

# CS388: Natural Language Processing

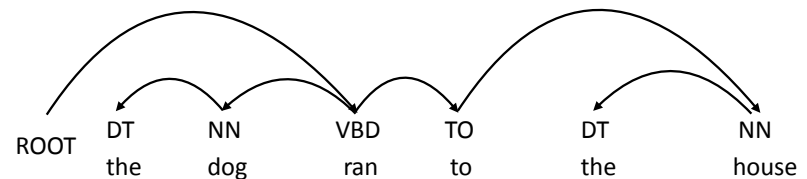
## Lecture 14: Semantics I

Greg Durrett



## 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



## Recall: Shift-Reduce Parsing

ROOT  
I ate some spaghetti bolognese

- State: **Stack:** [ROOT I ate] **Buffer:** [some spaghetti bolognese]
- Left-arc (reduce operation): Let  $\sigma$  denote the stack
  - "Pop two elements, add an arc, put them back on the stack"
  - $\sigma[w_{-2}, w_{-1}] \rightarrow \sigma[w_{-1}]$ ,  $w_{-2}$  is now a child of  $w_{-1}$
- Train a classifier to make these decisions sequentially — that classifier can parse sentences for you



## 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 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

## Model Theoretic Semantics



## Model Theoretic Semantics

- ▶ Key idea: can ground out natural language expressions in set-theoretic expressions called *models* of those sentences
- ▶ Natural language statement  $S \Rightarrow$  interpretation of  $S$  that models it
  - She likes going to that restaurant*
    - ▶ Interpretation: defines who *she* and *that restaurant* are, make it able to be concretely evaluated with respect to a *world*
- ▶ Entailment (statement A implies statement B) reduces to: in all worlds where A is true, B is true
- ▶ Our modeling language is *first-order logic*



## First-order Logic

- ▶ Powerful logic formalism including things like entities, relations, and quantifications
- Lady Gaga sings*
- ▶ *sings* is a *predicate* (with one argument), function  $f$ : entity  $\rightarrow$  true/false
  - ▶  $\text{sings}(\text{Lady Gaga}) = \text{true or false}$ , have to execute this against some database (*world*)
  - ▶  $[[\text{sings}]] = \text{denotation}$ , set of entities which sing (found by executing this predicate on the world — we'll come back to this)



## Quantification

- ▶ Universal quantification: “forall” operator
  - ▶  $\forall x \text{ sings}(x) \vee \text{dances}(x) \rightarrow \text{performs}(x)$   
*“Everyone who sings or dances performs”*
- ▶ Existential quantification: “there exists” operator
  - ▶  $\exists x \text{ sings}(x)$     *“Someone sings”*
- ▶ Source of ambiguity! *“Everyone is friends with someone”*
  - ▶  $\forall x \exists y \text{ friend}(x,y)$
  - ▶  $\exists y \forall x \text{ friend}(x,y)$



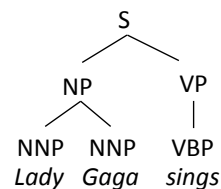
## Logic in NLP

- ▶ 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
  - ▶ 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. Maybe know:  $\forall x \text{ musician}(x) \Rightarrow \text{performer}(x)$   
 Then:  $\text{performer}(\text{Lady Gaga}) \wedge \text{performer}(\text{Eminem})$

## Compositional Semantics with First-Order Logic



## Montague Semantics



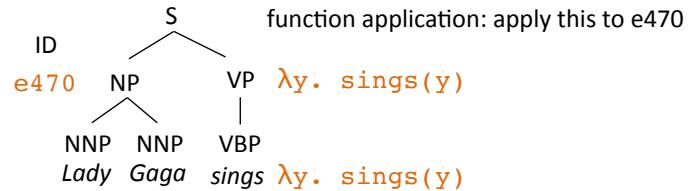
Id	Name	Alias	Birthdate	Sings?
e470	Stefani Germanotta	Lady Gaga	3/28/1986	T
e728	Marshall Mathers	Eminem	10/17/1972	T

