Syntactic and semantic parsing for natural language understanding

2. Question answering

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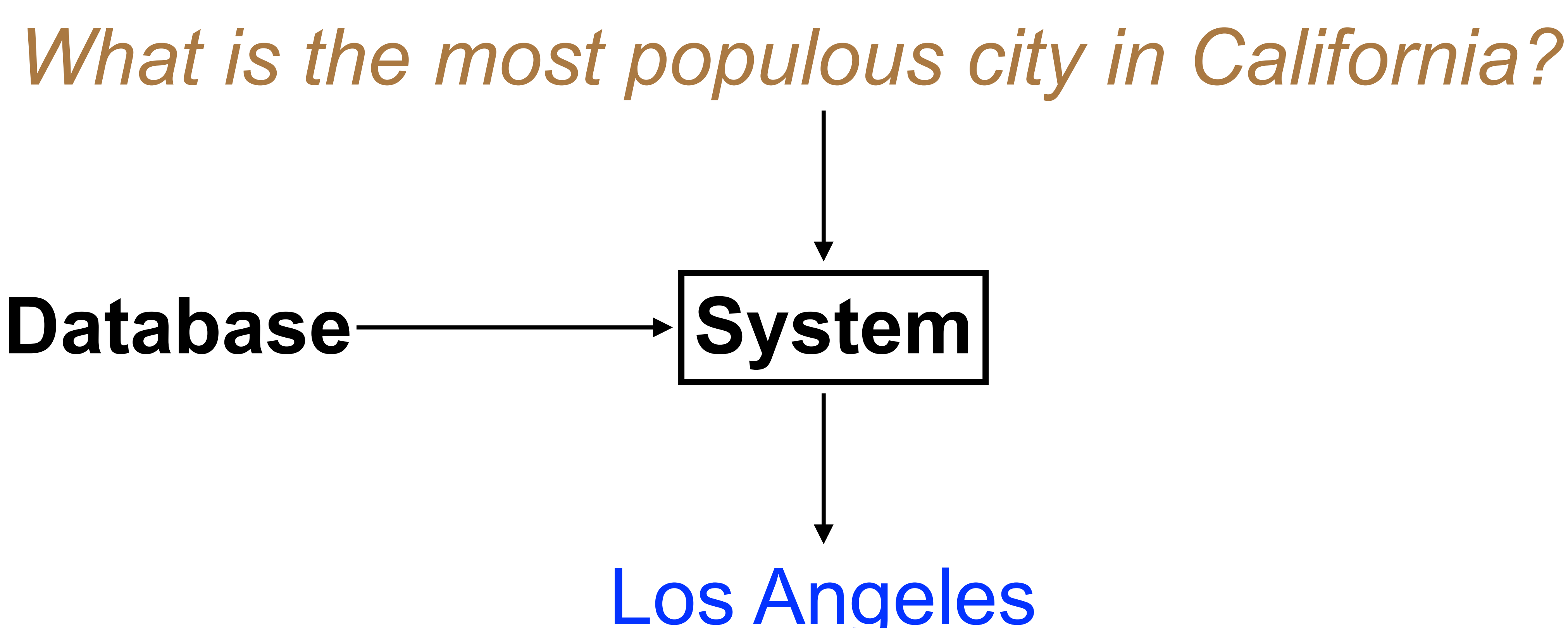
Question answering

- **Main focus:** question answering with external **database**
- System may convert an input question into a query to the database, and obtain the answer



Outline

- Difference between RTE and QA
  - Pure bottom-up approach like ccg2lambda is difficult for QA
  - Grounding is necessary
- Top-down semantic parsing for QA
  - Learning CCG from sentence/logical form pairs
  - Learning dependency-based compositional semantics
    - an approach to learn semantic parsing without supervision to logical forms

Concrete task: querying SPARQL

- Often a specific database accepts a predefined query language
  - e.g., Freebase is a very large open domain database, which accepts SPARQL
  - So our task is converting an input sentence into a SPARQL query

Input: *How many teams participate in UEFA?*

SPARQL:

```
select count(?x) where {
  ?a Team ?x .
  ?a League Uefa .
}
```

Equivalent lambda-expression: $count(\lambda x.\exists a.Team(x, a) \wedge League(a, Uefa))$

Problem

How many teams participate in UEFA?

Desirable logical-form	$count(\lambda x.\exists a.Team(x, a) \wedge League(a, Uefa))$
Parser output	$count(\lambda x.\exists a.Team(x, a) \wedge Participate(a, Uefa))$

- Consider running a CCG parser to get a logical form
  - We can convert a logical expression into a SPARQL query by rules

- However, DB query must be written with keywords in the DB
  - Because the language used in DB is strict
  - This is in contrast to RTE, where the logical forms are inputs to a prover that uses the knowledge on word variations internally

Grounding

- For QA, we need to find the mapping from words in the input to corresponding DB keywords
- Technique to find such mappings is called **grounding**
  - In general, grounding connects a sentence with a real word entity
  - e.g., image grounding: we describe “panda” (text) by a figure of pandas (real entity)
  - In DB, the real entity is DB keywords (e.g., *League*)
- The bottom-up approaches we discussed so far (for RTE) are not related with grounding, so they are called a **non-grounding** approach

Partly bottom-up approach?

- So for DB, I don't know the fully bottom-up (non-grounding) approach built on a CCG parser or other parsers

- There is only a hybrid approach between bottom-up and top-down approach
  - First, parse an input sentence with a CCG parser to obtain a **non-grounding logical form**
  - Then convert it into a **grounded logical form** to be able to query to DB (using the idea of weak supervision, described later)
  - See: Reddy et al. Large-scale Semantic Parsing without Question-Answer Pairs. TACL 2016.

