



**THE OHIO STATE
UNIVERSITY**

CSE 5525: Foundations of Speech and Language Processing

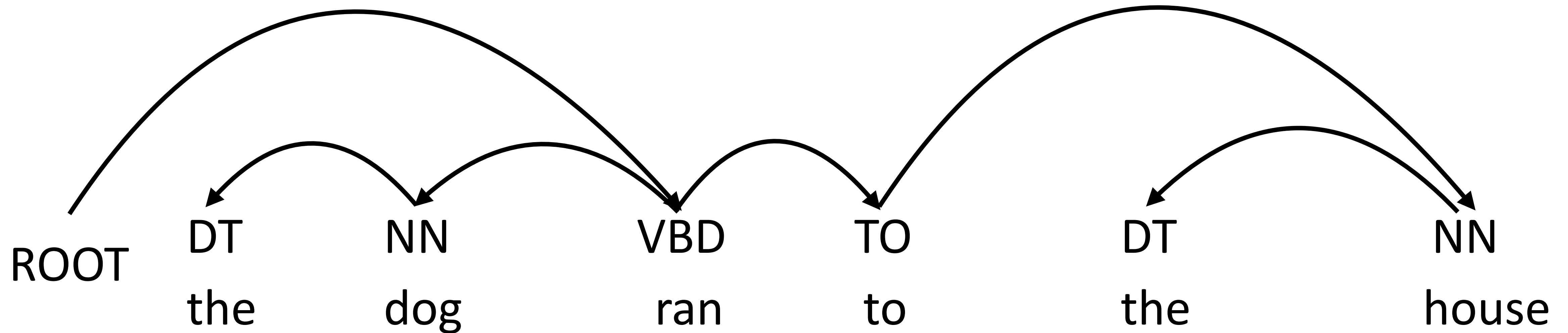
Semantics

Huan Sun (CSE@OSU)

Many thanks to Prof. Greg Durrett @ UT Austin for sharing his slides.
Some images/examples were from the two textbooks by (1) Jurafsky and Martin and (2) Eisenstein.

Recall: Dependencies

- ▶ Dependency syntax: syntactic structure is defined by dependencies
 - ▶ Head (parent, governor) connected to dependent (child, modifier)
 - ▶ Each word has exactly one parent except for the ROOT symbol
 - ▶ Dependencies must form a directed acyclic graph



- LEFTARC: Assert a head-dependent relation between the word at the top of the stack and the word directly beneath it; remove the lower word from the stack.
- RIGHTARC: Assert a head-dependent relation between the second word on the stack and the word at the top; remove the word at the top of the stack;
- SHIFT: Remove the word from the front of the input buffer and push it onto the stack.

Recall: arc standard approach; Shift-reduce parsing

Step	Stack	Word List	Action	Relation Added
0	[root]	[book, me, the, morning, flight]	SHIFT	
1	[root, book]	[me, the, morning, flight]	SHIFT	
2	[root, book, me]	[the, morning, flight]	RIGHTARC	(book → me)
3	[root, book]	[the, morning, flight]	SHIFT	
4	[root, book, the]	[morning, flight]	SHIFT	
5	[root, book, the, morning]	[flight]	SHIFT	
6	[root, book, the, morning, flight]	[]	LEFTARC	(morning ← flight)
7	[root, book, the, flight]	[]	LEFTARC	(the ← flight)
8	[root, book, flight]	[]	RIGHTARC	(book → flight)
9	[root, book]	[]	RIGHTARC	(root → book)
10	[root]	[]	Done	

Figure 15.7 Trace of a transition-based parse.

Where are we now?

- ▶ Early in the class: bags of word (classifiers) => sequences of words (sequence modeling)
- ▶ Now we can understand sentences in terms of tree structures as well

Where are we now?

- ▶ Early in the class: bags of word (classifiers) => sequences of words (sequence modeling)
- ▶ Now we can understand sentences in terms of tree structures as well
- ▶ Why is this useful? What does this allow us to do?
- ▶ We're going to see how syntactic parsing can be a stepping stone towards more formal representations of language meaning

Today

- ▶ Montague semantics*:
 - ▶ Model theoretic semantics
 - ▶ Compositional semantics with first-order logic
- ▶ CCG parsing for database queries
- ▶ Lambda-DCS for question answering

*The approach of algorithmically building up meaning representations from a series of operations on the syntactic structure of a sentence is generally attributed to the philosopher Richard Montague, who published a series of influential papers on the topic in the early 1970s (Chapter 12.3.1, Eisenstein)

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Model-Theoretic Semantics

Meaning Representation

- ▶ To be useful, a meaning representation must meet several criteria:
 - **c1:** it should be unambiguous: unlike natural language, there should be exactly one meaning per statement;
 - **c2:** it should provide a way to link language to external knowledge, observations, and actions;
 - **c3:** it should support computational **inference**, so that meanings can be combined to derive additional knowledge;
 - **c4:** it should be expressive enough to cover the full range of things that people talk about in natural language.

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Meaning Representation

- ▶ What does it mean for a statement to be unambiguous?

Programming languages:

$$\llbracket 5+3 \rrbracket = \llbracket (4*4) - (3*3) + 1 \rrbracket = \llbracket ((8)) \rrbracket = 8.$$

- ▶ The output of a program (or, **denotation**) determined by **constants** (e.g., 4, 3) and **relations** (e.g., +, -)

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How about **double(4)**? Is it unambiguous?

depends on the meaning of **double**, which is defined in a **world model** M .

-
- ▶ As long as the denotation of a statement in model M can be computed unambiguously, it can be said to be unambiguous.

