DEEPCODER:
LEARNING TO WRITE PROGRAMS

Balog et. al. ICLR 2017

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CS 294 - 159
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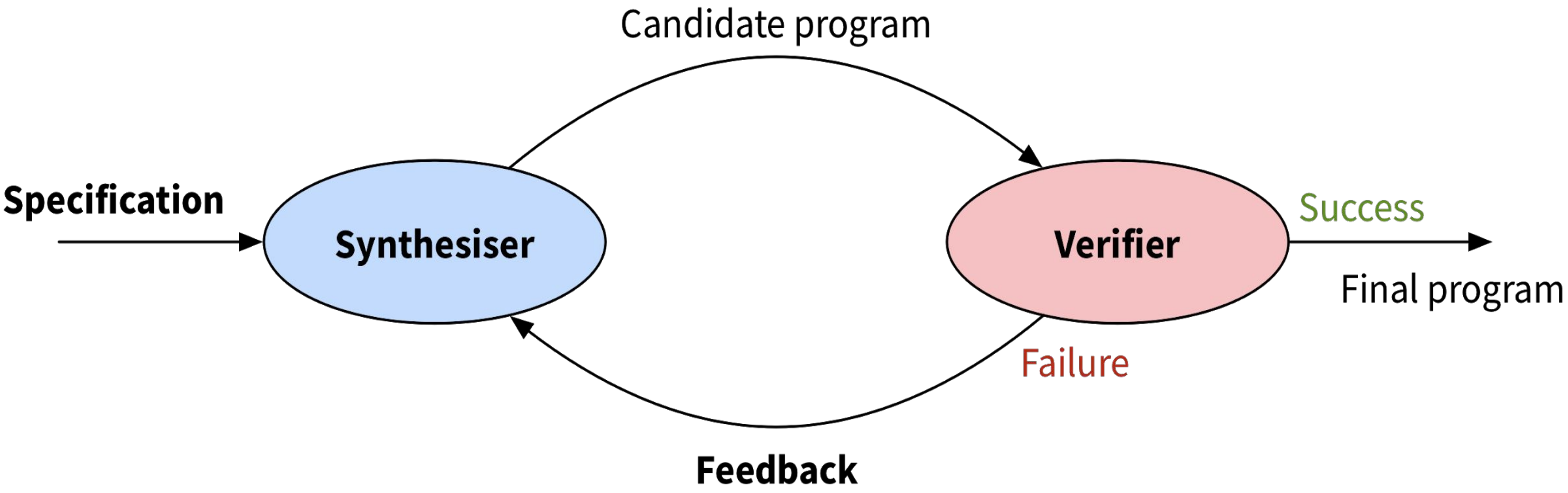
Outline

- Brief Overview: Program Synthesis
    - Components and Challenges
- Which does Deep Coder actually solve??
- Proposed Approach: Learning Inductive Program Synthesis (LIPS)
- Key Results
- Main Contribution
- Limitations
- Discussion

Brief Overview: Program Synthesis



Counter Example Guided Inductive Synthesis

Image Courtesy: https://homes.cs.washington.edu/~bornholt/post/synthesis-explained.html

Synthesis

- Typically search techniques are employed for the synthesis
    - Enumerative Search
        - Enumerate programs: typically from smaller to larger
        - Which order do we enumerate the programs ? **DeepCoder !!!**
    - Stochastic Search
        - Search landscape not smooth

```
t ← [int]
p ← [int]
c ← MAP (-1) t
d ← MAP (-1) p
e ← ZIPWITH (+) c d
f ← MINIMUM e
```

Proposed Approach: Learning Inductive Program Synthesis (LIPS)

- DSL and Attributes
- Data Generation
- Machine Learning Model
- Search

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Proposed Approach: Learning Inductive Program Synthesis (LIPS)

- **DSL and Attributes**
- Data Generation
- Machine Learning Model
- Search

- Expressive Enough so that it actually can solve the problem
- Restrictive Enough to limit search space