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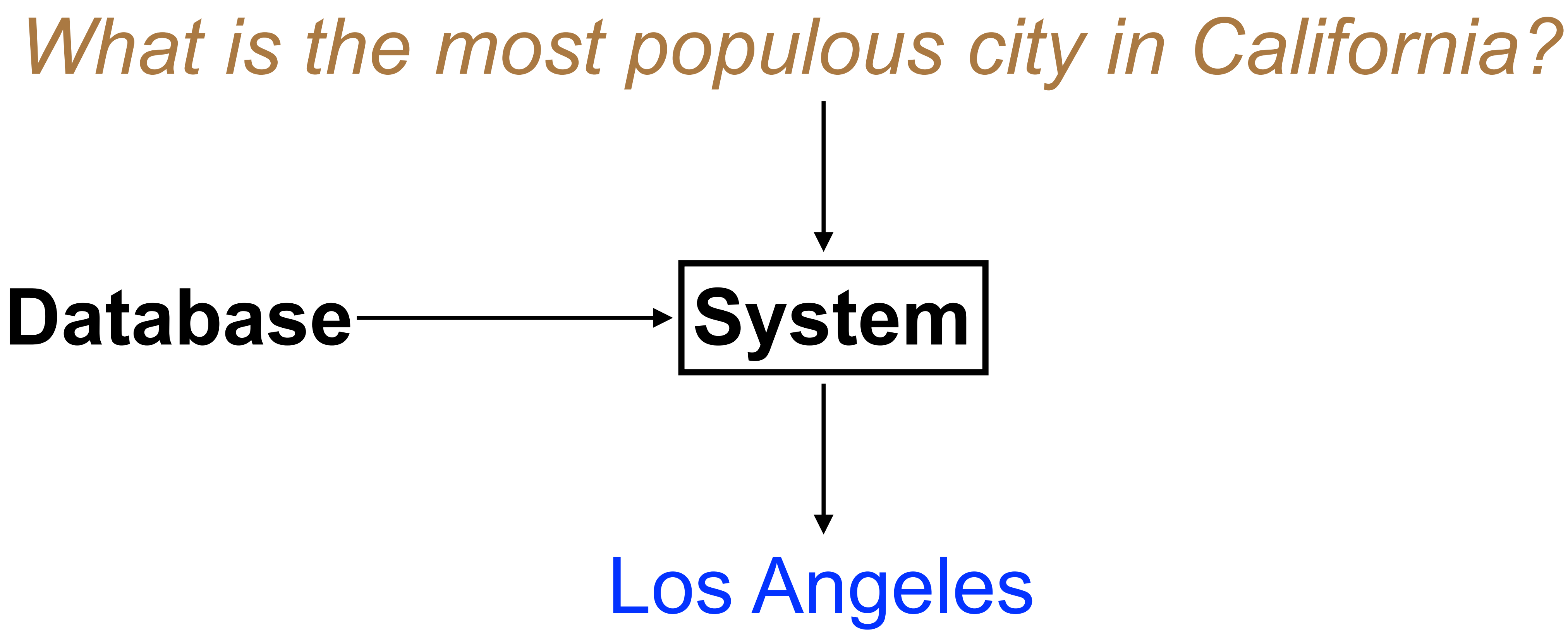
Problem: obtaining logical forms



- What **system** does:
  - Convert a sentence into a logical form (query) ⇒ difficult
  - Obtain the answer by querying to the database ⇒ deterministic
- **Challenge is how to convert a sentence into logical form**

Two different top-down approaches

- Top-down approaches are further divided into two, based on the form of supervision
  - **Fully supervised approach**:
    - Each training data is (sentence, logical form) pair
    - e.g., (*What's Bulgaria's capital?*, *λx.capital(x, bulgaria)*)
    - Pro: Learning is more tractable
    - Con: Preparing many logical forms by hand is costly
  - **Weakly supervised approach**:
    - Each training data is (sentence, answer) pair
    - e.g., (*What's Bulgaria's capital?*, Sofia)
    - Logical form is **a latent variable in a model**
    - Much more challenging, but much more cheaper

Short history

- Fully-supervised approach was dominated until ~2011, 2012
- 2011, a successful weakly-supervised approach appeared:
  - Liang et al,. Learning dependency-based compositional semantics. In *ACL* 2011.
  - Since then, weak supervision becomes a popular approach
- Advantage of weak supervision is **scalability**:
  - Writing logical form is impossible for ordinary people
  - But answering a question does not require linguistic knowledge
    - ⇒ We can use crowdsourcing to collect the data cheaply!

Fully supervised approach

Training data:

a) What states border Texas
$\lambda x.state(x) \wedge borders(x, texas)$

b) What is the largest state
$\arg\max(\lambda x.state(x), \lambda x.size(x))$

c) What states border the state that borders the most states
$\lambda x.state(x) \wedge borders(x, \arg\max(\lambda y.state(y),$
$\lambda y.count(\lambda z.state(z) \wedge borders(y, z))))$

training a parser

How many states border Oregon? → Semantic parser → $count(\lambda x.state(x) \wedge borders(x, oregon))$

Note on logical forms of DB query

- How can we read *count(λx.state(x) ∧ borders(x, oregon))*?

- *λx.f(x)* is a function
  - In DB query, a function can be seen as a set (entities satisfying f(x) relation)

- So *count(λx.f(x))* returns the size of entities satisfying *f(x)*

- We assume a DB, which keeps unary and binary relations
  - *λx.borders(x, oregon)* is a operation retrieving all entries where the second column is *oregon*
  - *state(x)* restricts the results to the values found in **state**

state

california
texas
nevada
…
…

border

california	*oregon*
nevada	*oregon*
~~*long view*~~	*oregon*
nevada	*utah*
…	

CCG can help?

Training data:

a) What states border Texas
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$\lambda y.count(\lambda z.state(z) \wedge borders(y, z))))$

- **Yes**
  - There are many approaches with this supervision relied on CCG
  - Zettlemoyer & Collins, 2005, 2007; Kwiatkowski et al., 2010, 2011; Artzi & Zettolemoyer, 2011, 2013; etc.
- Difference from RTE:
  - We do not use the output of CCG parser, but induce the grammar