Model-Theoretic Semantics Approach

- ▶ Addresses c1 (no ambiguity) and c2 (connecting language with external knowledge/observations/actions)
- ▶ e.g. connect the meaning of “the capital of Georgia” with a world model that includes a knowledge base

Model-Theoretic Semantics

- ▶ Addresses c1 (no ambiguity) and c2 (connecting language with external knowledge/observations/actions)
 - ▶ Criterion c3: meaning representation supports inference ($A \Rightarrow B$)
 - ▶ Criterion c4: meaning representation be sufficiently expressive
-
- ▶ The most mature is the language of *first-order logic*

First-order Logic

- ▶ Powerful logic formalism including things like constants/entities, relations/predicates, and quantifiers

Lady Gaga sings

- ▶ *sings* is a *predicate* (with one argument); function $f: \text{entity} \rightarrow \text{true/false}$
- ▶ $\text{sings}(\text{Lady Gaga}) = \text{true or false}$, which we can find out by executing this against some database (*world*)
- ▶ $[[\text{sings}]] = \textit{denotation}$, set of entities which sing (found by executing this predicate on the *world* — we'll come back to this)

Quantifiers

▶ **Universal quantifier:** “forall” operator

▶ $\forall x \text{ sings}(x) \vee \text{ dances}(x) \rightarrow \text{ performs}(x)$

“Everyone who sings or dances performs”

Quantifiers

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▶ **Existential quantifiers:** “there exists” operator

▶ $\exists x \text{ sings}(x)$ *“Someone sings”*

Quantifiers

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“Everyone who sings or dances performs”

▶ **Existential quantifiers:** “there exists” operator

▶ $\exists x \text{ sings}(x)$ *“Someone sings”*

▶ **Source of ambiguity!** *“Everyone is friends with someone”*

▶ $\forall x \exists y \text{ friend}(x,y)$

▶ $\exists y \forall x \text{ friend}(x,y)$

Logic in NLP Tasks

- ▶ Question answering (or, semantic parsing):

Who are all the American singers named Amy?

$\lambda x. \text{nationality}(x, \text{USA}) \wedge \text{sings}(x) \wedge \text{firstName}(x, \text{Amy})$

- ▶ **Lambda calculus**: (logical form for the question)

Logic in NLP

- ▶ Question answering:

Who are all the American singers named Amy?

$\lambda x. \text{nationality}(x, \text{USA}) \wedge \text{sings}(x) \wedge \text{firstName}(x, \text{Amy})$

- ▶ **Function** that maps from x to true/false, like `filter`. Execute this on the *world* to answer the question (x 's that meet these constraints are answers)
- ▶ Lambda calculus: powerful system for expressing these functions

Logic in NLP

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- ▶ Lambda calculus: powerful system for expressing these functions

- ▶ Information extraction: *Lady Gaga and Eminem are both musicians*

$\text{musician}(\text{Lady Gaga}) \wedge \text{musician}(\text{Eminem})$

- ▶ Can now do **reasoning**. If knowing: $\forall x \text{ musician}(x) \Rightarrow \text{performer}(x)$

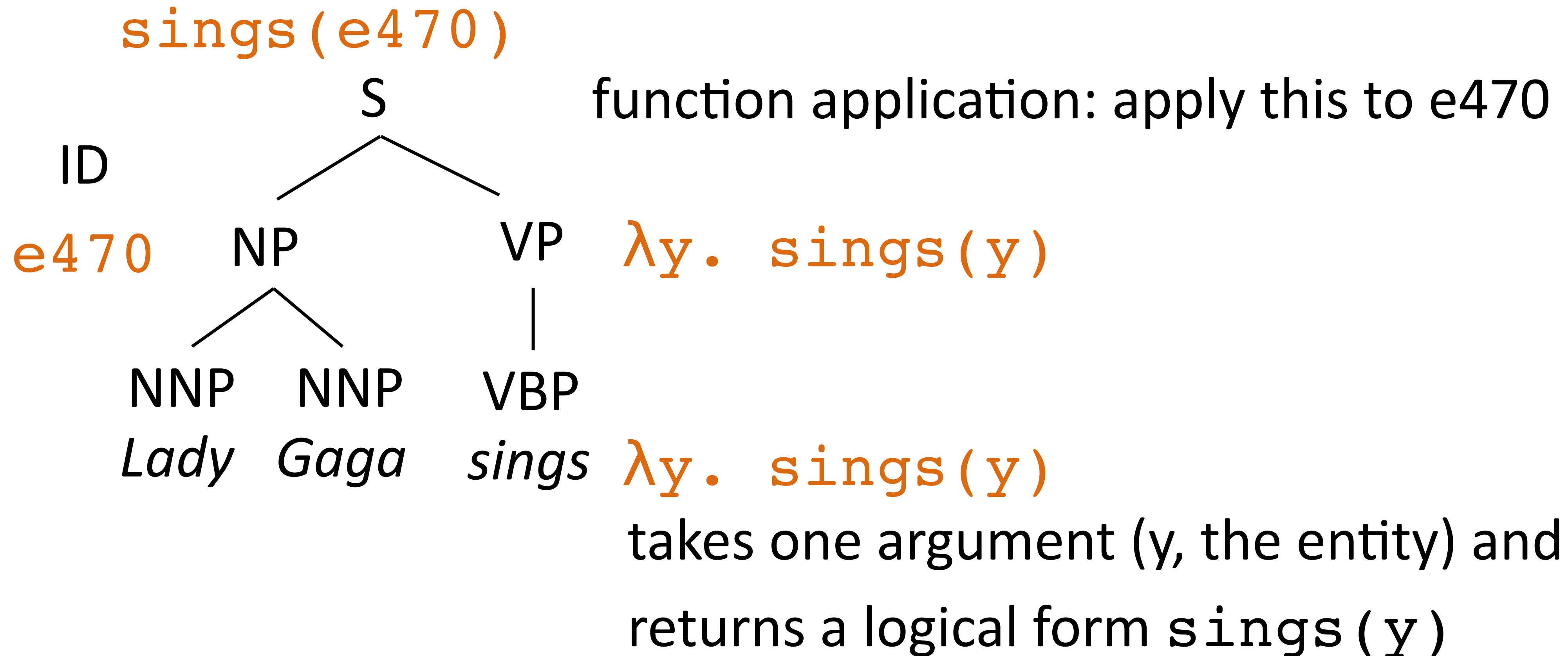
Then: $\text{performer}(\text{Lady Gaga}) \wedge \text{performer}(\text{Eminem})$

Today

- ▶ Montague semantics*:
 - ▶ Model theoretic semantics
 - ▶ **Compositional semantics with first-order logic (For Offline Reading)**
- ▶ CCG parsing for database queries
- ▶ Lambda-DCS for question answering

