



# NEURI: Diversifying DNN Generation via Inductive Rule Inference

Jiawei Liu, Jinjun Peng, Yuyao Wang, Lingming Zhang  
*ESEC/FSE 2023 @ San Francisco*



UNIVERSITY OF  
**ILLINOIS**  
URBANA-CHAMPAIGN



COLUMBIA UNIVERSITY  
IN THE CITY OF NEW YORK

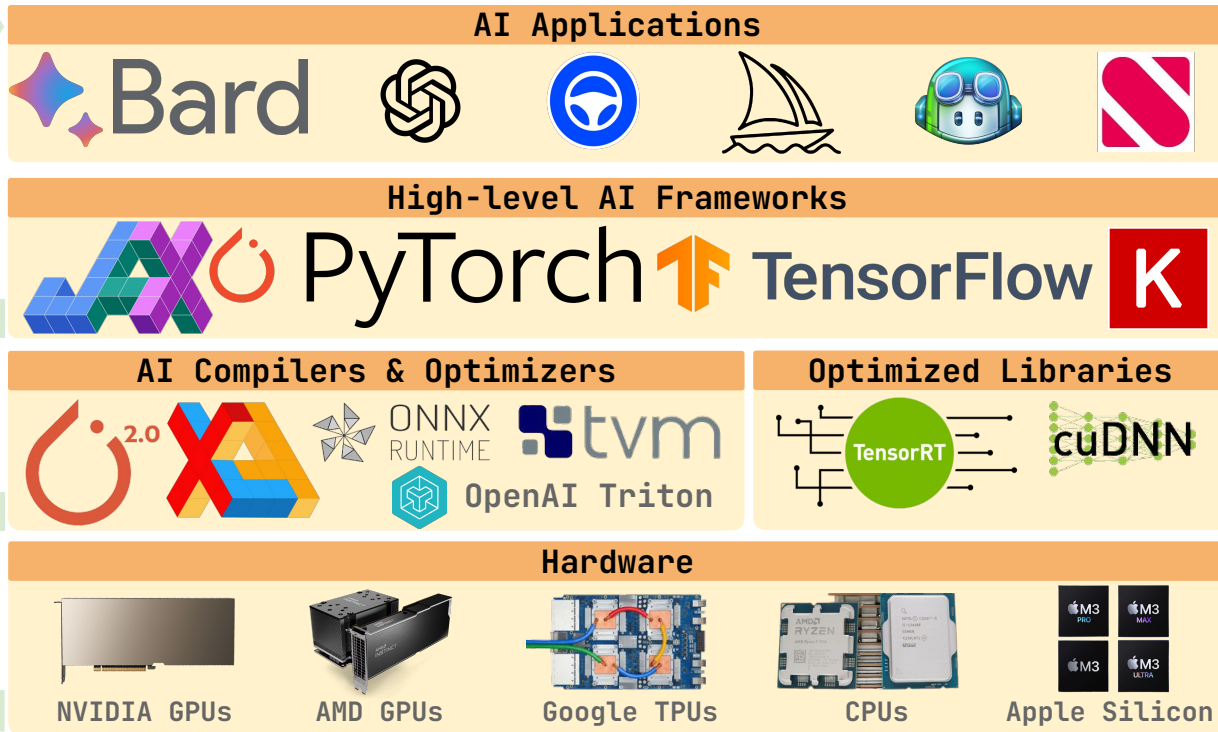


南京大學

NANJING UNIVERSITY

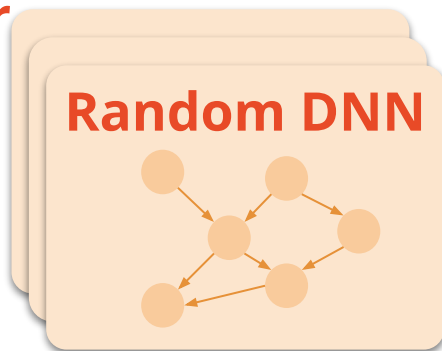
# DL System Correctness is Crucial

Safety  
Functionality  
User experience

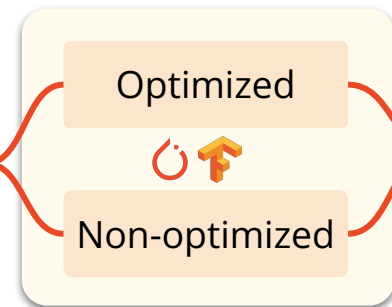


# Generating Models as Tests

Test Generator  
=  
Model Generator



DL Framework



Oracle



NeuRI [This work]  
NNSmith [ASPLOS 23]  
Muffin [ICSE 22]  
...

How to Generate  
Valid Models?

# Generating Valid Models

- **DNN model:** a directed graph of operators
- **Operator:** a function transforming tensors to tensors
- **Model validity** requires each operator to be
  - **Legally** constructed
