Deep Reinforcement Learning for Program Verification and Synthesis

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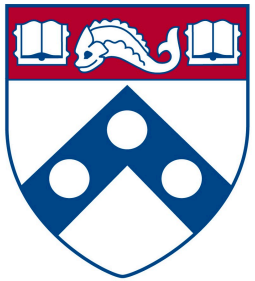

University of Pennsylvania
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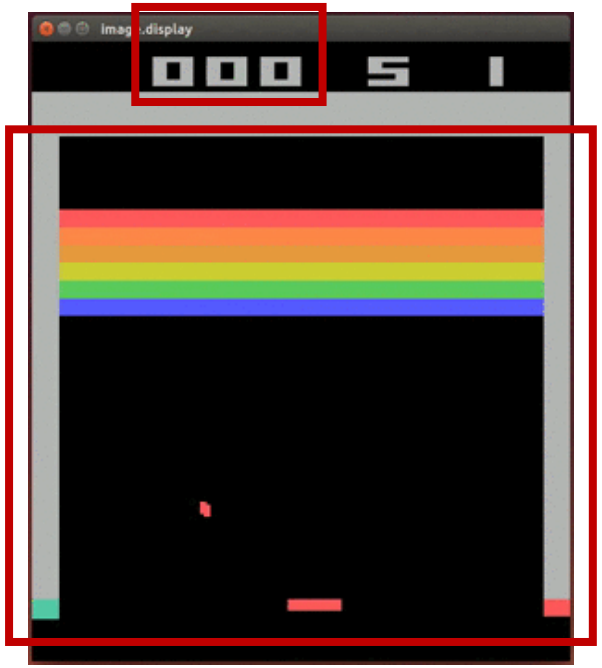
The Success of Deep Reinforcement Learning

Reward

State

"fix-sized 2D raw pixels"



Action

(move left, move right)

Neural Policy

$P(action \mid state)$

"automatically learned from self-play"

The Success of Deep Reinforcement Learning

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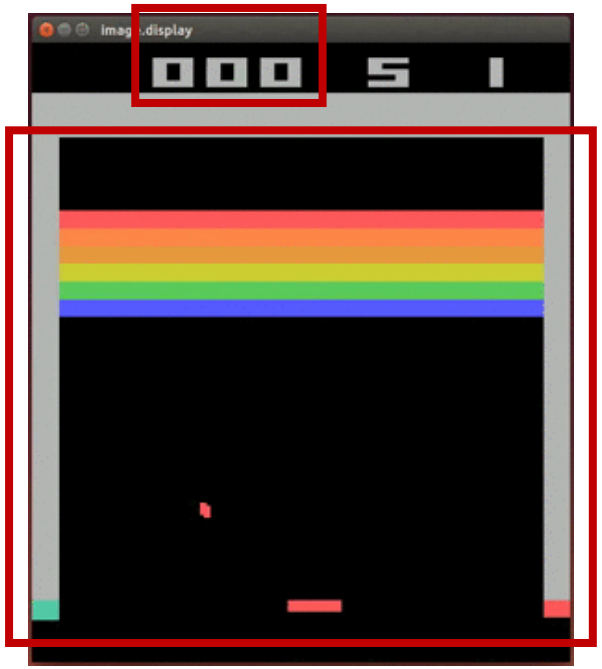

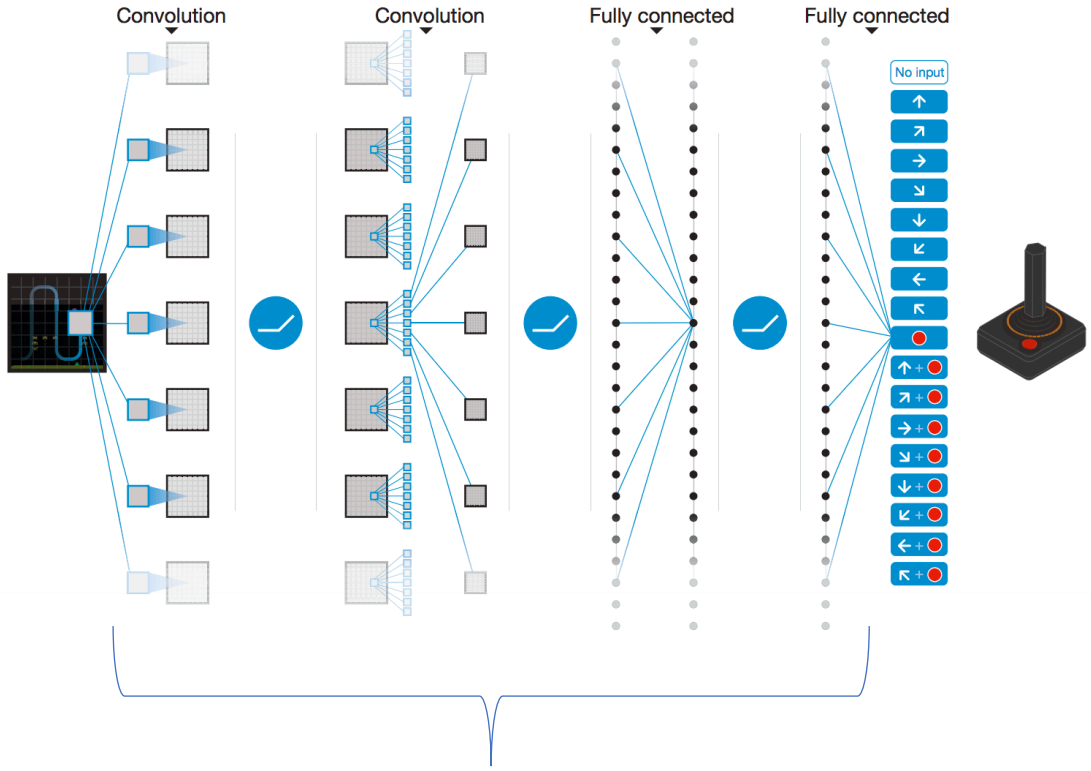

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$$\mathrm{P}(action \mid state)$$

