

Learning From and About Context in Semantic Parsing

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Mapping Sentences to Meaning

Texas borders Kansas.

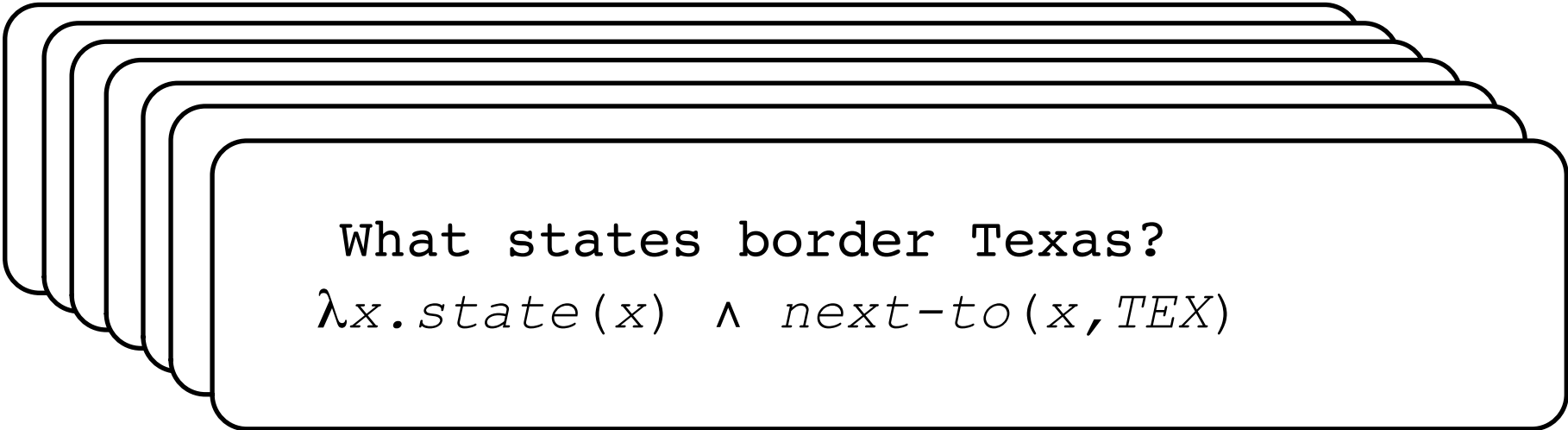
next-to(TEX, KAN)

Mapping Sentences to Meaning

What states border Texas?

$\lambda x. state(x) \wedge next-to(x, TEX)$

Mapping Sentences to Meaning



What states border Texas?
 $\lambda x. state(x) \wedge next-to(x, TEX)$

Machine Learning Problem

Given: Many input, output pairs

Learn: A function that maps sentences to lambda-calculus expressions

More Examples

Input: What is the largest state?

Output: $\text{argmax}(\lambda x. \text{state}(x), \lambda y. \text{size}(y))$

Input: What states border the largest state?

Output: $\lambda z. \text{state}(z) \wedge \text{borders}(z, \text{argmax}(\lambda x. \text{state}(x), \lambda y. \text{size}(y)))$

Input: What states border states that border states ... that border Texas?

Output: $\lambda x. \text{state}(x) \wedge \exists y. \text{state}(y) \wedge \exists z. \text{state}(z) \wedge \dots \wedge \text{borders}(x, y) \wedge \text{borders}(y, z) \wedge \text{borders}(z, \text{texas})$

Related Work

Supervised semantic parsing with:

Machine Translation

[Papineni et al. 2007; Wong, Mooney 2006,
2007; Matuszek et al. 2010]

Inducting Logic Programming

[Zelle, Money 1996; Tang, Mooney 2000;
Thompson, Mooney 2002]

Prob. CFG Parsing

[Miller et al. 2006; Ge, Mooney 2006]

Prob. PDA

[He, Young 2005, 2006]

Support Vector Machines

[Kate, Mooney 2006; Nguyen et al. 2006]

Perceptron-style Learning

[Zettlemoyer, Collins 2005, 2007]

Higher-order unification

[Kwiatkowski 2010,2011]

Less supervision:

Question-Answers Semi-supervision

[Clarke et al. 2010, Liang et al. 2011]

Confidence-driven Unsupervised

[Goldwasser et al. 2011]

Learning from Natural Instructions

[Goldwasser and Roth, 2011]

Learning from Conversations

[Artzi and Zettlemoyer, 2011]

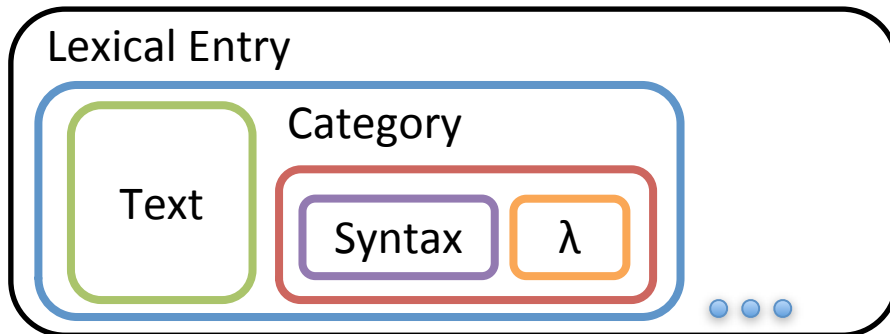
Talk Outline

- Representing and recovering meaning with CCG
- Learning context-dependent semantic analyses
- Learning from conversations with no meaning annotations

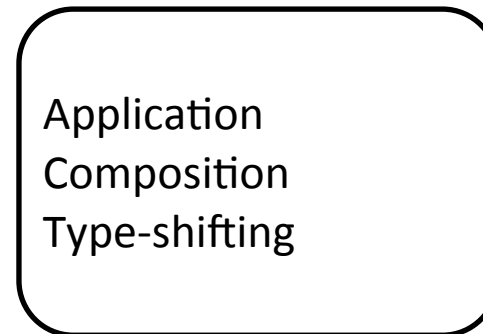
Parsing with CCGs

i'd like to go	from	seattle	to	denver
S/N	$(N \setminus N)/NP$	NP	$(N \setminus N)/NP$	NP
$\lambda f.f$	$\lambda y.\lambda f.\lambda x.f(x) \wedge from(x, y)$	SEA	$\lambda y.\lambda f.\lambda x.f(x) \wedge to(x, y)$	DEN
	$(N \setminus N)$	$\lambda f.\lambda x.f(x) \wedge from(x, SEA)$	$(N \setminus N)$	$\lambda f.\lambda x.f(x) \wedge to(x, DEN)$
	$N \setminus N$		$\lambda f.\lambda x.f(x) \wedge from(x, SEA) \wedge to(x, DEN)$	
	N		$\lambda x.from(x, SEA) \wedge to(x, DEN)$	
	S		$\lambda x.from(x, SEA) \wedge to(x, DEN)$	

Lexicon



Combinators

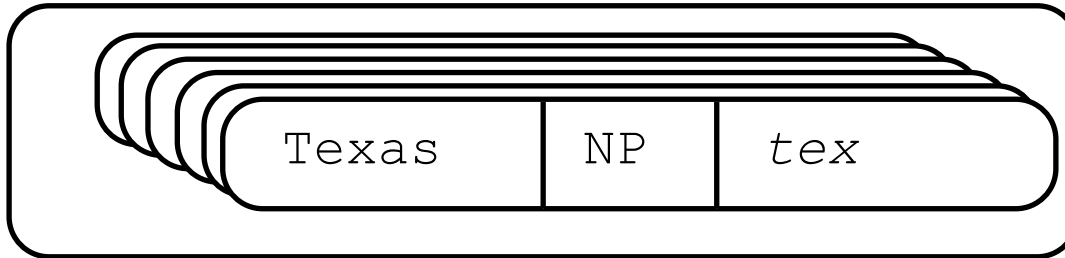


[Steedman 96,00]

Probabilistic CCGs

Lexicon:

$\Lambda =$



Parameters:

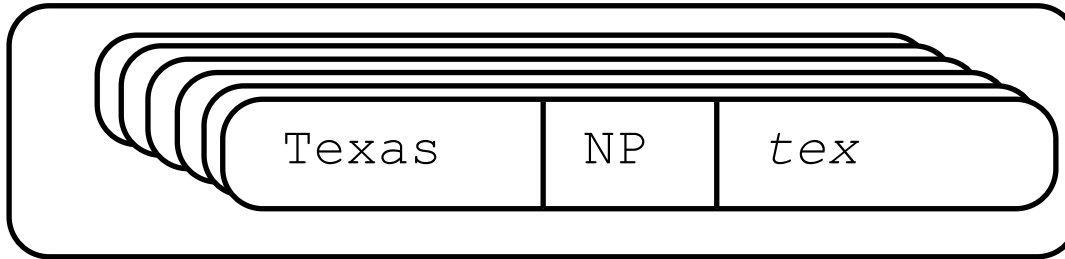
, θ

Probabilistic CCGs

Lexicon:

Parameters:

$\Lambda =$



, θ

Probability distribution: sentence x , parse y , logical form z

- Log-linear model:

$$P(y, z|x; \theta, \Lambda) = \frac{e^{\theta \cdot \phi(x, y, z)}}{\sum_{(y', z')} e^{\theta \cdot \phi(x, y', z')}}$$

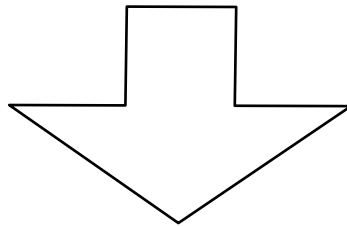
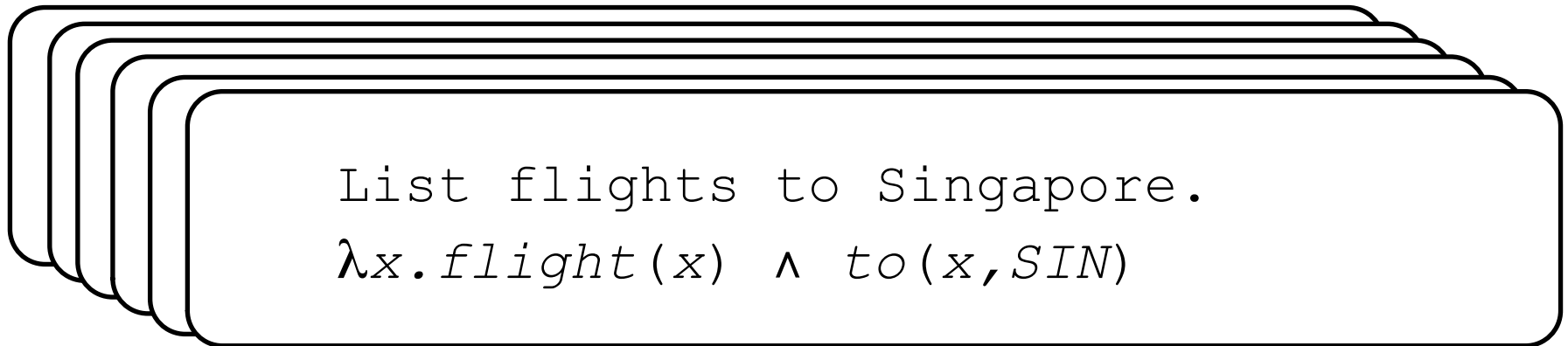
- Parsing:

$$f(x) = \arg \max_z p(z|x; \theta, \Lambda)$$

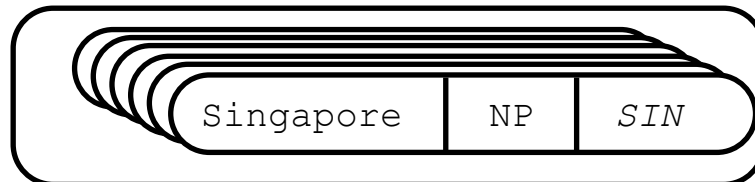
$$\text{where } p(z|x; \theta, \Lambda) = \sum_y p(y, z|x; \theta, \Lambda)$$

Background: Context-independent Learning

Training Examples:



CCG Lexicon:



Parameters:

, w

A Multilingual Learning Algorithm

Key challenge: learn from data with different natural languages and meaning representations

English, logical-form:

NL: what states border texas

MR: $\lambda x. state(x) \wedge next_to(x, tex)$

Turkish, functional query language:

NL: texas a siniri olan eyaletler nelerdir

MR: $answer(state(next_to_2(stateid\ tex)))$

A Multilingual Learning Algorithm

Key challenge: learn from data with different natural languages and meaning representations

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Turkish, functional query language:

NL: texas a siniri olan eyaletler nelerdir

MR: $answer(state(next_to_2(stateid\ tex)))$

Approach: use higher-order unification to recursively split the input LF

Example Learned Lexical Entries

English	Turkish
<p>population of $\vdash NP/NP : \lambda x.population(x)$ smallest $\vdash NP/(S NP) : \lambda f.arg\ min(y, f(y), size(y))$ what $\vdash S NP/(S NP) : \lambda f\lambda x.f(x)$ border $\vdash S NP/NP : \lambda x\lambda y.next_to(y, x)$ state $\vdash S NP : \lambda x.state(x)$ most $\vdash NP/(S NP)\ (S NP)\ (S NP NP) :$ $\lambda f\lambda g\lambda h\lambda x.argmax(y, g(y), count(z, f(z, y) \wedge h(z)))$</p>	<p>nedir $\vdash S\ NP\ \backslash\ (NP NP) : \lambda f\lambda x.f(x)$ sehir $\vdash S NP : \lambda x.city(x)$ nufus yogunlugu $\vdash NP NP : \lambda x.density(x)$ siniri $\vdash S NP/NP : \lambda x\lambda y.next_to(y, x)$ kac tane $\vdash S\ NP\ \backslash\ (S NP NP)\ \backslash\ (S NP) :$ $\lambda f\lambda g\lambda x.count(y, f(y) \wedge g(y, x))$ ya siniri $\vdash S NP\ \backslash\ NP : \lambda x\lambda y.next_to(y, x)$</p>
Japanese	Spanish
<p>no $\vdash NP NP/(NP NP) : \lambda f\lambda x.f(x)$ shuu $\vdash S NP : \lambda x.state(x)$ nan desu ka $\vdash S\ NP\ \backslash\ (NP NP) : \lambda f\lambda x.f(x)$ wa $\vdash NP NP\ \backslash\ (NP NP) : \lambda f\lambda x.f(x)$ ikutsu $\vdash NP (S NP)\ \backslash\ (S NP (S NP)) :$ $\lambda f\lambda g.count(x, f(g(x)))$ chiiki $\vdash NP\ \backslash\ NP : \lambda x.area(x)$</p>	<p>en $\vdash S NP/NP : \lambda x\lambda y.loc(y, x)$ que es la $\vdash S/NP/(NP NP) : \lambda f\lambda x.f(x)$ pequena $\vdash NP\ \backslash\ (S NP)\ \backslash\ (NP NP) :$ $\lambda g\lambda f.arg\ min(y, f(y), g(y))$ estado $\vdash S NP : \lambda x.state(x)$ mas $\vdash S\ \backslash\ (S NP)\ \backslash\ (S NP)\ \backslash\ (NP NP (S NP)) :$ $\lambda f\lambda g\lambda h.argmax(x, h(x), f(g, x))$ mayores $\vdash S NP\ \backslash\ (S NP) : \lambda f\lambda x.f(x) \wedge major(x)$</p>

Learning Context-dependent Mappings from Sentences to Logical Form

[Zettlemoyer & Collins, ACL 2009]

Context-dependent Analysis

Show me flights from New York to Singapore.

Which of those are nonstop?

Show me the cheapest one.

What about connecting?

Context-dependent Analysis

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.

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Context-dependent Analysis

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$\lambda x. flight(x) \wedge from(x, NYC) \wedge to(x, SIN)$

Which of those are nonstop?

$\lambda x. flight(x) \wedge from(x, NYC) \wedge to(x, SIN) \wedge nonstop(x)$

Show me the cheapest one.

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Context-dependent Analysis

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Which of those are nonstop?

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Show me the cheapest one.

$argmax(\lambda x. flight(x) \wedge from(x, NYC) \wedge to(x, SIN) \wedge nonstop(x),$
 $\lambda y. cost(y))$

What about connecting?

Context-dependent Analysis

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Show me the cheapest one.

$argmax(\lambda x. flight(x) \wedge from(x, NYC) \wedge to(x, SIN) \wedge nonstop(x),$
 $\lambda y. cost(y))$

What about connecting?

$argmax(\lambda x. flight(x) \wedge from(x, NYC) \wedge to(x, SIN) \wedge connect(x),$
 $\lambda y. cost(y))$

A Supervised Learning Problem

Each training example:
a sequence 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

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

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

Show me the cheapest?

F

$argmax(\lambda x. flight(x) \wedge from(x, NEW) \wedge to(x, SEA) \wedge day(x, FRI),$
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[Zettlemoyer & Collins, 2009]

A Supervised Learning Problem

Goal: Find a function F

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$\lambda x. flight(x) \wedge to(x, SEA)$
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Show me the cheapest?

F

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

Key Challenges:

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

[Zettlemoyer & Collins, 2009]

An Example Analysis

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.

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An Example Analysis

Context:

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

Current sentence:

List ones from Newark on Friday.

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Step 1: Context-independent parse

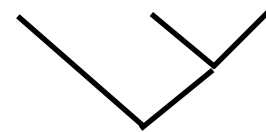
An Example Analysis

Context:

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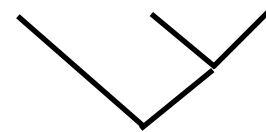
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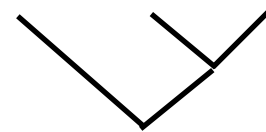
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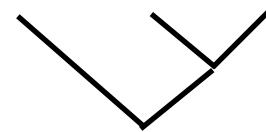
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Step 1: Context-independent parse

Step 2: Resolve reference

An Example Analysis

Context:

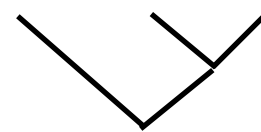
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Current sentence:

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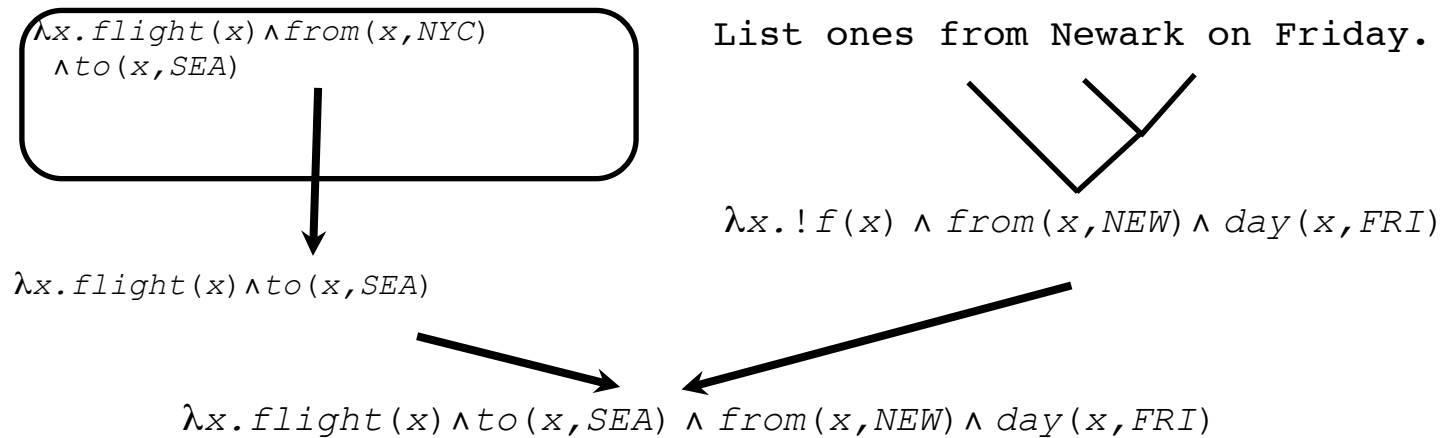
$\lambda x. flight(x) \wedge to(x, SEA)$

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

Step 1: Context-independent parse

Step 2: Resolve reference

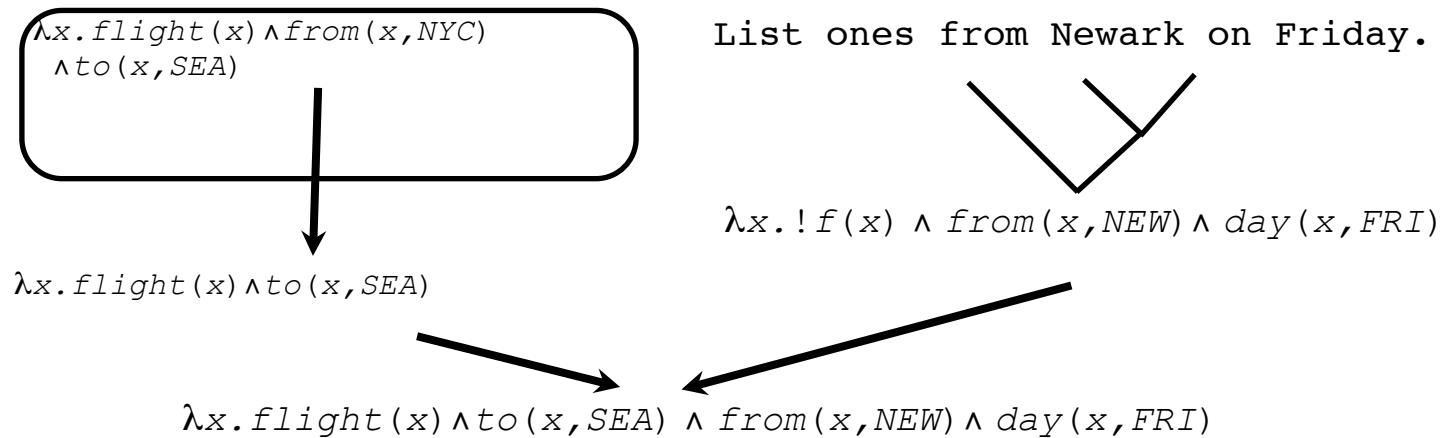
Derivations



Three step process:

- Step 1: Context-independent parsing
- Step 2: Resolve all references
- Step 3: Optionally, perform an elaboration

Derivations

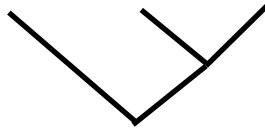


Three step process:

- ▶ Step 1: Context-independent parsing
- Step 2: Resolve all references
- Step 3: Optionally, perform an elaboration

Step I: Referential lexical items

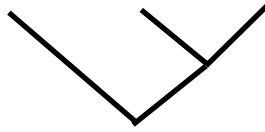
List ones from Newark on Friday.



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

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

ones	N	$\lambda x. !f(x)$
it	NP	$!e$
...		

Step I: Type-shifting operations

Second extension:

Add type-shifting operators for elliptical expressions

the cheapest

NP/N

$\lambda g. \text{argmin}(g, \lambda y. \text{cost}(y))$

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the cheapest

NP/N

$\lambda g. \mathit{argmin}(g, \lambda y. \mathit{cost}(y))$

NP

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

Step I: Type-shifting operations

Second extension:

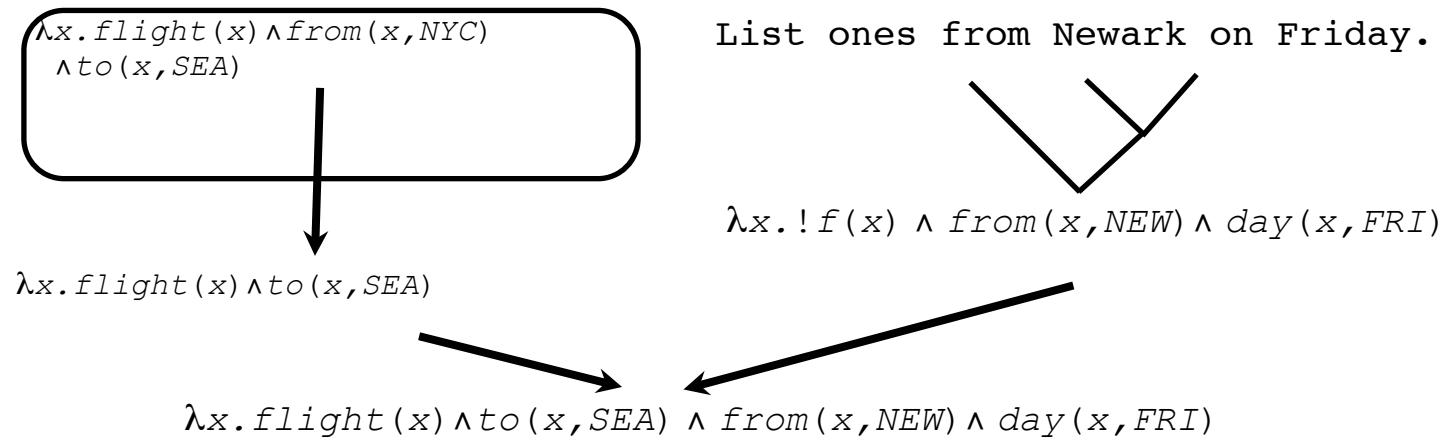
Add type-shifting operators for elliptical expressions

$$\frac{\text{the cheapest}}{\text{NP/N}} \\ \lambda g. \mathit{argmin}(g, \lambda y. \mathit{cost}(y)) \\ \frac{}{\text{NP}} \\ \mathit{argmin}(\lambda x. !f(x), \lambda y. \mathit{cost}(y))$$

