Neuro-Symbolic Execution: Augmenting Symbolic Execution with Neural Constraints

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Symbolic Execution for Bug Finding

KLEE

Pex

Angr

Kite

SAGE

jCUTE

Manticore

TRITON

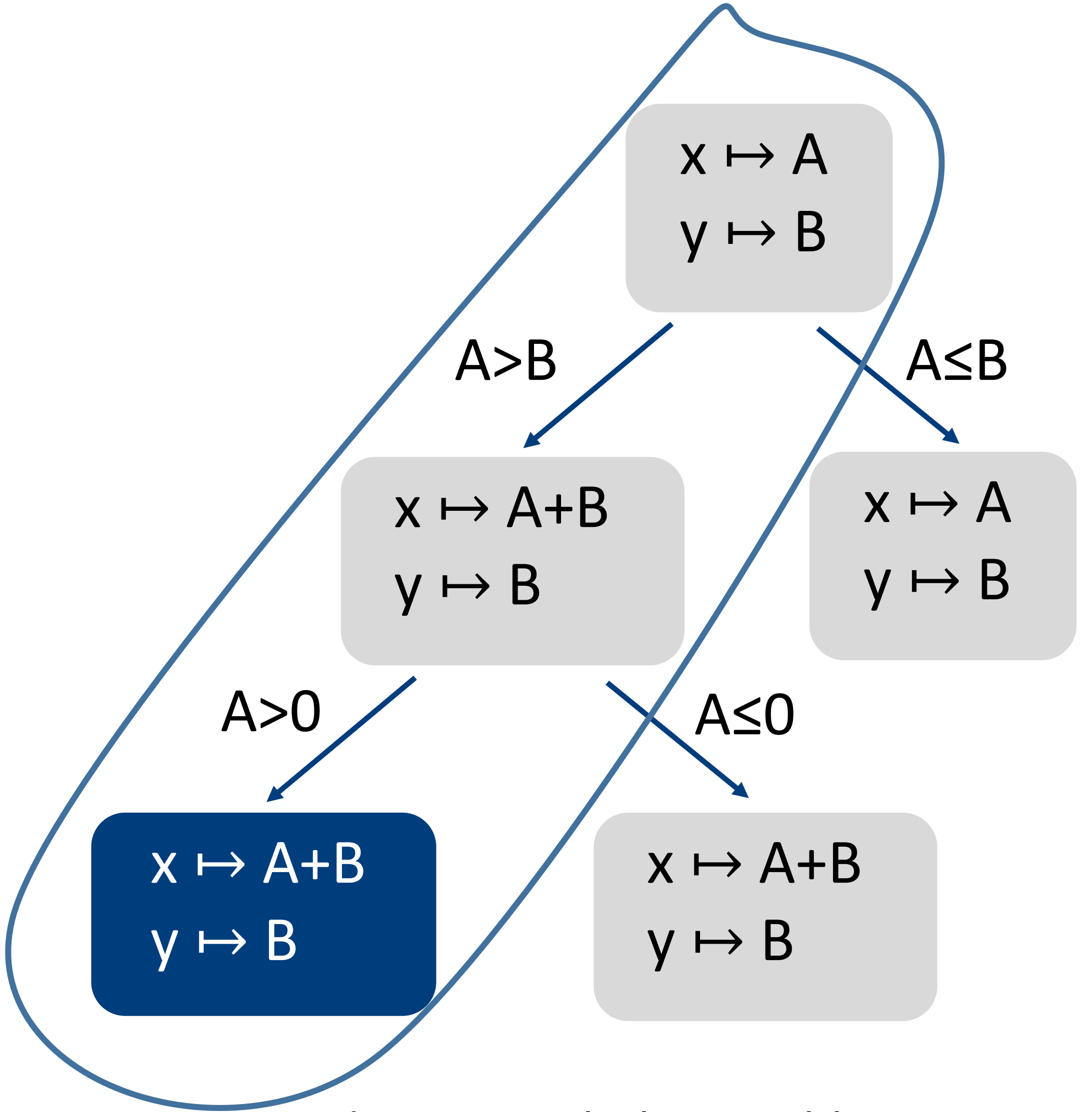
Dynamic Binary Analysis

S^{2}E

Recap: Symbolic Execution (SE)

```
def f (x, y):
 if (x>y)
    x = x+y
    if (x-y > 0)
     assert false
 return (x, y)
```

Dynamic Symbolic Execution (DSE):
A widely used variation of SE



x ↦ A
y ↦ B

A>B

A≤B

x ↦ A+B
y ↦ B

x ↦ A
y ↦ B

A>0

A≤0

x ↦ A+B
y ↦ B

x ↦ A+B
y ↦ B

A and B are symbolic variables

Fundamental Limitations of Classic DSE

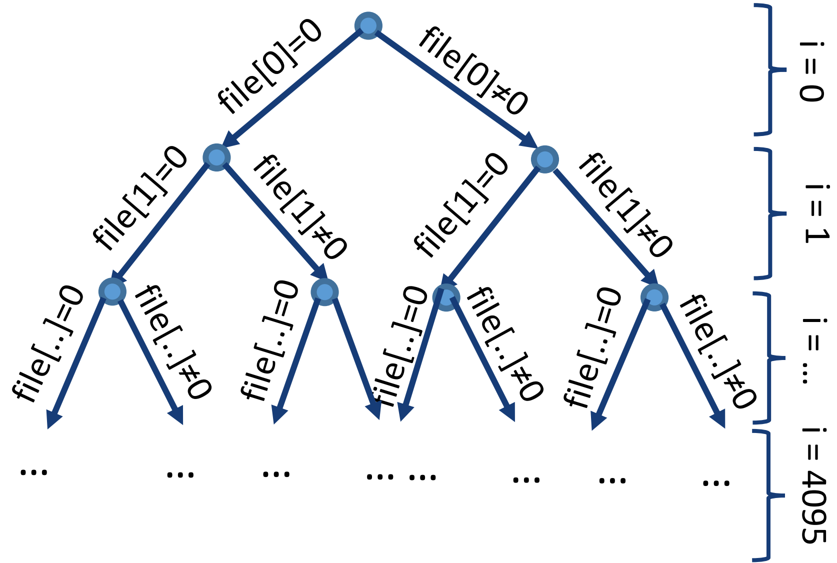
```
int main (…) {
  if (strlen(filename)>1 && filename[0]==‘-’)
    exit(1)
  copy_data(…);
  …
}
void copy_data(..., int *file,...) {
  static double data[4096], value;
  read_double_value(file, ... );
  value = fabs (data [0]);
  for(i=0; i<4096; i++)
    if(file[i] == 0.0) count++;
  data[1] /= (value+count-3);
  …
}
```