Inducing CCG from logical forms

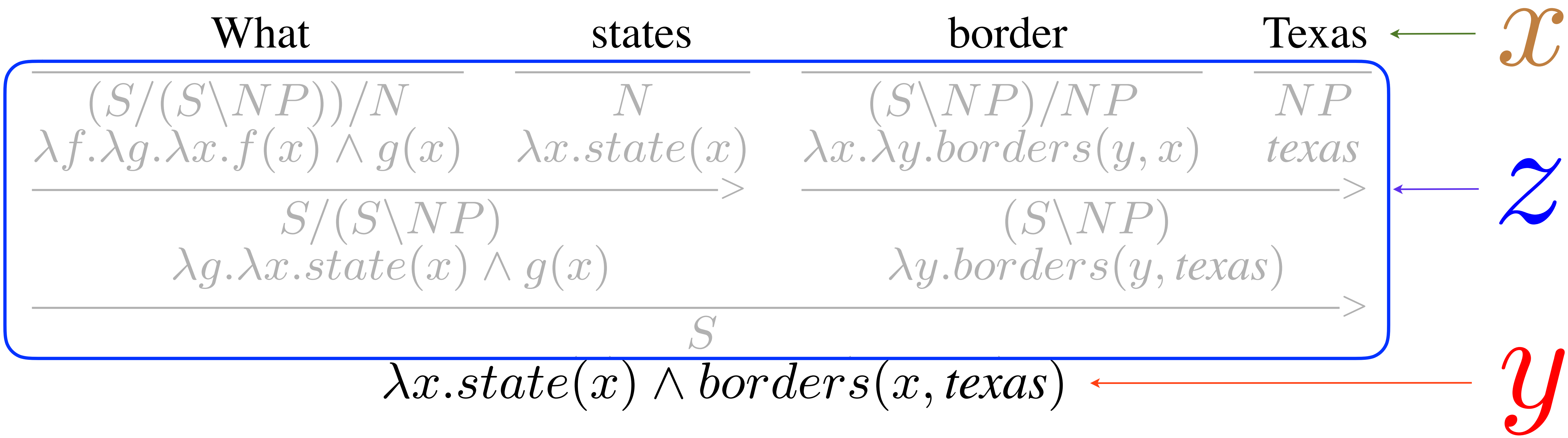
$$
\begin{array}{cccc|c}
\text{What} & \text{states} & \text{border} & \text{Texas} & x \\
\hline
(S/(S\backslash NP))/N & N & (S\backslash NP)/NP & NP & \\
\lambda f.\lambda g.\lambda x.f(x) \wedge g(x) & \lambda x.state(x) & \lambda x.\lambda y.borders(y,x) & texas & \\
\hline
\multicolumn{2}{c}{S/(S\backslash NP) \quad >} & \multicolumn{2}{c|}{(S\backslash NP) \quad >} & z \\
\multicolumn{2}{c}{\lambda g.\lambda x.state(x) \wedge g(x)} & \multicolumn{2}{c|}{\lambda y.borders(y, texas)} & \\
\hline
\multicolumn{4}{c|}{S \quad >} & \\
\multicolumn{4}{c|}{\lambda x.state(x) \wedge borders(x, texas)} & y
\end{array}
$$

- We treat CCG derivation as a latent variable (z) in the model
- Objective function: $\sum_{i=1}^{n} \log \left(\sum_{z} p(y, z | x, \theta) \right)$
  - maximize the likelihood marginalizing z
  - can be done by a variant of SGD (or a latent-variable perceptron)

Why we don’t use existing parsers?

- Probably the main reason is historical
  - We can of course utilize the results of existing CCG parsers
  - But the approach without existing parsers succeeded and got more popular
  - Note that even using other parsers, grounding (supervised learning by gold logical forms) is necessary
- Advantage of inducing grammar (not using existing parsers):
  - Free from parsing errors (error propagation)
  - (Possibly) developing a system for other languages is easier
    - CCG parsers are not available in many languages

Is this fully-supervised?



- In some sense, this approach is also a kind of weakly-supervised approach
  - in that we do not assume a gold syntactic derivation into the desired logical form (y)
  - We infer the latent CCG derivation (z) that bridges x and y
  - EM-like algorithm

Assumption (seed knowledge)

- Knowledge about CCG rules:
  - forward/backward application/composition, etc.
  - e.g., X/Y: f Y/Z: g → X/Z: λx.f(g x) (>B)
- **Type of logical form** for each CCG category
  - NP : *a* (constant)
  - N : $\lambda x.p(x)$
  - S\NP/NP : $\lambda x.\lambda y.p(x,y)$
- Initial lexicon (domain-independent important words):
  - What: S/(S\NP)/N: $\lambda f.\lambda g.\lambda x.f(x) \wedge g(x)$

Finding categories on words

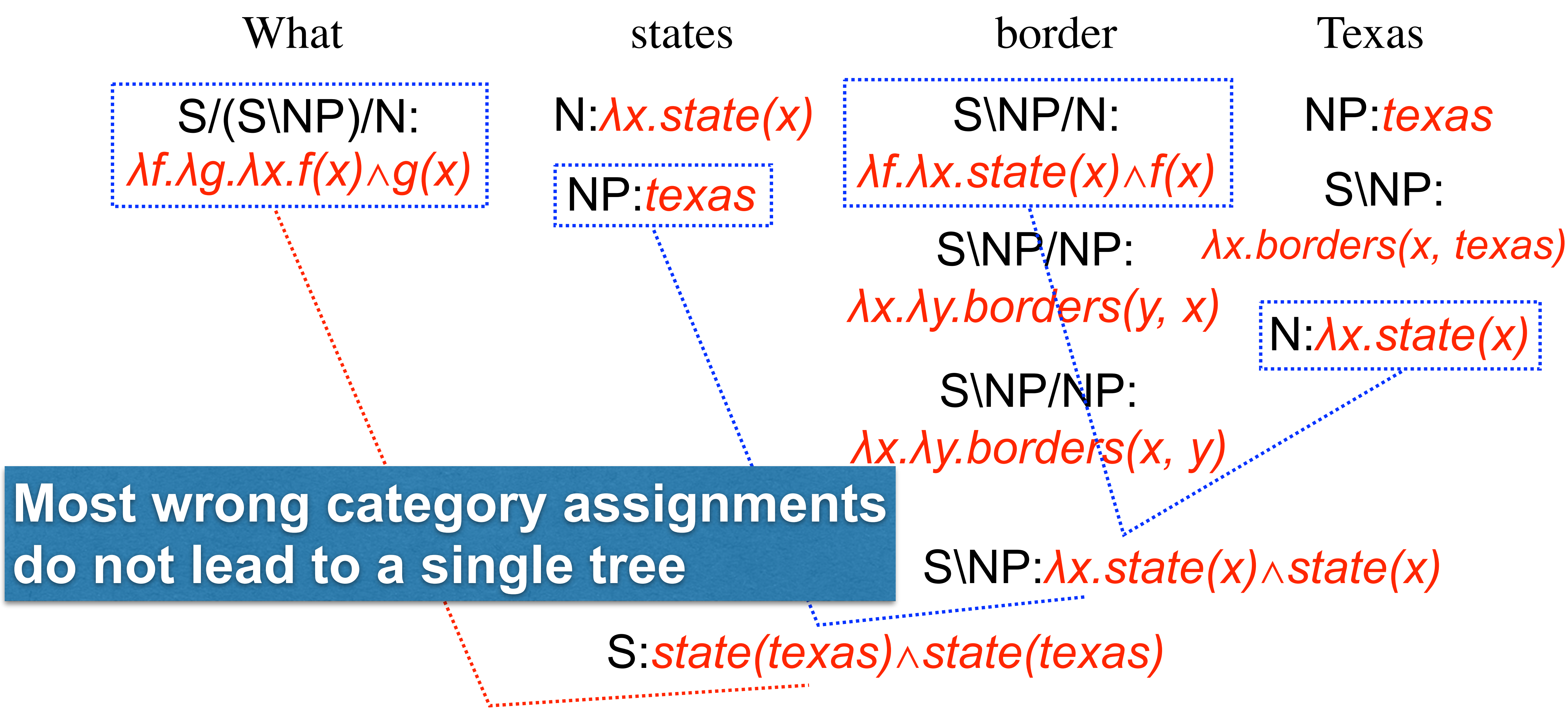
What states border Texas

$$\lambda x.state(x) \wedge borders(x, texas)$$

NP .... *texas*
N .... *λx.state(x)*
S\NP/NP .... *λx.λy.borders(x, y)*
S\NP/NP .... *λx.λy.borders(y, x)*
S\NP .... *λx.borders(x, texas)*
S/(S\NP)/N .... *λf.λg.λx.f(x)∧g(x)*
S\NP/N .... *λf.λx.state(x)∧f(x)*
… …

