Semantic Parsing with Dual Learning

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Ruisheng Cao*, Su Zhu*, Chen Liu, Jieyu Li and Kai Yu





MoE Kev Lab of Artificial Intelligence SpeechLab, Department of Computer Science and Engineering Shanghai Jiao Tong University, Shanghai, China

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Outline

Introduction and Motivation

Dual Learning Framework for Semantic Parsing

Experimental Results

Conclusion

What is Semantic Parsing

```
Question: show me all flights from washington
                                                semantic
Logical form:
                                                 parsing
  (lambda $0 e (and
      (from $0 washington: ci) (flight $0))
                        Execution
                                      Knowledge Base
                     results
                                           (KB)
```

Bottlenecks 1: data hungry

• Semantic annotation is labor-intensive and time-consuming

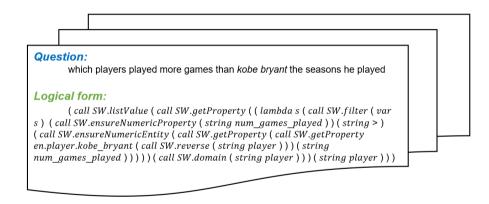


Figure: Training example from dataset OVERNIGHT

Bottlenecks 2: constrained decoding

Output space should be strictly constrained

Question:

show me all flights from washington

```
Correct logical form:
 lambda $0 e ( and ( from $0 washington:ci ) ( flight $0 ) ) )
Frror at structure level:
                                     missing parentheses
 lambda $0 e ( and ( from $0 washington:ci ( flight $0 ) ) )
Error at semantic level:
                            not type flight
 lambda $0 e ( and ( from washington:ci | $0 ) ( flight $0 ) )
```

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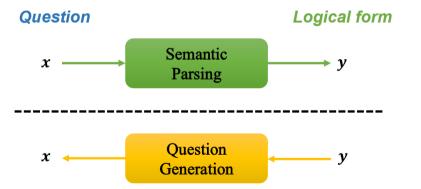
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Our method: Overview

 $\boldsymbol{\mathcal{X}}$: show me all flights from washington

y: (lambda \$0 e (and (from \$0 washington:ci) (flight \$0)))



Our method: Overview

 \boldsymbol{x} : raw input question

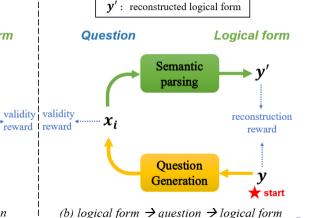
 y_i : intermediate logical form

x': reconstructed question

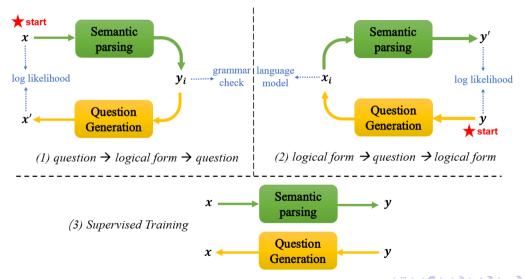
y: raw input logical form x_i : intermediate question

.

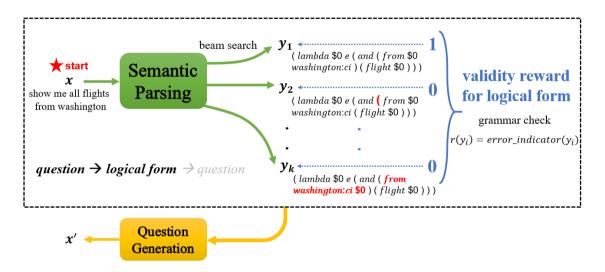
Question Logical form *start Semantic parsing reconstruction reward **Ouestion** Generation (a) question \rightarrow logical form \rightarrow question



