Neural Symbolic Machines

Semantic Parsing on Freebase with Weak Supervision

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- Motivation: Semantic Parsing and Program Induction
- Neural Symbolic Machines
 - Key-Variable Memory
 - Code Assistance
 - Augmented REINFORCE
- Experiments and analysis

Semantic Parsing: Language to Programs



[Berant, et al 2013; Liang 2013]

Weak supervision (easy to collect)

Question Answering with Knowledge Base



WebQuestionsSP Dataset

- 5,810 questions Google Suggest API & Amazon MTurk¹
- Remove invalid QA pairs²
- 3,098 training examples, 1,639 testing examples remaining
- Open-domain, and contains grammatical error
- Multiple entities as answer => macro-averaged F1

Grammatical error

Multiple entities

- What do Michelle Obama do for a living?
- What character did Natalie Portman play in Star Wars?
- What currency do you use in Costa Rica?
- What did Obama study in school?
- What killed Sammy Davis Jr?

writer, lawyer Padme Amidala Costa Rican colon political science throat cancer

(Scalable) Neural Program Induction

• Impressive works to show NN can learn addition and sorting, but...



Output



RESET

observation

• The learned operations are not as scalable and precise.



 Why not use existing modules that are scalable, precise and interpretable?





I'm Feeling Lucky

Google Search

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Neural Symbolic Machines



Simple Seq2Seq model is not enough



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Key-Variable Memory for Compositionality



• A linearised bottom-up derivation of the recursive program.



Key-Variable Memory: Save Intermediate Value



Key-Variable Memory: Reuse Intermediate Value



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Code Assistance: Prune Search Space



Pen and paper

Code Assistance: Syntactic Constraint



Decoder Vocab

Code Assistance: Syntactic Constraint



Decoder Vocab

Code Assistance: Semantic Constraint



Code Assistance: Semantic Constraint



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REINFORCE Training



Iterative Maximum Likelihood Training (Hard EM)

$$J^{ML}(\theta) = \sum_{q} \log P(a_{0:T}^{best}(q)|q,\theta)$$

Augmented REINFORCE

stabilize training

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Distributed Architecture

• 200 actors, 1 learner, 50 Knowledge Graph servers

Generated Programs

- Question: "what college did russell wilson go to?"
- Generated program:

```
(hop v1 /people/person/education)
(hop v2 /education/education/institution)
(filter v3 v0 /common/topic/notable_types )
<EOP>
```

In which

• Distribution of the length of generated programs

#Expressions	0	1	2	3
Percentage	0.4%	62.9%	29.8%	6.9%
<i>F1</i>	0.0	73.5	59.9	70.3

New State-of-the-Art on *WebQuestionsSP*

- First end-to-end neural network to achieve SOTA on semantic parsing with weak supervision over large knowledge base
- The performance is approaching SOTA with full supervision

Model	Avg. Prec.@1	Avg. Rec.@1	Avg. F1@1	Acc.@1
STAGG	67.3	73.1	66.8	58.8
NSM – our model	70.8	76.0	69.0	59.5
STAGG (full supervision)	70.9	80.3	71.7	63.9

Augmented REINFORCE

- REINFORCE get stuck at local maxima
- Iterative ML training is not directly optimizing the F1 score
- Augmented REINFORCE obtains the best performances

Settings	Train Avg. F1@1	Valid Avg. F1@1
iterative ML only	68.6	60.1
REINFORCE only	55.1	47.8
Augmented REINFORCE	83.0	67.2

Thanks!