#1 Limitations of SMT Solvers

#2 Unmodeled Semantics

#3 Path Explosion

Candidate Vulerability Point (CVP): Divide-by-zero



2^{4096} **paths**

Contributions

- **Neuro-symbolic execution**
  - A new approach to tackle the limitations of DSE
  - Reasons about exact (symbolic) & approximate constraints (neural nets)
- **A Tool – NeuEx**
  - Enhances the widely used DSE engine (KLEE)
- **Evaluation**
  - Finds **94%** more bugs than KLEE in 12 hours

Problem

Inputs:

1. Source code
2. Symbolic Variables (e.g., `filename` & `file`)
3. Candidate Vulnerability Points (CVPs)
    - Divide by zero
    - Buffer overflow

Outputs:

Validated Exploits

```
int main (…) {
  if (strlen(filename)>1 && filename[0]==‘-’)
    exit(1)
  copy_data(…);
  …
}
void copy_data(..., int *file...) {
  static double data[4096], value;
  read_double_value(file, ... );
  value = fabs (data [0]);
  for(i=0; i<4096; i++)
    if(file[i] == 0.0) count++;
  data[1] /= (value+count-3);
  …
}
```

CVP: Divide-by-zero

Key Insights

Values of Symbolic Variables

Values of Vulnerable Variables in CVP

Learn an approximation with small number of I/O examples

```
int main (…) {
  if (strlen filename >1 && filename[0]==‘-’)
    exit(1)
  copy_data(…);
  …
}
void copy_data(..., int * file ...) {





  data[1] /= (value+count-3);
  …
}
```

CVP: Divide-by-zero

Key Insights

Approximation:

$$count == \Sigma_{i\in[0,4095]}\ sign(file[i] == 0)$$
$$\wedge\ a == file[0] + 256\ file[1]$$
$$\wedge\ s == sign(file[1] < 127)$$
$$\wedge\ \max == (2\times s - 1)\times a\ - 256^2 \times (s\ - 1)$$

Machine learning can learn such an approximation

```
int main (…) {
  if (strlen filename >1 && filename[0]==‘-’)
    exit(1)
  copy_data(…);
  …
}
void copy_data(..., int * file ...) {
  static double data[4096], value;
  read_double_value(file, ... );
  value = fabs (data [0]);
  for(i=0; i<4096; i++)
    if(file[i] == 0.0) count++;
  data[1] /= (value+count-3);
  …
}
```

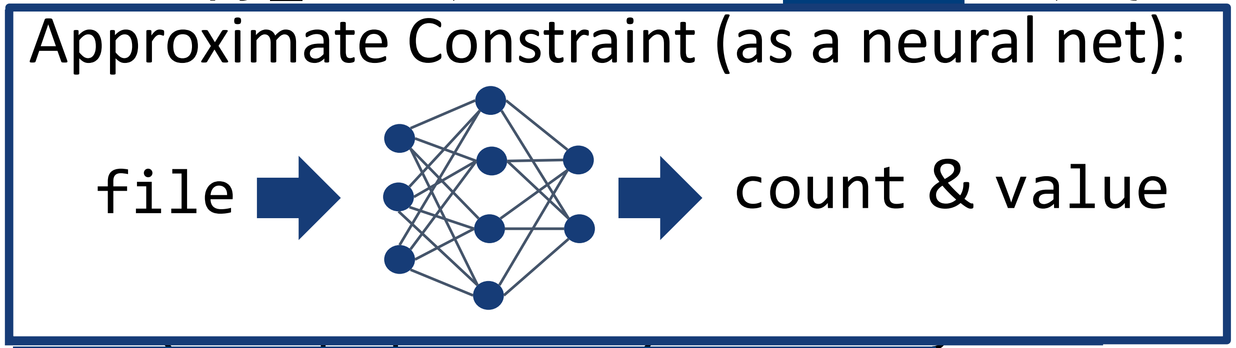
CVP: Divide-by-zero

Approach

1. Neural nets can represent a large category of functions (universal approximation theorem).

2. Multiple applications show that neural nets are learnable for many practical functions.

```
int main (…) {
  if (strlen filename >1 && filename[0]==‘-’)
    exit(1)
  copy_data(…);
  …
}
void copy_data(..., int * file ...) {
```