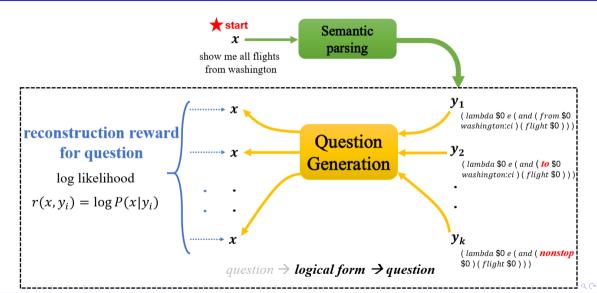
Training Procedure: 3 stages



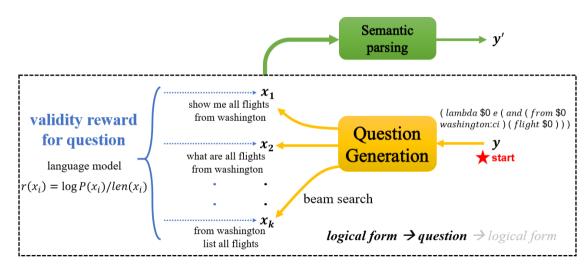
1. loop starts from question



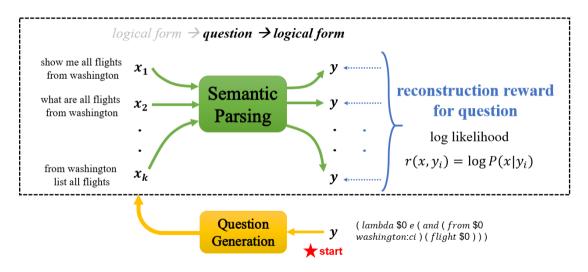
1. loop starts from question



2. loop starts from logical form



2. loop starts from logical form



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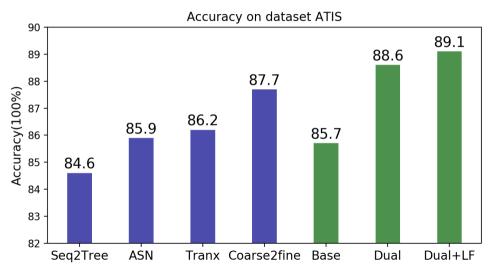
Synthesize more logical forms

Sampling and modification based on ontology (4592 more logical forms for ATIS)

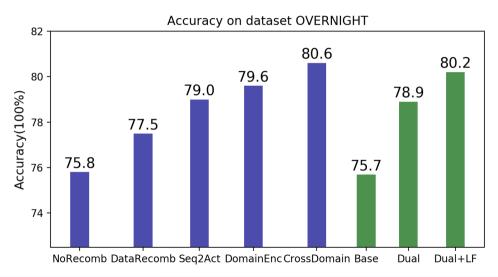
```
1. (lambda $0 e (and (flight $0) (class type $0
  first:cl) ( from $0 ci0) ( to $0 ci1)))
2. (lambda $0 e (and (flight $0) (oneway $0) (from
  $0 ci0) (to $0 ci1)))
                            secification D
             first:cl.type = coach:cl.type
         one way.args0 = round trip.args0
                           entity/predicate replacement
 1. (lambda $0 e (and (flight $0)) (class type $0
   coach:cl) ( from $0 ci0) ( to $0 ci1)))
 2. (lambda $0 e (and (flight $0) (round trip $0) (
   from $0 ci0) (to $0 ci1)))
```

Directly revise grammar rules on OVERNIGHT (500 more logical forms on avg)

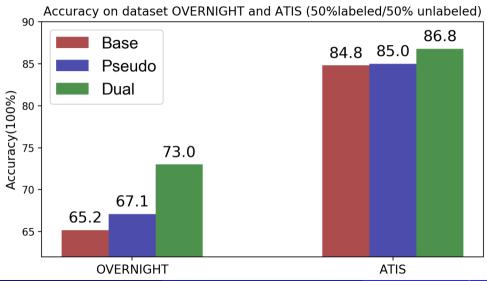
Results: ATIS



Results: OVERNIGHT



Semi-supervised experiment: 50%labeled/50%unlabeled



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Core idea

Leverage query generation model and obtain effective feedback signals to enhance the semantic parsing process.