- ▶ 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
- ▶  $[[ \text{Lady Gaga} ]]$  = e470      ▶  $[[ \text{sings}(\text{e470}) ]]$  = True  
 denotation of this string is an entity      denotation of this expression is T/F



## Montague Semantics

$sings(e470)$



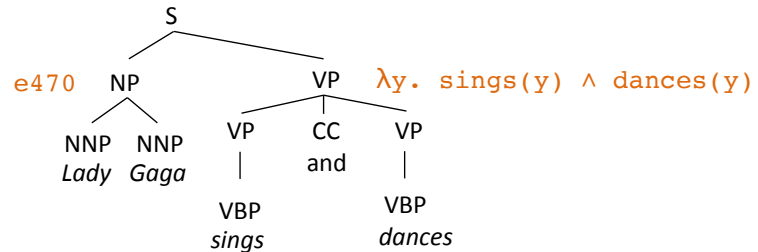
takes one argument ( $y$ , the entity) and returns a logical form  $sings(y)$

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



## Parses to Logical Forms

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

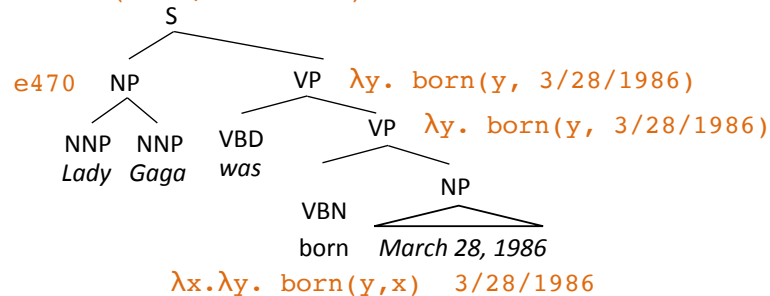


- General rules: VP:  $\lambda y. a(y) \wedge b(y) \rightarrow VP: \lambda y. a(y)$  CC VP:  $\lambda y. b(y)$   
S:  $f(x) \rightarrow NP: x$  VP:  $f$



## Parses to Logical Forms

$born(e470, 3/28/1986)$



- 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

- Adverbs/temporality: *Lady Gaga sang well yesterday*  
 $sings(Lady\ Gaga, time=yesterday, manner=well)$
- “Neo-Davidsonian” view of events: things with many properties:  
 $\exists e. type(e, sing) \wedge agent(e, e470) \wedge manner(e, well) \wedge time(e, ...)$
- Quantification: *Everyone is friends with someone*  
 $\exists y \forall x friend(x, y)$  (one friend)  $\forall x \exists y friend(x, y)$  (different friends)
- Same syntactic parse for both! So syntax doesn't resolve all ambiguities
- Indefinite: *Amy ate a waffle*  $\exists w. waffle(w) \wedge ate(Amy, w)$
- Generic: *Cats eat mice* (all cats eat mice? most cats? some cats?)



## Semantic Parsing

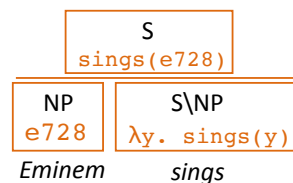
- ▶ For question answering, syntactic parsing doesn't tell you everything you want to know, but indicates the right structure
- ▶ Solution: *semantic parsing*: many forms of this task depending on semantic formalisms
- ▶ Two today: CCG (looks like what we've been doing) and lambda-DCS
- ▶ Applications: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