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DRL for program reasoning

Atari Games	raw pixels size is fixed	Convolutional Neural Network	Simple & Limited number of actions
Program			

DRL for program reasoning

Atari Games	raw pixels size is fixed	Convolutional Neural Network	Simple & Limited number of actions
Program	***structured*** data size ***varies***	***Graph Neural Network***	***Actions specified in a Context-free Grammar***

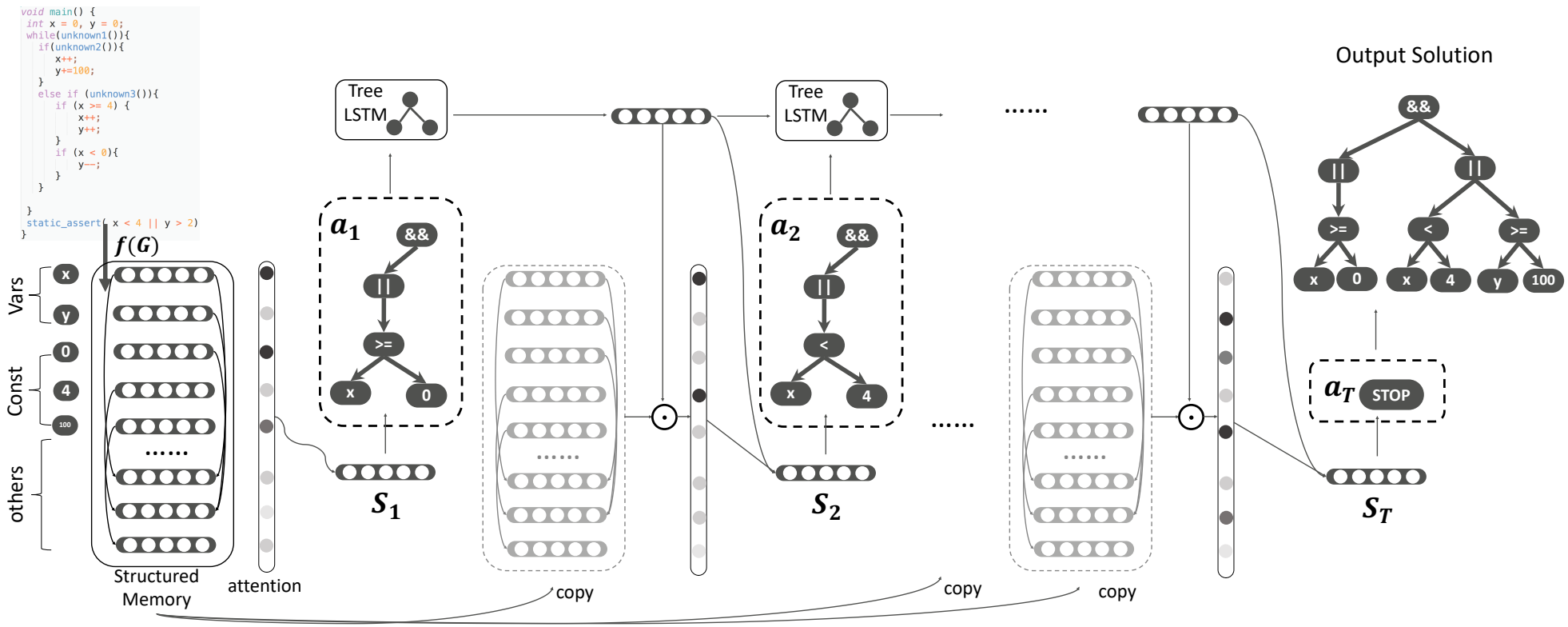
Learning loop invariant

Program	Loop Invariant
$x := -50;$ **while** $(x<0)$ { $\quad x := x+y;$ $\quad y := y+1$ } **assert**$(y>0)$	$(x<0 \vee y>0)$

Requirement:

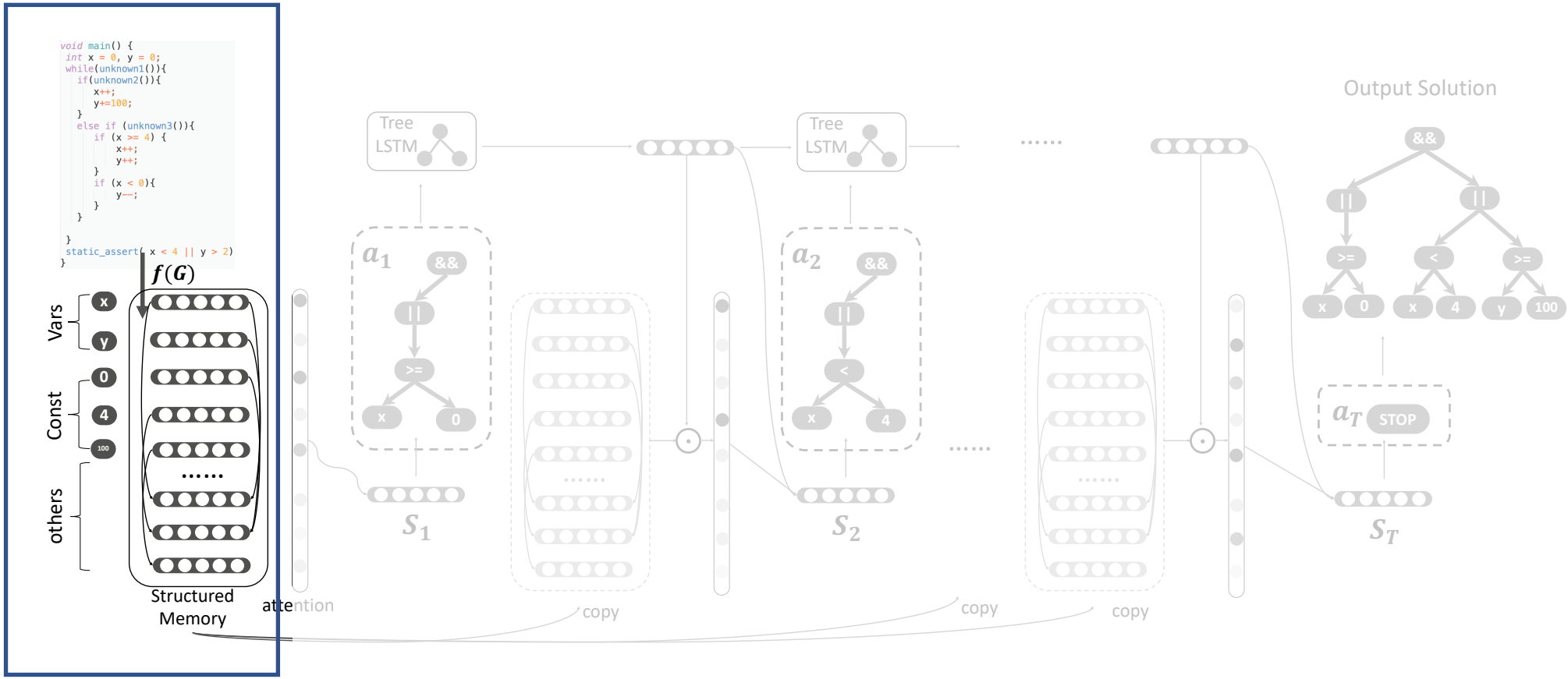
$$\forall x,y: \begin{cases} \texttt{true} \Rightarrow I[-50/x] & (pre) \\ I \wedge x<0 \Rightarrow I[(y+1)/y,(x+y)/x] & (inv) \\ I \wedge x \geq 0 \Rightarrow y>0 & (post) \end{cases}$$

Approach overview



Approach overview

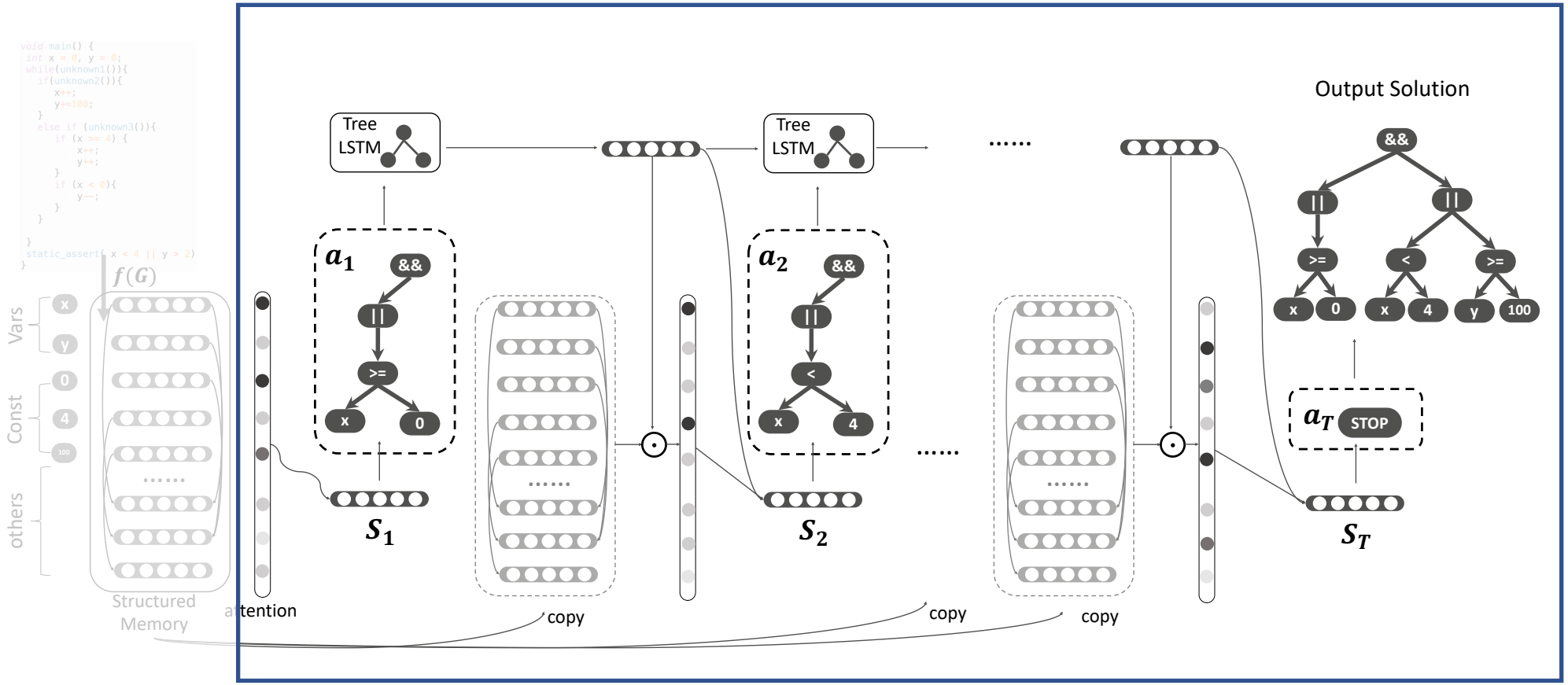
Representation Learning ”turn a program into a collection of high dimensional vectors”



