CS388: Natural Language Processing
Lecture 13: Semantics I

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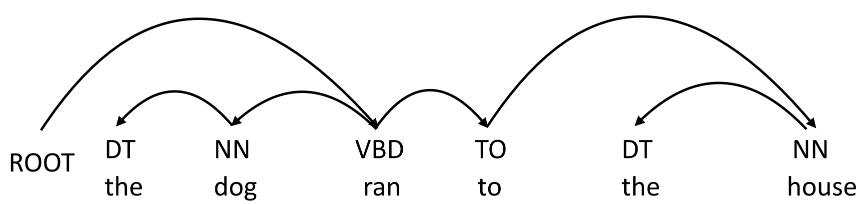
Slides adapted from Dan Klein, UC Berkeley

Administrivia

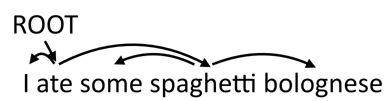
- Mini 2 due *today* at 5pm

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



- State: Stack: [ROOT I ate] Buffer: [some spaghetti bolognese]

- Left-arc (reduce operation): Let σ denote the stack
  - "Pop two elements, add an arc, put them back on the stack"

$\boxed{\sigma | w_{-2}, w_{-1}} \rightarrow \boxed{\sigma | w_{-1}}$, w_{-2} is now a child of w_{-1}

- State: Stack: [ROOT ate] Buffer: [some spaghetti bolognese]

I

Where are we now?

- Early in the class: sentences are just sequences of words
- Now we can understand them 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

- First-order logic
- Compositional semantics with first-order logic
- CCG parsing for database queries
- Lambda-DCS for question answering

First-Order Logic

First-order Logic

- Powerful logic formalism including things like entities, relations, and quantifications
- Propositions: let a = *It is day*, b = *It is night*
  - $a \vee b$ = either a is true or b is true, $a \Rightarrow \neg b$ = a implies not b
- More complex statements: "*Lady Gaga sings*"
- sings is a *predicate* (with one argument), function f: entity => true/false
- sings(Lady Gaga) = true or false, have to execute this against some database (called a *world*)
- [[sings]] = *denotation*, set of entities which sing (sort of like executing this predicate on the world — we'll come back to this)

Quantification

- Universal quantification: "forall" operator
  - $\forall x \; sings(x) \lor dances(x) \Rightarrow performs(x)$

    "Everyone who sings or dances performs"
- Existential quantification: "there exists" operator
  - $\exists x \; sings(x)$ *"Someone sings"*
- Source of ambiguity! "*Everyone is friends with someone*"
  - $\forall x \; \exists y \; friend(x,y)$
  - $\exists y \; \forall x \; friend(x,y)$

Logic in NLP

- Question answering:

  Who are all the American singers named Amy?

  $\lambda x.\; nationality(x,USA) \land sings(x) \land firstName(x,Amy)$

  - 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*

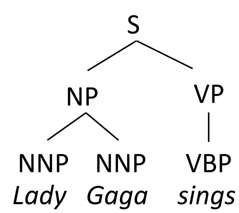
  $musician(Lady\ Gaga) \land musician(Eminem)$

  - Can now do reasoning. Maybe know: $\forall x \; musician(x) \Rightarrow performer(x)$

    Then: $performer(Lady\ Gaga) \land performer(Eminem)$

Compositional Semantics with First-Order Logic

Truth-Conditional Semantics



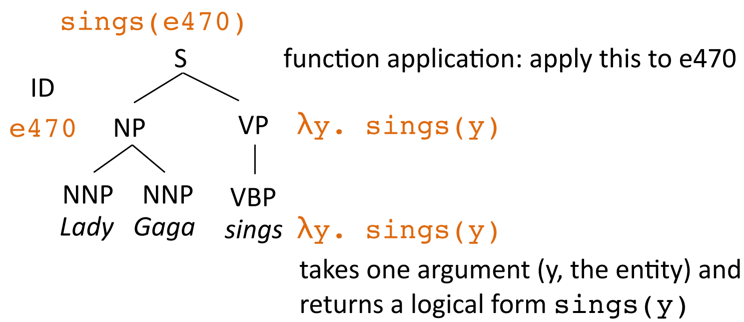
Id	Name	Alias	Birthdate	Sings?
e470	Stefani Germanotta	Lady Gaga	3/28/1986	T
e728	Marshall Mathers	Eminem	10/17/1972	T