$$A/B : g \quad \Rightarrow \quad A : g(\lambda x. !f(x))$$

where g is a function with input type $\langle e, t \rangle$

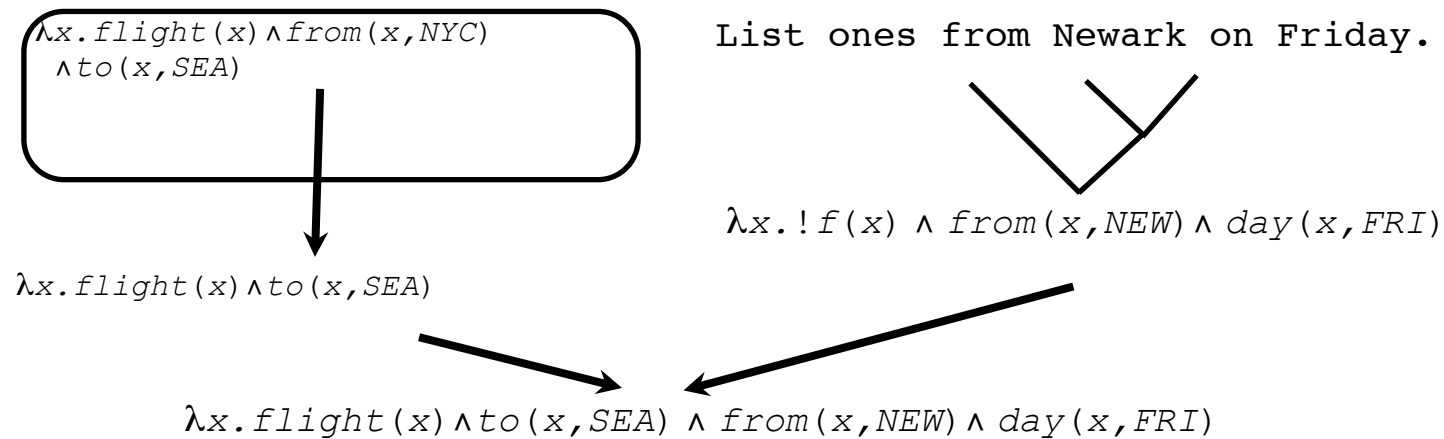
Derivations



Three step process:

- Step 1: Context-independent parsing
- ➡ Step 2: Resolve all references
- Step 3: Optionally, perform an elaboration

Step 2: Resolving References



For each reference:

1. Select a (sub)expression from the context
2. Substitute into current analysis

Step 2: Selecting from Context

For each logical form in context,
enumerate e and $\langle e, t \rangle$ type subexpressions:

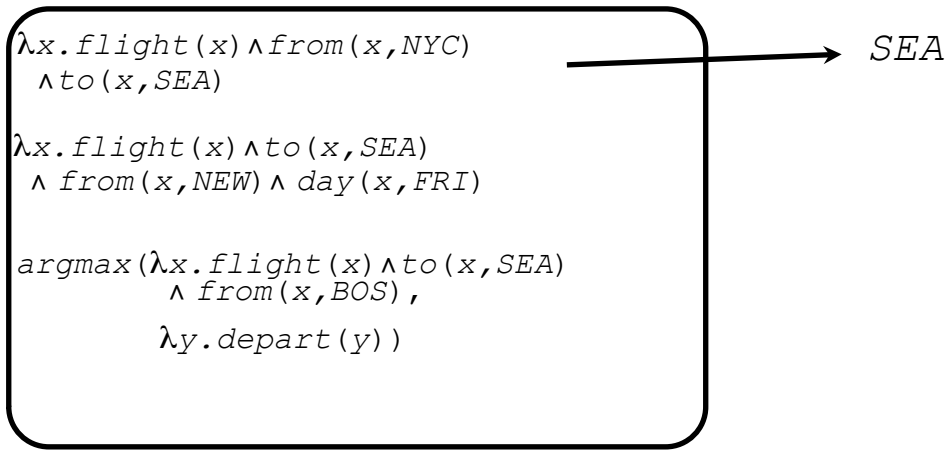
Context:

```
 $\lambda x. flight(x) \wedge from(x, NYC)$   
   $\wedge to(x, SEA)$   
  
 $\lambda x. flight(x) \wedge to(x, SEA)$   
   $\wedge from(x, NEW) \wedge day(x, FRI)$   
  
 $argmax(\lambda x. flight(x) \wedge to(x, SEA)$   
   $\wedge from(x, BOS),$   
   $\lambda y. depart(y))$ 
```

Step 2: Selecting from Context

For each logical form in context,
enumerate e and $\langle e, t \rangle$ type subexpressions:

Context:



The diagram shows a rounded rectangular box containing three logical forms. An arrow points from the first logical form to the text 'SEA' on the right.

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

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

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

NYC

Step 2: Selecting from Context

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 $\wedge to(x, SEA)$

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

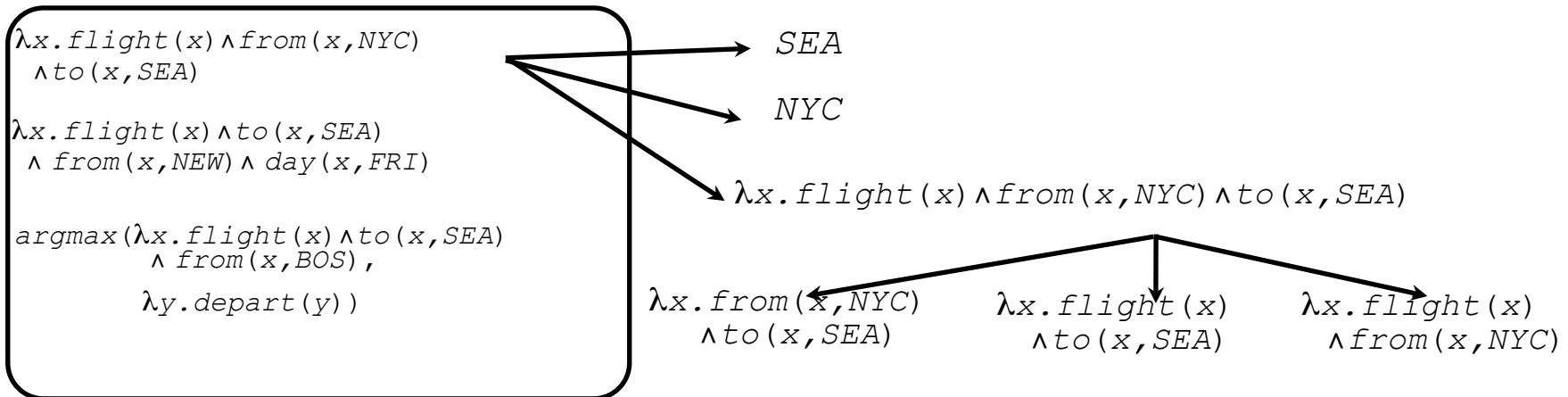
NYC

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

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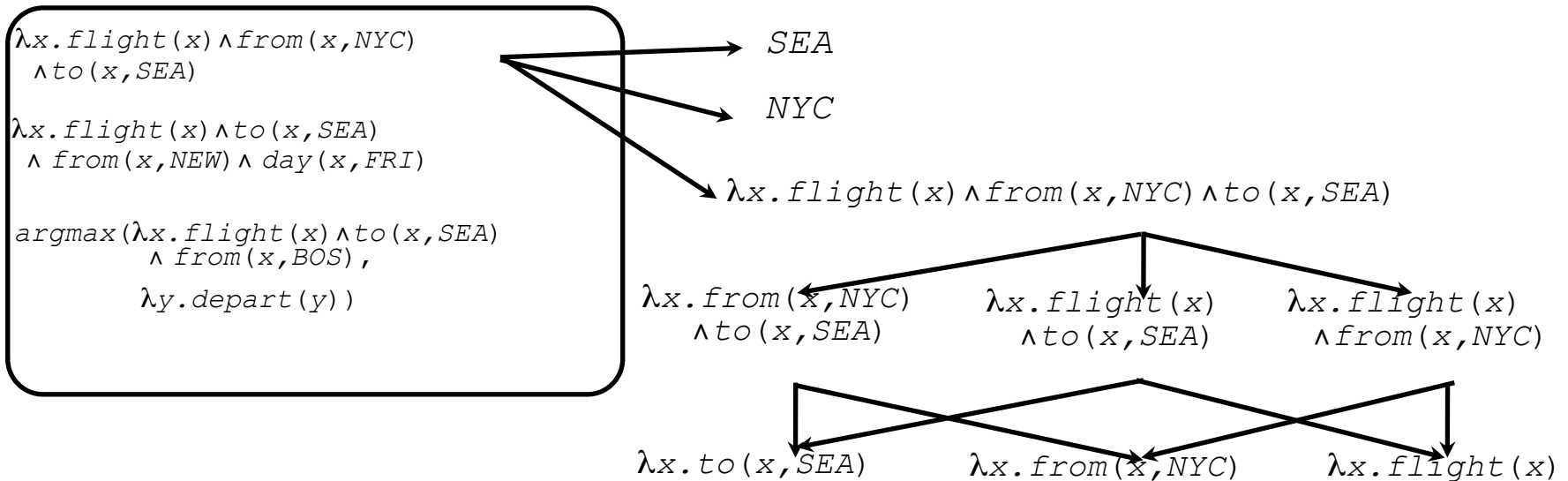
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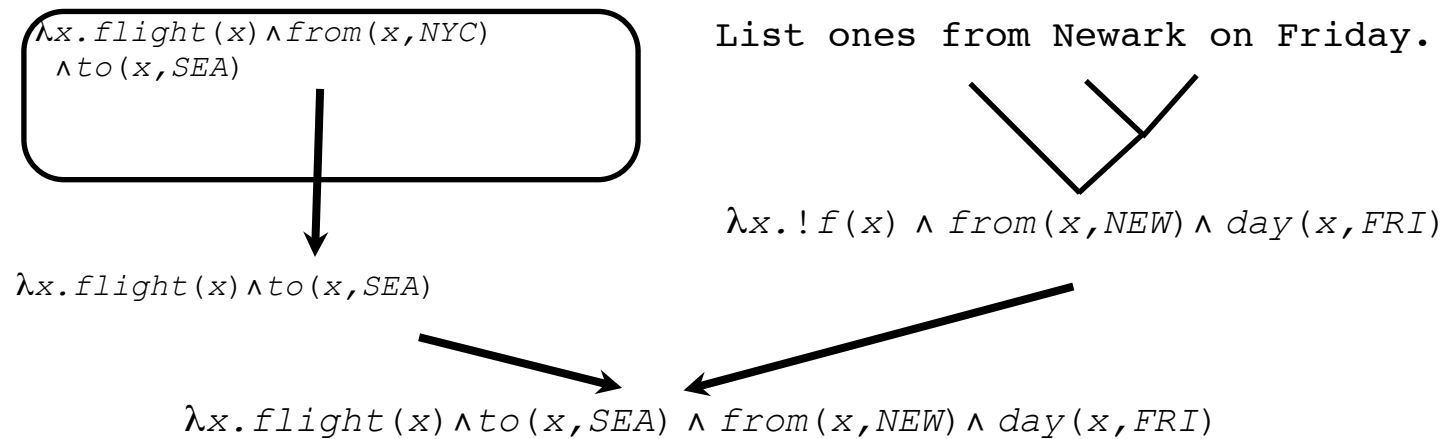
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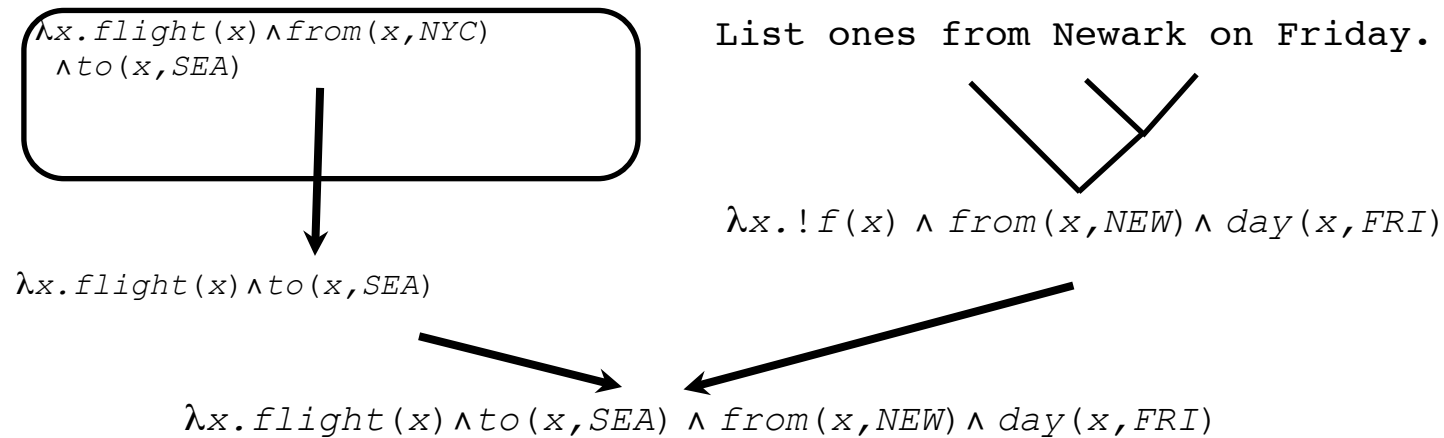
Step 2: Resolving References



For each reference:

- Select an expression from the context
- Substitute into current analysis

Derivations



Three step process:

- Step 1: Context-independent parsing
- Step 2: Resolve all references
- Step 3: Optionally, perform an elaboration

Step 3: Elaboration operations

Show me the latest flight from New York to Seattle.

