Natural Language Processing

Berkeley NLP

Compositional Semantics

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Truth-Conditional Semantics

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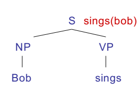
Truth-Conditional Semantics

- Linguistic expressions:
  - “Bob sings”
- Logical translations:
  - sings(bob)
  - Could be p_1218(e_397)
- Denotation:
  - [[bob]] = some specific person (in some context)
  - [[sings(bob)]] = ???
- Types on translations:
  - bob : e (for entity)
  - sings(bob) : t (for truth-value)



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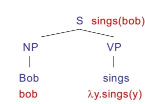
Truth-Conditional Semantics

- Proper names:
  - Refer directly to some entity in the world
  - Bob : bob [[bob]]^{w} → ???
- Sentences:
  - Are either true or false (given how the world actually is)
  - Bob sings : sings(bob)



- So what about verbs (and verb phrases)?
  - sings must combine with bob to produce sings(bob)
  - The λ-calculus is a notation for functions whose arguments are not yet filled.
  - sings : λx.sings(x)
  - This is a *predicate* – a function which takes an entity (type e) and produces a truth value (type t). We can write its type as e→t.
  - Adjectives?

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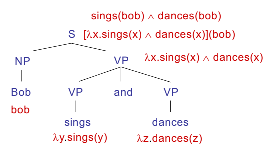
Compositional Semantics

- So now we have meanings for the words
- How do we know how to combine words?
- Associate a combination rule with each grammar rule:
  - S : $\beta(\alpha) \rightarrow$ NP : α VP : β (function application)
  - VP : $\lambda x . \alpha(x) \wedge \beta(x) \rightarrow$ VP : α and : $\varnothing$ VP : β (intersection)
- Example:



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Denotation

- What do we do with logical translations?
  - Translation language (logical form) has fewer ambiguities
  - Can check truth value against a database
    - Denotation ("evaluation") calculated using the database
  - More usefully: assert truth and modify a database, either explicitly or implicitly eg prove a consequence from asserted axioms
  - Questions: check whether a statement in a corpus entails the (question, answer) pair:
    - "Bob sings and dances" $\rightarrow$ "Who sings?" + "Bob"
  - Chain together facts and use them for comprehension

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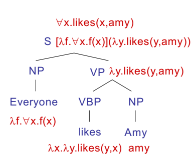
Other Cases

- Transitive verbs:
  - likes : $\lambda x.\lambda y.likes(y,x)$
  - Two-place predicates of type $e \rightarrow (e \rightarrow t)$.
  - likes Amy : $\lambda y.likes(y,Amy)$ is just like a one-place predicate.
- Quantifiers:
  - What does "Everyone" mean here?
  - Everyone : $\lambda f.\forall x.f(x)$
  - Mostly works, but some problems
    - Have to change our NP/VP rule.
    - Won't work for "Amy likes everyone."
  - "Everyone likes someone."
  - This gets tricky quickly!



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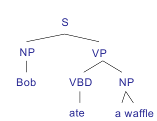
Indefinites

- First try
  - "Bob ate a waffle" : ate(bob,waffle)
  - "Amy ate a waffle" : ate(amy,waffle)
- Can't be right!
  - $\exists$ x : waffle(x) $\wedge$ ate(bob,x)
  - What does the translation of "a" have to be?
  - What about "the"?
  - What about "every"?



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Grounding

- Grounding
  - So why does the translation likes : $\lambda x.\lambda y.likes(y,x)$ have anything to do with actual liking?
  - It doesn't (unless the denotation model says so)
  - Sometimes that's enough: wire up bought to the appropriate entry in a database
- Meaning postulates
  - Insist, e.g $\forall x,y.likes(y,x) \rightarrow knows(y,x)$
  - This gets into lexical semantics issues
- Statistical version?

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Tense and Events

- In general, you don't get far with verbs as predicates
- Better to have event variables e
  - "Alice danced" : danced(alice)
  - $\exists$ e : dance(e) $\wedge$ agent(e,alice) $\wedge$ (time(e) < now)
- Event variables let you talk about non-trivial tense / aspect structures
  - "Alice had been dancing when Bob sneezed"
  - $\exists$ e, e' : dance(e) $\wedge$ agent(e,alice) $\wedge$
    sneeze(e') $\wedge$ agent(e',bob) $\wedge$
    (start(e) < start(e') $\wedge$ end(e) = end(e')) $\wedge$
    (time(e') < now)

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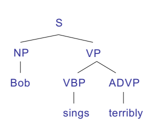
Adverbs

- What about adverbs?
  - "Bob sings terribly"
  - terribly(sings(bob))?
  - (terribly(sings))(bob)?
  - $\exists$e present(e) $\wedge$ type(e, singing) $\wedge$ agent(e,bob) $\wedge$ manner(e, terrible) ?
  - It's really not this simple…



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Propositional Attitudes

- "Bob thinks that I am a gummi bear"
  - thinks(bob, gummi(me)) ?
  - thinks(bob, "I am a gummi bear") ?
  - thinks(bob, ^gummi(me)) ?
- Usual solution involves intensions (^X) which are, roughly, the set of possible worlds (or conditions) in which X is true
- Hard to deal with computationally
  - Modeling other agents models, etc
  - Can come up in simple dialog scenarios, e.g., if you want to talk about what your bill claims you bought vs. what you actually bought