- First step is decomposing the final logical form into smaller pieces
- Corresponding CCG categories are limited due to the type constraints (isomorphism)

How learning proceeds?



- There is no constraint between each word and category
  - **Learning this mapping is the main challenge**
- We want to find mapping leading to the correct logical form

How learning proceeds?

What states border Texas

S/(S\NP)/N: $\lambda f.\lambda g.\lambda x.f(x) \wedge g(x)$

N: $\lambda x.state(x)$

NP: $texas$

S\NP/N: $\lambda f.\lambda x.state(x) \wedge f(x)$

S\NP/NP: $\lambda x.\lambda y.borders(y, x)$

NP: $texas$

S\NP: $\lambda x.borders(x, texas)$

N: $\lambda x.state(x)$

S/(S\NP): $\lambda g.\lambda x.state(x) \wedge g(x)$

S\NP/NP: $\lambda x.\lambda y.borders(x, y)$

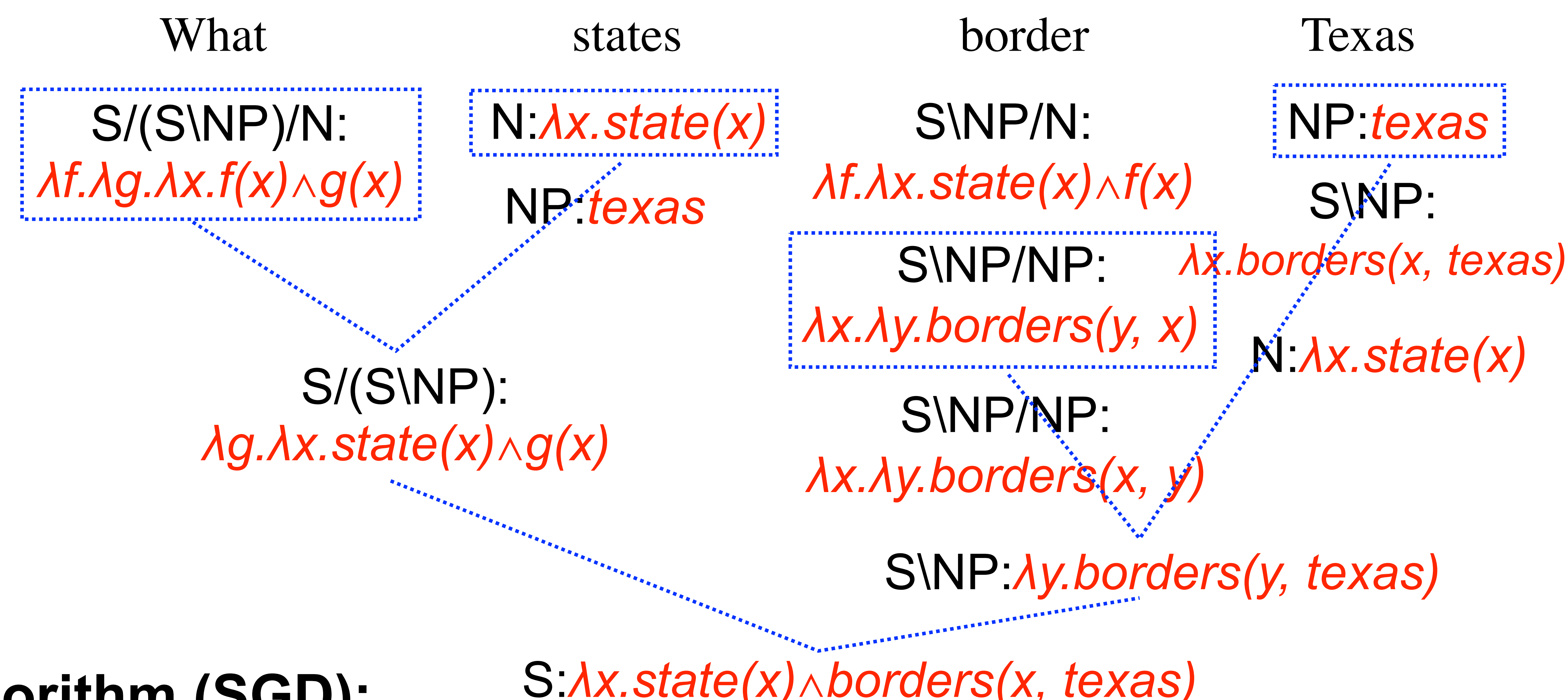
S\NP: $\lambda y.borders(texas, y)$

S: $\lambda x.state(x) \wedge borders(texas, x)$

Other incorrect category assignments (mostly) lead to wrong logical forms

gold: $\lambda x.state(x) \wedge borders(x, texas)$

How learning proceeds?



Algorithm (SGD):

for each (sentence, logical form) pair:

1. find derivations leading to the given logical form
2. strengthen the weights appeared in the found derivations

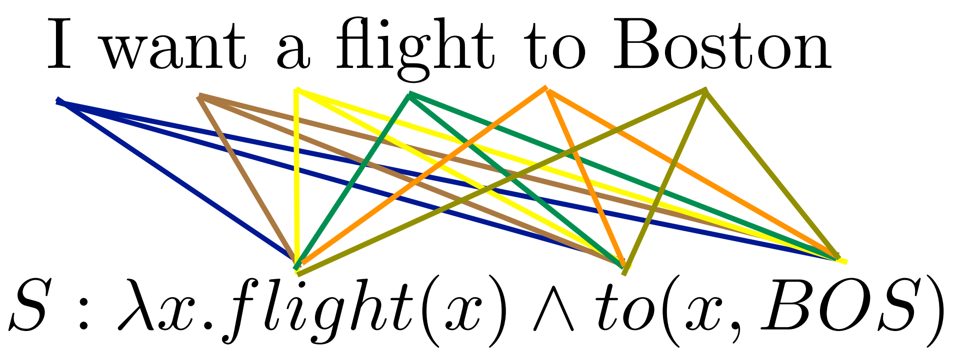
states → N:*λx.state(x)*	5.0 ⇒ 5.8	(+0.8)
states → NP:*texas*	0.2 ⇒ -0.5	(-0.7)

Why did this approach succeed?