Approach overview

Reinforcement Learning

”reduce loop invariant generation as a multiple step decision problem”



Representation learning for source code

```
while (y < 1000) {
    x = x + y
    y = y + 1
}
```

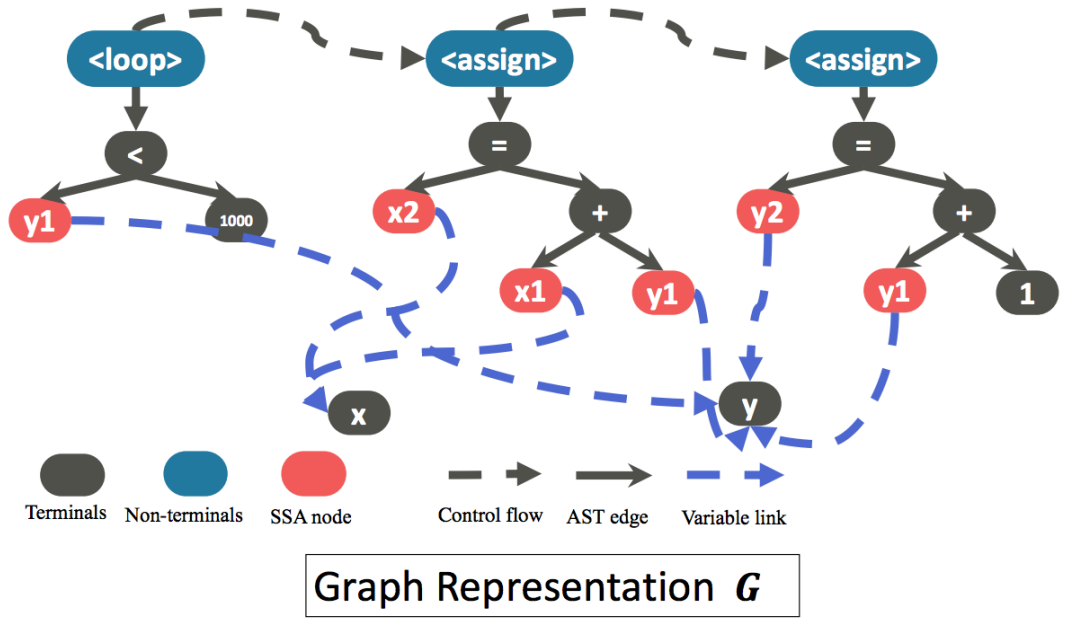
SSA

$x_1 = \phi(x_0, x_2)$
$y_1 = \phi(y_0, y_2)$

```
while (y1 < 1000) {
    x2 = x1 + y
    y2 = y1 + 1
}
```