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Trickier Stuff

- Non-Intersective Adjectives
  - green ball : $\lambda x.[green(x) \wedge ball(x)]$
  - fake diamond : $\lambda x.[fake(x) \wedge diamond(x)]$? $\longrightarrow$ $\lambda x.[fake(diamond(x))$
- Generalized Quantifiers
  - the : $\lambda f.[\textit{unique-member}(f)]$
  - all : $\lambda f.\ \lambda g\ [\forall x.f(x) \rightarrow g(x)]$
  - most?
  - Could do with more general second order predicates, too (why worse?)
    - the(cat, meows), all(cat, meows)
- Generics
  - "Cats like naps"
  - "The players scored a goal"
- Pronouns (and bound anaphora)
  - "If you have a dime, put it in the meter."
- … the list goes on and on!

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Scope Ambiguities

- Quantifier scope
  - "All majors take a data science class"
  - "Someone took each of the electives"
  - "Everyone didn't hand in their exam"
- Deciding between readings
  - Multiple ways to work this out
    - Make it syntactic (movement)
    - Make it lexical (type-shifting)

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Modeling Uncertainty

- Big difference between statistical disambiguation and statistical reasoning.

  The scout saw the enemy soldiers with night goggles.

  - With probabilistic parsers, can say things like "72% belief that the PP attaches to the NP."
  - That means that *probably* the enemy has night vision goggles.
  - However, you can't throw a logical assertion into a theorem prover with 72% confidence.
  - Use this to decide the expected utility of calling reinforcements?
- Do we need probabilistic reasoning, not just probabilistic disambiguation followed by symbolic reasoning?

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Logical Form Translation

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CCG Parsing

- Combinatory Categorial Grammar
  - Fully (mono-) lexicalized grammar
  - Categories encode argument sequences
  - Very closely related to the lambda calculus
  - Can have spurious ambiguities (why?)

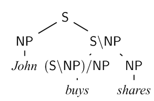
John ⊢ NP : *john′*

shares ⊢ NP : *shares′*

buys ⊢ (S\NP)/NP : $\lambda x.\lambda y.buys' xy$

sleeps ⊢ S\NP : $\lambda x.sleeps' x$

well ⊢ (S\NP)\(S\NP) : $\lambda f.\lambda x.well'(fx)$



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Mapping to LF: Zettlemoyer & Collins 05/07

The task:

Input: `List one way flights to Prague.`

Output: $\lambda x.flight(x) \land one\_way(x) \land to(x,PRG)$

Challenging learning problem:

- Derivations (or parses) are not annotated
- Approach: [Zettlemoyer & Collins 2005]
- Learn a lexicon and parameters for a weighted Combinatory Categorial Grammar (CCG)

[Slides from Luke Zettlemoyer]

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Background

- Combinatory Categorial Grammar (CCG)
- Weighted CCGs
- Learning lexical entries: GENLEX

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CCG Lexicon

Words	Category
flights	N : $\lambda x.flight(x)$
to	(N\N)/NP : $\lambda x.\lambda f.\lambda y.f(x) \land to(y,x)$
Prague	NP : PRG
New York city	NP : NYC
...	...

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Parsing Rules (Combinators)

Application
- `X/Y : f      Y : a  =>  X : f(a)`
- `  Y : a    X\Y : f  =>  X : f(a)`

Composition
- `X/Y : f   Y/Z : g   =>  X/Z : λx.f(g(x))`
- `Y\Z : f   X\Y : g   =>  X\Z : λx.f(g(x))`

Additional rules:
- Type Raising
- Crossed Composition

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CCG Parsing

Show me	flights	to	Prague
S/N $\lambda f.f$	N $\lambda x.flight(x)$	(N\N)/NP $\lambda y.\lambda f.\lambda x.f(y) \wedge to(x,y)$	NP PRG

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

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

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

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Weighted CCG

Given a log-linear model with a CCG lexicon Λ, a feature vector f, and weights w.
- The best parse is:

$$y^* = \underset{y}{\operatorname{argmax}} \; w \cdot f(x,y)$$

Where we consider all possible parses y for the sentence x given the lexicon Λ.

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Lexical Generation

Input Training Example

Sentence: Show me flights to Prague.
Logic Form: $\lambda x.flight(x) \wedge to(x,PRG)$

Output Lexicon

Words	Category
Show me	S/N : $\lambda f.f$
flights	N : $\lambda x.flight(x)$
to	(N\N)/NP : $\lambda x.\lambda f.\lambda y.f(x) \wedge to(y,x)$
Prague	NP : PRG
...	...

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GENLEX: Substrings X Categories

Input Training Example

Sentence: `Show me flights to Prague.`
Logic Form: $\lambda x.flight(x) \wedge to(x, PRG)$

Output Lexicon

All possible substrings:

```
Show
me
flights
...
Show me
Show me flights
Show me flights to
...
```

X

Categories created by rules that trigger on the logical form:

$NP : PRG$
$N : \lambda x.flight(x)$
$(S\backslash NP)/NP : \lambda x.\lambda y.to(y,x)$
$(N\backslash N)/NP : \lambda y.\lambda f.\lambda x. \ldots$
...