- Strong inductive bias of CCG
  - Combinatory rules of CCG highly restrict the candidate lexical categories → facilitate mapping of words and categories
  - Such implicit bias to help machine learning algorithm is called "inductive bias", which is essential for many NLP systems
- Sentences are not complex
  - Question sentences are not very complex
  - They are typically 5~10 words
    - search space for a model is not so quite large

Later extensions

- Zettlemoyer and Collins (UAI 2005)
  - first approach; described so far
  - use some initial lexicon (e.g., *what, every*)
- Kwiatokovski et al., (EMNLP 2010)
  - Reducing supervision signals by learning mapping of every word



  - using alignment technique in machine translation (IBM model) to obtain better initial parameters
- Kwiatokovski et al., (EMNLP 2011)
  - Further refinements in the probabilistic model

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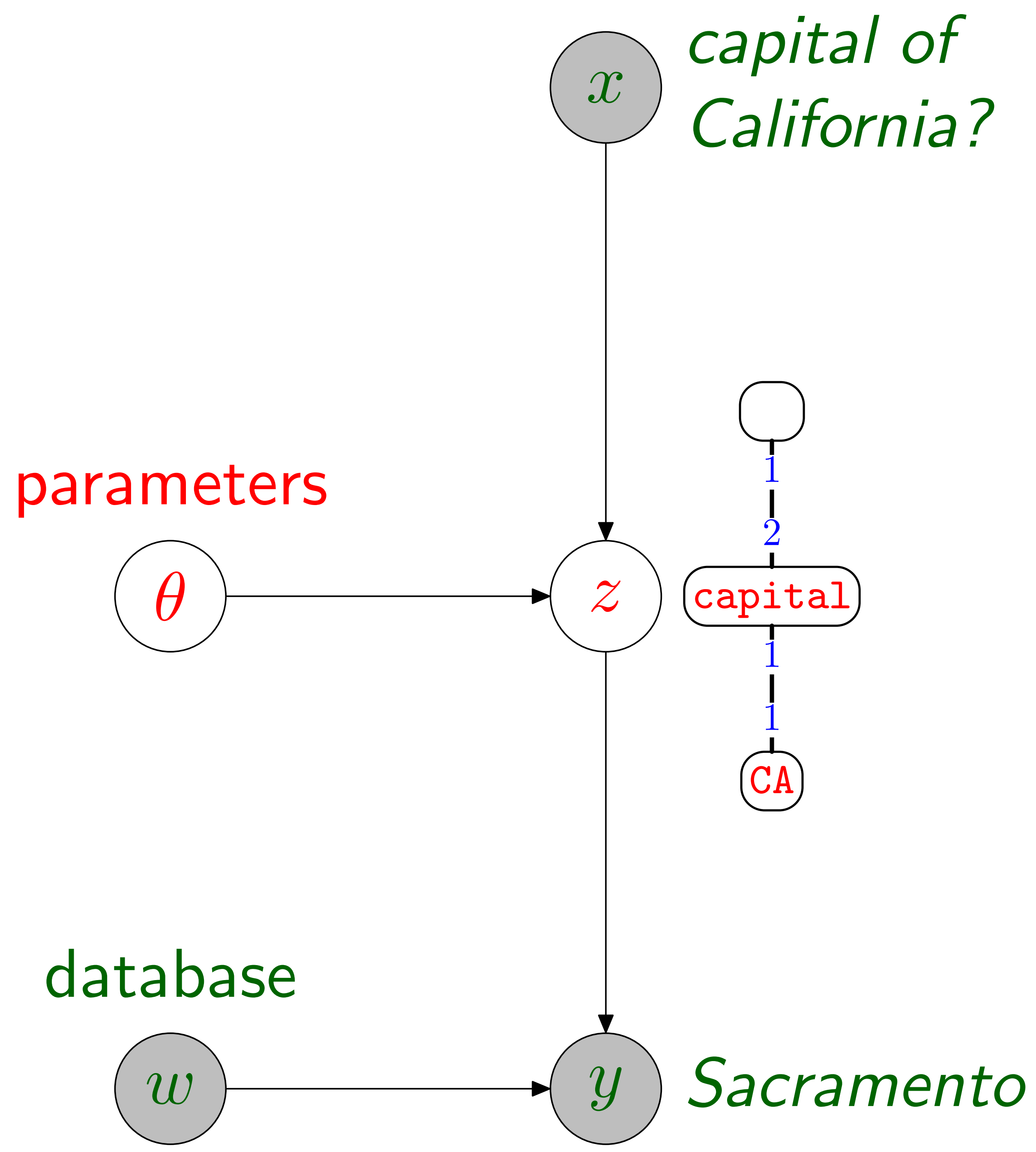
Weakly-supervised approach

- CCG induction requires (sentence, logical form) pairs, but annotating logical forms are costly
  - requires expert knowledge
- Can we learn a semantic parser only from (sentence, answer) pairs?
  - Liang et al. showed this is possible
  - **Idea:**
    - Logical form is treated as a latent variable in the model
    - This logical form is simpler (weaker than first-order logic) and aimed at querying DB (**very task-specific**)
    - Learning correct logicals form via SGD-like algorithm

Logical form is latent variable



Semantic Parsing: $p(z \mid x, \theta)$
(probabilistic)

Interpretation: $p(y \mid z, w)$
(deterministic)

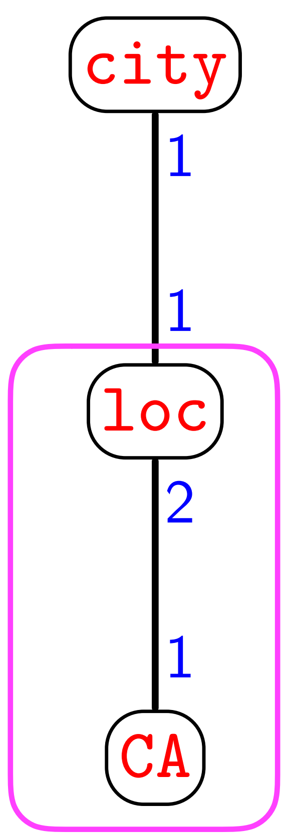
Figure from Liang et al., Learning dependency-based compositional semantics. In ACL 2011.