  - Taking inputs of **reasonable** shapes/dimensions
  - Different operators have different constraints

## Invalid Model

ksize larger than input sizes

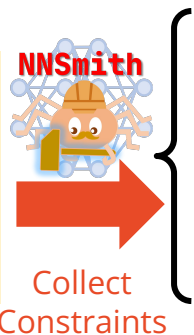
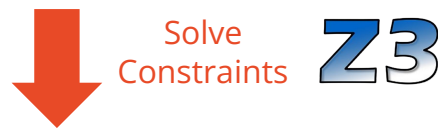
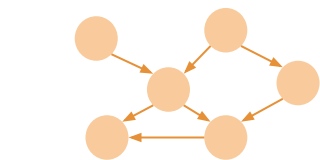
```
x = ... # shape=[1, 3, 32, 32]  
y = avg_pool(x, ksize=33)
```

# Solver-aided Model Generation

A constraint solving approach by NNSmith [ASPLOS 23]

- **Define** composable constraints for each operator
- **Accumulate & solve** model-wise constraints

```
x= input() # [x0, x1, x2]
y= relu(x) # [y0, y1, y2]
z= pool(y, ksize, stride)
```

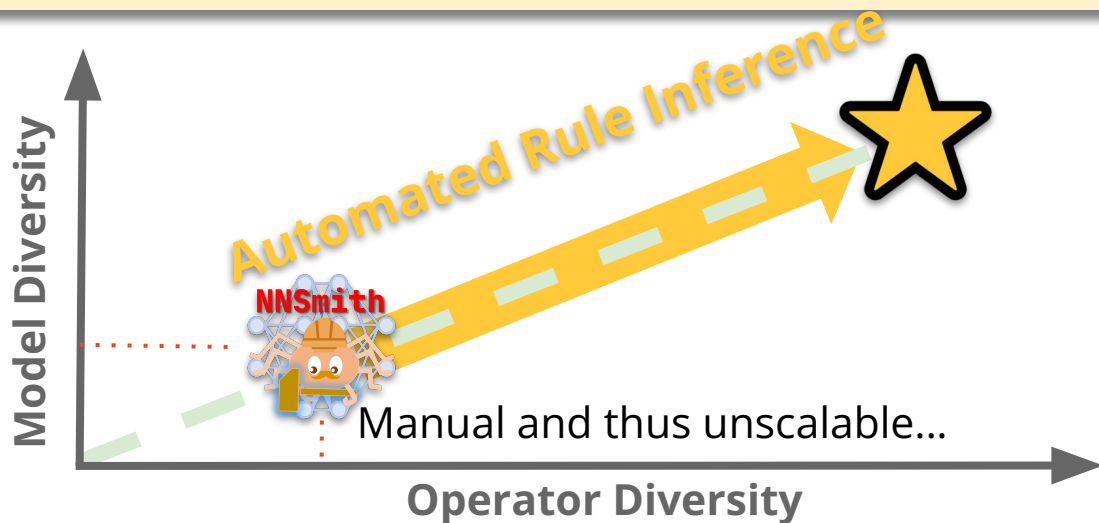

$$\left\{ \begin{array}{l} [x_0, x_1, x_2] = x.\text{shape} > 0 \\ [y_0, y_1, y_2] = y.\text{shape} = x.\text{shape} \\ (y_1 - \text{ksize}) // \text{stride} > 0 \\ (y_2 - \text{ksize}) // \text{stride} > 0 \\ \dots \end{array} \right.$$