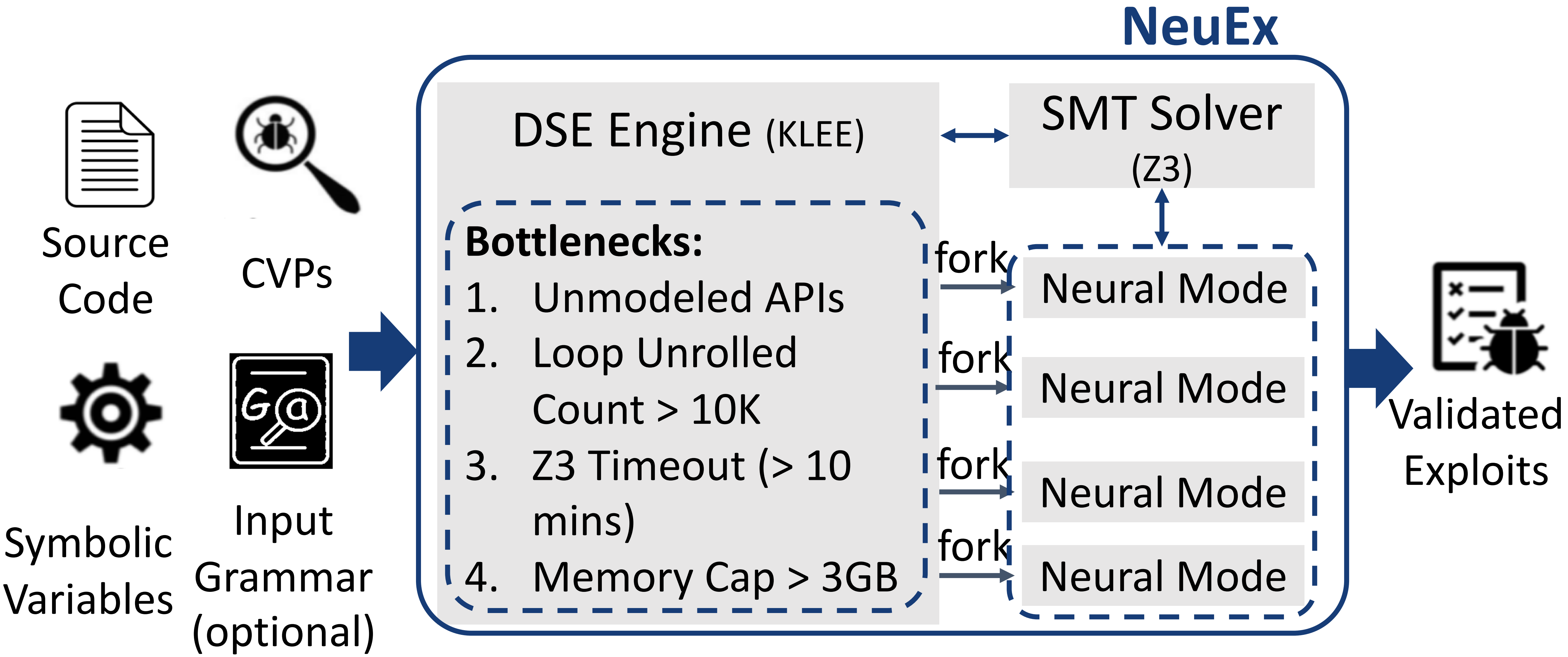
Approximate Constraint (as a neural net):

file → count & value

```
  data[1] /= (value+count-3);
  …
}
```

CVP: Divide-by-zero

NeuEx Overview



Source Code

CVPs

Symbolic Variables

Input Grammar (optional)

NeuEx

DSE Engine (KLEE)

SMT Solver (Z3)

Bottlenecks:

1. Unmodeled APIs
2. Loop Unrolled Count > 10K
3. Z3 Timeout (> 10 mins)
4. Memory Cap > 3GB

Neural Mode

Neural Mode

Neural Mode

Neural Mode

Validated Exploits

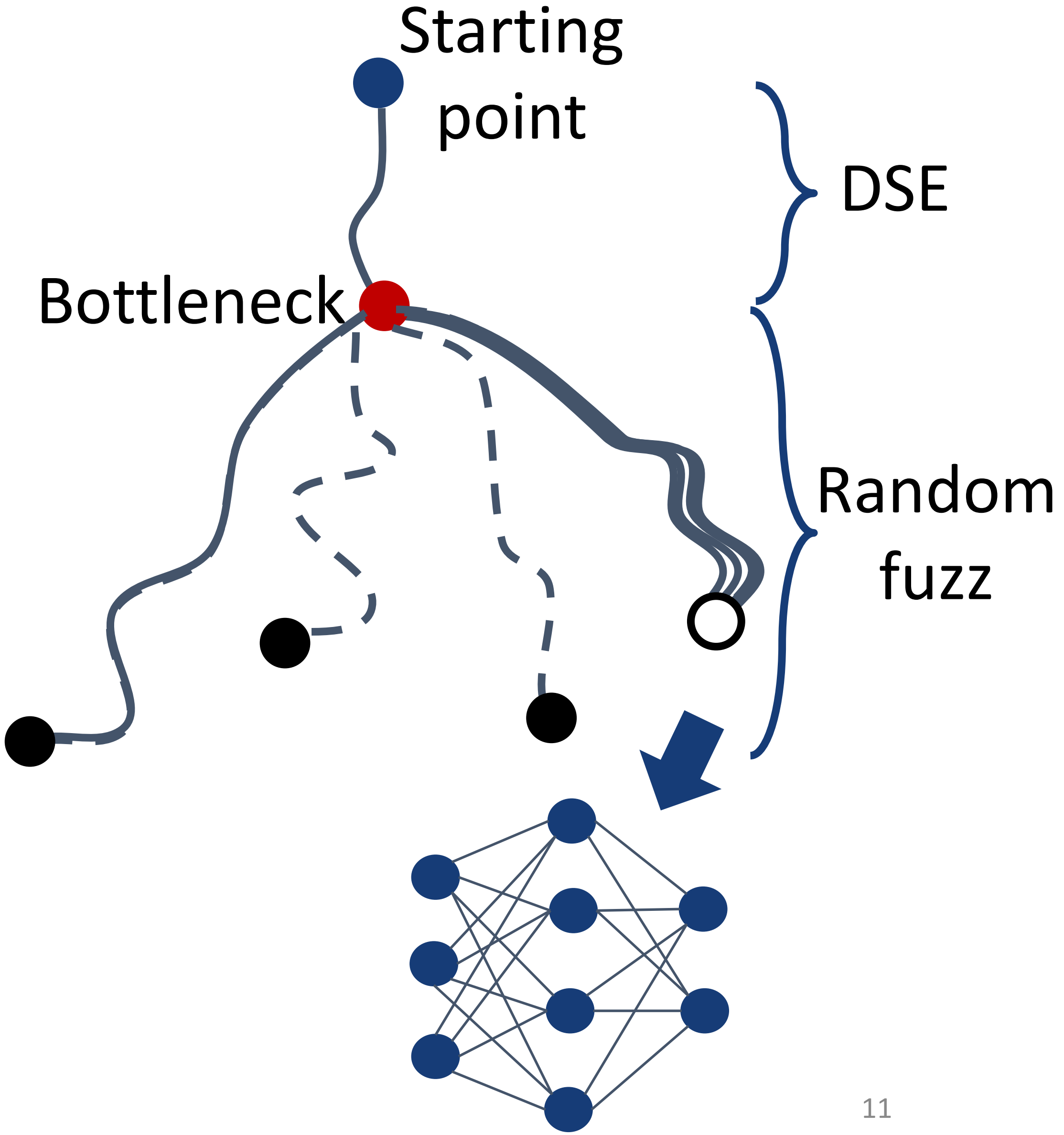
Neural Mode

Reaching CVPs

Collecting I/O Examples

Training

Solving



Generated Constraints

1. Reachability constraints:

$$strlen(filename) \leq 1$$
$$\lor\ filename \neq '-'$$

$$\land$$

$$N\colon infile \rightarrow (value, count)$$

2. Vulnerability condition:

$$value + count - 3 == 0$$

```
int main (…) {
  if (strlen(filename)>1 && filename[0]==‘-’)
    exit(1)
  copy_data(…);
  …
}
void copy_data(..., int *file,...) {
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  for(i=0; i<4096; i++)
    if(file[i] == 0.0) count++;
  data[1] /= (value+count-3);
  …
}
```

CVP: Divide-by-zero

Constraint Solving

1. Reachability constraints:

$$strlen(filename) \leq 1$$
$$\vee\ filename \neq '-'$$

$\wedge$

$$N: infile \rightarrow (\boxed{value, count})$$

2. Vulnerability condition:

$$\boxed{value + count} - 3 == 0$$

Purely symbolic constraints:
No variable shared with neural constraints

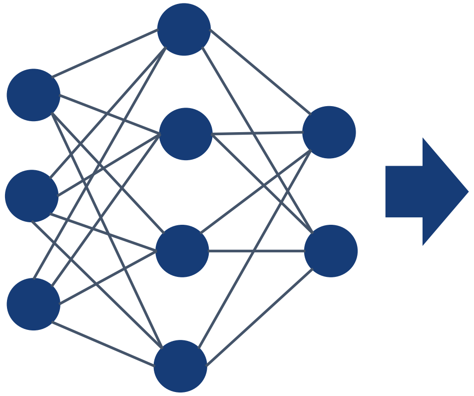
➡ SMT solver

Mixed constraints:
Including both neural constraints and symbolic constraints with shared variables

How to Solve Mixed Constraints?

Design Choice 1:

Neural net → CNF



$(X_1 \wedge Y_1) \vee (X_2 \wedge Y_2) \vee \cdots \vee (X_n \wedge Y_n)$

The number of clauses increases drastically with the neural net complexity

Design Choice 2:

Symbolic constraints → Optimization objective of the neural net

Encoding Symbolic Constraints as an Optimization Objective

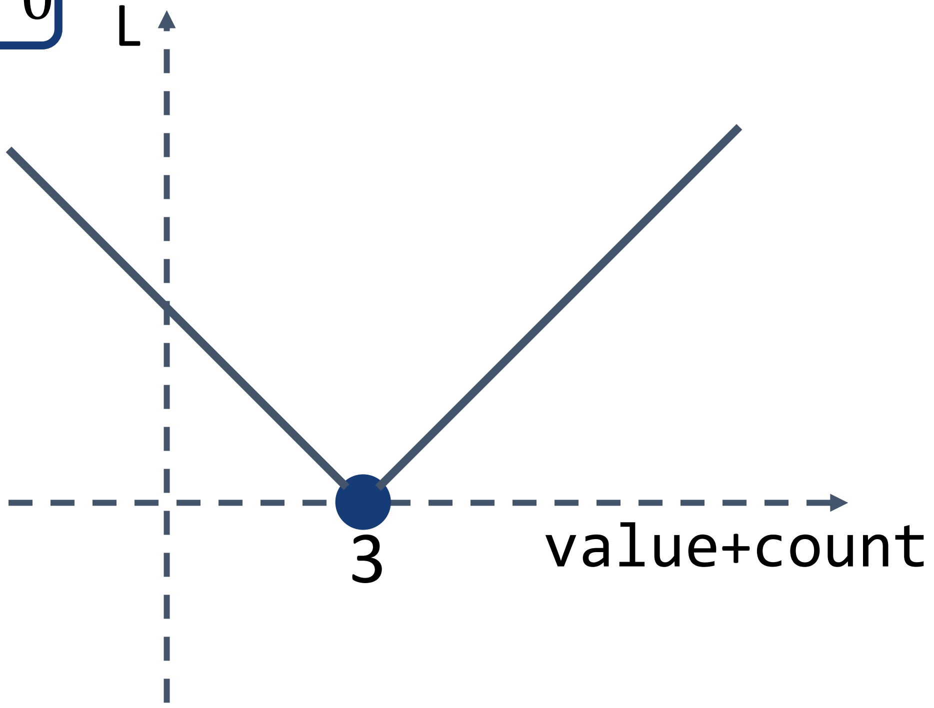
$N: infile \rightarrow (value, count) \wedge \boxed{value + count - 3 == 0}$

Symbolic constraint

Criterion for crafting the loss function:
The minimum point of the loss function satisfies the symbolic constraints.