$\text{argmax}(\lambda x. \text{flight}(x) \wedge \text{from}(x, \text{NYC}) \wedge \text{to}(x, \text{SEA}) ,$
 $\lambda y. \text{time}(y))$

on Friday

Step 3: Elaboration operations

Show me the latest flight from New York to Seattle.

$$\operatorname{argmax}(\lambda x. \text{flight}(x) \wedge \text{from}(x, \text{NYC}) \wedge \text{to}(x, \text{SEA}), \\ \lambda y. \text{time}(y))$$

on Friday

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

Step 3: Elaboration operations

$\text{argmax}(\lambda x. \text{flight}(x) \wedge \text{to}(x, \text{SEA}) \wedge$
 $\text{from}(x, \text{NYC}),$
 $\lambda y. \text{time}(y))$

on Friday



$\lambda x. \text{day}(x, \text{FRI})$

Step 3: Elaboration operations

$\text{argmax}(\lambda x. \text{flight}(x) \wedge \text{to}(x, \text{SEA}) \wedge$
 $\text{from}(x, \text{NYC}),$
 $\lambda y. \text{time}(y))$



$\lambda f. \text{argmax}(\lambda x. \text{flight}(x) \wedge \text{to}(x, \text{SEA}) \wedge$
 $\text{from}(x, \text{NYC}) \wedge f(x),$
 $\lambda y. \text{time}(y))$

on Friday



$\lambda x. \text{day}(x, \text{FRI})$

Step 3: Elaboration operations

$\text{argmax}(\lambda x. \text{flight}(x) \wedge \text{to}(x, \text{SEA}) \wedge$
 $\text{from}(x, \text{NYC}),$
 $\lambda y. \text{time}(y))$



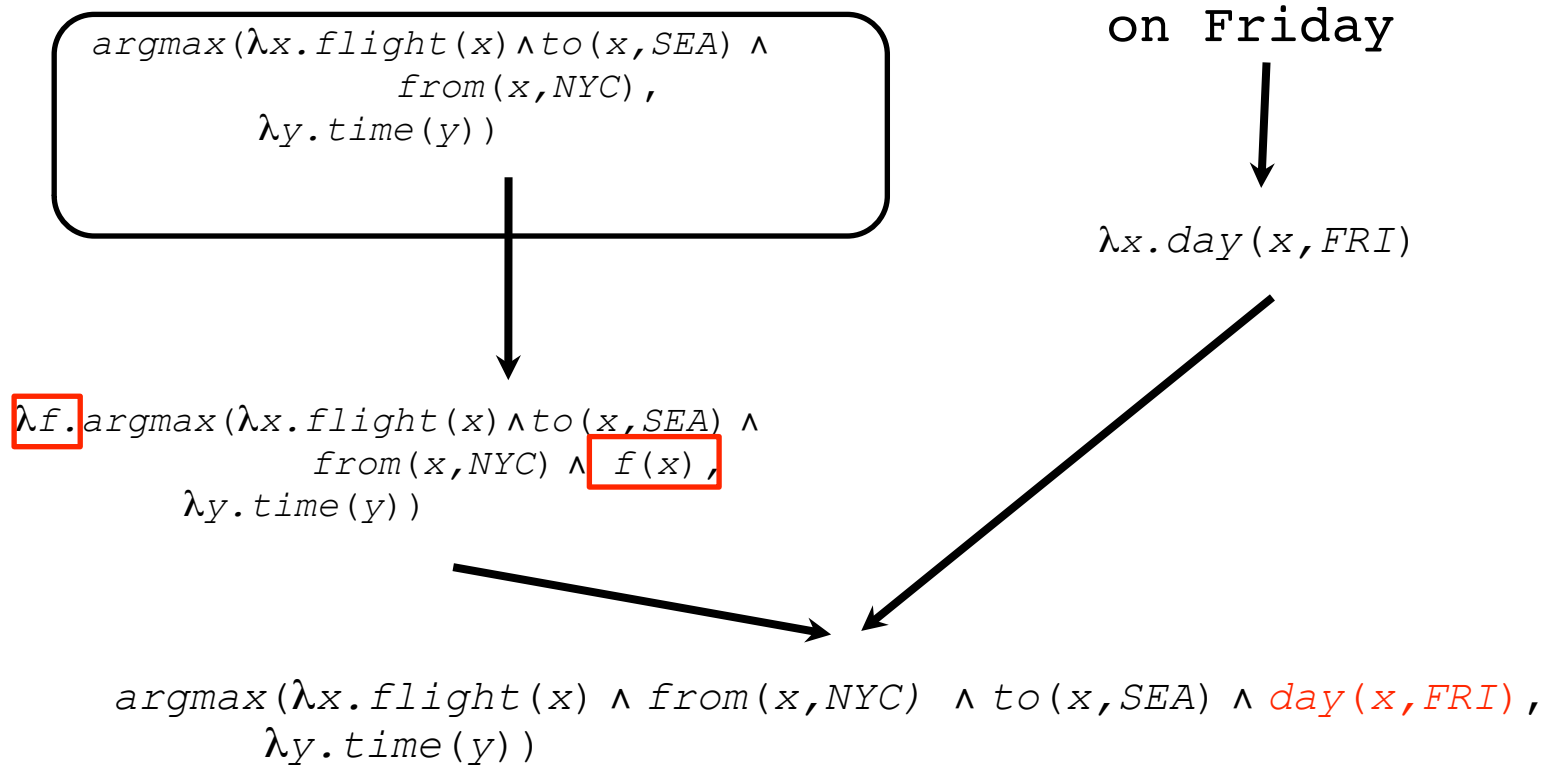
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 $\text{from}(x, \text{NYC}) \wedge f(x),$
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on Friday

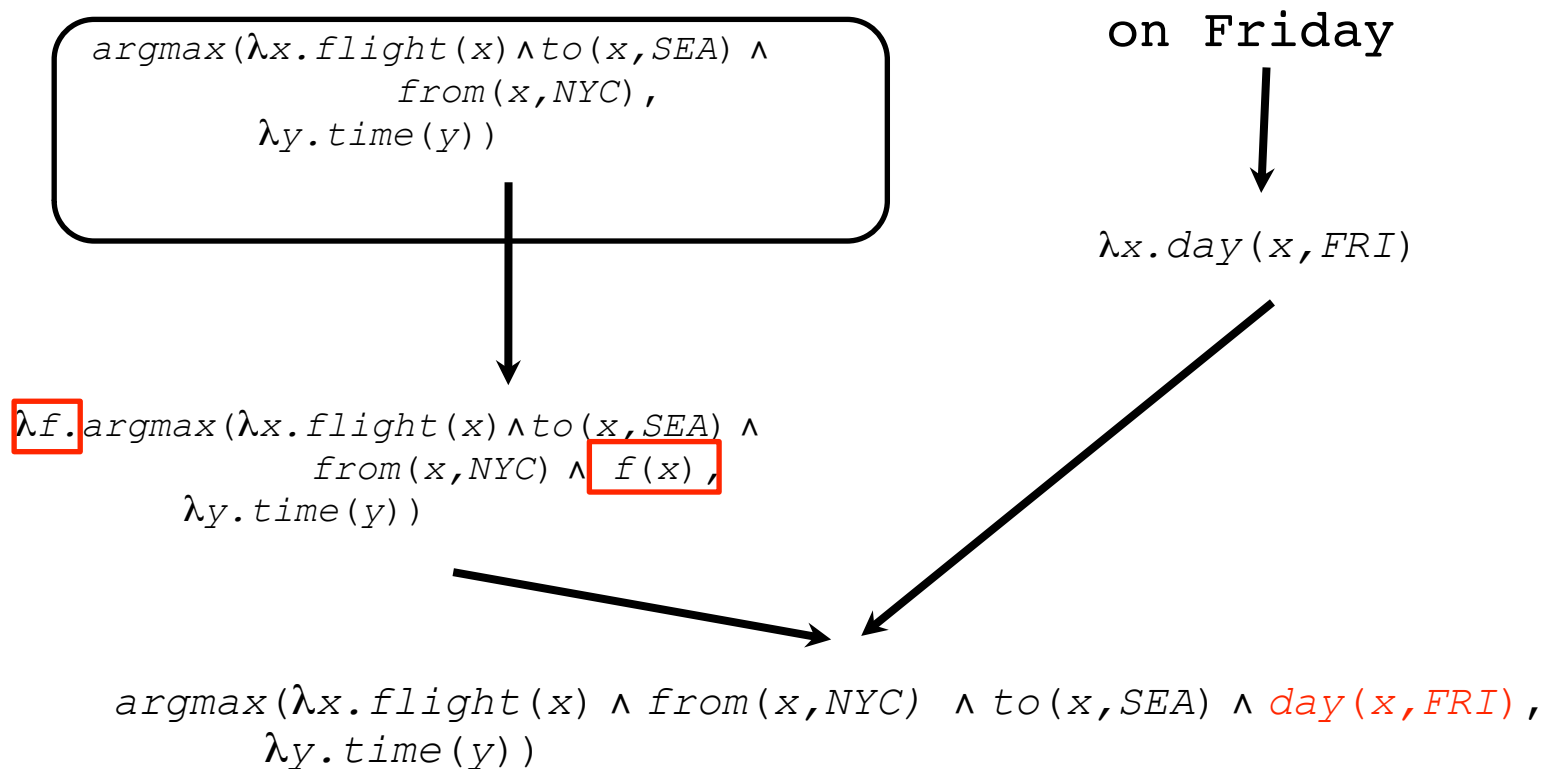


$\lambda x. \text{day}(x, \text{FRI})$

Step 3: Elaboration operations



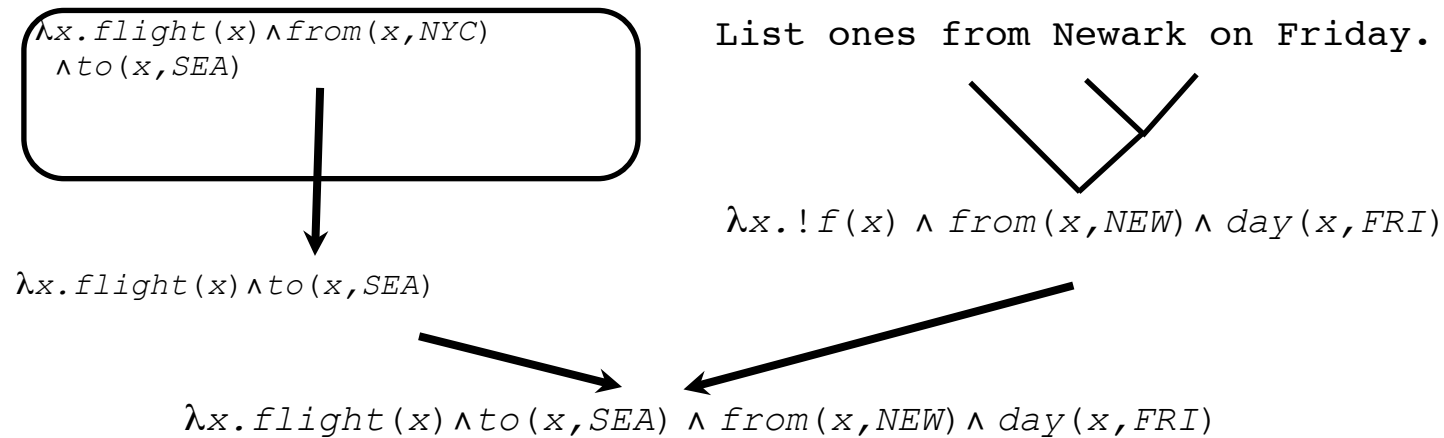
Step 3: Elaboration operations



Possible elaborations:

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

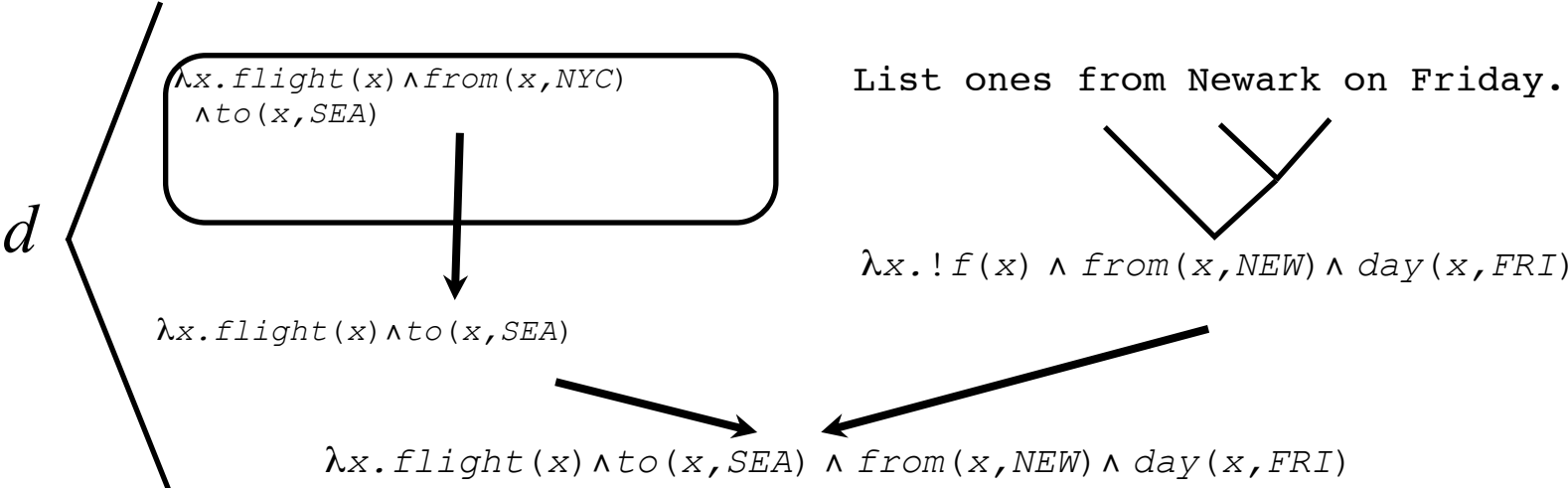
Derivations



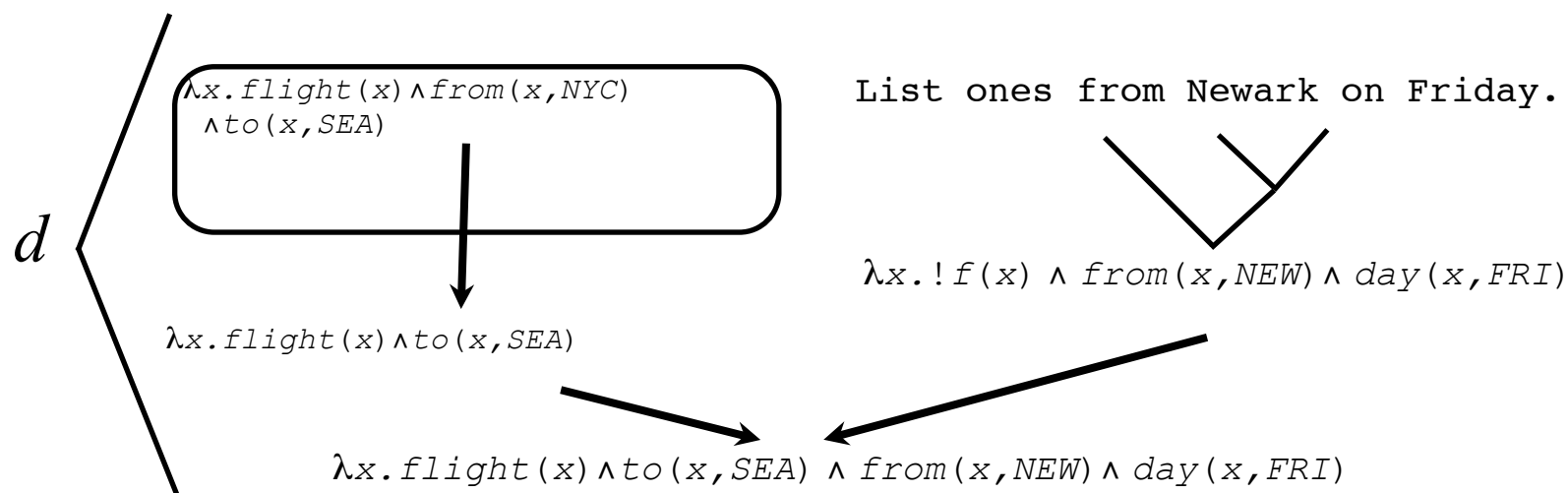
Three step process:

- Step 1: Context-independent parsing
- Step 2: Resolve all references
- Step 3: Optionally, perform an elaboration

Scoring Derivations



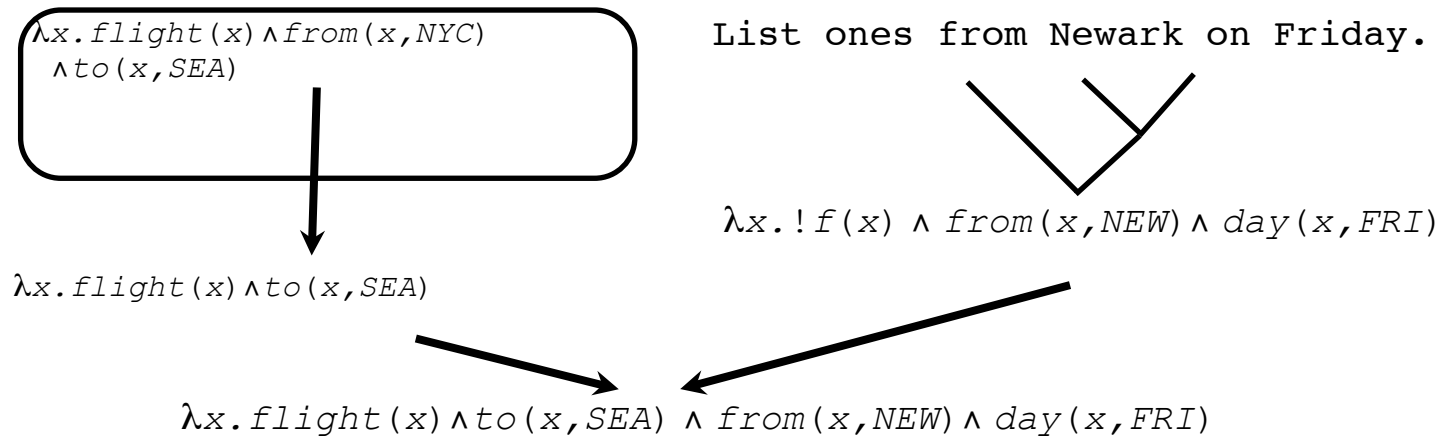
Scoring Derivations



Weighted linear model:

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

Features for Derivations: $f(d)$

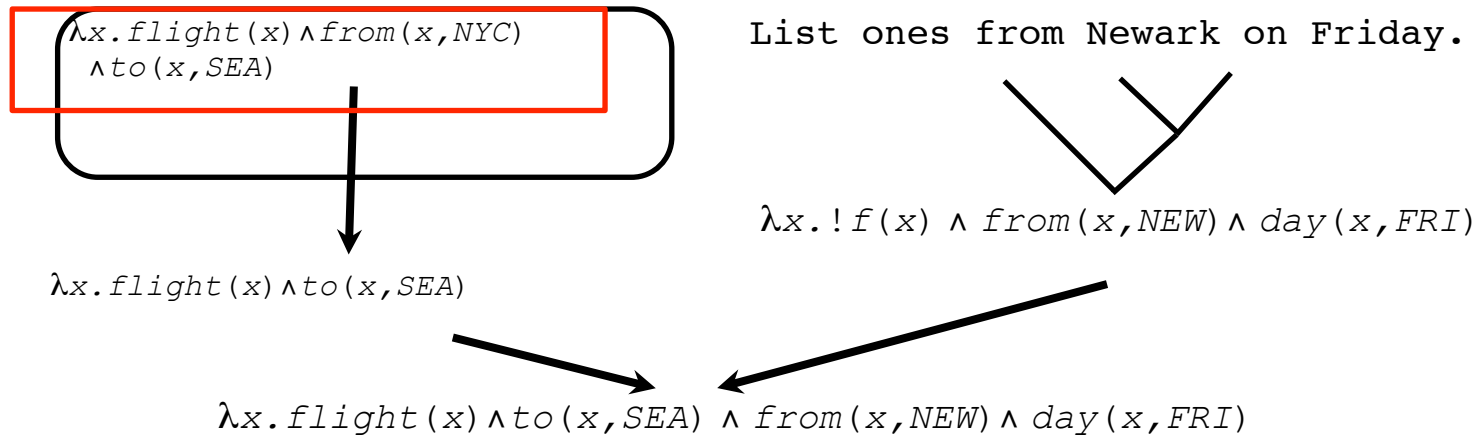


Parsing features: set from Zettlemoyer and Collins (2007)

Context features:

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

Features for Derivations: $f(d)$

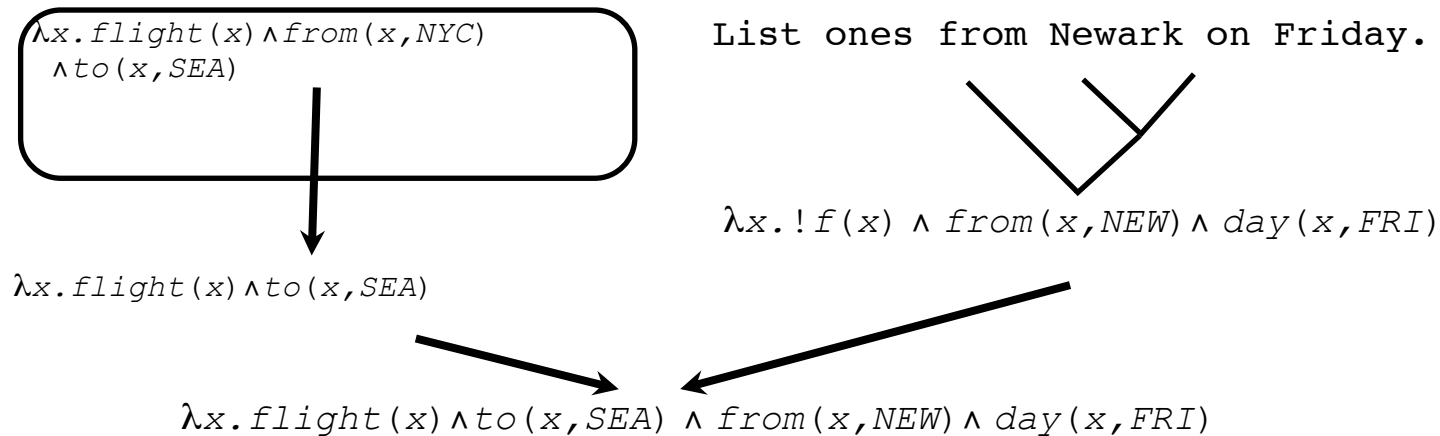


Parsing features: set from Zettlemoyer and Collins (2007)

Context features:

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

Features for Derivations: $f(d)$

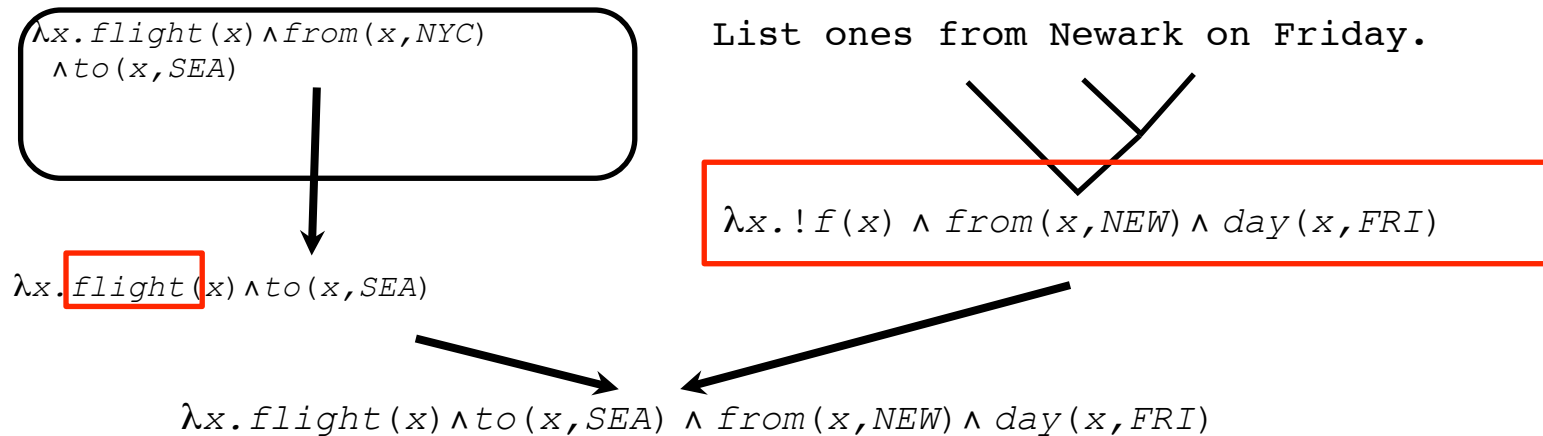


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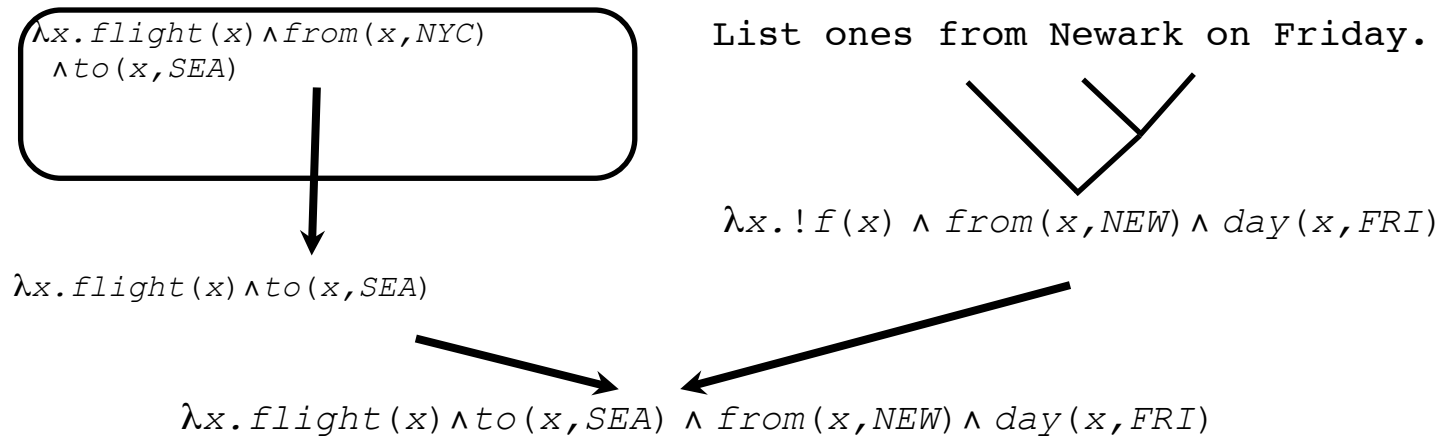


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Features for Derivations: $f(d)$

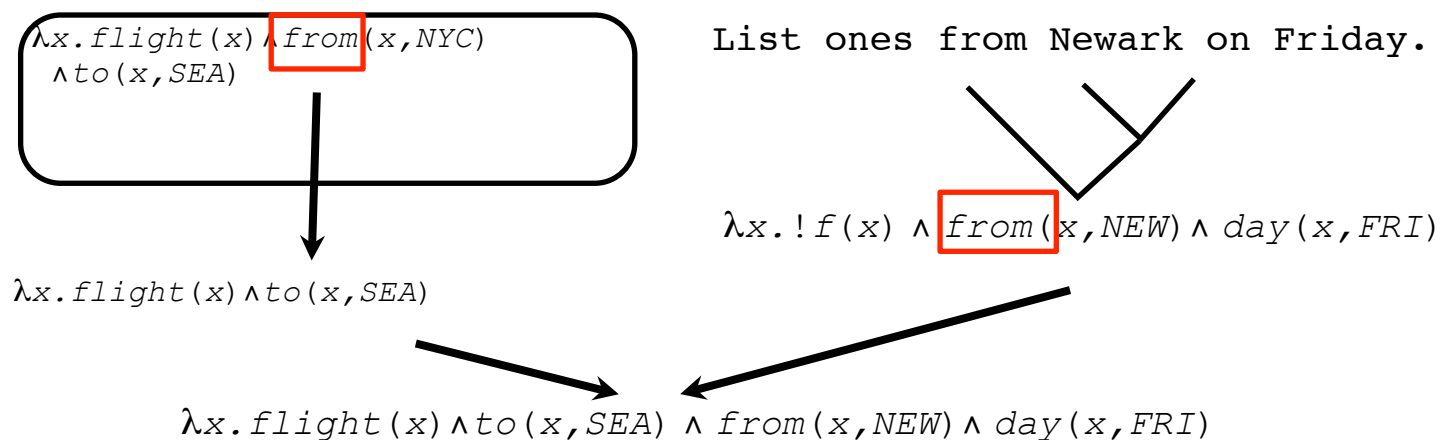


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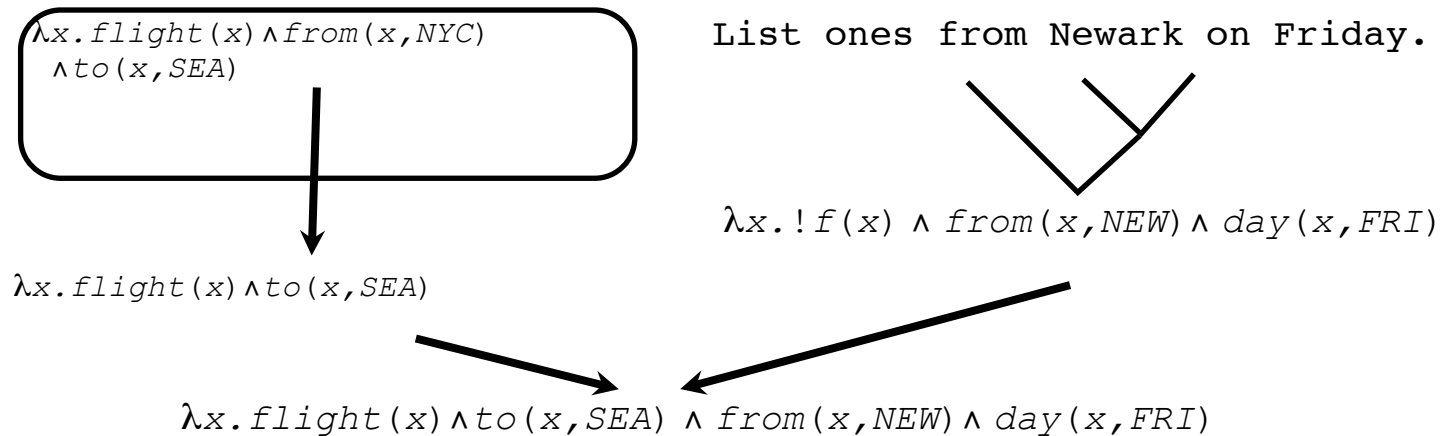


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Parsing features: set from Zettlemoyer and Collins (2007)

Context features:

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- Copy indicators, for all predicates $\{flight, from, to, \dots\}$
- Deletion indicators, for all pairs of predicates $\{(from, flight), (from, from), (from, to), \dots\}$

Inference and Learning

Two computations:

- Best derivation:

$$d^* = \arg \max_d w \cdot f(d)$$

- Best derivation with final logical form z :

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

We use a beam search algorithm.

Inference and Learning

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$$d^* = \arg \max_d w \cdot f(d)$$

- Best derivation with final logical form z :

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

We use a beam search algorithm.

Learning:

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

Inputs: Training set $\{I_i \mid i = 1 \dots n\}$ of interactions. Each interaction $I = \{(w_{i,j}, z_{i,j}) \mid j = 1 \dots n_i\}$ is a sequence of sentences and logical forms. Initial parameters w . Number of iterations T .

Output: Parameters w .

Inputs: Training set $\{I_i \mid i = 1 \dots n\}$ of interactions. Each interaction $I = \{(w_{i,j}, z_{i,j}) \mid j = 1 \dots n_i\}$ is a sequence of sentences and logical forms. Initial parameters w . Number of iterations T .

Computation:

For $t = 1 \dots T, i = 1 \dots n$: (Iterate interactions)

Set $C = \{\}$ (Reset Context)

For $j = 1 \dots n_i$: (Iterate training examples)

Output: Parameters w .

Inputs: Training set $\{I_i \mid i = 1 \dots n\}$ of interactions. Each interaction $I = \{(w_{i,j}, z_{i,j}) \mid j = 1 \dots n_i\}$ is a sequence of sentences and logical forms. Initial parameters w . Number of iterations T .

Computation:

For $t = 1 \dots T, i = 1 \dots n$: (Iterate interactions)

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Step 3: Update context: Append $z_{i,j}$ to C

Output: Parameters w .

Inputs: Training set $\{I_i \mid i = 1 \dots n\}$ of interactions. Each interaction $I = \{(w_{i,j}, z_{i,j}) \mid j = 1 \dots n_i\}$ is a sequence of sentences and logical forms. Initial parameters w . Number of iterations T .

Computation:

For $t = 1 \dots T$, $i = 1 \dots n$: (Iterate interactions)

Set $C = \{\}$ (Reset Context)

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Step 1: Check Correctness

- Find best analysis: $d^* = \arg \max_d w \cdot f(d)$
- If correct: $L(d^*) == z_{i,j}$, go to the Step 3.

Step 3: Update context: Append $z_{i,j}$ to C

Output: Parameters w .

Inputs: Training set $\{I_i \mid i = 1 \dots n\}$ of interactions. Each interaction $I = \{(w_{i,j}, z_{i,j}) \mid j = 1 \dots n_i\}$ is a sequence of sentences and logical forms. Initial parameters w . Number of iterations T .

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- Find best analysis: $d^* = \arg \max_d w \cdot f(d)$
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Step 2: Update Parameters

- Find best correct analysis $d' = \arg \max_{d \text{ s.t. } L(d) = z_{i,j}} w \cdot f(d)$
- Update parameters: $w = w + f(d') - f(d^*)$

Step 3: Update context: Append $z_{i,j}$ to C

Output: Parameters w .

Inputs: Training set $\{I_i \mid i = 1 \dots n\}$ of interactions. Each interaction $I = \{(w_{i,j}, z_{i,j}) \mid j = 1 \dots n_i\}$ is a sequence of sentences and logical forms. Initial parameters w . Number of iterations T .

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

Step 3: Update context: Append $z_{i,j}$ to C

Output: Parameters w .

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

Miller et al. [1996]

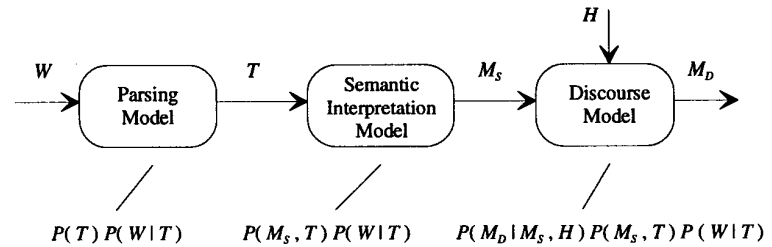


Figure 1: Overview of statistical processing.

Step 1: Semantic parsing

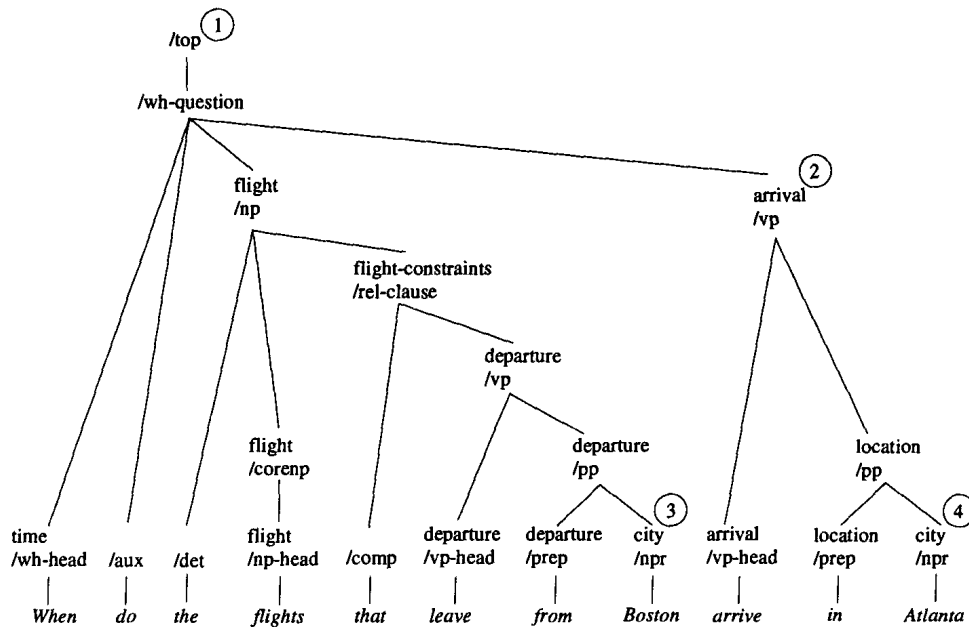


Figure 2: A sample parse tree.