Proposed Approach: Learning Inductive Program Synthesis (LIPS)

- **DSL and Attributes**
- Data Generation
- Machine Learning Model
- Search

- **Attribute vector**
    - Maps the program to a vector
- Works as a link between the ML component and the search component

Proposed Approach: Learning Inductive Program Synthesis (LIPS)

- DSL and Attributes
- **Data Generation**
- Machine Learning Model
- Search

- Should be feasible to generate a large dataset
- Set of Programs in the DSL
- **Attribute Vectors**
- **Set of I/O examples**

Proposed Approach: Learning Inductive Program Synthesis (LIPS)

- DSL and Attributes
- Data Generation
- **Machine Learning Model**
- Search

- Learns a distribution over attribute vectors
- **P(Attribute Vectors |Set of I/O examples)**

Proposed Approach: Learning Inductive Program Synthesis (LIPS)

- DSL and Attributes
- Data Generation
- Machine Learning Model
- **Search**

- **P(Attribute Vectors|Set of examples)**
- Guided by the distribution learned by the model

Deep Coder: DSL

```
t ← [int]
p ← [int]
c ← MAP (-1) t
d ← MAP (-1) p
e ← ZIPWITH (+) c d
f ← MINIMUM e
```

```
x ← [int]
y ← [int]
c ← SORT x
d ← SORT y
e ← REVERSE d
f ← ZIPWITH (*) d e
g ← SUM f
```

First-order functions: HEAD, LAST, TAKE, DROP, ACCESS, MINIMUM, MAXIMUM, REVERSE, SORT, SUM
Higher-order Functions: MAP, FILTER, COUNT, ZIPWITH, SCANL1
Lambdas: (+1), (-1), (*2), (/2), (*(-1)), (**2), (*3), (/3), (*4), (/4) - map, (+), (-), (*), MIN, MAX - ZIPWITH, SCANL1
Predicates (>0), (<0), (%2==0), (%2==1)