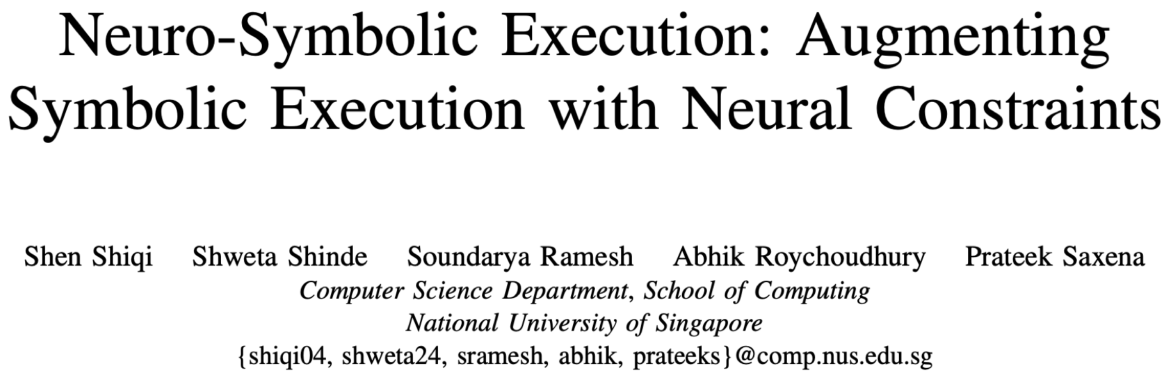
One possible encoding:

$$L = abs(value + count - 3)$$



Encoding Symbolic Constraints as an Optimization Objective

NeuEx supports many symbolic constraints. Checkout the paper for the complete grammar and the corresponding loss functions.



Neuro-Symbolic Execution: Augmenting Symbolic Execution with Neural Constraints

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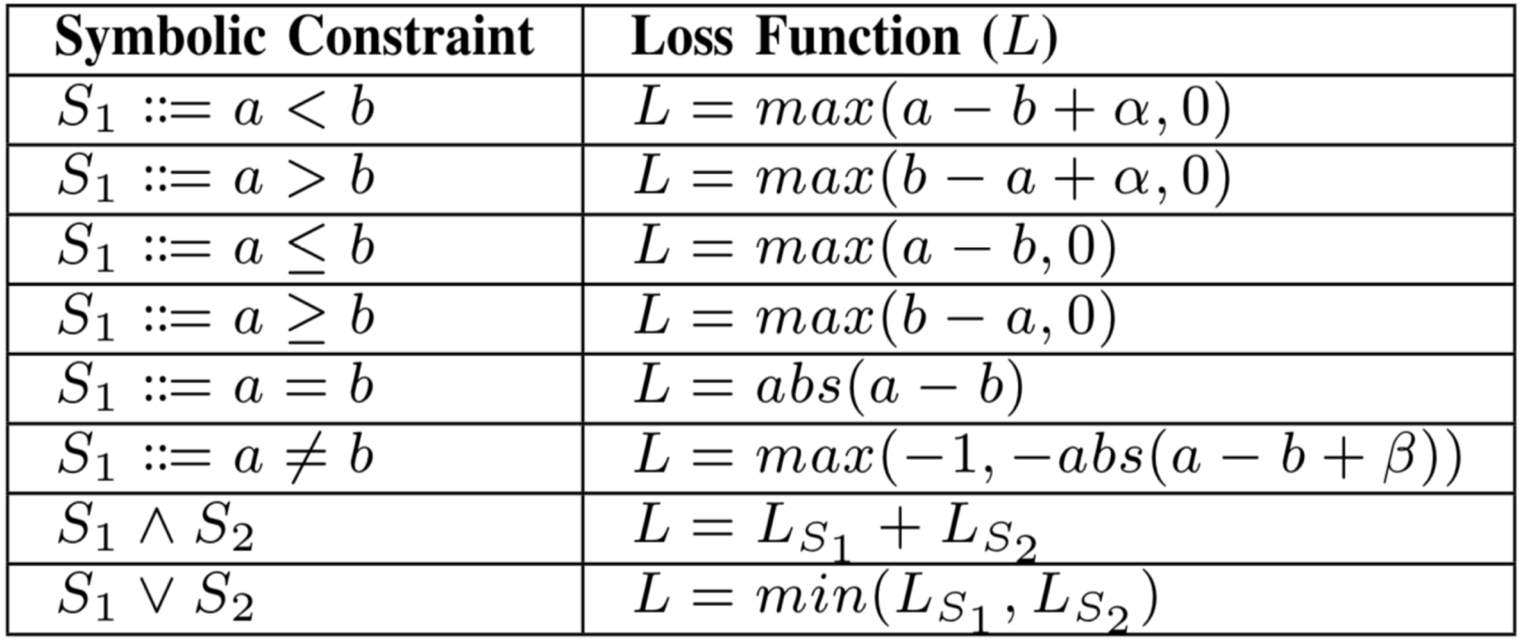
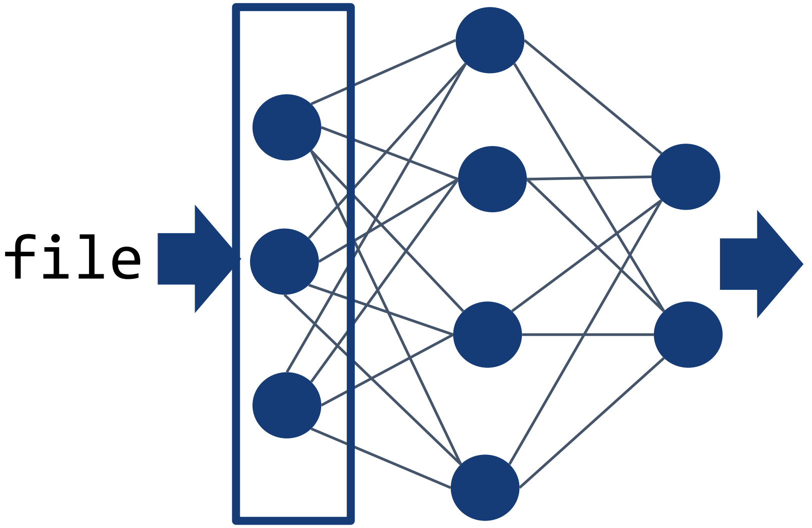


