Learning Context-dependent Mappings from Sentences to Logical Form

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Show me flights from New York to Singapore.

Which of those are nonstop?

Show me the cheapest one.

Show me flights from New York to Singapore. $\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SIN)$

Which of those are nonstop?

Show me the cheapest one.

Show me flights from New York to Singapore. $\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SIN)$

Which of those are nonstop? $\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SIN) \wedge nonstop(x)$

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Which of those are nonstop? $\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SIN) \wedge nonstop(x)$

Show me the cheapest one. $argmax(\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SIN) \wedge nonstop(x),$ $\lambda y.cost(y))$

Show me flights from New York to Singapore. $\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SIN)$

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A Supervised Learning Problem

Training Examples: sequences of sentences and logical forms

```
Show me flights from New York to Seattle.
\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SEA)
```

```
List ones from Newark on Friday.
\lambda x.flight(x) \wedge from(x, NEW) \wedge to(x, SEA) \wedge day(x, FRI)
```

```
Show me the cheapest.
```

```
argmax(\lambda x.flight(x) \wedge from(x,NEW) \wedge to(x,SEA) \wedge day(x,FRI), \\ \lambda y.cost(y))
```

A Supervised Learning Problem

Goal: Find a function f

λx.flight(x) \Lambda to(x,SEA)
\Lambda from(x,NEW) \Lambda day(x,FRI)

Show me the cheapest?



 $argmax(\lambda x.flight(x) \wedge from(x,NEW) \wedge to(x,SEA) \wedge day(x,FRI), \\ \lambda y.cost(y))$

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Show me the cheapest?



 $argmax(\lambda x.flight(x) \wedge from(x,NEW) \wedge to(x,SEA) \wedge day(x,FRI), \\ \lambda y.cost(y))$

Key Challenges:

- Structured input and output (lambda calculus)
- Hidden variables (only annotate final logical forms)

Talk Outline

- Sketch of the Approach
- Context-sensitive Derivations
- A Learning Algorithm
- Evaluation

Show me flights from New York to Seattle. $\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SEA)$

List ones from Newark on Friday.

Context:

Current sentence:

List ones from Newark on Friday.

Context:

Current sentence:

List ones from Newark on Friday.

Context:

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List ones from Newark on Friday.



 $\lambda x.! f(x) \wedge from(x, NEW) \wedge day(x, FRI)$



Context:

Current sentence:

List ones from Newark on Friday.



 $\lambda x.! f(x) \wedge from(x, NEW) \wedge day(x, FRI)$

Context:

Current sentence:

List ones from Newark on Friday.



 $\lambda x.!f(x) \wedge from(x, NEW) \wedge day(x, FRI)$

Step 1: Context-independent parse Step 2: Resolve reference



 $\lambda x.flight(x) \wedge to(x,SEA)$

Step I: Context-independent parse
Step 2: Resolve reference



Step 1: Context-independent parse Step 2: Resolve reference

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Derivations



Three step process:

- •Step I: Context-independent parsing
- Step 2: Resolve all references
- Step 3: Optionally, perform an elaboration

Derivations



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List	flights	to	Singapore
S/N	N	(N\N)/NP	NP
$\lambda f.f(x)$	$\lambda x.flight(x)$	$\lambda y. \lambda f. \lambda x. f(x) \land to(x, y)$	sin
		N/I	1
		$\lambda f. \lambda x. f(x) \land$	to(x,sin)
	N		
	λχ	$flight(x) \wedge to(x)$	sin)
		S	

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			1
		$\lambda f. \lambda x. f(x) \land$	to(x,sin)
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		$\lambda f. \lambda x. f(x) \land$	to(x,sin)
	N		
	λχ	$flight(x) \wedge to(x)$	sin)
		S	

Step I: Referential lexical items

List ones from Newark on Friday.



 $\lambda x.! f(x) \wedge from(x, NEW) \wedge day(x, FRI)$

Step I: Referential lexical items

List ones from Newark on Friday.