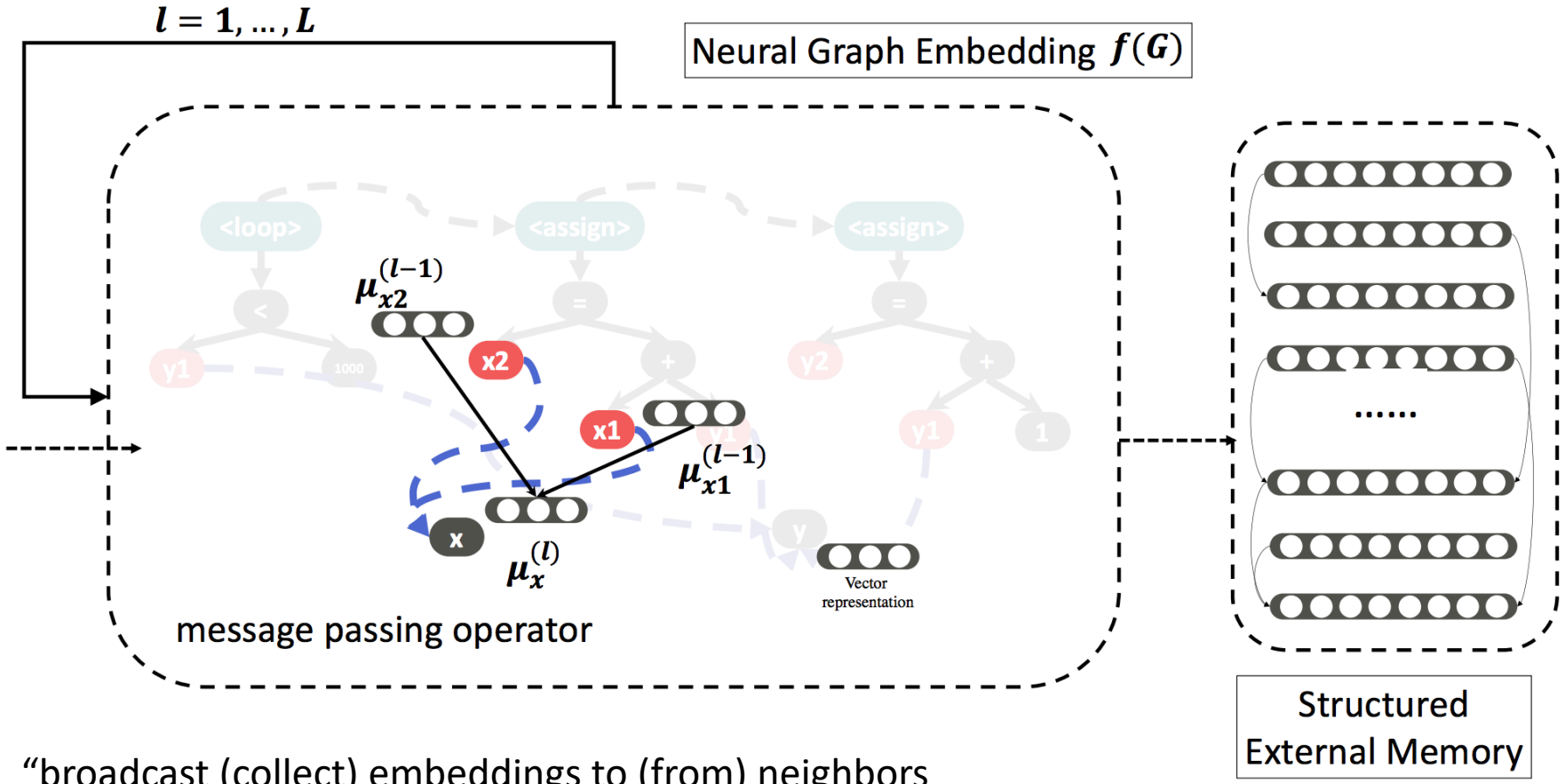
Source Code

```
while (y < 1000)
{
  x  = (x + y);
  y  = (y + 1);
}
```