Symbolic Constraint	**Loss Function** (L)
$S_1 ::= a < b$	$L = max(a - b + \alpha, 0)$
$S_1 ::= a > b$	$L = max(b - a + \alpha, 0)$
$S_1 ::= a \leq b$	$L = max(a - b, 0)$
$S_1 ::= a \geq b$	$L = max(b - a, 0)$
$S_1 ::= a = b$	$L = abs(a - b)$
$S_1 ::= a \neq b$	$L = max(-1, -abs(a - b + \beta))$
$S_1 \wedge S_2$	$L = L_{S_1} + L_{S_2}$
$S_1 \vee S_2$	$L = min(L_{S_1}, L_{S_2})$

Solving Mixed Constraints via Gradient Descent



Gradient: $\nabla_{file} L$

`file`

`count,value`

`count`	`value`	`loss`
257	20	274
1	20	18
0	20	17
…	…	…
0	3	0

`file`: 000…

Concretely validate the exploit

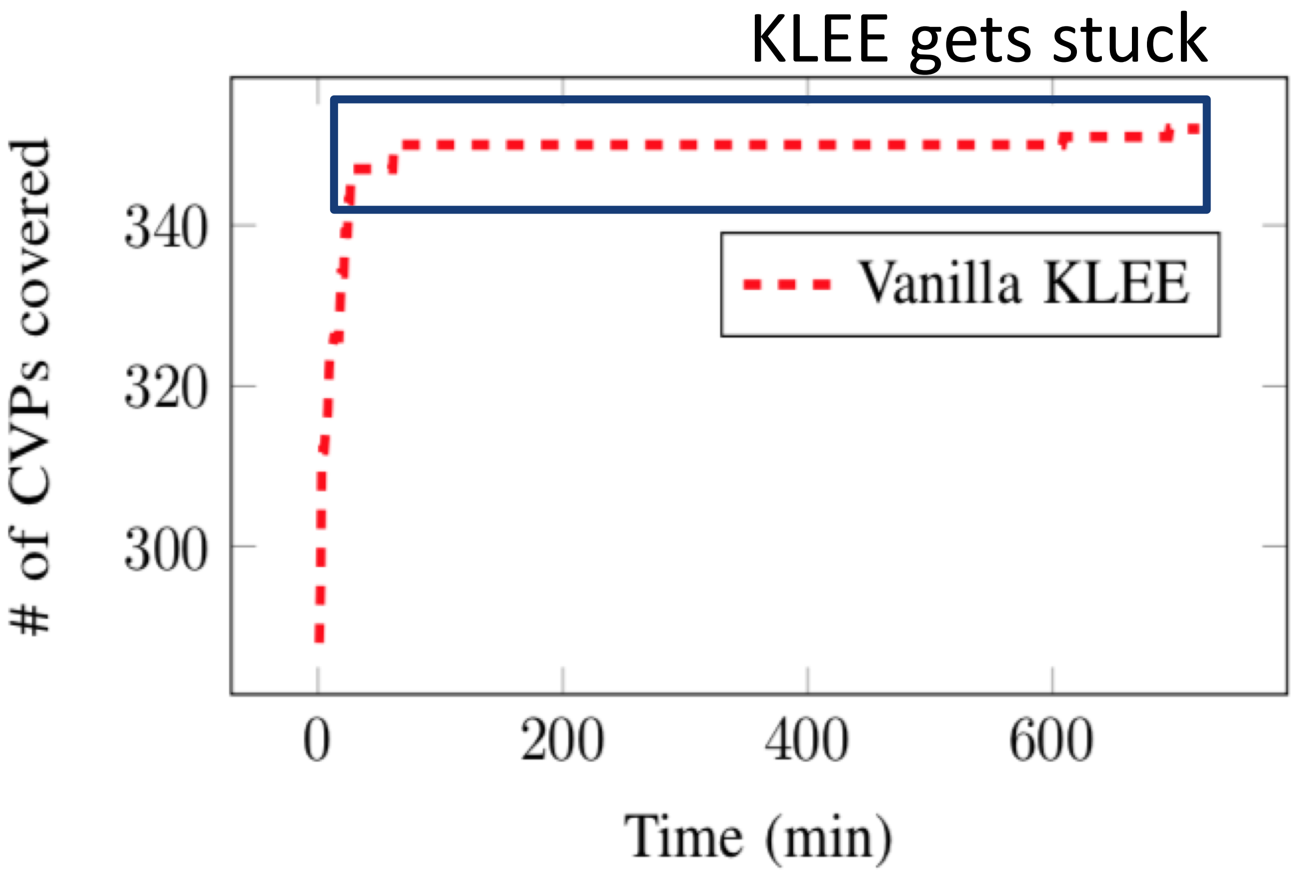
Evaluation

- **Recall**: Neural mode is only triggered when DSE encounters bottlenecks
- **Benchmarks**: 7 Programs known to be difficult for classic DSE
  - 4 Real programs
    - cURL: Data transferring
    - SQLite: Database
    - libTIFF: Image processing
    - libsndfile: Audio processing
  - LESE benchmarks
    - BIND, Sendmail, and WuFTP