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Montague Semantics

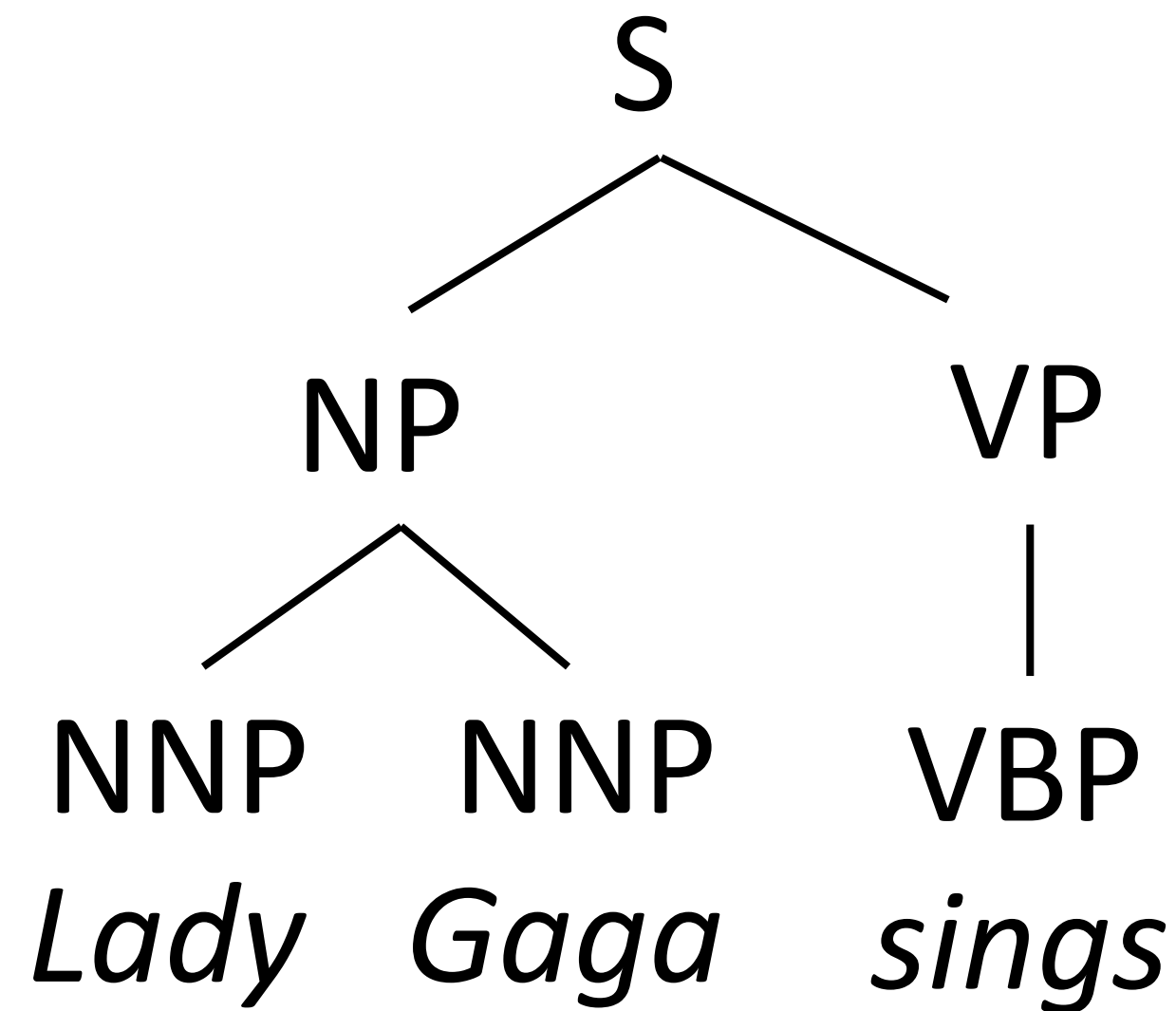


- ▶ We can use the syntactic parse as a bridge to the lambda-calculus representation, build up a logical form (our model) *compositionally*

▶ (For Offline Reading)

Background

(For Offline Reading)



Id	Name	Alias	Birthdate	Sings?
e470	Stefani Germanotta	Lady Gaga	3/28/1986	T
e728	Marshall Mathers	Eminem	10/17/1972	T

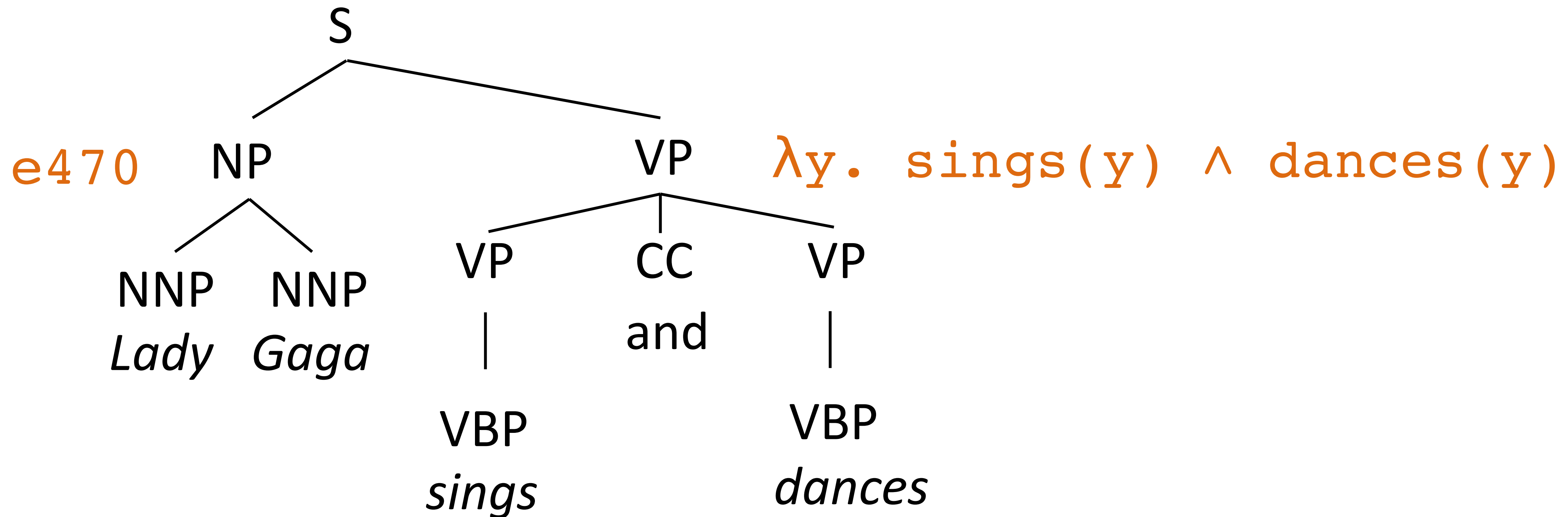
- ▶ Database containing entities, predicates, etc.