## CCG Parsing



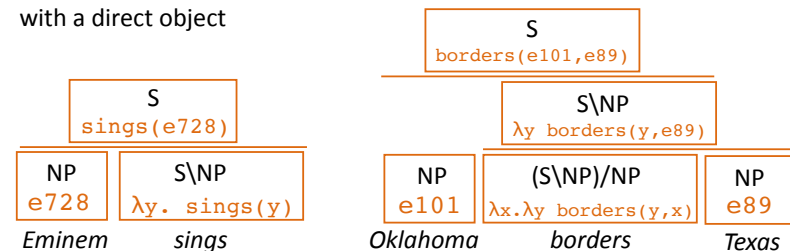
## Combinatory Categorical Grammar

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

What	states	border	Texas
$(S/(S \backslash NP))/N$ $\lambda f. \lambda g. \lambda x. f(x) \wedge g(x)$	$N$ $\lambda x. state(x)$	$(S \backslash NP)/NP$ $\lambda x. \lambda y. borders(y, x)$	$NP$ $texas$
$\xrightarrow{\hspace{10em}}$			
$(S \backslash NP)$ $\lambda y. borders(y, texas)$			

- ▶ “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 phrase (*border Texas*)

Zettlemoyer and Collins (2005)



## CCG Parsing

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$S/(S \backslash NP)$ $\lambda g. \lambda x. state(x) \wedge g(x)$		$(S \backslash NP)$ $\lambda y. borders(y, texas)$	
$\xrightarrow{\hspace{10em}}$			
$S$ $\lambda x. state(x) \wedge borders(x, texas)$			

- ▶ “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 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

Show me	flights	to	Prague
$S/N$ $\lambda f. f$	$N$ $\lambda x. flight(x)$	$(N \backslash N)/NP$ $\lambda y. \lambda f. \lambda x. f(y) \wedge to(x, y)$	$NP$ $PRG$
$\xrightarrow{\hspace{10em}}$			
$N \backslash N$ $\lambda f. \lambda x. f(x) \wedge to(x, PRG)$			
$\xrightarrow{\hspace{10em}}$			
$N$ $\lambda x. flight(x) \wedge to(x, PRG)$			
$\xrightarrow{\hspace{10em}}$			
$S$ $\lambda x. flight(x) \wedge to(x, PRG)$			

- ▶ “to” needs an NP (destination) and N (parent)

Slide credit: Dan Klein



## CCG Parsing

- ▶ Many ways to build these parsers

- ▶ One approach: run a “supertagger” (tags the sentence with complex labels), then run the parser

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

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

Zettlemoyer and Collins (2005)



## Building CCG Parsers

- Model: log-linear model over derivations with features on rules:

$$P(d|x) \propto \exp w^T \left( \sum_{r \in d} f(r, x) \right)$$

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

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

Eminem                      sings

- Can parse with a variant of CKY

Zettlemoyer and Collins (2005)



## 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  $(S/(S \backslash NP))/N$  |  $\lambda f. \lambda g. \lambda x. f(x) \wedge g(x)$
- How do we infer that without being told it?

Zettlemoyer and Collins (2005)



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

- Chunks inferred from the logic form based on rules:

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

- 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**
- ...

Zettlemoyer and Collins (2005)