Graph Representation G

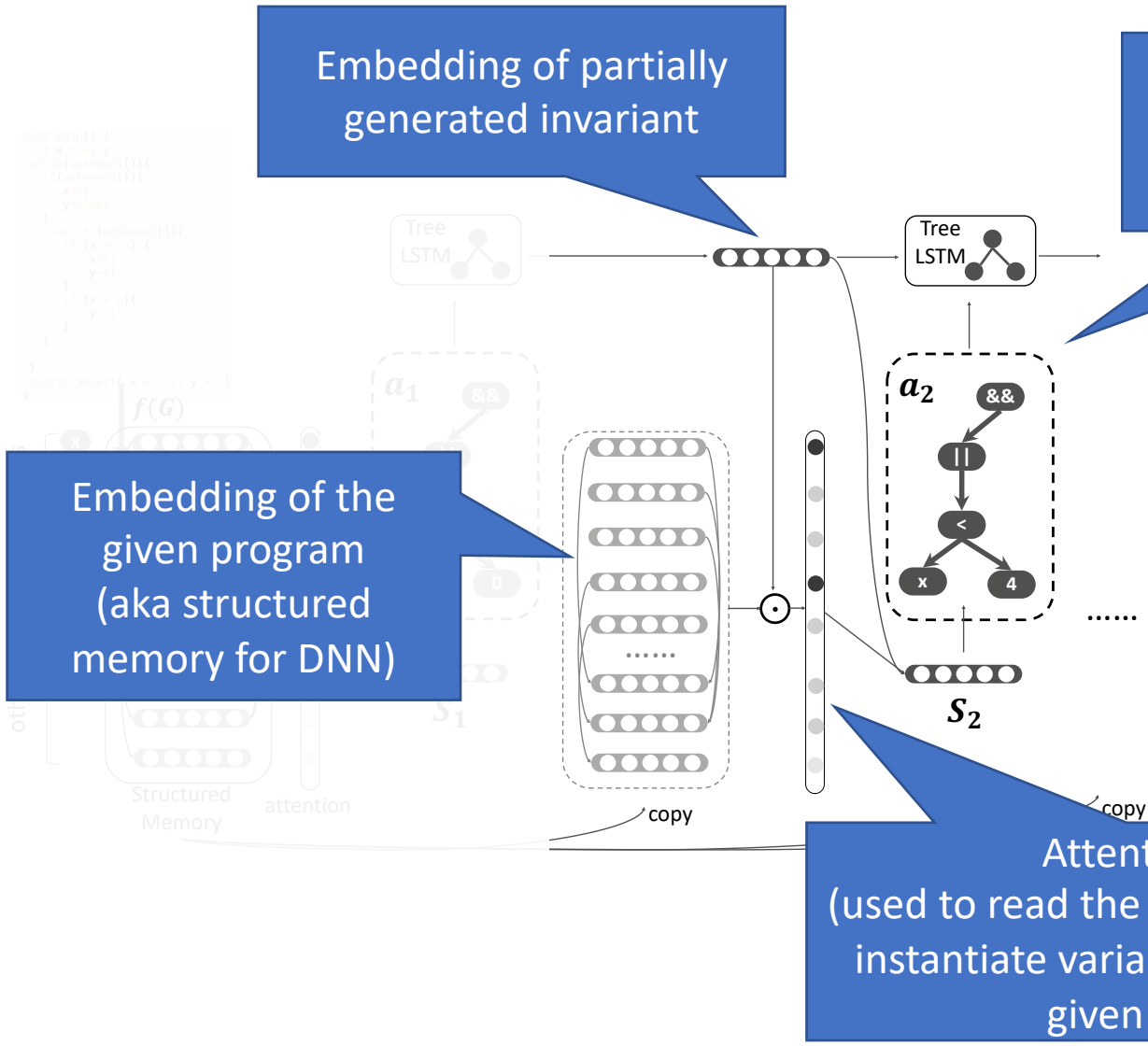
Representation learning for source code



"broadcast (collect) embeddings to (from) neighbors and perform non-linear transformation; repeat for L iterations"

"turn a piece of code into something readable by DNNs"

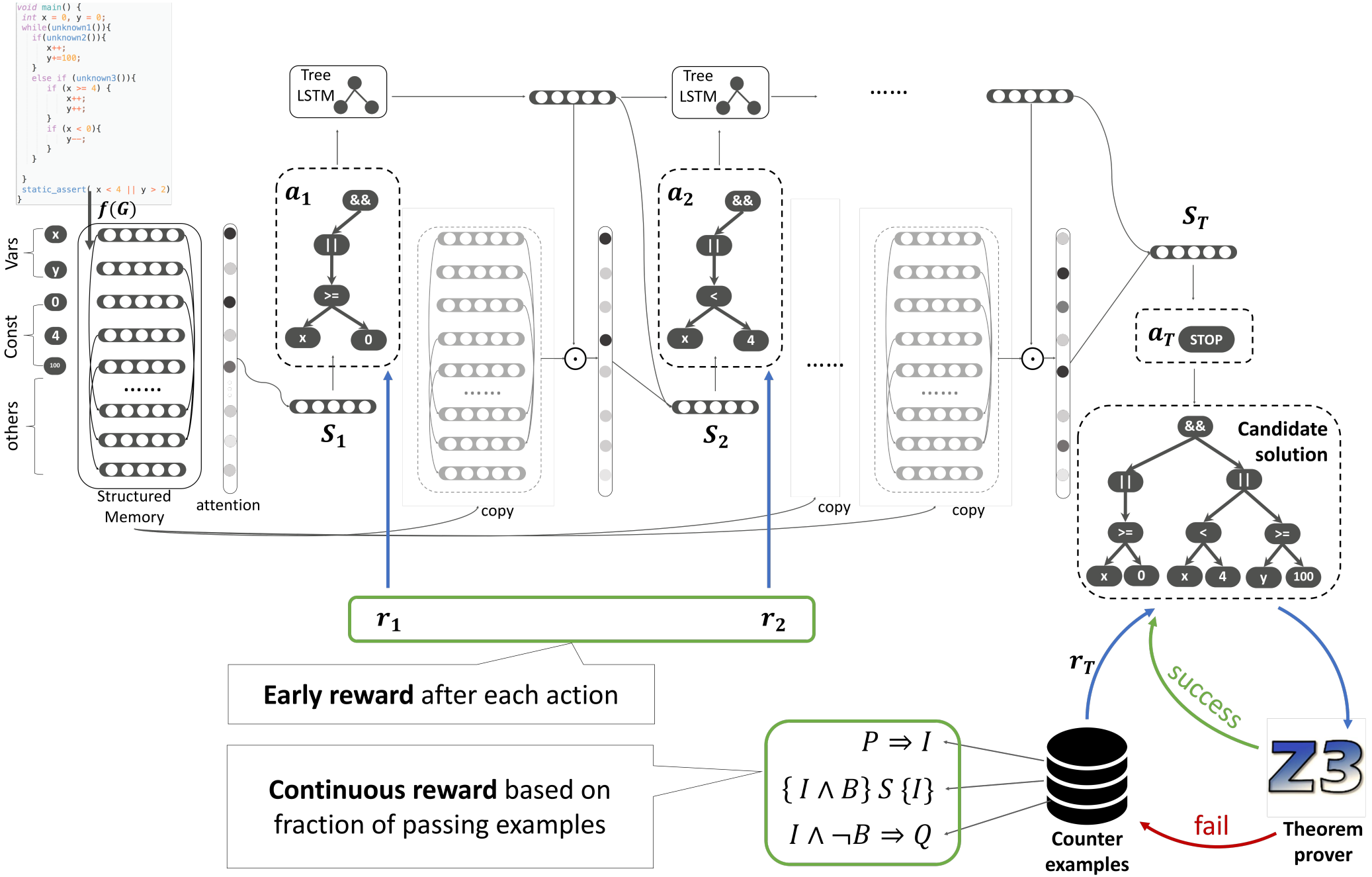
Reinforcement learning for invariant generation