- ▶ Sentence expresses something about the world which is either true or false
- ▶ Denotation: evaluation of some expression against this database
 - ▶ $[[\textit{Lady Gaga}]] = e470$
denotation of this string is an entity
 - ▶ $[[\textit{sings}(e470)]] = \text{True}$
denotation of this expression is T/F

Parses to Logical Forms

(For Offline Reading)

$sings(e470) \wedge dances(e470)$



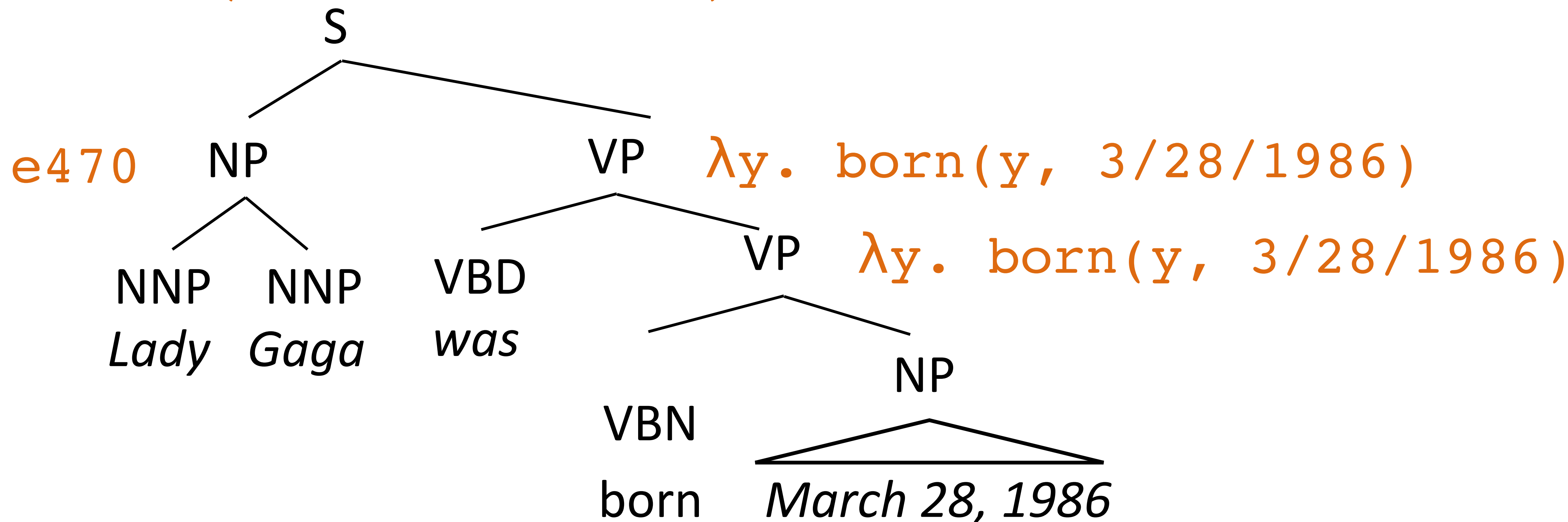
$\lambda y. sings(y) \quad \lambda y. dances(y)$

- ▶ General rules: $VP: \lambda y. a(y) \wedge b(y) \rightarrow VP: \lambda y. a(y) \text{ CC } VP: \lambda y. b(y)$
 $S: f(x) \rightarrow NP: x \text{ VP: } f$

Parses to Logical Forms

(For Offline Reading)

$\text{born}(e470, 3/28/1986)$



- ▶ Function takes two arguments: first x (date), then y (entity)
- ▶ How to handle tense: should we indicate that this happened in the past?

Tricky things

(For Offline Reading)

- ▶ Adverbs/temporality: *Lady Gaga sang well yesterday*

$\text{sings}(\text{Lady Gaga}, \text{time=yesterday}, \text{manner=well})$

- ▶ “Neo-Davidsonian” view of events: things with many properties:

$\exists e. \text{type}(e, \text{sing}) \wedge \text{agent}(e, e470) \wedge \text{manner}(e, \text{well}) \wedge \text{time}(e, \dots)$

- ▶ Quantification: *Everyone is friends with someone*

$\exists y \forall x \text{ friend}(x, y)$ $\forall x \exists y \text{ friend}(x, y)$
(one friend) (different friends)

- ▶ Same syntactic parse for both! So syntax doesn't resolve all ambiguities

- ▶ Indefinite: *Amy ate a waffle* $\exists w. \text{waffle}(w) \wedge \text{ate}(\text{Amy}, w)$

- ▶ Generic: *Cats eat mice* (all cats eat mice? most cats? some cats?)