## GENLEX

Rules		Categories produced from logical form
Input Trigger	Output Category	$\arg \max(\lambda x. \text{state}(x) \wedge \text{borders}(x, \text{texas}), \lambda x. \text{size}(x))$
constant <i>c</i>	$NP : c$	$NP : \text{texas}$
arity one predicate $p_1$	$N : \lambda x. p_1(x)$	$N : \lambda x. \text{state}(x)$
arity one predicate $p_1$	$S \backslash NP : \lambda x. p_1(x)$	$S \backslash NP : \lambda x. \text{state}(x)$
arity two predicate $p_2$	$(S \backslash NP)/NP : \lambda x. \lambda y. p_2(y, x)$	$(S \backslash NP)/NP : \lambda x. \lambda y. \text{borders}(y, x)$
arity two predicate $p_2$	$(S \backslash NP)/NP : \lambda x. \lambda y. p_2(x, y)$	$(S \backslash NP)/NP : \lambda x. \lambda y. \text{borders}(x, y)$
arity one predicate $p_1$	$N/N : \lambda g. \lambda x. p_1(x) \wedge g(x)$	$N/N : \lambda g. \lambda x. \text{state}(x) \wedge g(x)$
literal with arity two predicate $p_2$ and constant second argument <i>c</i>	$N/N : \lambda g. \lambda x. p_2(x, c) \wedge g(x)$	$N/N : \lambda g. \lambda x. \text{borders}(x, \text{texas}) \wedge g(x)$
arity two predicate $p_2$	$(N \backslash N)/NP : \lambda x. \lambda g. \lambda y. p_2(x, y) \wedge g(x)$	$(N \backslash N)/NP : \lambda g. \lambda x. \lambda y. \text{borders}(x, y) \wedge g(x)$
an $\arg \max / \min$ with second argument arity one function <i>f</i>	$NP/N : \lambda g. \arg \max / \min(g, \lambda x. f(x))$	$NP/N : \lambda g. \arg \max(g, \lambda x. \text{size}(x))$
an arity one numeric-ranged function <i>f</i>	$S/NP : \lambda x. f(x)$	$S/NP : \lambda x. \text{size}(x)$

- Very complex and hand-engineered way of taking lambda calculus expressions and “backsolving” for the derivation

Zettlemoyer and Collins (2005)



## Learning

- ▶ Iterative procedure like the EM algorithm: estimate “best” parses that derive each logical form, retrain the parser using these parses with supervised learning
- ▶ We’ll talk about a simpler form of this in a few slides

Zettlemoyer and Collins (2005)



## Applications

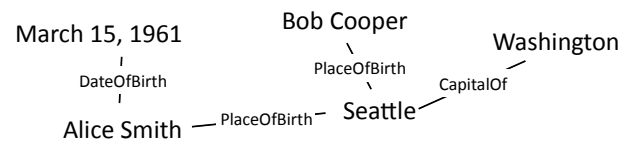
- ▶ GeoQuery: answering questions about states (~80% accuracy)
- ▶ Jobs: answering questions about job postings (~80% accuracy)
- ▶ ATIS: flight search
- ▶ Can do well on all of these tasks if you handcraft systems and use plenty of training data: these domains aren’t that rich
- ▶ What about broader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

## 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



- ▶ [[PlaceOfBirth]] = set of pairs of (person, location)

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





## Lambda-DCS

Lambda-DCS

Lambda calculus

Seattle

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

PlaceOfBirth

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

PlaceOfBirth.Seattle

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

- 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

March 15, 1961

Bob Cooper

Washington

DateOfBirth

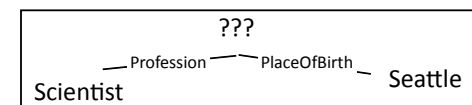
PlaceOfBirth

CapitalOf

Alice Smith

Seattle

— Profession —  
Scientist



“list of scientists born in Seattle”

Profession.Scientist  $\wedge$   
PlaceOfBirth.Seattle

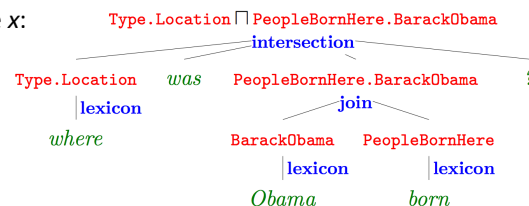
- Execute this fragment against Freebase, returns Alice Smith (and others)

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



## Parsing into Lambda-DCS

- Derivation  $d$  on sentence  $x$ :



- No more explicit syntax in these derivations like we had in CCG

- 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

Berant et al. (2013)



## Parsing with Lambda-DCS

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

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

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  $d$

Berant et al. (2013)



## Takeaways

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- ▶ 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.
- ▶ Next time: neural net methods for doing this that rely less on having explicit grammars