Include:

1. Complex loops
2. Floating-point variables
3. Unmodeled APIs

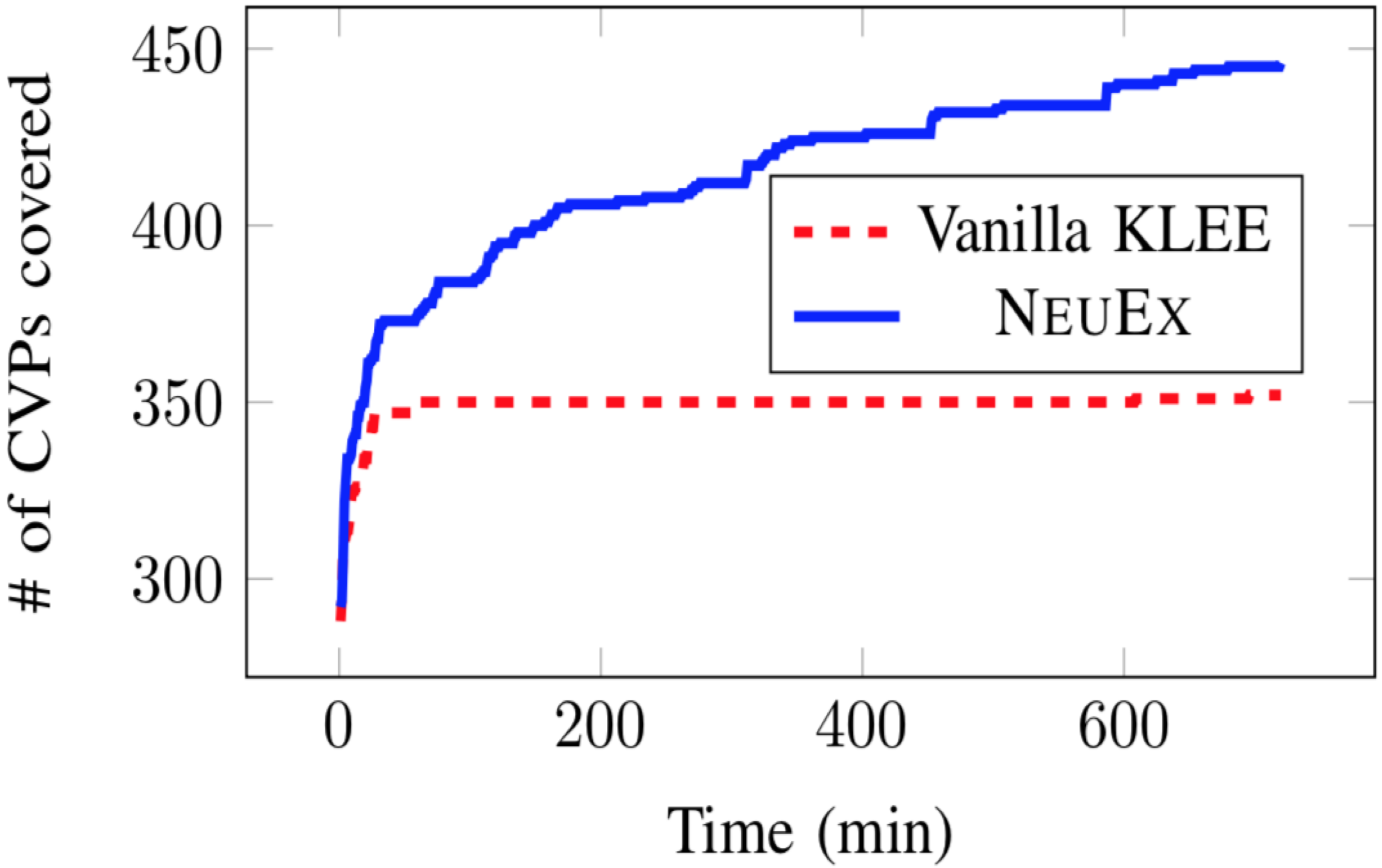
CVP Coverage & Bottlenecks for DSE



# of bottlenecks: 61

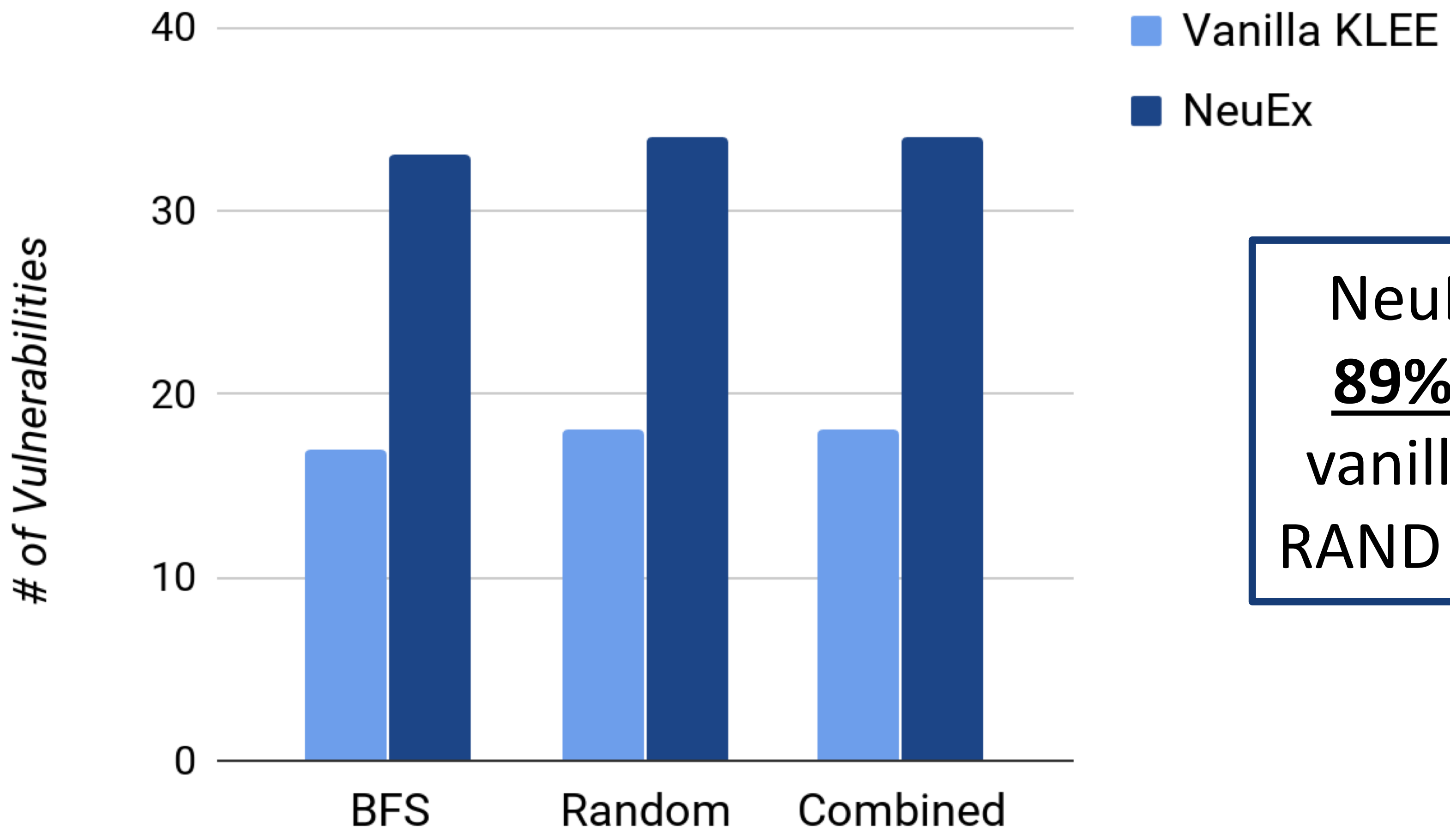
- Unmodeled APIs (6)
- Complicated loops (53)
- Z3 timeout (1)
- Memory exhaustion (1)

CVP Coverage of NeuEx vs KLEE



The number of CVPs reached or covered by NeuEx is **<u>25%</u>** higher than vanilla KLEE.

of Bugs Found by NeuEx vs KLEE



NeuEx finds **94%** and **89%** more bugs than vanilla KLEE in BFS and RAND mode in 12 hours.

Comparison to DSE Extensions

LESE