- Database containing entities, predicates, etc.
- Truth-conditional semantics: sentence expresses something about the world which is either true or false
- Denotation: evaluation of some expression against this database
- `[[`*Lady Gaga*`]] = e470`

  denotation of this string is an entity
- `[[sings(e470)]] = True`

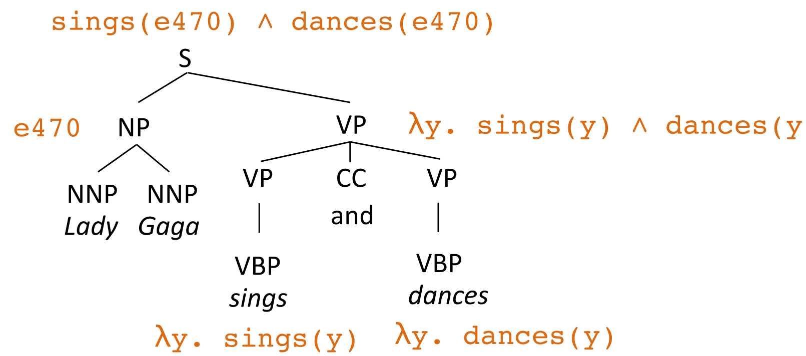
  denotation of this expression is T/F

Parses to Logical Forms



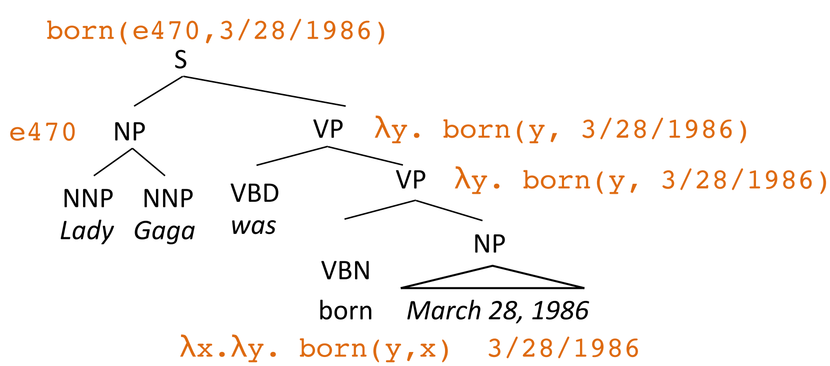
- We can use the syntactic parse as a bridge to the lambda-calculus representation, build up a logical form *compositionally*

Parses to Logical Forms



- General rules: VP: λy. a(y) ∧ b(y) -> VP: λy. a(y) CC VP: λy. b(y)
  S: f(x) -> NP: x VP: f

Parses to Logical Forms



- 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)`

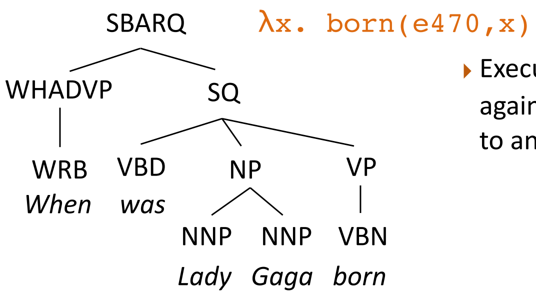
  - "Neo-Davidsonian" view of events: things with many properties:

  `∃e. type(e,sing) ∧ agent(e,e470) ∧ manner(e,well) ∧ time(e,…)`
- Quantification: *Everyone is friends with someone*

  `∃y ∀x friend(x,y)` (one friend)   `∀x ∃y friend(x,y)` (different friends)

  - Same syntactic parse for both! So syntax doesn't resolve all ambiguities
- Indefinite: *Amy ate a waffle* `∃w. waffle(w) ∧ ate(Amy,w)`
- Generic: *Cats eat mice* (all cats eat mice? most cats? some cats?)