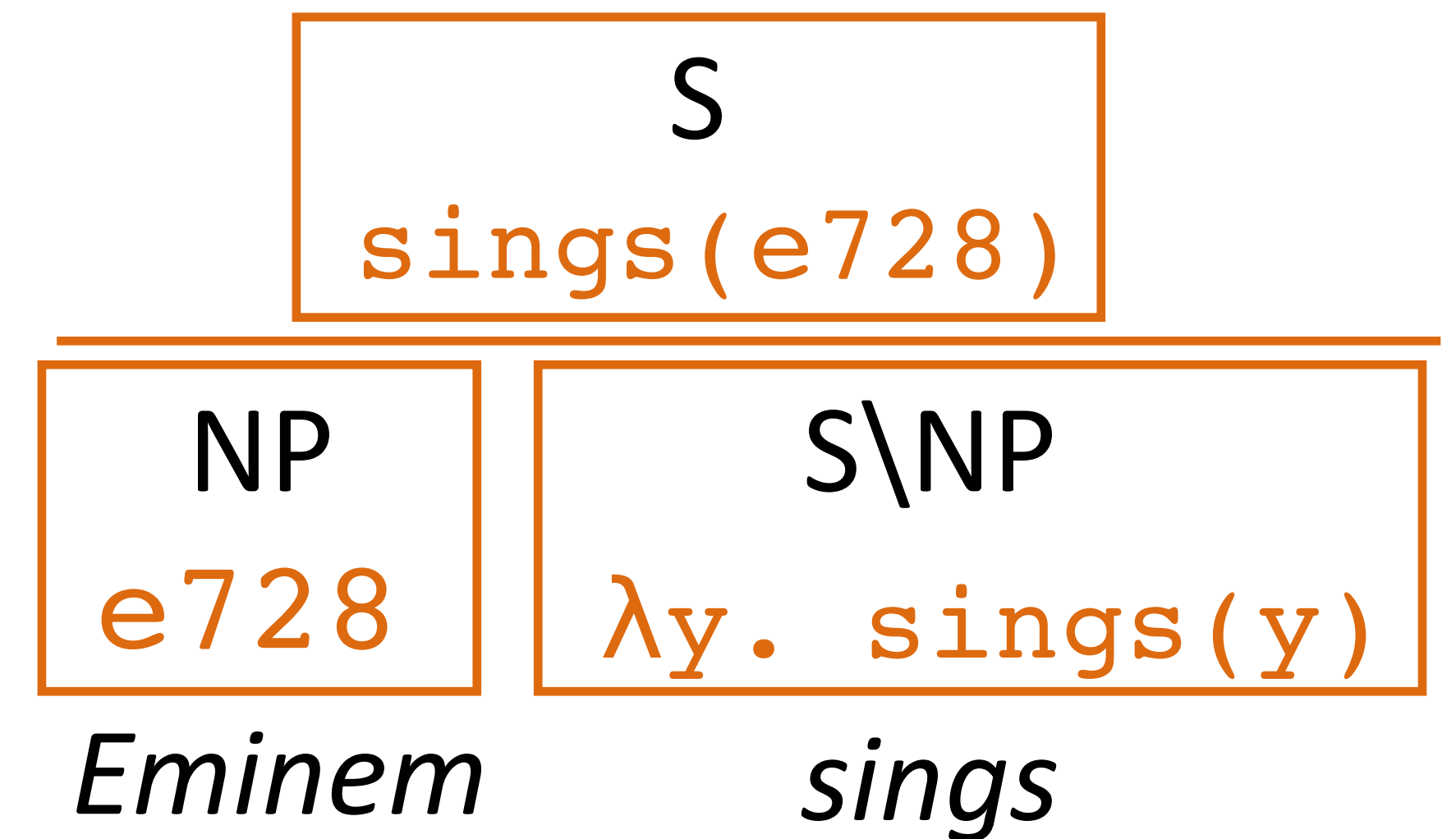
Semantic Parsing

- ▶ For question answering, syntactic parsing doesn't tell you everything you want to know, but indicates the right structure
- ▶ Solution: *semantic parsing* (many forms of this task depending on semantic formalisms)
- ▶ Two today: CCG (looks like what we've been doing) and lambda-DCS
- ▶ Applications: database querying/question answer: produce lambda-calculus expressions that can be executed in these contexts

CCG Parsing

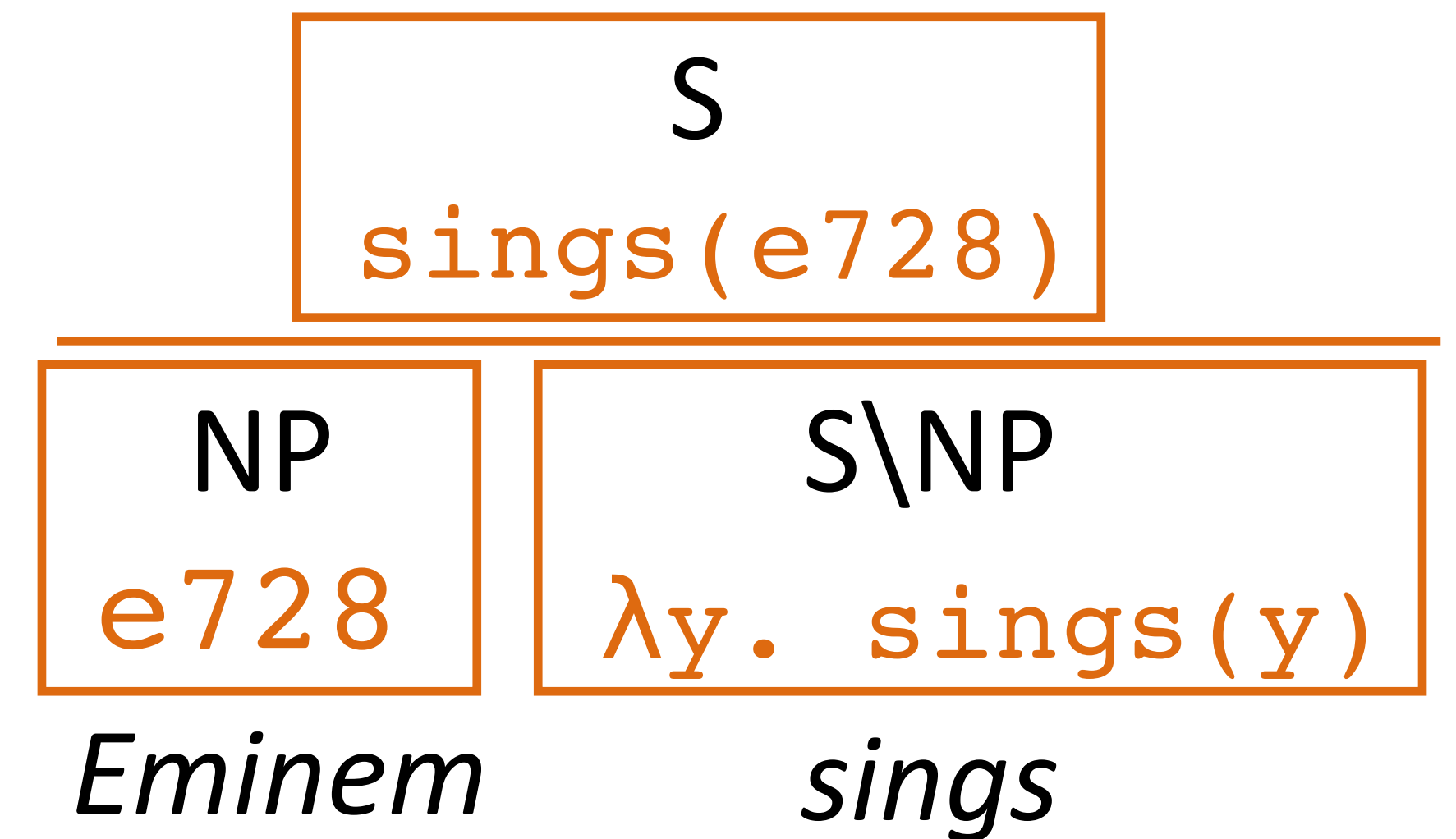
Combinatory Categorical Grammar

- ▶ Steedman+Szabolcsi (1980s): formalism bridging syntax and semantics
- ▶ Parallel derivations of syntactic parse and lambda calculus expression