- Structured Approach for Loop Reasoning
  - **Two orders** of magnitude slower on average

Veritesting

- Combination of DSE + static analysis
  - **Fails to find bugs** in 12 hours
  - Poor instruction coverage

Key Takeaways

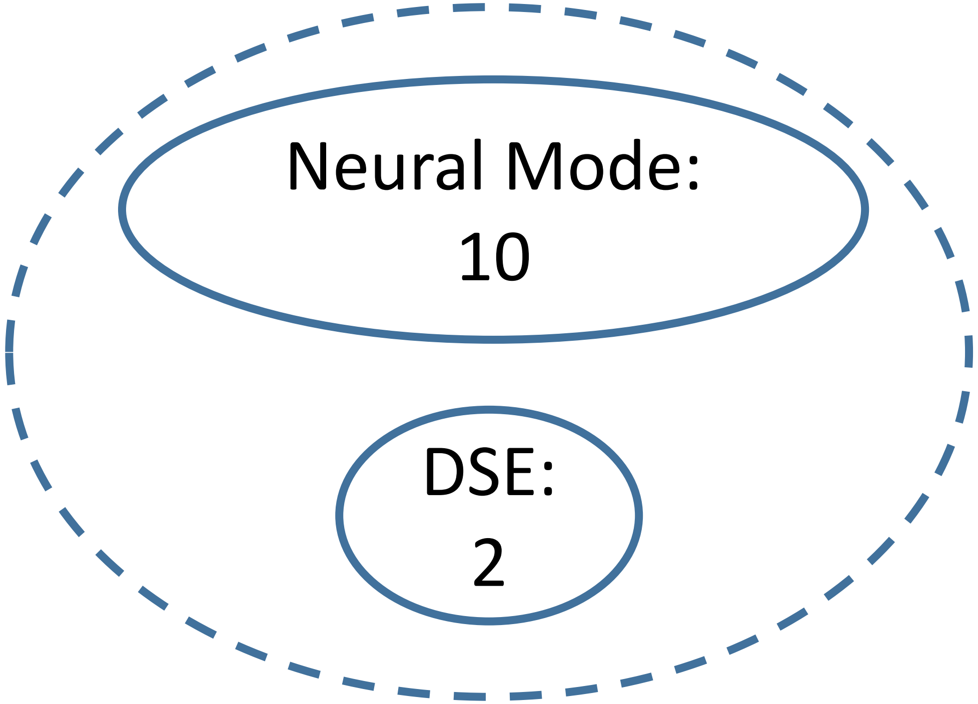
A new approach: Neuro-Symbolic Execution

- Resolves fundamental bottlenecks of DSE
- First to learn unstructured representation not amenable to SMT solver
- Unique use of optimization techniques and SMT for solving constraints

Evaluation

- Finds **94%** more bugs than KLEE within 12 hours

Backup: New Bugs



NeuEx: 12

Neural Mode:
10

DSE:
2