Step 2: Select frame and fill slot values

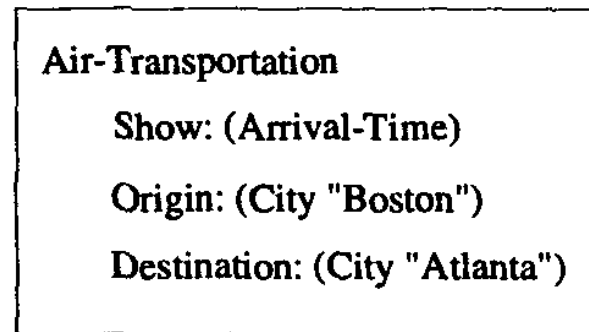


Figure 3: A sample semantic frame.

Step 3: Optionally copy slot values from previous frames

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]
- **Metric:** accuracy recovering fully correct meanings

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]
- **Metric:** accuracy recovering fully correct meanings
- **Results:**
 - 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
$M=0$	45.4
$M=1$	79.8
$M=2$	81.0
$M=3$	82.1
$M=4$	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

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

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

Show me the cheapest?

F

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

Key challenges:

- Structured input and output, hidden structure not annotated

Solution:

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

Bootstrapping Semantic Parsers from Conversations

[Artzi & Zettlemoyer, EMNLP 2011]



Task Oriented Dialog

SYSTEM how can i help you ?

USER i ' d like to go from richmond to atlantic city on june seventh

SYSTEM leaving richmond on thursday, june seventh arriving in atlantic city leaving at what time ?

USER eight a. m.

SYSTEM leaving in the morning what airline would you prefer ?

USER u. s. air

SYSTEM i currently have you leaving richmond on thursday, june seventh in the morning arriving in atlantic city flying on u. s. air . is this correct ?

USER yes

SYSTEM o . k . then . where would you like to go next ?

USER richmond

[conversation continues]

Dialog and Semantics

- Many dialog systems use semantic parsers.
- Supervised learning of such parsers is expensive.
- Can computers learn through raw conversations?

Learning from Conversations

- Human-machine dialogs aim to achieve a **goal**.
- A well-defined goal allows the system to **recover** from failures.

System Recovery

SYSTEM: how can i help you?

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

System Recovery

SYSTEM:

how can i help you?

USER:

i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

 *System fails*

System Recovery

SYSTEM: how can i help you?

USER:

i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city?

 *System fails*

System Recovery

SYSTEM: how can i help you?

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city?

USER: atlanta georgia

System Recovery

SYSTEM: how can i help you?

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city?

USER: atlanta georgia



SYSTEM: leaving atlanta. going to which city?

System Recovery

SYSTEM: how can i help you?

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city?

USER: atlanta georgia



SYSTEM: leaving atlanta. going to which city?

USER: london

System Recovery

SYSTEM: how can i help you?

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city?

USER: atlanta georgia 

SYSTEM: leaving atlanta. going to which city?

USER: london 

SYSTEM: arriving in london england. what date would you like to depart atlanta?

System Recovery

SYSTEM: how can i help you?

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city?

USER: atlanta georgia 

SYSTEM: leaving atlanta. going to which city?

USER: london 

SYSTEM: arriving in london england. what date would you like to depart atlanta?

USER: september twenty fourth in the early evening

[conversation continues]

Automatically Annotated Logs

SYSTEM: how can i help you? (*OPEN_TASK*)

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city? (*ASK: $\lambda x. from(fl, x)$*)

USER: atlanta georgia

SYSTEM: leaving atlanta. (*CONFIRM: $from(fl, ATL)$*) going to which city? (*ASK: $\lambda x. to(fl, x)$*)

USER: london

[conversation continues]

Automatically Annotated Logs

SYSTEM: how can i help you? (*OPEN_TASK*)

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

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USER: atlanta georgia

SYSTEM: leaving atlanta. (*CONFIRM: $from(fl, ATL)$*) going to which city? (*ASK: $\lambda x. to(fl, x)$*)

USER: london

[conversation continues]

System utterance



Automatically Annotated Logs

SYSTEM: how can i help you? (OPEN_TASK)

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city? (ASK: $\lambda x. \text{from}(fl, x)$)

USER: atlanta georgia

SYSTEM: leaving atlanta. (CONFIRM: $\text{from}(fl, ATL)$) going to which city? (ASK: $\lambda x. \text{to}(fl, x)$)

USER: london

[conversation continues]

System utterance

Natural Language

Automatically Annotated Logs

SYSTEM: how can i help you? **(OPEN_TASK)**

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city? **(ASK: $\lambda x.from(fl, x)$)**

USER: atlanta georgia

SYSTEM: leaving atlanta. **(CONFIRM $from(fl, ATL)$)** going to which city? **(ASK $\lambda x.to(fl, x)$)**

USER: london

[conversation continues]

System utterance

Natural Language

Speech Act

Automatically Annotated Logs

SYSTEM: how can i help you? (**OPEN_TASK**)

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city? (**ASK:** $\lambda x.from(fl, x)$)

USER: atlanta georgia

SYSTEM: leaving atlanta. (**CONFIRM:** $from(fl, ATL)$) going to which city? (**ASK:** $\lambda x.to(fl, x)$)

USER: london

[conversation continues]

System utterance

Natural Language

Speech Act

Logical Meaning

Automatically Annotated Logs

SYSTEM: how can i help you? (*OPEN_TASK*)

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

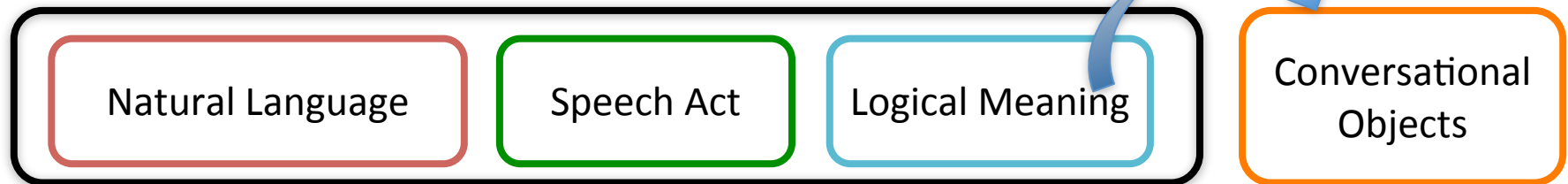
SYSTEM: leaving what city? (*ASK: $\lambda x. \text{from}(fl, x)$*)

USER: atlanta georgia

SYSTEM: leaving atlanta. (*CONFIRM: $\text{from}(fl, ATL)$*) going to which city? (*ASK: $\lambda x. \text{to}(fl, x)$*)

USER: london

[conversation continues]
System utterance



Automatically Annotated Logs

SYSTEM: how can i help you? (*OPEN_TASK*)

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

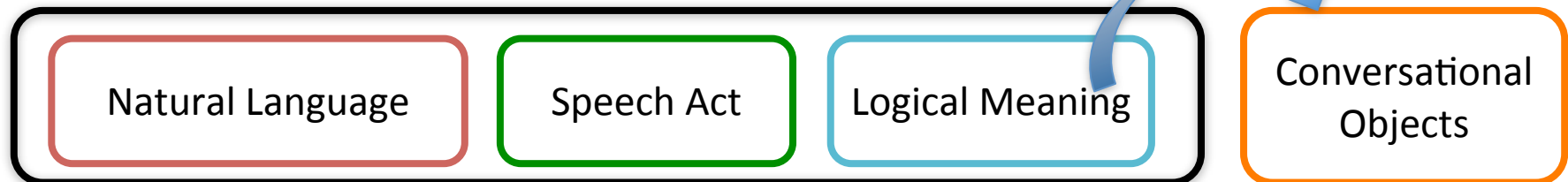
SYSTEM: leaving what city? (*ASK: $\lambda x. from(fl, x)$*)

USER: atlanta georgia

SYSTEM: leaving atlanta. (*CONFIRM: $from(fl, ATL)$*) going to which city? (*ASK: $\lambda x. to(fl, x)$*)

USER: london

[conversation continues]
System utterance



One Training Example

SYSTEM: how can i help you? (*OPEN_TASK*)

USER:

i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city? (*ASK: $\lambda x.from(fl, x)$*)

USER:

atlanta georgia

SYSTEM: leaving atlanta. (*CONFIRM: $from(fl, ATL)$*) going to which city? (*ASK: $\lambda x.to(fl, x)$*)

USER:

london

[conversation continues]

Supervised Case

i want to fly from new york to los angeles

$$\lambda x. \text{from}(x, NYC) \wedge \text{to}(x, LA)$$

Loss Signal Instead of Labels

$$\mathcal{L} : \langle z, \mathcal{C} \rangle \rightarrow \mathbb{R}$$

i want to fly from new york to los angeles

Loss Signal Instead of Labels

$$\mathcal{L} : \langle z, \mathcal{C} \rangle \rightarrow \mathbb{R}$$

i want to fly from new york to los angeles

$$\lambda x. \text{from}(x, NYC) \wedge \text{to}(x, LA)$$

$$\lambda x. \text{from}(x, NYC) \wedge \text{from}(x, LA)$$

$$\lambda x. \text{from}(x, LA)$$

$$\lambda x []. \text{to}(x[0], NYC) \wedge \text{from}(x[1], LA)$$

...

Loss Signal Instead of Labels

$$\mathcal{L} : \langle z, \mathcal{C} \rangle \rightarrow \mathbb{R}$$

i want to fly from new york to los angeles

- 1 -1.8 $\lambda x. \text{from}(x, NYC) \wedge \text{to}(x, LA)$
- 4 2.0 $\lambda x. \text{from}(x, NYC) \wedge \text{from}(x, LA)$
- 2 -0.9 $\lambda x. \text{from}(x, LA)$
- 3 1.5 $\lambda x []. \text{to}(x[0], NYC) \wedge \text{from}(x[1], LA)$

...

Computing Conversation Loss

1. Select the relevant subset of system utterances
2. Align the logical expression to content from selected system utterances
3. Score the alignment

Conversation Loss

SYSTEM: how can i help you (OPEN_TASK)

USER: i want to fly from new york to los angeles

SYSTEM: from new york. (CONFIRM: $from(fl, NYC)$) to where? (ASK: $\lambda x.to(fl, x)$)

USER: los angeles

SYSTEM: flying to los angeles. (CONFIRM: $to(fl, LA)$) where do you want to go from los angeles? (ASK: $\lambda x.to(fl2, x) \wedge from(fl2, LA)$)

USER: back to new york

SYSTEM: from los angeles to new york (CONFIRM: $from(fl2, LA) \wedge to(fl2, NYC)$)

SYSTEM: i have a direct flight from new york to los angeles for \$480. ok? (OFFER:

[conversation continues]

Segmenting

SYSTEM: how can i help you (OPEN_TASK)

USER: i want to fly from new york to los angeles

SYSTEM: from new york. (CONFIRM: *from(f1, NYC)*) to where? (ASK: $\lambda x.to(f1, x)$)

USER: los angeles

SYSTEM: flying to los angeles. (CONFIRM: *to(f1, LA)*) where do you want to go from los angeles? ? (ASK: $\lambda x.to(f12, x) \wedge from(f12, LA)$)

USER: back to new york

SYSTEM: from los angeles to new york (CONFIRM: *from(f12, LA) \wedge to(f12, NYC)*)

SYSTEM: i have a direct flight from new york to los angeles for \$480. ok? (OFFER:

[conversation continues]

Extract Properties

SYSTEM: how can i help you (OPEN_TASK)

USER: i want to fly from new york to los angeles

SYSTEM: from new york. (CONFIRM: from(fl, NYC)) to where? (ASK: $\lambda x.to(fl, x)$)

USER: los angeles

SYSTEM: flying to los angeles. (CONFIRM: to(fl, LA)) where do you want to go from los angeles? ? (ASK: $\lambda x.to(fl2, x) \wedge from(fl2, LA)$)

USER: back to new york

SYSTEM: from los angeles to new york (CONFIRM: from(fl2, LA) \wedge to(fl2, NYC))

SYSTEM: i have a direct flight from new york to los angeles for \$480. ok? (OFFER: [conversation continues])

[conversation continues]

Property

(from, fl, NYC)

(to, fl, LA)

(from, fl2, LA)

(to, fl2, NYC)



Extract Properties

SYSTEM: how can i help you (OPEN_TASK)

USER: i want to fly from new york to los angeles

SYSTEM: from new york. (CONFIRM: $from(fl, NYC)$) to where? (ASK: $\lambda x.to(fl, x)$)

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USER: back to new york

SYSTEM: from los angeles to new york
(CONFIRM: $from(fl2, LA) \wedge to(fl2, NYC)$)

SYSTEM: i have a direct flight from new york to los angeles for \$480. ok? (OFFER: [conversation continues])

[conversation continues]



<u>Property</u>	<u>Loss</u>
$(from, fl, NYC)$	-0.5
(to, fl, LA)	-0.83
$(from, fl2, LA)$	-0.16
$(to, fl2, NYC)$	-0.16

Comparing Two Candidates

USER: i want to fly from new york to los angeles

$\lambda x. \text{from}(x, NYC) \wedge \text{to}(x, LA)$

Alignment: $x \rightarrow fl$

$$\text{Loss} = -0.5 - 0.83 = -1.33$$

<u>Property</u>	<u>Loss</u>
(from, fl, NYC)	-0.5
(to, fl, LA)	-0.83
$(\text{from}, fl2, LA)$	-0.16
$(\text{to}, fl2, NYC)$	-0.16