Deep Coder: Attribute Vector

One-Hot Vector of the functions and lambdas

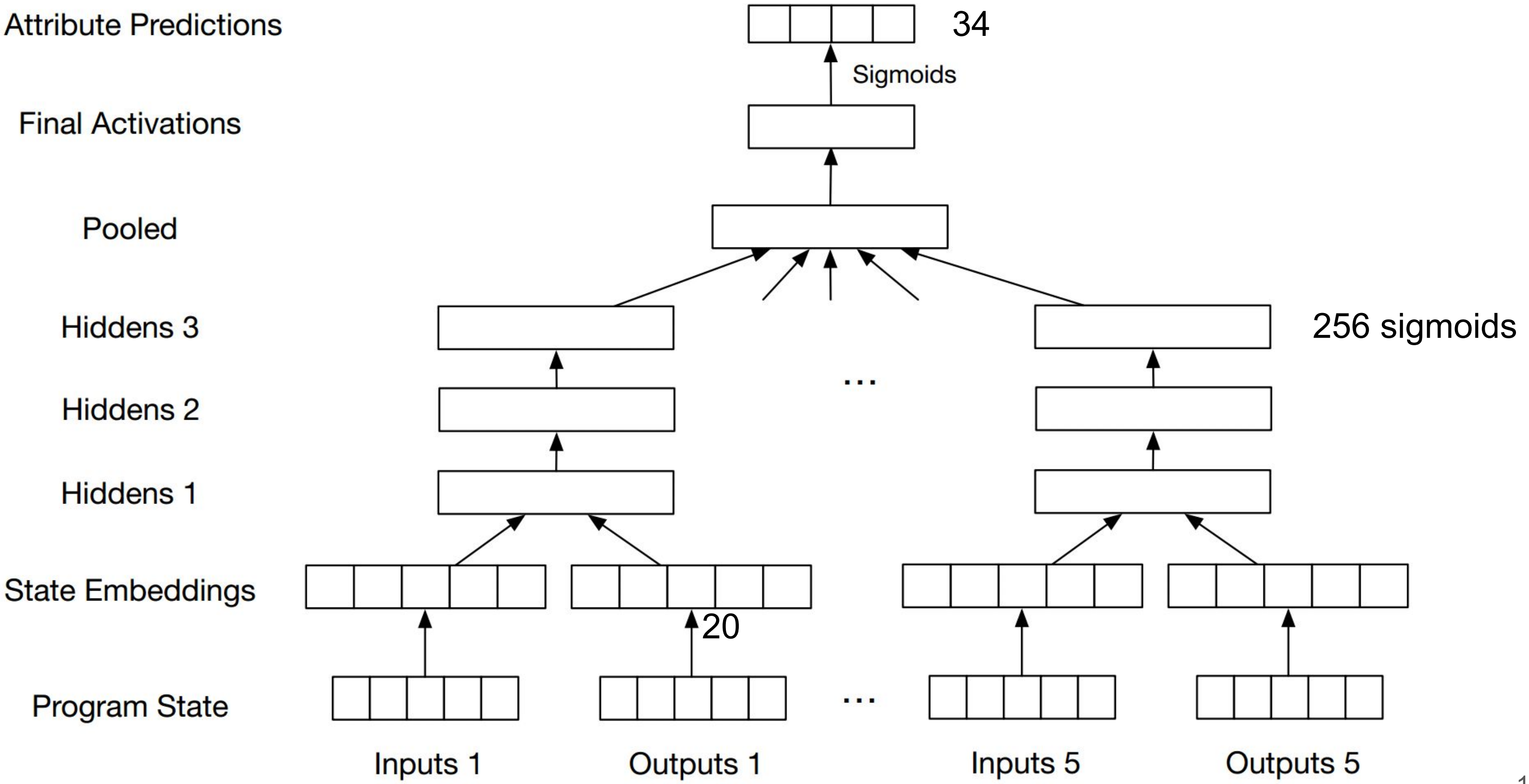
First-order functions: HEAD, LAST, TAKE, DROP, ACCESS, MINIMUM, MAXIMUM, REVERSE, SORT, SUM
Higher-order Functions: MAP, FILTER, COUNT, ZIPWITH, SCANL1
Lambdas: (+1), (-1), (*2), (/2), (*(-1)), (**2), (*3), (/3), (*4), (/4) - map, (+), (-), (*), MIN, MAX - ZIPWITH, SCANL1
Predicates (>0), (<0), (%2==0), (%2==1)

Deep Coder: Data Generation

- Synthetic Program Generation
    - Pruning
- Run programs to generate inputs from outputs

a ← [int]	**An input-output example:**
b ← FILTER (<0) a	*Input*:
c ← MAP (*4) b	[-17, -3, 4, 11, 0, -5, -9, 13, 6, 6, -8, 11]
d ← SORT c	*Output*:
e ← REVERSE d	[-12, -20, -32, -36, -68]

Deep Coder: ML Model



Deep Coder: Search Component

- Depth-first search ~ 3 × 10^6 programs per second with caching
- “Sort and add” enumeration
- Sketch
- λ^2

Key Results

Timeout needed	DFS			Enumeration			λ^2
to solve	20%	40%	60%	20%	40%	60%	20%
Baseline	$163s$	$2887s$	$6832s$	$8181s$	$>10^4 s$	$>10^4 s$	$463s$
DeepCoder	$24s$	$514s$	$2654s$	$9s$	$264s$	$4640s$	$48s$
Speedup	**6.8×**	**5.6×**	**2.6×**	**907×**	**>37×**	**>2×**	**9.6×**