P := P and P | P or P | E
E := e <= e | e < e | …
e := var | constant | e + e | e – e

Here, we are essentially learning the following distribution (which maximizes the reward discussed next)

$$\mathrm{P}(pred \mid program, partial\ invariant)$$

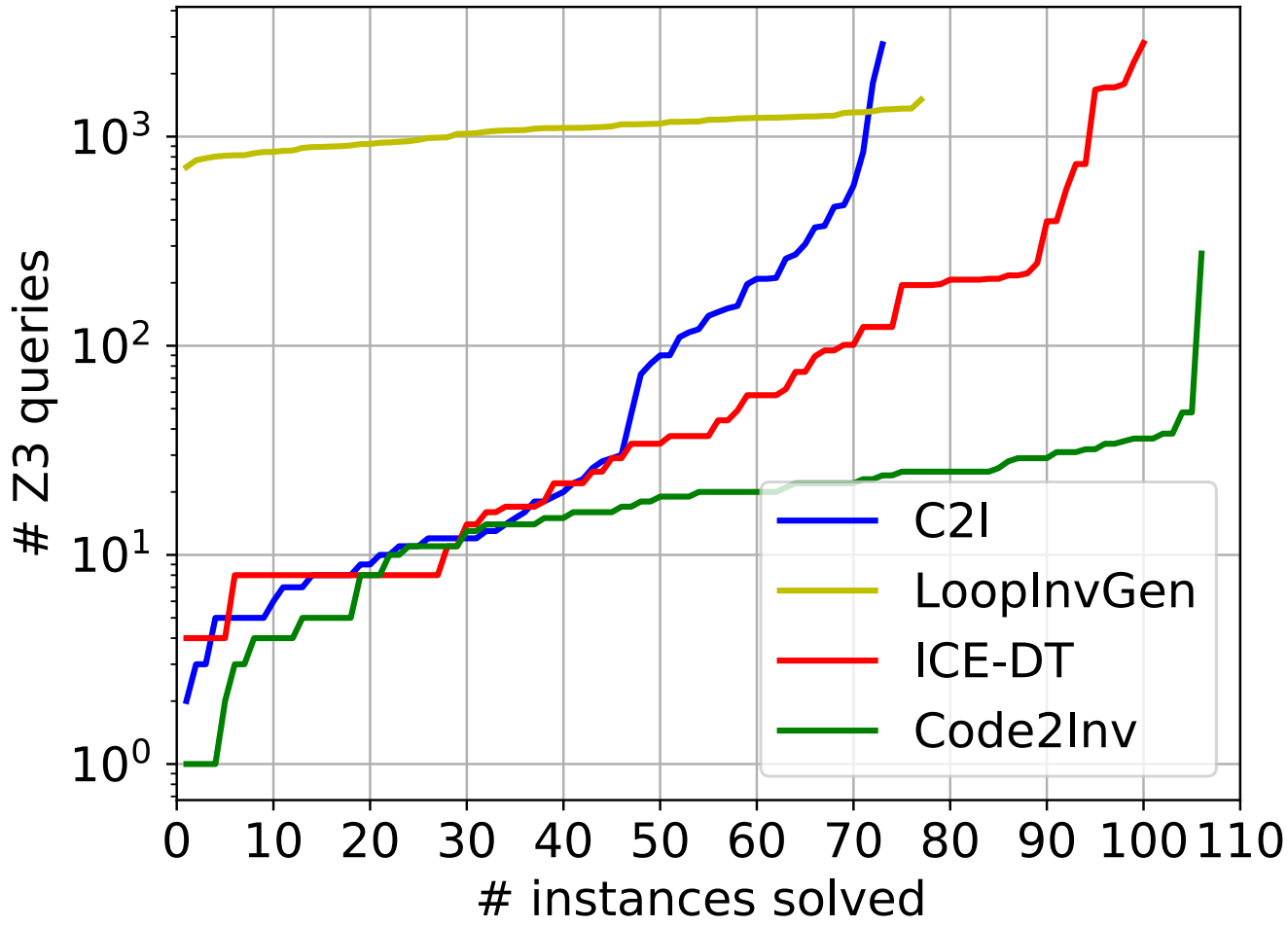

void main() {
int x = 0, y = 0;
while(unknown1()){
if(unknown2()){
x++;
y+=100;
}
else if (unknown3()){
if (x >= 4) {
x++;
y++;
}
if (x < 0){
y--;
}
}
}
static_assert(x < 4 || y > 2)
}
$f(G)$
Vars
Const
others
x
y
0
4
100
Structured Memory
attention
Tree LSTM
Tree LSTM
.....
a_1
a_2
&&
||
>=
<
x
0
4
S_1
S_2
copy
copy
copy
S_T
a_T
STOP
Candidate solution
r_1
r_2
Early reward after each action
Continuous reward based on fraction of passing examples
$P \Rightarrow I$
$\{I \wedge B\}\, S\, \{I\}$
$I \wedge \neg B \Rightarrow Q$
r_T
success
fail
Counter examples
Theorem prover
Z3