- Semantic parsing framework based on dual learning algorithm
- Utilize both labeled and unlabeled samples
- Implicit constraint signal incorporated into reward

Thanks & QA

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References I



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Neural semantic parsing over multiple knowledge-bases.

In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 623–628.



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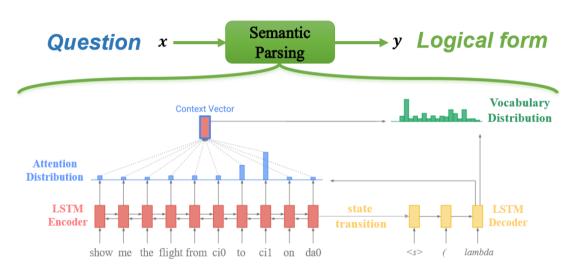
Data recombination for neural semantic parsing. arXiv preprint arXiv:1606.03622.



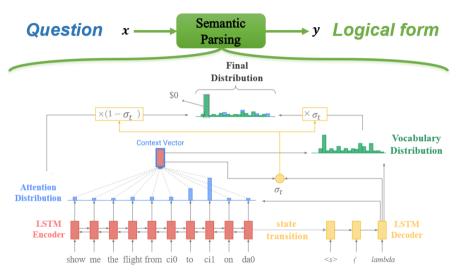
Su. Y. and Yan, X. (2017).

Cross-domain semantic parsing via paraphrasing. arXiv preprint arXiv:1704.05974.

Baseline Model: Att

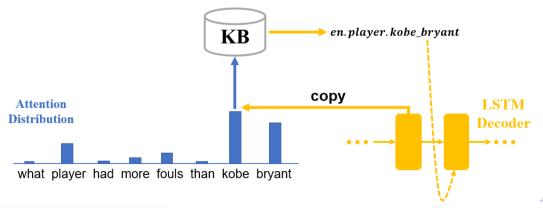


Baseline Model: AttPtr



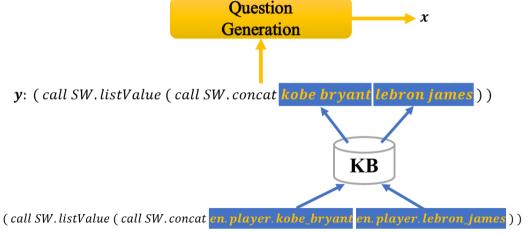
Semantic Parsing (Entity Mapping)

- Entities are identified by Universal Resource Identifier(URI) in Knowledge Base(KB)
 kobe bryant → en.player.kobe_bryant
- After copying, map words to corresponding URI

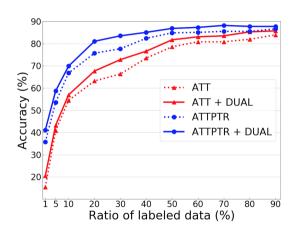


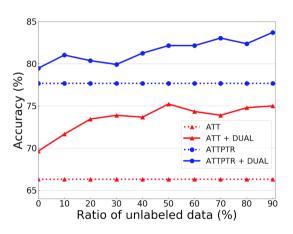
uestion Generation (Reverse Entity Mapping)

Reversely map KB entity to possible noun phrase before QG



Semi-supervised: vary ratio between labeled and unlabeled data





- unlabeled data = train set labeled data
- labeled data = 30%, fixed

Different choice for logical form validity reward

Method	Validity	ATIS	Overnight
Атт	LM_{lf}	80.6	71.5
+ Dual	grammar check	81.7	72.9
ATTPTR	LM_{lf}	86.2	71.4
+ Dual	grammar check	86.8	73.0

- labeled data = 50%, unlabeled data = 50%
- LM_{If} means using a logical form language model for validity reward
- "grammar check" means using the structure and semantic check