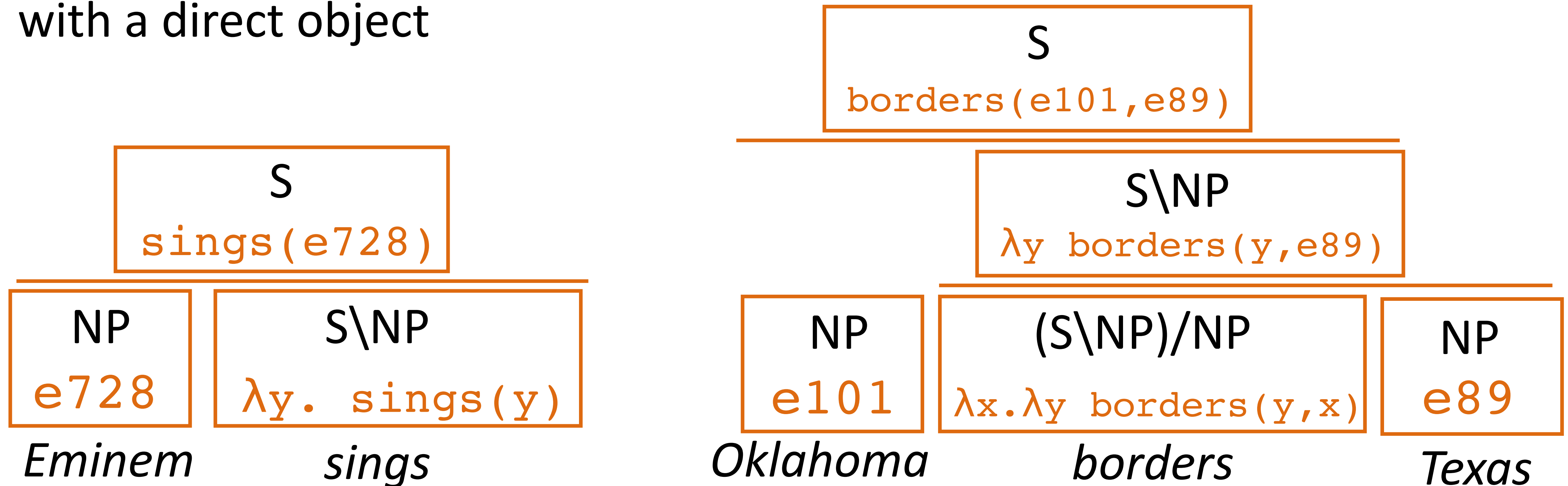
Combinatory Categorical Grammar

- ▶ Steedman+Szabolcsi (1980s): formalism bridging syntax and semantics
- ▶ **Parallel derivations of syntactic parse and lambda calculus expression**
- ▶ Syntactic categories (for this lecture): S, NP, “slash” categories
- ▶ S\NP: “if I combine with an NP on my left side, I form a sentence” — verb or vp
- ▶ When you apply this, there has to be a parallel instance of function application on the semantics side



Combinatory Categorical Grammar

- ▶ Steedman+Szabolcsi 1980s: formalism bridging syntax and semantics
- ▶ Syntactic categories (for this lecture): S, NP, “slash” categories
 - ▶ $S \backslash NP$: “if I combine with an NP on my left side, I form a sentence” — verb
 - ▶ $(S \backslash NP) / NP$: “I need an NP on my right and then on my left” — verb with a direct object



CCG Parsing

<div style="border-bottom: 1px solid black; margin-bottom: 5px;"> <p>What</p> </div> $\frac{(S/(S\backslash NP))/N}{\lambda f.\lambda g.\lambda x.f(x) \wedge g(x)}$	<div style="border-bottom: 1px solid black; margin-bottom: 5px;"> <p>states</p> </div> $\frac{N}{\lambda x.state(x)}$	<div style="border-bottom: 1px solid black; margin-bottom: 5px;"> <p>border</p> </div> $\frac{(S\backslash NP)/NP}{\lambda x.\lambda y.borders(y, x)}$	<div style="border-bottom: 1px solid black; margin-bottom: 5px;"> <p>Texas</p> </div> $\frac{NP}{texas}$
		$\xrightarrow{\hspace{10em}}$	
		$\frac{(S\backslash NP)}{\lambda y.borders(y, texas)}$	

- ▶ “What” is a **very** complex type: needs a noun and needs a $S\backslash NP$ to form a sentence. $S\backslash NP$ is basically a verb or verb phrase (*border Texas*)

CCG Parsing

What	states	border	Texas
$(S/(S \setminus NP))/N$	N	$(S \setminus NP)/NP$	NP
$\lambda f. \lambda g. \lambda x. f(x) \wedge g(x)$	$\lambda x. state(x)$	$\lambda x. \lambda y. borders(y, x)$	$texas$
$S/(S \setminus NP)$		$(S \setminus NP)$	
$\lambda g. \lambda x. state(x) \wedge g(x)$		$\lambda y. borders(y, texas)$	
S			
$\lambda x. state(x) \wedge borders(x, texas)$			

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$S/(S \setminus NP)$		$(S \setminus NP)$	
$\lambda g. \lambda x. state(x) \wedge g(x)$		$\lambda y. borders(y, texas)$	
S			
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- ▶ “What” is a **very** complex type: needs a noun and needs a $S \setminus NP$ to form a sentence. $S \setminus NP$ is basically a verb phrase (*border Texas*)
- ▶ **Lexicon** is highly ambiguous — all the challenge of CCG parsing is in picking the right **lexicon** entries

Zettlemoyer and Collins (2005)

CCG Parsing

- ▶ Many ways to build these parsers
- ▶ One approach: run a “supertagger” (tagging the sentence with complex labels), then run the parser

What	states	border	Texas
$\frac{(S/(S \setminus NP))/N}{\lambda f. \lambda g. \lambda x. f(x) \wedge g(x)}$	$\frac{N}{\lambda x. state(x)}$	$\frac{(S \setminus NP)/NP}{\lambda x. \lambda y. borders(y, x)}$	$\frac{NP}{texas}$

- ▶ Parsing is easy once you have the tags, so we’ve reduced it to a (hard) tagging problem

Building CCG Parsers

- Model: **log-linear model** over derivations, with features on rules:
- $$P(d|x) \propto \exp w^\top \left(\sum_{r \in d} f(r, x) \right)$$

$$f \left(\begin{array}{c} \boxed{\text{S}} \\ \text{sings}(e728) \end{array} \right) = \text{Indicator}(\text{S} \rightarrow \text{NP S}\backslash\text{NP})$$

$$f \left(\begin{array}{c} \boxed{\text{NP}} \\ e728 \end{array} \right) \quad f \left(\begin{array}{c} \boxed{\text{S}\backslash\text{NP}} \\ \lambda y. \text{sings}(y) \end{array} \right) = \text{Indicator}(\text{S}\backslash\text{NP} \rightarrow \text{sings})$$