 $\lambda x.! f(x) \wedge from(x, NEW) \wedge day(x, FRI)$

First extension:

Add referential lexical items



Second extension:

Add type-shifting operators for elliptical expressions

the cheapest

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NP/N

 $\lambda g.argmin(g, \lambda y.cost(y))$

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NP/N

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NP

 $argmin(\lambda x.!f(x), \lambda y.cost(y))$

Second extension:

Add type-shifting operators for elliptical expressions

the cheapest

NP/N

 $\lambda g.argmin(g, \lambda y.cost(y))$

NP argmin(λx . ! f(x), λy . cost(y))

A/B : $g \Rightarrow A$: $g(\lambda_X.!f(x))$ where g is a function with input type <e, t>

Derivations



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Derivations



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Step 2: Resolving References



For each reference:

- Select an expression from the context
- Substitute into current analysis
For each logical form in context, enumerate e and <e, t> type subexpressions:

Context:

λx.flight(x) ^ to(x,SEA)
^ from(x,NEW) ^ day(x,FRI)

argmax(λx.flight(x)∧to(x,SEA) ∧ from(x,BOS), λy.depart(y))

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Context:











Step 2: Resolving References



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Derivations



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Derivations



Three step process:

- •Step I: Context-independent parsing
- Step 2: Resolve all references

Step 3: Optionally, perform an elaboration

Show me the latest flight from New York to Seattle. $argmax(\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SEA),$ $\lambda y.time(y))$

on Friday $argmax(\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SEA) \wedge day(x,FRI),$ $\lambda y.time(y))$

argmax(λx.flight(x) \Lambda to(x,SEA) \Lambda
from(x,NYC),
\Lambda y.time(y))













 $argmax(\lambda x.flight(x) \wedge from(x,NYC) \wedge to(x,SEA) \wedge day(x,FRI), \\ \lambda y.time(y))$



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Possible elaborations:

- Potentially expand any embedded variable
- Can do deletions on elaboration function

Derivations



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Scoring Derivations

Scoring Derivations

Weighted linear model:

- •Introduce features: f(d)
- •Compute scores for derivations: $w \cdot f(d)$

- Distance indicators, for integers (0,1,2,...)
- Copy indicators, for all predicates {flight, from, to, ...}
- Deletion indicators, for all pairs of predicates {(from, flight), (from, from), (from, to), ...}

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Parsing features: set from Zettlemoyer and Collins (2007) Context features:

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Inference and Learning

Two computations:

- Best derivation: $d^* = \arg \max_d w \cdot f(d)$
- Best derivation with final logical form z:

$$d' = \arg \max_{d \ s.t. \ L(d)=z} w \cdot f(d)$$

We use a beam search algorithm.

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Learning:

 Hidden variable version of the structured perceptron algorithm [Liang et al., 2006] [Zettlemoyer & Collins, 2007]

Computation:

For t = 1...T, i = 1...n: (Iterate interactions) Set $C = \{\}$ (Reset Context) For $j = 1...n_i$: (Iterate training examples)

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• If correct:
$$L(d^*) == z_{i,j}$$
, go to the Step 3.

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Step 3: Update context: Append $z_{i,j}$ to C Output: Parameters w.

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Step 2: Update Parameters

• Find best correct analysis: $d' = \arg \max_{\substack{d \ s.t. \ L(d) = z_{i,i}}} w \cdot f(d)$

• Update parameters: $w = w + f(d') - f(d^*)$

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Evaluation

- Domain: ATIS travel database queries
 - 399 training interactions (3813 sentences)
 - 127 test interactions (826 sentences)
- Comparison: previous state-of-the-art [Miller et al. 1996]
 - requires full annotation of all syntactic, semantic, and context-resolution decisions
 - decision tree learning

The Miller et al. [1996] Approach



Figure 2: A sample parse tree.

Step 3: Optionally copy slot values from previous frames

Evaluation

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- Metric: accuracy recovering fully correct meanings

Evaluation

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- Comparison: previous state-of-the-art [Miller et al. 1996]
- Metric: accuracy recovering fully correct meanings
- Result: improved accuracy
 - 78.4% => 83.7%
 - less engineering effort: only annotated final meanings

Varying the Length of a Context Window M

ATIS Development Set:

Context Length	Accuracy
<i>M</i> =0	45.4
M=1	79.8
<i>M</i> =2	81.0
M=3	82.I
<i>M</i> =4	81.6
M=10	81.4

Example Learned Feature Weights

Negative weights:

• Distance features: (1,2,3,...)

Positive weights:

- Copy features: flight, from, to
- •Deletion features:(from, from),
 (nonstop, connect),
 (during-day, time)

Summary



 $argmax(\lambda x.flight(x) \wedge from(x,NEW) \wedge to(x,SEA) \wedge day(x,FRI), \\ \lambda y.cost(y))$

Key challenges:

• Structured input and output, hidden structure not annotated

Solution:

- Analysis: two-stage approach
- Learn: how to incorporate meaning from the context

The End