$\{x_0=1, x_1=8, x_2=8, \text{ksize}=3, \dots\}$

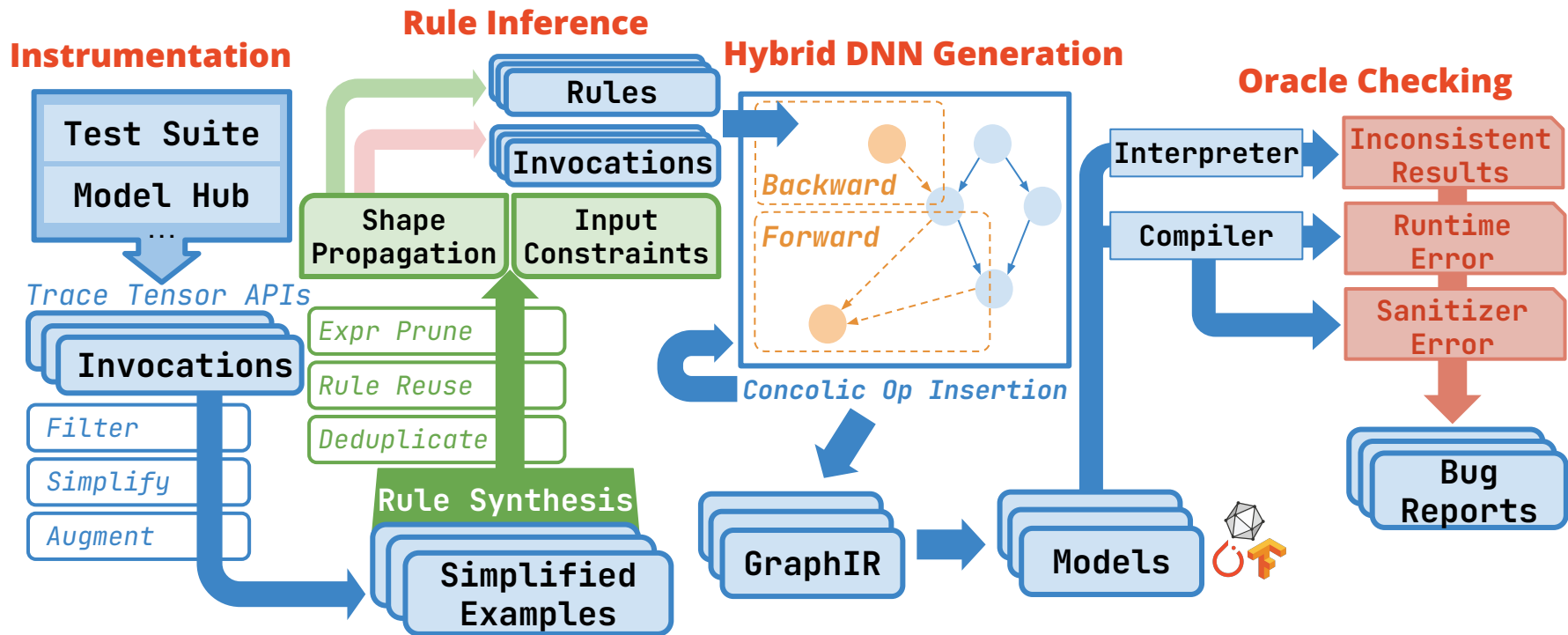
# Diversifying Valid Models

- **Model diversity** is determined by **operator diversity**
- NNSmith manually supports **~60** operator rules

Can we *automatically* synthesize operator rules?