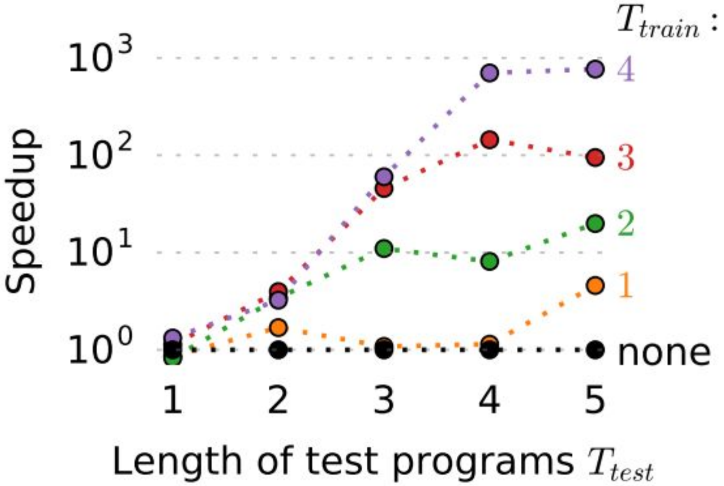
- Baseline: Simple Prior as Function Probabilities
- Training Programs: length 1 to 4
- 100: Test Programs length 5 (Search Space in the order of 10^10)

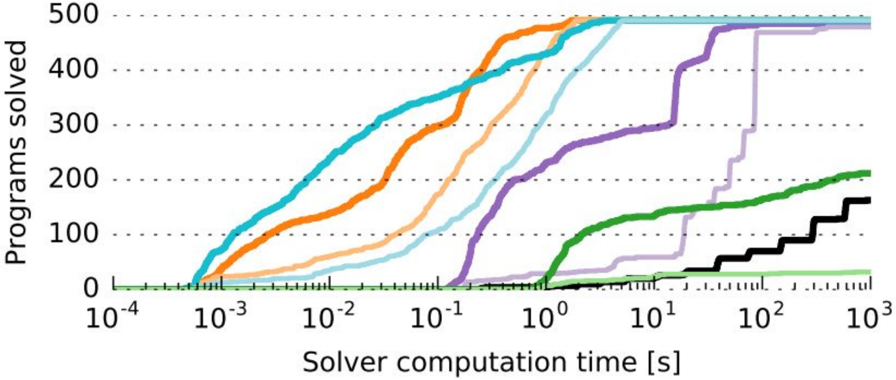
Key Results

- RNN Encoder and Decoder: Beam search was used to explore likely programs predicted by the RNN

- Solution comparable with the other techniques when searching for programs of lengths $T \leq 2$
  - where the search space size is very small (on the order of 10^3).

Other Results





- DFS: using neural network
- DFS: using prior order
- L2: Sort and add using neural network
- L2: Sort and add in prior order
- Enumeration: Sort and add using neural network
- Enumeration: Sort and add in prior order
- Beam search
- Sketch: Sort and add using neural network
- Sketch: Sort and add in prior order

Main Contribution & Impact

Neural-Guided Search

- Using weak supervision to guide-search in the program space
- Can be used as a component of the existing framework

Possible Improvements/Limitations

- Very restricted problem domain
- Learns distribution over input data
  - Can not utilizes/condition on partial/intermediate programs as it generates
- Does not learn anything about function order/dependency
- No notion of how good the found program is/ no sense of program ranking
  - The problem is under-specified
  - There may be more than one program that may conform the I/O
    - The returned program may not be the one the user wants
- Learning Longer Programs with Loops/ Conditionals

Discussion

- End-to-end Deep Program Synthesis vs. Neural-Guided Search
- Deep Learning + Stochastic Search ??
- Using Natural Language as specification and encode ?
- Explainability & Program Synthesis
- Detecting wrong predictions and back-track ?

Some Useful Papers/Blog Posts

- Program Synthesis in 2017-18 by Alex Polozov: https://alexpolozov.com/blog/program-synthesis-2018/

- Program Synthesis Basics: https://homes.cs.washington.edu/~bornholt/post/synthesis-explained.html

- Open Review: https://openreview.net/forum?id=ByldLrqlx
- Neuro-Symbolic Program Synthesis. Emilio Parisotto , Abdel-rahman Mohamed , Rishabh Singh , Lihong Li , Dengyong Zhou, Pushmeet Kohli
  - End-to-end Synthesis, RNN based