DCS

Dependency-based compositional semantics

For *"city in California"*

DCS tree



Constraints

$c \in \texttt{city}$

$c_1 = \ell_1$

$\ell \in \texttt{loc}$

$\ell_2 = s_1$

$s \in \texttt{CA}$

Database

`city`

San Francisco
Chicago
Boston
...

`loc`

Mount Shasta	California
San Francisco	**California**
Boston	Massachusetts
...	...

`CA`

California

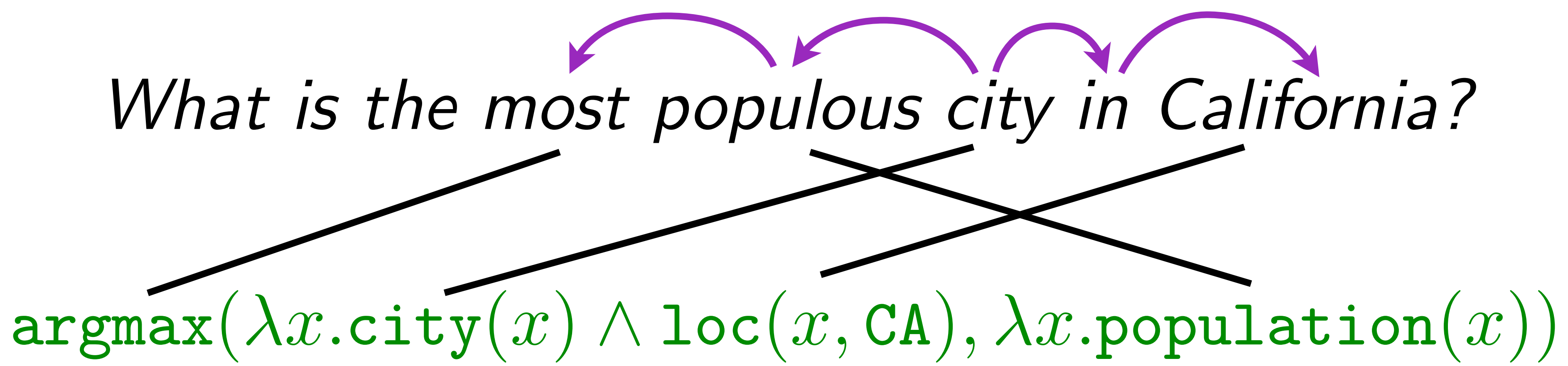
A subtree represents a set

(Rows of `loc` where 2nd column is `CA`)

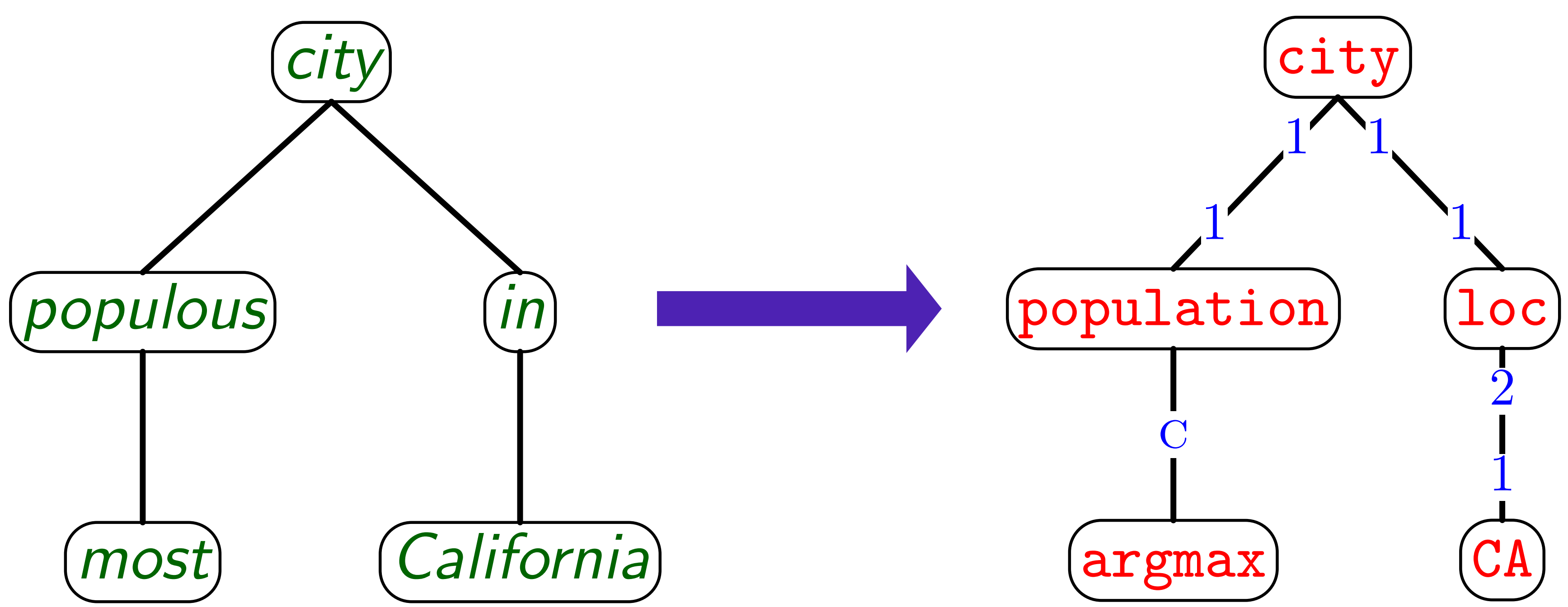
Figure from Liang et al., Learning dependency-based compositional semantics. In ACL 2011.