$\lambda x []. \text{from}(x[0], NYC) \wedge \text{from}(x[1], LA)$

Alignment: $x[0] \rightarrow fl, x[1] \rightarrow fl2$

$$\text{Loss} = -0.5 - 0.16 = -0.66$$

Comparing Two Candidates

USER: i want to fly from new york to los angeles

$\lambda x. from(x, NYC) \wedge to(x, LA)$ ✓

Alignment: $x \rightarrow fl$

$$Loss = -0.5 - 0.83 = -1.33$$

<u>Property</u>	<u>Loss</u>
$(from, fl, NYC)$	-0.5
(to, fl, LA)	-0.83
$(from, fl2, LA)$	-0.16
$(to, fl2, NYC)$	-0.16

$\lambda x []. from(x[0], NYC) \wedge from(x[1], LA)$ ✗

Alignment: $x[0] \rightarrow fl, x[1] \rightarrow fl2$

$$Loss = -0.5 - 0.16 = -0.66$$

Learning Algorithm

- Online
- Loss-driven
- 2 steps:
 - Lexical generation
 - Parameter update [Singh-Miller and Collins 2007]

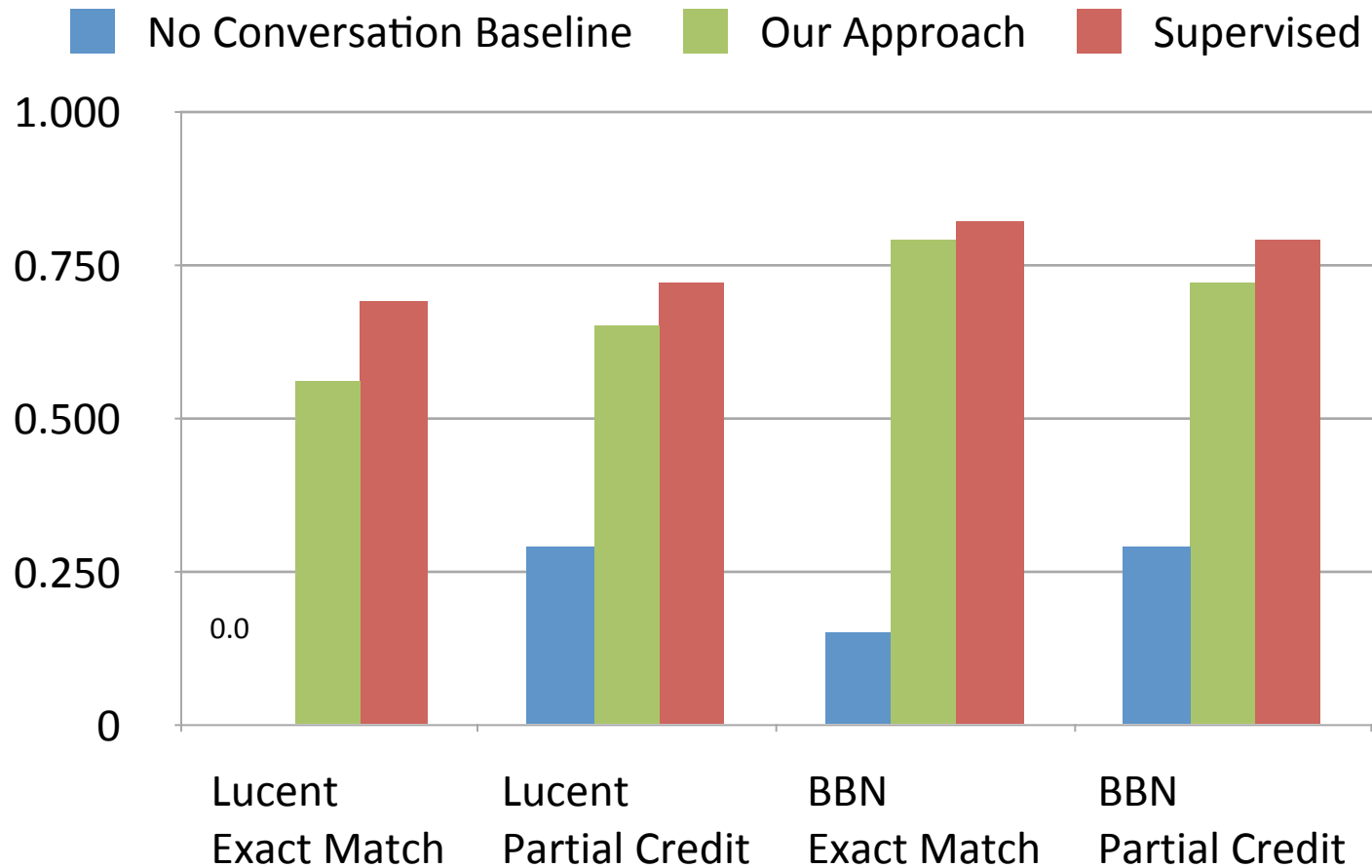
DARPA Communicator

- Raw conversational logs [Walker et al. 2002]
- Annotated system utterances

	Lucent		BBN	
	Train	Test	Train	Test
Conversations	144	70	71	91
Context Independent Utterances	208	96	67	67

Results: Evaluation Data

F1 Measure



Contributions

- Learning to do context-dependent semantic parsing
 - Complex, hidden variable problem
 - Learn distribution over derivations
- Learning from conversation logs
 - Loss driven, requiring no annotations
 - First step towards autonomous, self-improving dialog systems

Current Work: Self-learning dialog systems

Goal: learn full dialog semantic parser the produces context-dependent analyses

USER: i would like to fly from atlanta georgia to london england on september twenty fourth in the early evening i would like to return on october first departing from london in the late morning

SYSTEM: leaving what city? (*ASK: λx .from(fl, x)*)

USER: atlanta georgia.

SYSTEM: leaving atlanta. (*CONF:from(fl,ATL)*) going to which city? (*ASK: λx .to(fl, x)*)

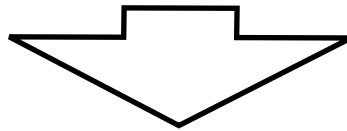
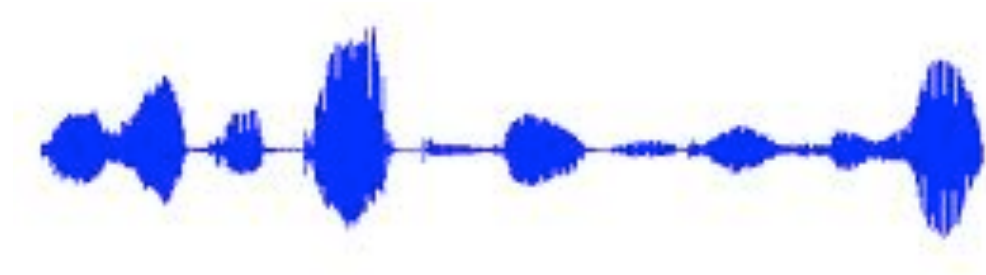
USER london

SYSTEM: arriving in (*CONF:to(fl, LON)*) what date would to depart Atlanta? (*ASK: λx .from(fl, ATL) \wedge depart-date(fl, x)*)

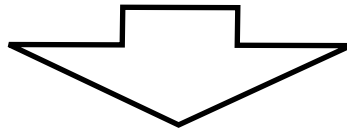
USER september twenty fourth in the early evening

[conversation continues]

Current Work: Mapping Speech to Logical Form



Uh, flights New York to Singapore, sure



ACCEPT: $\lambda x. flight(x) \wedge from(x, NYC) \wedge to(x, SIN)$

Current Work: Learning Grounded Language

Challenge: Learn to sportscast, given only text and the game log

Purple10 is rushing down the field with only three defenders

Purple10 passes out front to Purple9 near the side

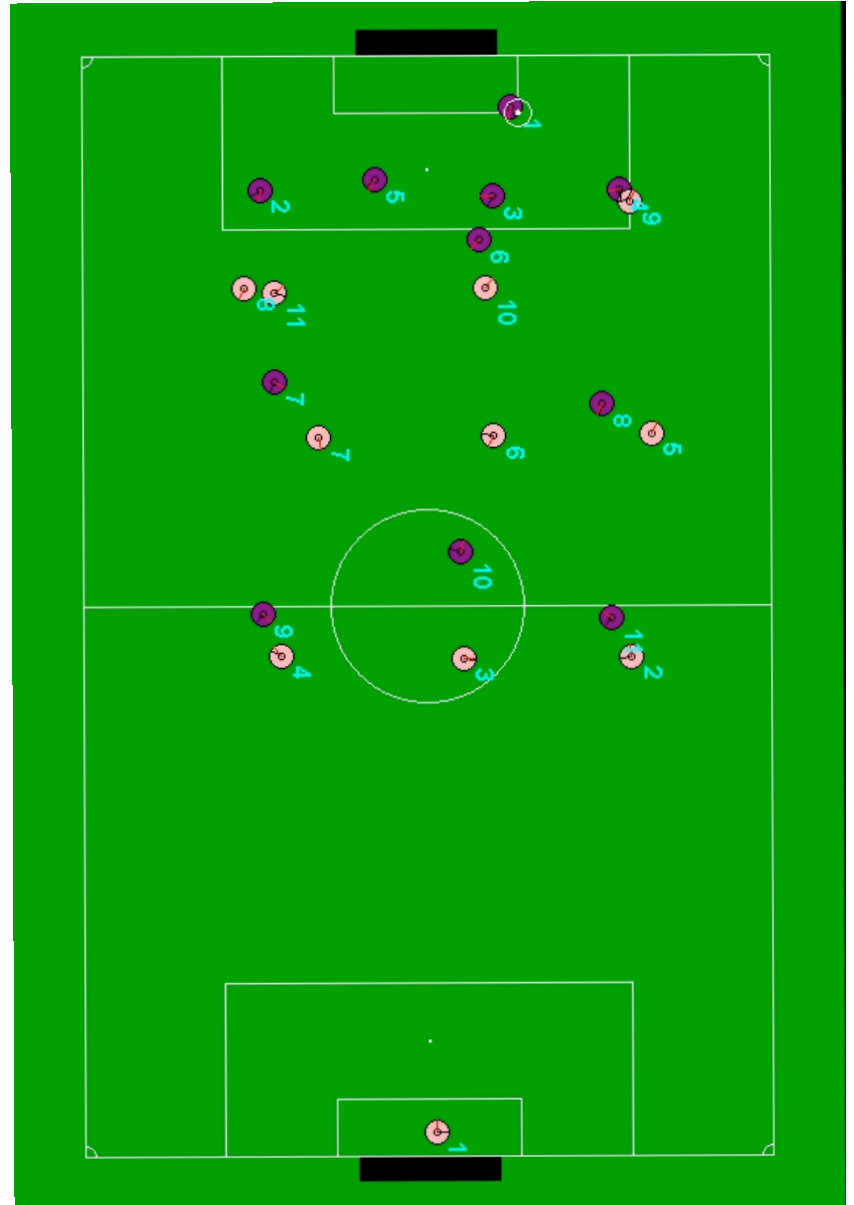
Purple9 passes back to Purple10 in the middle

Purple10 again has a good chance to score a goal here

Purple10 dribbles toward the goal
Pink3 tries to stay in front of Purple10

Purple10 passes to Purple9 on the side while getting open

....











A Joint Model for Naming Objects

These are the ones
that are not blue



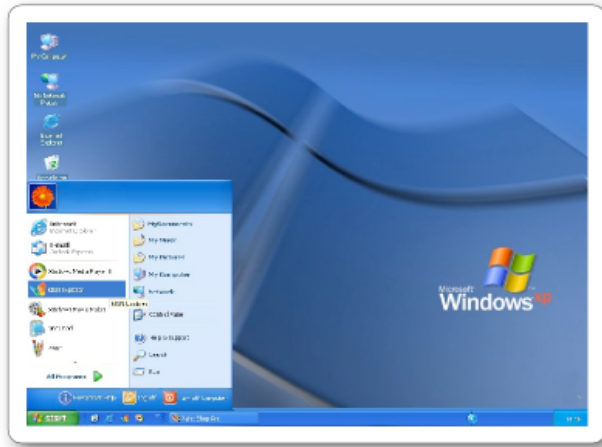
$\lambda x. \neg color(x, blue)$



Blue	Green	Round	Broccoli
			
	...		•
		...	•
...			•
			

Future: General language use in grounded settings

Conversational interaction in simulated environments:



- Can gather user input: *Which printer do you want to use?*
- Can help with learning: *Can you show me how to X?*

Learning through explanation in robotic environments:



Can we teach the robot to play?

- *This is a pawn.*
- *Pawns can move forward one square at a time.*
- *unless it is the first move, then they can ...*

Learning About and From Context in Semantic Parsing

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for more info:

<http://www.cs.washington.edu/homes/lasz/>