QA from Parsing



- Execute this function against a knowledge base to answer the question
- Tricky to parse due to wh-movement…would be easier if we said *Lady Gaga was born when*

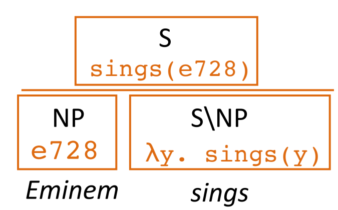
Semantic Parsing

- 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

CCG Parsing

Combinatory Categorial 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
- When you apply this, there has to be a parallel instance of function application on the semantics side



Combinatory Categorial Grammar

- Steedman+Szabolcsi 1980s: formalism bridging syntax and semantics
- 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
  - (S\NP)/NP: “I need an NP on my right and then on my left” — verb with a direct object

S
`sings(e728)`

NP `e728` | S\NP `λy. sings(y)`

Eminem *sings*

S
`borders(e101,e89)`

S\NP
`λy borders(y,e89)`

NP `e101` | (S\NP)/NP `λx.λy borders(y,x)` | NP `e89`

Oklahoma *borders* *Texas*

CCG Parsing

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

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

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

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

- “What” is a ***very*** complex type: needs a noun and needs a S\NP to form a sentence. S\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	N	(N\N)/NP	NP
$\lambda f.f$	$\lambda x.flight(x)$	$\lambda y.\lambda f.\lambda x.f(y) \wedge to(x,y)$	PRG

N\N
$\lambda f.\lambda x.f(x) \wedge to(x,PRG)$

N
$\lambda x.flight(x) \wedge to(x,PRG)$

S
$\lambda x.flight(x) \wedge to(x,PRG)$

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

Slide credit: Dan Klein

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(S `sings(e728)`) = Indicator(S -> NP S\NP)

f(NP `e728`) f(S\NP `λy. sings(y)`) = Indicator(S\NP -> *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 `λx. state(x) ∧ borders(x, 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 | `λf.λg.λx. f(x) ∧ 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 `λx. state(x) ∧ borders(x, e89)`

- Chunks inferred from the logic form based on rules:
  - NP: `e89`
  - (S\NP)/NP: `λx. λy. 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: Input Trigger	Rules: Output Category	Categories produced from logical form $\arg\max(\lambda x.state(x) \wedge borders(x, texas), \lambda x.size(x))$
constant c	$NP : c$	$NP : texas$
arity one predicate p_1	$N : \lambda x.p_1(x)$	$N : \lambda x.state(x)$
arity one predicate p_1	$S\backslash NP : \lambda x.p_1(x)$	$S\backslash NP : \lambda x.state(x)$
arity two predicate p_2	$(S\backslash NP)/NP : \lambda x.\lambda y.p_2(y, x)$	$(S\backslash NP)/NP : \lambda x.\lambda y.borders(y, x)$
arity two predicate p_2	$(S\backslash NP)/NP : \lambda x.\lambda y.p_2(x, y)$	$(S\backslash NP)/NP : \lambda x.\lambda y.borders(x, y)$
arity one predicate p_1	$N/N : \lambda g.\lambda x.p_1(x) \wedge g(x)$	$N/N : \lambda g.\lambda x.state(x) \wedge g(x)$
literal with arity two predicate p_2 and constant second argument c	$N/N : \lambda g.\lambda x.p_2(x, c) \wedge g(x)$	$N/N : \lambda g.\lambda x.borders(x, texas) \wedge g(x)$
arity two predicate p_2	$(N\backslash N)/NP : \lambda x.\lambda g.\lambda y.p_2(x, y) \wedge g(x)$	$(N\backslash N)/NP : \lambda g.\lambda x.\lambda y.borders(x, y) \wedge g(x)$
an arg max / min with second argument arity one function f	$NP/N : \lambda g.\arg\max / \min(g, \lambda x.f(x))$	$NP/N : \lambda g.\arg\max(g, \lambda x.size(x))$
an arity one numeric-ranged function f	$S/NP : \lambda x.f(x)$	$S/NP : \lambda x.size(x)$

