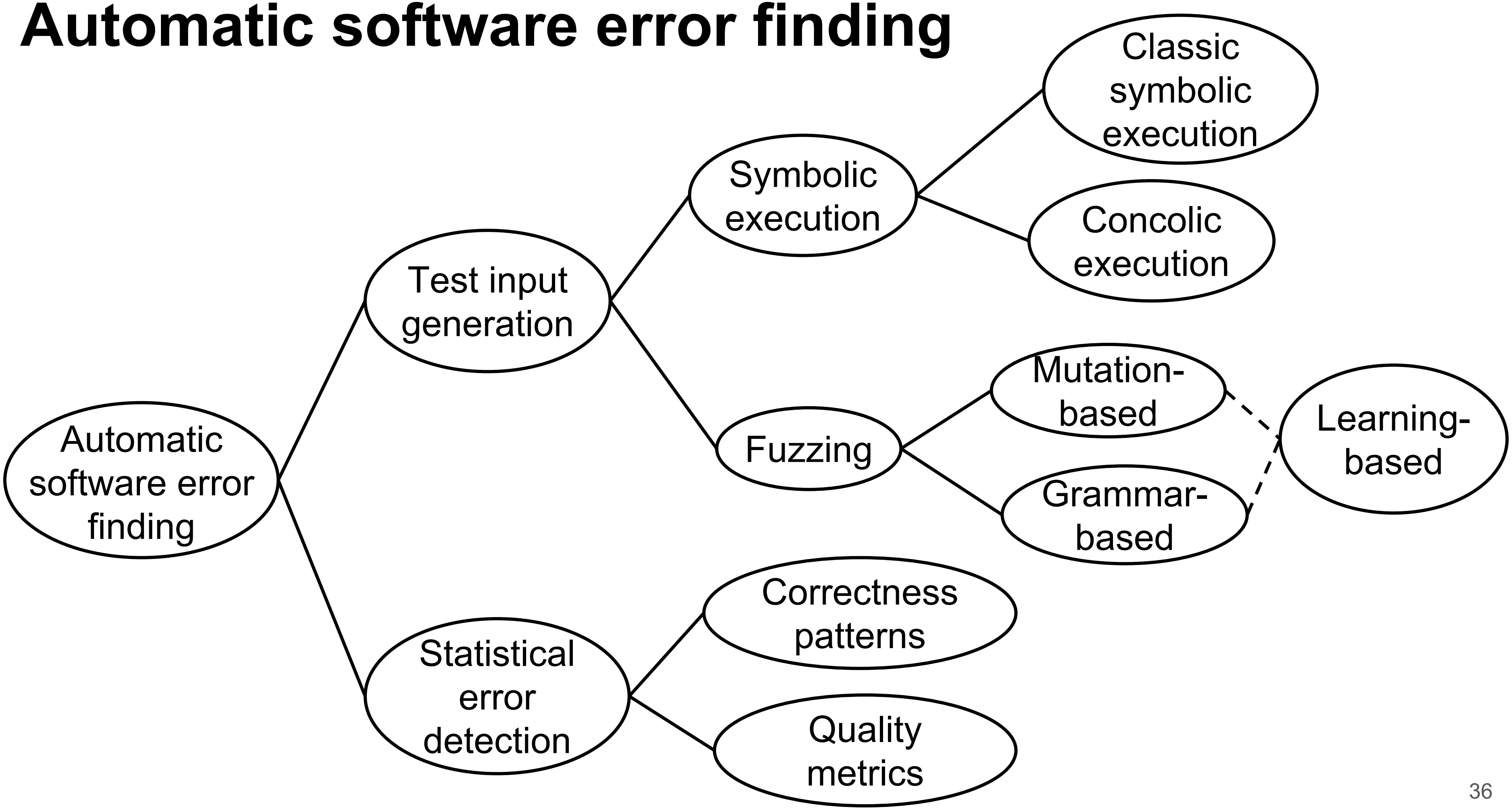
Comparative view

System	Proxy for error detection	Source-target	Transfer learning type
DeepBugs [31]	Correctness patterns	Same	N/A
Bugs as Deviant Behaviour [30]	Correctness patterns	Same	N/A
Naturalness [32]	Quality metrics	Same	N/A
TCA+ [34]	Quality metrics	Different	Domain adaptation
Semi-supervised Defect Prediction [33]	Quality metrics	Different	Inductive transfer learning

Statistical error detection



Automatic software error finding



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Transfer Learning

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