[Zettlemoyer & Collins 2005]

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Robustness

The lexical entries that work for:

Show me	the latest	flight	from Boston	to Prague	on Friday
S/NP	NP/N	N	N\N	N\N	N\N
...	...	...	...	...	...

Will not parse:

```
Boston to Prague the latest on Friday
  NP      N\N       NP/N        N\N
  ...     ...       ...         ...
```

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Relaxed Parsing Rules

Two changes
- Add application and composition rules that relax word order
- Add type shifting rules to recover missing words

These rules significantly relax the grammar
- Introduce features to count the number of times each new rule is used in a parse

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Review: Application

```
X/Y : f     Y : a    =>   X : f(a)
Y : a     X\Y : f    =>   X : f(a)
```

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Disharmonic Application

- Reverse the direction of the principal category:

```
X\Y : f       Y : a    =>   X : f(a)
Y : a       X/Y : f    =>   X : f(a)
```

```
  flights              one way
-------------    -------------------------
      N                   N/N
 λx.flight(x)     λf.λx.f(x)∧one_way(x)
-------------------------------------------
                    N
        λx.flight(x)∧one_way(x)
```

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Missing content words

Insert missing semantic content

- NP : c => N\N : λf.λx.f(x) ∧ p(x,c)

```
   flights             Boston                  to Prague
-------------   ---------------------   ------------------------
      N                  NP                       N\N
 λx.flight(x)            BOS              λf.λx.f(x)∧to(x,PRG)
                ---------------------
                         N\N
                λf.λx.f(x)∧from(x,BOS)
-------------------------------------
                 N
    λx.flight(x)∧from(x,BOS)
----------------------------------------------------------------
                              N
          λx.flight(x)∧from(x,BOS)∧to(x,PRG)
```

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Missing content-free words

Bypass missing nouns

- N\N : f => N : f(λx.true)

```
       Northwest Air                  to Prague
----------------------------   --------------------------
            N/N                          N\N
  λf.λx.f(x)∧airline(x,NWA)       λf.λx.f(x)∧to(x,PRG)
                               --------------------------
                                          N
                                     λx.to(x,PRG)
----------------------------------------------------------
                          N
           λx.airline(x,NWA) ∧ to(x,PRG)
```

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Inputs: Training set $\{(x_i, z_i) \mid i=1 \ldots n\}$ of sentences and logical forms. Initial lexicon Λ. Initial parameters w. Number of iterations T.

Training: For $t = 1 \ldots T$, $i = 1 \ldots n$:

Step 1: Check Correctness

- Let $y^* = \arg\max_y w \cdot f(x_i, y)$
- If $L(y^*) = z_i$, go to the next example

Step 2: Lexical Generation

- Set $\lambda = \Lambda \cup \text{GENLEX}(x_i, z_i)$
- Let $\hat{y} = \arg\max_{y \text{ s.t. } L(y)=z_i} w \cdot f(x_i, y)$
- Define λ_i to be the lexical entries in $\hat{y}$
- Set lexicon to $\Lambda = \Lambda \cup \lambda_i$

Step 3: Update Parameters

- Let $y' = \arg\max_y w \cdot f(x_i, y)$
- If $L(y') \neq z_i$
  - Set $w = w + f(x_i, \hat{y}) - f(x_i, y')$

Output: Lexicon Λ and parameters w.

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Related Work for Evaluation

Hidden Vector State Model: He and Young 2006
- Learns a probabilistic push-down automaton with EM
- Is integrated with speech recognition

λ-WASP: Wong & Mooney 2007
- Builds a synchronous CFG with statistical machine translation techniques
- Easily applied to different languages

Zettlemoyer and Collins 2005
- Uses GENLEX with maximum likelihood batch training and stricter grammar

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Two Natural Language Interfaces

ATIS (travel planning)
- Manually-transcribed speech queries
- 4500 training examples
- 500 example development set
- 500 test examples

Geo880 (geography)
- Edited sentences
- 600 training examples
- 280 test examples

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Evaluation Metrics

Precision, Recall, and F-measure for:
- Completely correct logical forms
- Attribute / value partial credit

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

is represented as:

$\{from = BOS,\ to = PRG\}$

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Two-Pass Parsing

Simple method to improve recall:
- For each test sentence that can not be parsed:
  - Reparse with word skipping
  - Every skipped word adds a constant penalty
  - Output the highest scoring new parse

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ATIS Test Set [Z+C 2007]

Exact Match Accuracy:

	Precision	Recall	F1
Single-Pass	90.61	81.92	**86.05**
Two-Pass	85.75	84.60	85.16

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Geo880 Test Set

Exact Match Accuracy:

	Precision	Recall	F1
Single-Pass	95.49	83.20	**88.93**
Two-Pass	91.63	86.07	88.76
Zettlemoyer & Collins 2005	96.25	79.29	86.95
Wong & Mooney 2007	93.72	80.00	86.31

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