Comparison to lambda expression

- Gap between syntax of sentence and lambda expression is large



- Syntax of DCS much resembles dependency structure

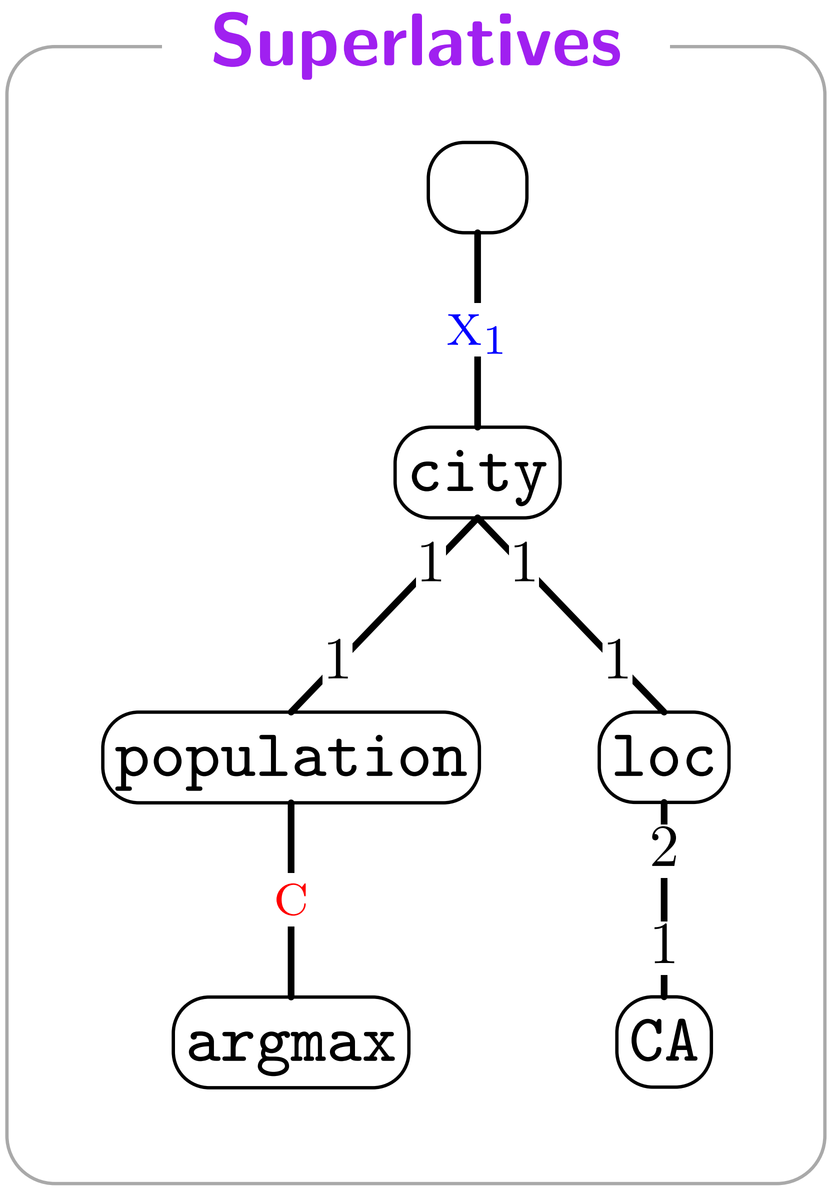


Trick for resemblance to dependency

most populous city in California

Execute at semantic scope

Mark at syntactic scope



- Explanation is simple, but actual mechanism is complex

Figure from Liang et al., Learning dependency-based compositional semantics. In ACL 2011.

Learning

- Basically the same as CCG-based approach
  - Though DCS resembles dependency structure, we do not use any existing parsers
- Difference: We do not have the correct logical form
  - **We can infer whether the created DCS tree is correct or not, by directly querying it to DB**
  - **If DB returns the correct answer, the DCS tree is probably correct (weak-supervision)**
  - Note: We can convert a DCS tree into a DB-specific logical form

Initial lexicon

				`city`	`city`			
				`state`	`state`			
				`river`	`river`			
			`argmax`	`population`	`population`		`CA`	
What	*is*	*the*	*most*	*populous*	*city*	*in*	*CA*	*?*

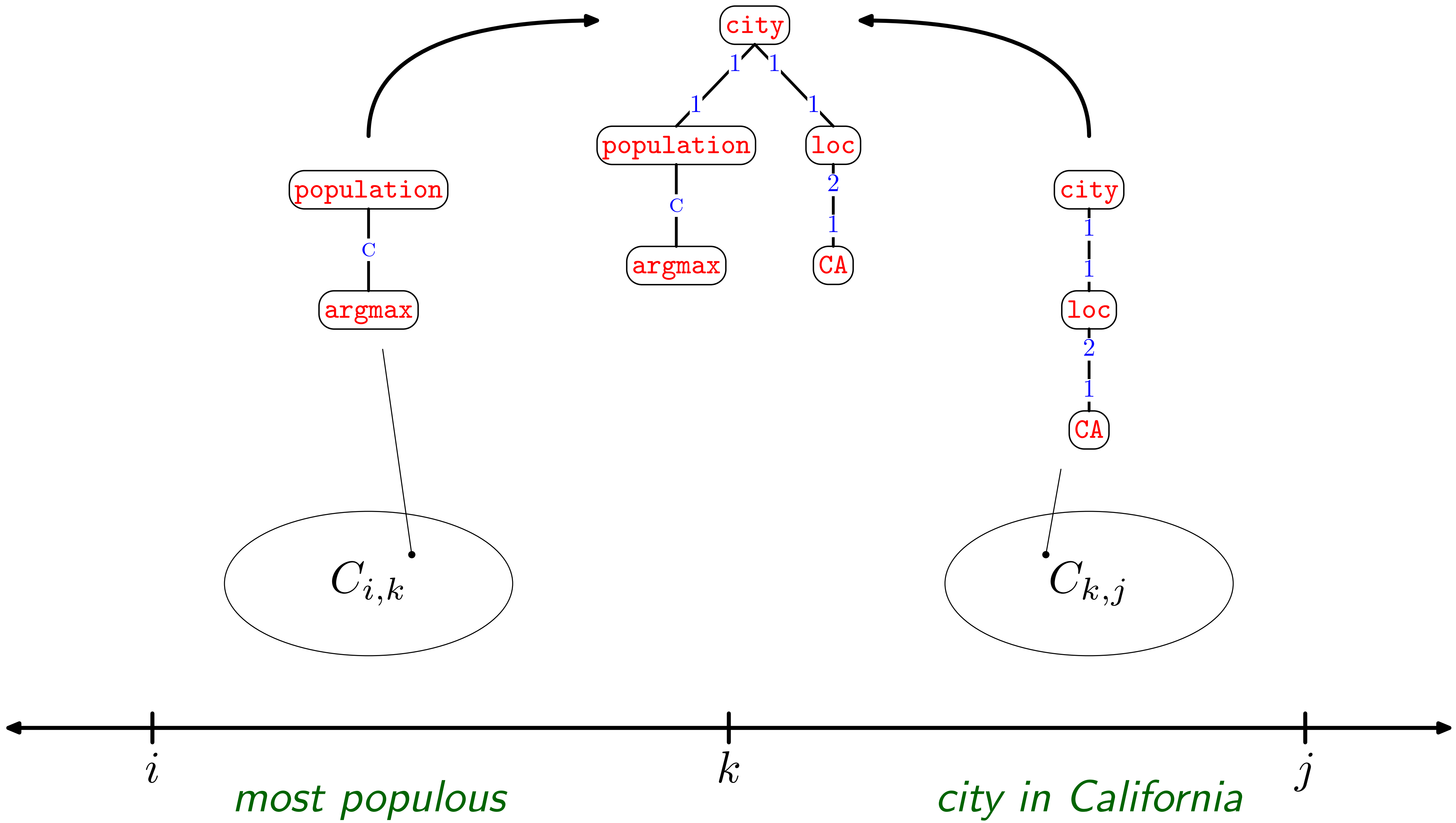
Lexical Triggers:

1. String match *CA* $\Rightarrow$ `CA`
2. Function words (20 words) *most* $\Rightarrow$ `argmax`
3. Nouns/adjectives *city* $\Rightarrow$ `city state river population`

- Learning from answer only is very hard
  - We assume some initial lexicon (more than initial CCG-based approach), which is necessary

Figure from Liang et al., Learning dependency-based compositional semantics. In ACL 2011.

SGD-like algorithm



- Find K-best DCS derivations under the current model (beam search)
- Push the weights of features appeared in derivations that return the correct answer

Figure from Liang et al., Learning dependency-based compositional semantics. In ACL 2011.

Results

On GEO, 600 training examples, 280 test examples

System	**Description**	**Lexicon**	**Logical forms**
ZC05	CCG [Zettlemoyer & Collins, 2005]	✗ ✗	✓
ZC07	relaxed CCG [Zettlemoyer & Collins, 2007]	✗ ✗	✓
KZGS10	CCG w/unification [Kwiatkowski et al., 2010]	✗ ✗	✓
DCS	our system	✓ ✗	✗
DCS$^+$	our system	✓ ✓	✗

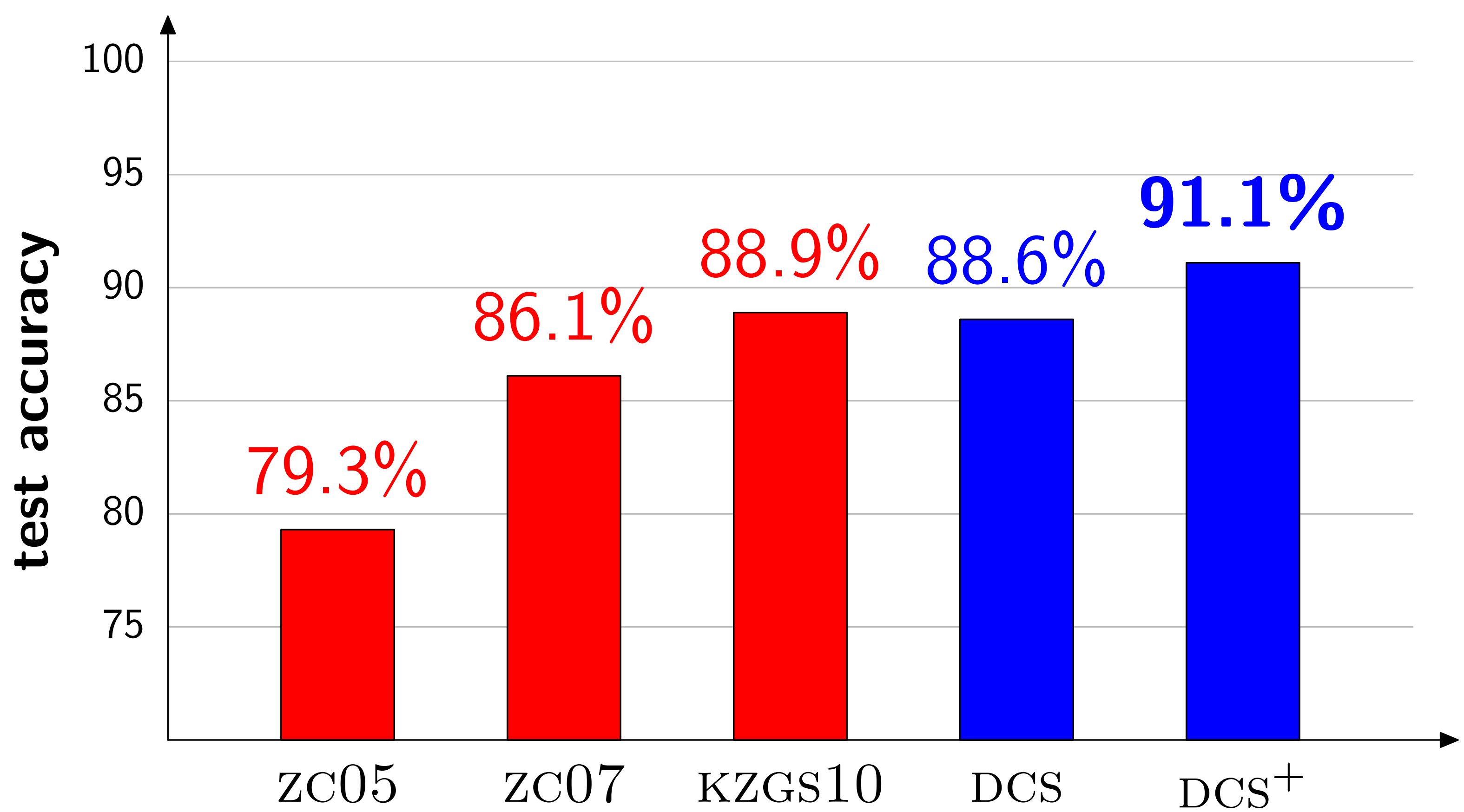


Figure from Liang et al., Learning dependency-based compositional semantics. In ACL 2011.

Conclusion

- Direction of CCG and lambda expression-based semantic parsing is **going to get a general semantic logical form that is task-independent**
  - But task-independent form is complex
  - Learning from (sentence, answer) paris assuming lambda expression is impossible
- DCS is simple, but has enough representation power to handle the present task (QA from DB)
- Reducing supervision is essential for NLP, and developing task-specific representation is important for this end

Plan of the last lecture

- We have seen a short history of semantic parsing for QA until DCS appeared in 2011
  - That time the domain was very limited (e.g., US geography)
  - Words are limited in a domain, and learning was not so hard
- In the last lecture, we discuss more recent research efforts
  - Open-domain QA (on Wikipedia, and Google Freebase)
  - QA from a semi-structured table
  - Context-dependent QA
  - (multi-modal QA?)