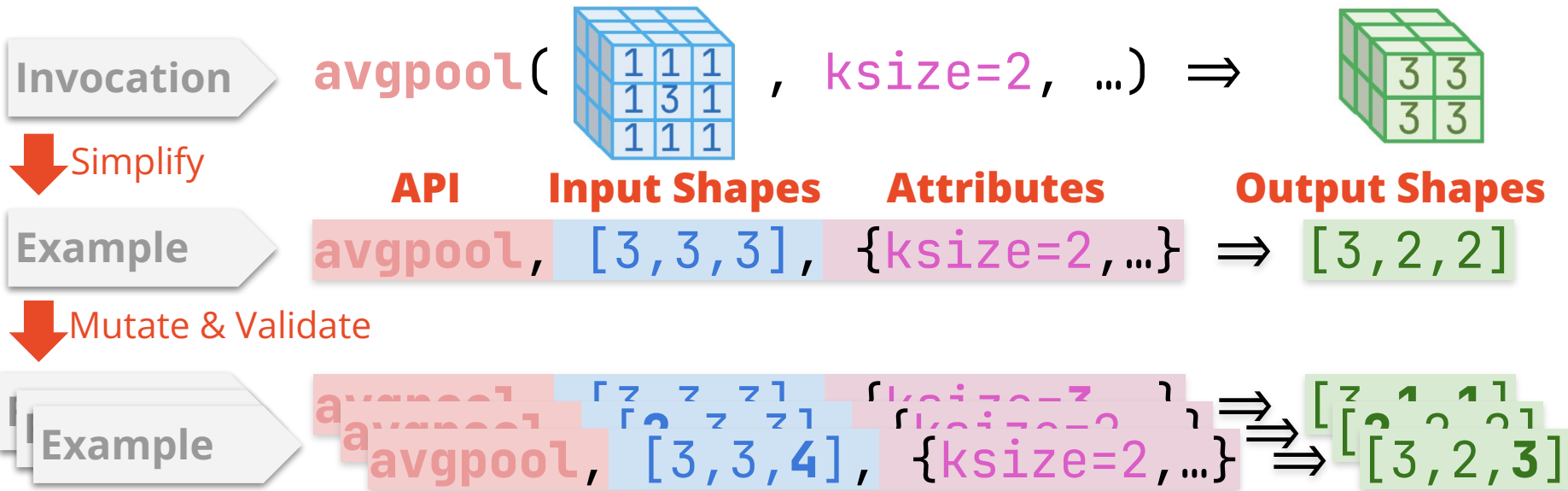


# NeuRI: Neural Net Rule Inference



# Instrumenting Concrete Operator Invocation

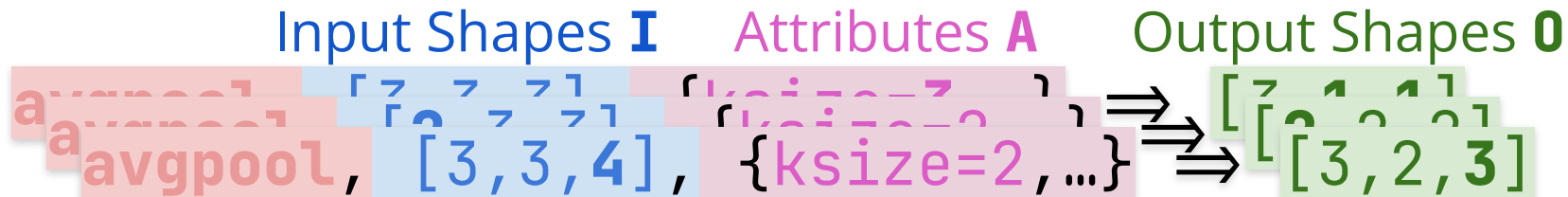
- Instrument operator invocations from regression tests
- Simplify the layout of invocations
- Create more records via mutation