Eminem *sings*

Building CCG Parsers

- ▶ Training data looks like pairs of sentences and logical forms

What states border Texas

$\lambda x. \text{state}(x) \wedge \text{borders}(x, \text{e89})$

Building CCG Parsers

- ▶ Training data looks like pairs of sentences and logical forms

What states border Texas $\lambda x. \text{state}(x) \wedge \text{borders}(x, \text{e89})$

- ▶ Problem: we don't know the derivation
 - ▶ Texas corresponds to NP | e89 in the logical form (easy to figure out)
 - ▶ What corresponds to (S/(S\NP))/N | $\lambda f. \lambda g. \lambda x. f(x) \wedge g(x)$
 - ▶ How do we infer that without being told it?

Lexicon

- ▶ GENLEX: takes sentence S and logical form L. Break up logical form into chunks C(L), assume any substring of S might map to any chunk

What states border Texas

$\lambda x. \text{state}(x) \wedge \text{borders}(x, \text{e89})$

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What states border Texas $\lambda x. \text{state}(x) \wedge \text{borders}(x, \text{e89})$

- ▶ Chunks inferred from the logic form based on rules:
 - ▶ NP: e89
 - ▶ (S\NP)/NP: $\lambda x. \lambda y. \text{borders}(x, y)$

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- ▶ Chunks inferred from the logic form based on rules:
 - ▶ NP: e89 ▶ (S\NP)/NP: $\lambda x. \lambda y. \text{borders}(x, y)$
- ▶ Any substring can parse to any of these in the lexicon
 - ▶ *Texas* -> NP: e89
 - ▶ *border Texas* -> NP: e89
 - ▶ *What states border Texas* -> NP: e89
 - ▶ ...

Zettlemoyer and Collins (2005)

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What states border Texas $\lambda x. \text{state}(x) \wedge \text{borders}(x, e89)$

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 - ▶ NP: e89 ▶ (S\NP)/NP: $\lambda x. \lambda y. \text{borders}(x, y)$

- ▶ Any substring can parse to any of these in the lexicon

- ▶ *Texas* -> NP: e89 is correct

- ▶ *border Texas* -> NP: e89

- ▶ *What states border Texas* -> NP: e89

- ▶ ...

learning from data

Zettlemoyer and Collins (2005)

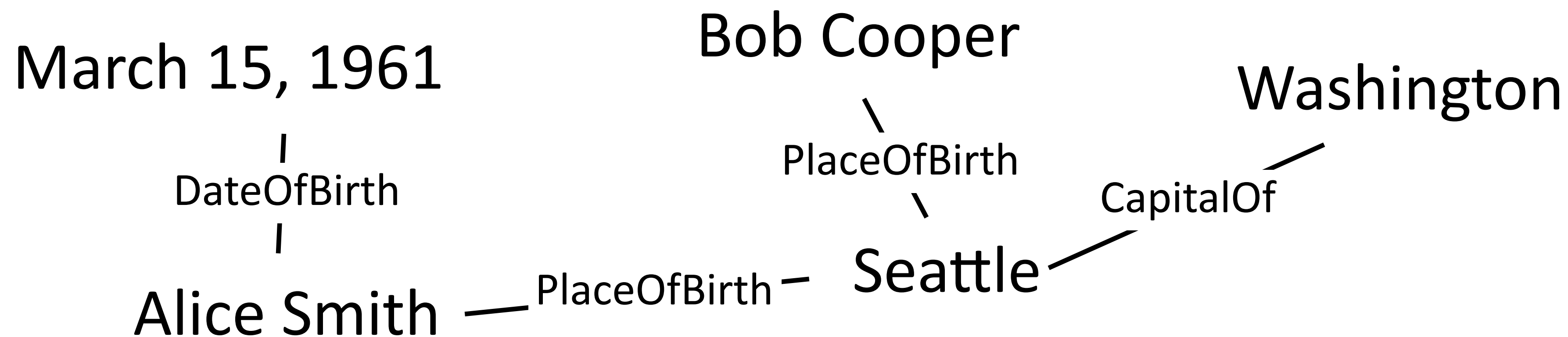
Applications

- ▶ GeoQuery: answering questions about states (~80% accuracy)
- ▶ Jobs: answering questions about job postings (~80% accuracy)
- ▶ ATIS: flight search
- ▶ Can do well on all of these tasks if you handcraft systems and use plenty of training data: these domains aren't that rich
- ▶ What about broader QA? A simpler form?

Lambda-DCS

Lambda-DCS

- ▶ Dependency-based compositional semantics — original version was less powerful than lambda calculus, **lambda-DCS is as powerful**
- ▶ Designed in the context of building a QA system from Freebase
- ▶ Freebase: set of entities and relations