- 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)

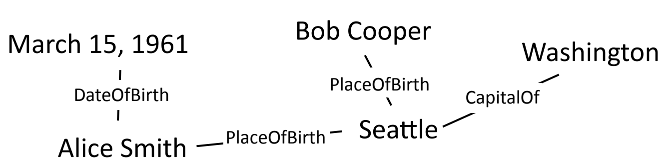
Applications

- 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`	λx. x = Seattle
`PlaceOfBirth`	λx.λy. PlaceOfBirth(x,y)
`PlaceOfBirth.Seattle`	λx. PlaceOfBirth(x,Seattle)

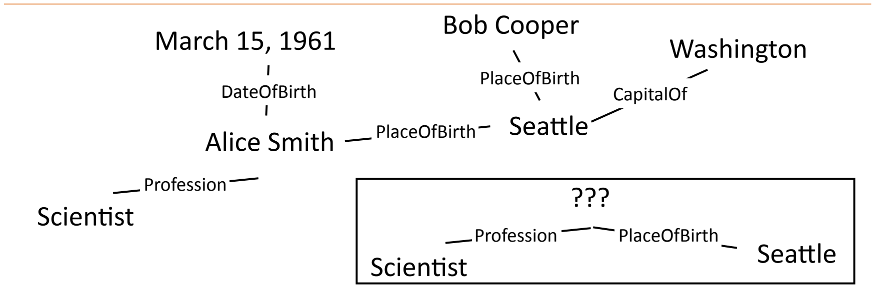
- Looks like a tree fragment over Freebase

??? — PlaceOfBirth — Seattle

Profession.Scientist ∧ PlaceOfBirth.Seattle	λx. Profession(x,Scientist) ∧ PlaceOfBirth(x,Seattle)

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

Lambda-DCS



"list of scientists born in Seattle"

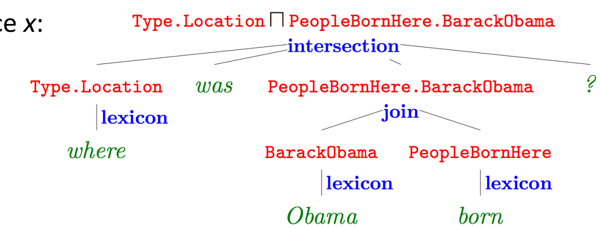
`Profession.Scientist ∧ PlaceOfBirth.Seattle`

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

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

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

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

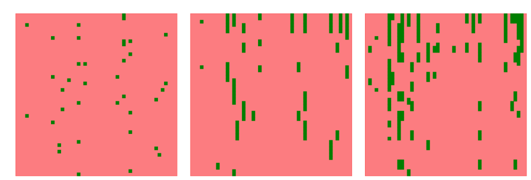
Let d* = highest-scoring derivation in the beam *with correct denotation*

Do a structured perceptron update towards d* away from d

Berant et al. (2013)

Learning

- Each vertical slice is the beam for one example. Green = correct denotation



0 iterations 1 iterations 2 iterations

- Only a small number of questions are even reachable by beam search initially (but some questions are very easy so even a totally untrained model can answer them)
- During training, more and more "good" derivations surface and will result in model updates

Berant et al. (2013)

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