Experimental evaluation

- We collect 133 benchmark programs

OOPSLA 2013, Dillig et al

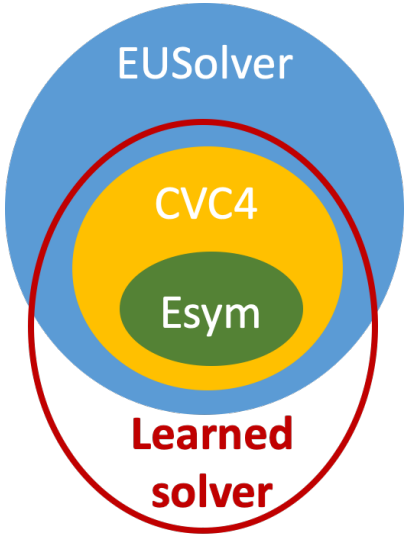
POPL 2016, Garag et al



Code and data: https://github.com/petablox/code2inv

Extension to program synthesis

- View a synthesis specification as a “program”
- Invariant generation is essentially program generation
- Initial results on 214 SyGuS tasks look promising



Thank you!

Q: how is the performance in term of running time?

- The running time for each solved instance takes up to 6 hours
  - All solvers have 6-hour limit (though other solvers tend to either solve an instance within 30 minutes or time out)
- Everything is done with a single thread CPU
- There is ***no training***, that is, each instance is solved from scratch (with randomly initialized weights)
  - View DRL as a smart search algorithm that evolves on the fly

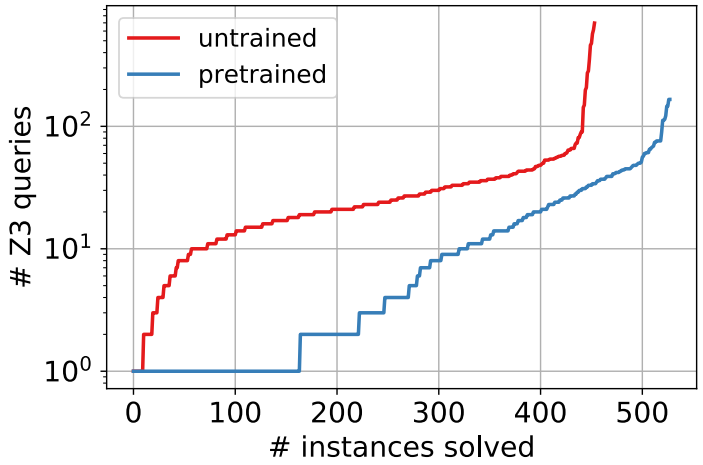
Q: how about the generation (suppose you do perform some pre-training)?

- We do not observe much generation across the collected benchmark, as they seem quite different from one to another.
  - Thus, pre-training does not help much
- We do have a generation study (see next two slides)

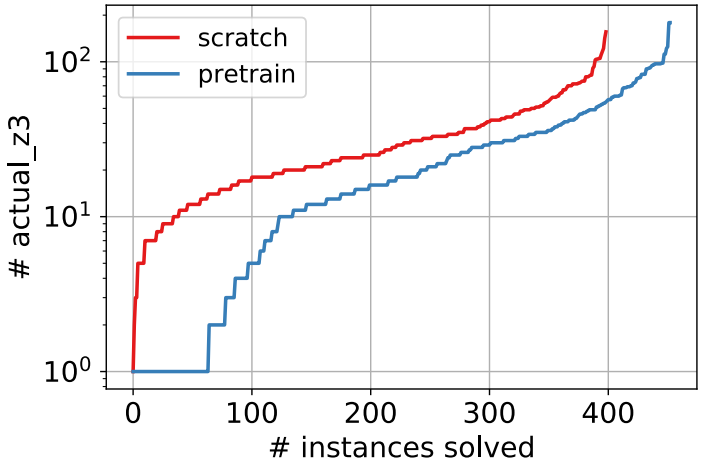
Generation study (injecting random statements)


```
void main (int n) {
    int x = 0
    int w = 0
    int m = 0
    int z = 0
    while (x < n) {
        z = z + 1
        if (unknown()) {
            m = x
            z = m + 1
        }
        x = x + 1
        w = m + x
    }
    if (n > 0) {
        assert (m < n)
    }
}
```

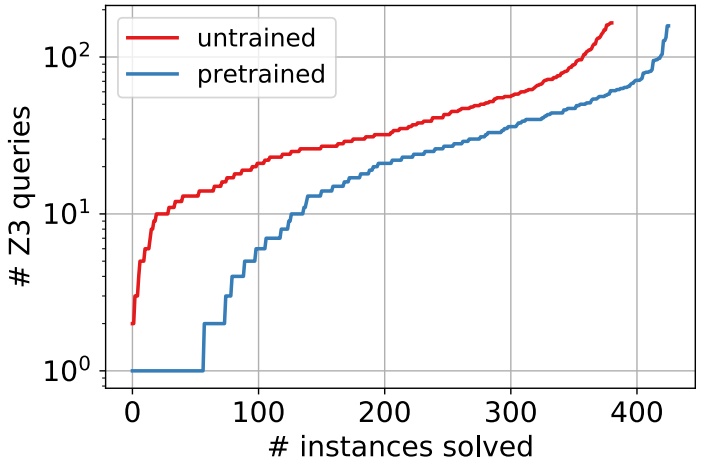
Generation study (evaluation)



1 confounding variable



3 confounding variables



5 confounding variables