- ▶ $[[\text{PlaceOfBirth}]] = \text{set of pairs of (person, location)}$

Lambda-DCS

Lambda-DCS

Seattle

PlaceOfBirth

PlaceOfBirth.Seattle

Lambda calculus

$\lambda x. x = \text{Seattle}$

$\lambda x. \lambda y. \text{PlaceOfBirth}(x, y)$

$\lambda x. \text{PlaceOfBirth}(x, \text{Seattle})$

- ▶ Looks like a tree fragment over Freebase

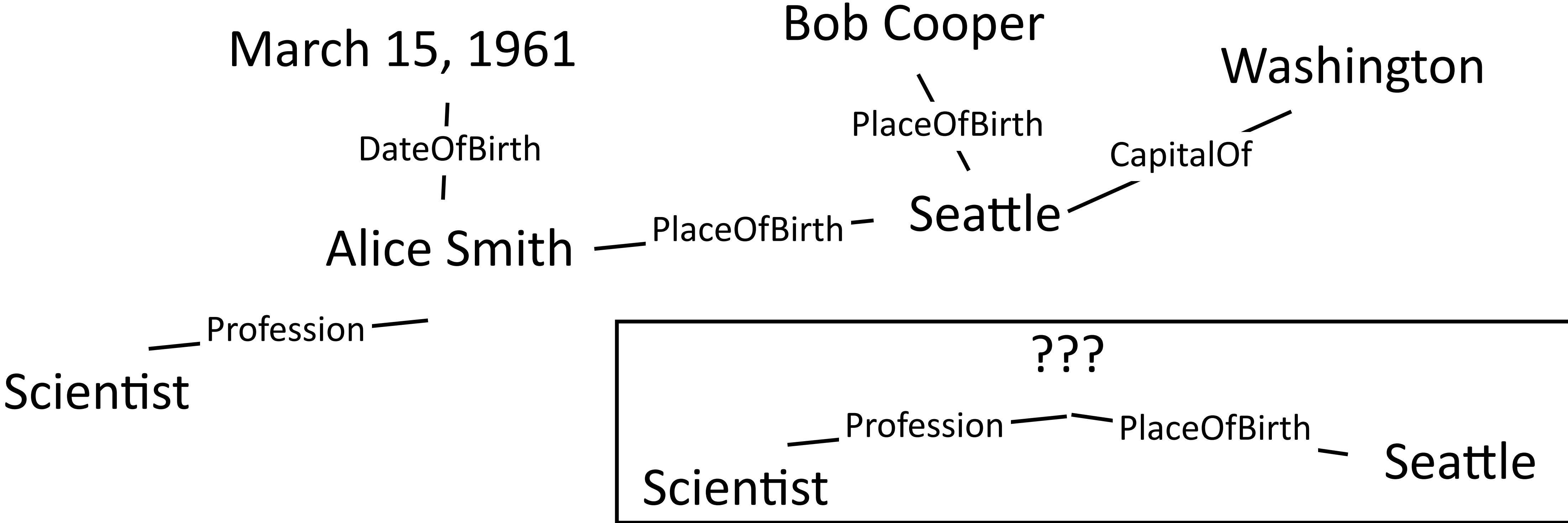
??? — PlaceOfBirth — Seattle

Profession.Scientist \wedge
PlaceOfBirth.Seattle

$\lambda x. \text{Profession}(x, \text{Scientist})$
 $\wedge \text{PlaceOfBirth}(x, \text{Seattle})$

Liang et al. (2011), Liang (2013)

Lambda-DCS



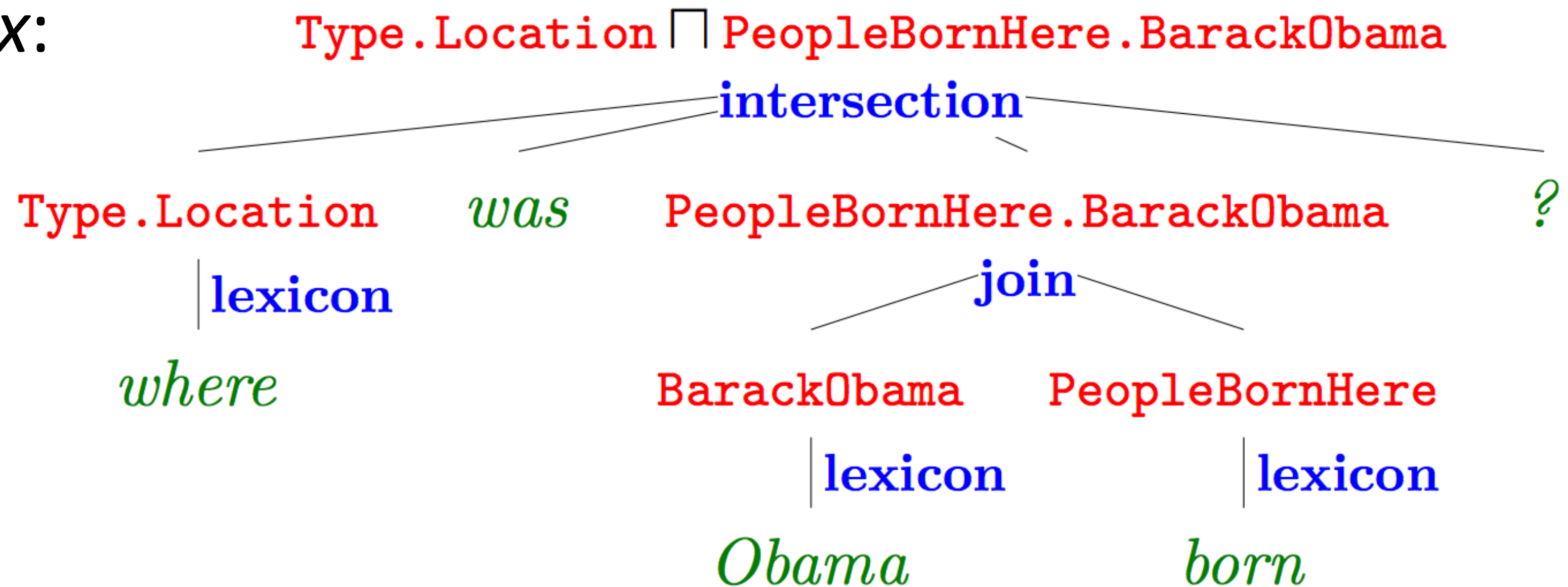
“list of scientists born in Seattle”

```
Profession.Scientist ^  
PlaceOfBirth.Seattle
```

- ▶ Execute this fragment against Freebase, returns Alice Smith (and others)

Parsing into Lambda-DCS

- ▶ Derivation d on sentence x :



- ▶ Building the lexicon: more sophisticated process than GENLEX, but can handle thousands of predicates

- ▶ Log-linear model with features on rules: $P(d|x) \propto \exp w^\top \left(\sum_{r \in d} f(r, x) \right)$

- ▶ Similar to CRF parsers

Parsing with Lambda-DCS

- ▶ Learn just from question-answer pairs: maximize the likelihood of the right denotation y with the derivation d marginalized out

$$\mathcal{O}(\theta) = \sum_{i=1}^n \log \sum_{d \in D(x) : \llbracket d.z \rrbracket_{\mathcal{K}} = y_i} p_{\theta}(d \mid x_i).$$

sum over derivations d such that the denotation of d on knowledge base K is y_i

For each example:

Run beam search to get a set of derivations

Let d = highest-scoring derivation in the beam

Let d^* = highest-scoring derivation in the beam *with correct denotation*

Do a structured perceptron update towards d^* away from d

Takeaways

- ▶ Can represent meaning with first order logic and lambda calculus
- ▶ Can bridge syntax and semantics and create semantic parsers that can interpret language into lambda-calculus expressions
- ▶ Useful for querying databases, question answering, etc.
- ▶ Recall: Previous encoder-decoder methods for doing this that rely less on having explicit grammars (HW3)