# Inferring Operator Rules from Records

Each type (e.g., operator) of records has **3 sets of symbols**



- **#1 Shape propagation:**  $\{o = f(A \cup I); o \in O\}$ 
  - $\{O_0=I_0, O_1=(I_1-ksize) // stride+1, O_2=(I_2-ksize) // stride+1\}$
  - #constraints = #output dimensions ( $|O|$ )
- **#2 Input constraints:**  $\{O = /< f(A \cup I); \dots\}$ 
  - $\{ksize>0, stride>0, O_*>0, \dots\}$
  - #constraints is variadic/unknown

# Inductive Rule Inference

Let  $f(\mathbf{A} \cup \mathbf{I})$  be an expression under arithmetic grammar

```
<expr> ::= <op> <expr><expr> | <item>
<item> ::= <symbol> | <literal>
<op> ::= + | - | × | ÷ | min | max | mod
<symbol> ::= Symbols from  $\mathbf{A} \cup \mathbf{I}$ 
<literal> ::= Constant integers
```

**Search-based Inductive Synthesis:** Enumerate all terms of the grammar s.t.  $\exists$  expr *satisfies* all collected examples

# Optimization: Pruning the Search Space

We **prune** the search space of possible term skeletons by

- **Bounded search:** limit the AST depth & `<literal>`
  - Prune **semantically equivalent** term skeletons
  - **Rarity pruning:**
    - Skip **constant sub-term** `<op> <literal><literal>`
    - One symbol only occur once in a term
- **Output** is a set of term **skeletons** pruned **ahead of time**
- At inference time, we **substitute** the holes in the skeleton → actual symbols for each type of records

# More Optimizations

- **Rule reusing**

- **Insight:** Operator rules can share similar patterns
- Before rule synthesis, try if the records match any of the inferred rules

- **Post deduplication**

- Inferred constraints are boilerplate: (i) **not readable** and (ii) **inefficient** when used in online solving
- Example:  $\{a + b + 1 > 0, a + b > 0\} \rightarrow \{a + b > 0\}$

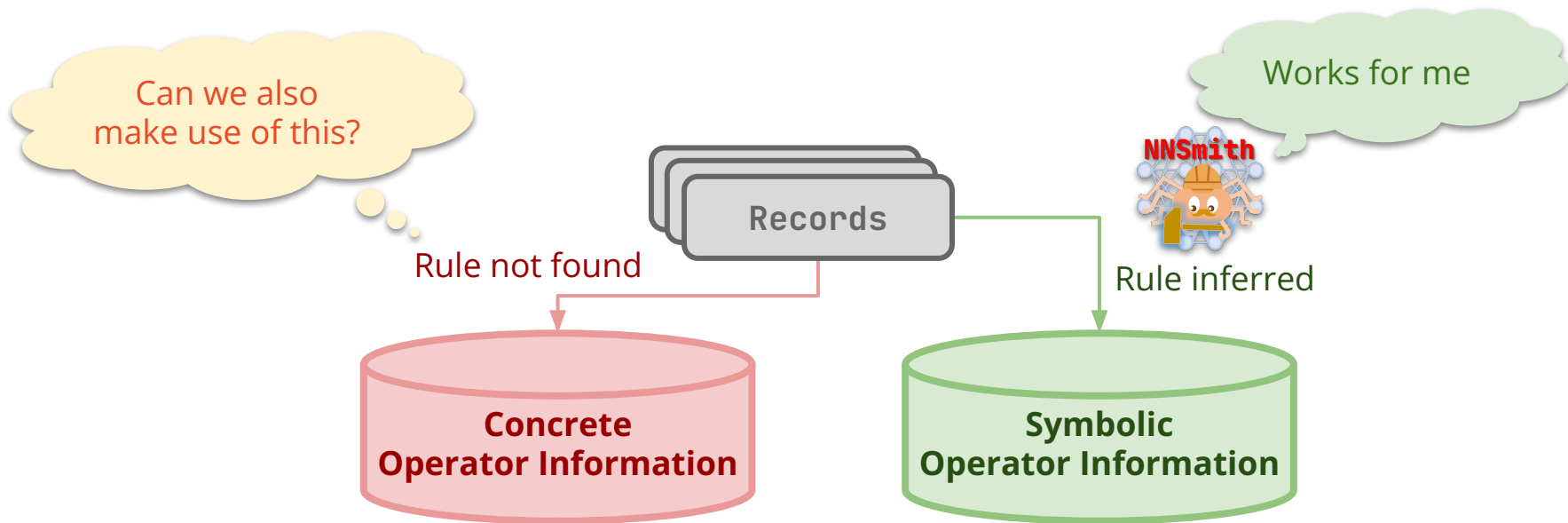
Given a set of *predicate* terms  $C$ , perform:

$$C = C - \{c\} \text{ iff } \text{conj}[C] \Leftrightarrow \text{conj}[C - \{c\}]$$

until a fixed point

# Model Generation

- Some rules are **inferred** and others are **not**
- NNSmith **only** works for **symbolic** operator (rule inferred)



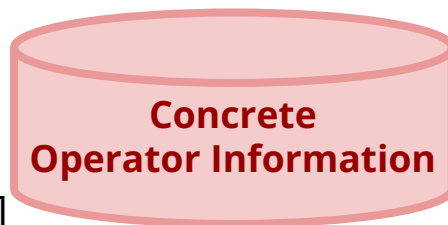
# Concolic Model Generation

Using both **concrete** + **symbolic** (concolic) information

- Constructing a graph ← Inserting an operator
- Inserting a **concrete** operator
  - Find invocations with exact shape match

```
x= input()      # [3, 16, 16]
y= pool(x, ...) # [3, 14, 14]
```

Query invocation w/  
input shape [3, 14, 14]



```
x= input()      # [3, 16, 16]
y= pool(x, ...) # [3, 14, 14]
z= attn(y, ...) # inserted
```

attn({}, ...)

# Concolic Model Generation

Using both **concrete** + **symbolic** (concolic) information

- Constructing a graph ← Inserting an operator
- Inserting a **concrete** operator
  - Find invocations with exact shape match
- Inserting a **symbolic** operator
  - Solve the constraints immediately to make the graph *fully concrete*

# Evaluation Setup

## Systems under Test

 **PyTorch**

- Torch Inductor
- Torch JIT

 **TensorFlow**

- XLA
- TensorFlow Lite

**NNSmith**  
ASPLOS 23

**Muffin**  
ICSE 22

**Variants  
of NeuRI**

**DeepREL**  
FSE 22

Model-Level Fuzzer

Op-Level Fuzzer



# Finding 100 Bugs in Four Months

🔥 51 bugs fixed; 81 bugs fixed or confirmed

🔥 9 bugs are marked as PyTorch **high priority**

🔥 1 security vulnerability **Moderate** 6.3 / 10





**Bug reports**

*"... the bugs you've reported are **high quality** ... don't look like specially fuzzed set that's impossible to see in **practice**. They did **reveal a few common themes** that are easy to encounter in **practice** ..."*

-- PyTorch Developer (#93357)

# Result Highlights

-  **24%** /  **15%** coverage improvement over SOTA NNSmith
- **95%** / **99%** generated (5-node) models are valid
- **~100ms** to generate and run a model on a single thread
- **4.6k rules** inferred by NeuRI in **1s** while Rosette...

Type	<1s	<10s	<100s	<1000s
NeuRI	4,660	4,700	4,716	4,758
Rosette	0	83	2,832	4,461

**A lot more interesting results detailed our paper!**

# Summarizing NeuRI



- **Automatically discovering operator rules!**
  - Collecting input-output examples via *instrumentation* + *mutation*
  - Efficient *inductive program synthesis* with domain optimizations
  - *Concolic generation* to maximize both symbolic & concrete information
- Found **100** bugs including high-priority & security ones!
- Everything open-sourced!

Paper



Code



Bug reports

