Outline of today's lecture

Lecture 7: Lexical semantics

Lexical semantics: semantic relations

Polysemy

Word sense disambiguation

Lexical semantics

- Limited domain: mapping to some knowledge base term(s). Knowledge base constrains possible meanings.
- Issues for broad coverage systems:
 - Boundary between lexical meaning and world knowledge.
 - Representing lexical meaning.
 - Acquiring representations.
 - Polysemy and multiword expressions.

- ► Formal semantics: extension what words denote (e.g., cat': the set of all cats). But
- ► Semantic primitives: e.g., *kill* means CAUSE (NOT (ALIVE)). But ...
- Meaning postulates:

$$\forall e, x, y [\mathsf{kill'}(e, x, y) \to \exists e' [\mathsf{cause'}(e, x, e') \land \mathsf{die'}(e', y)]]$$

- Ontological relationships: informal or formal (description logics): this lecture (informal approaches).
- ▶ Distributional approaches (lecture 8).

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Examples to think about

- tomato
- table
- thought
- democracy
- push
- sticky

Hyponymy: IS-A

- ► (a sense of) dog is a hyponym of (a sense of) animal
- animal is a hypernym of dog
- hyponymy relationships form a taxonomy
- works best for concrete nouns

Some issues concerning hyponymy

- not useful for all words: thought, democracy, push, sticky?
- ▶ individuation differences: is table a hyponym of furniture?
- multiple inheritance: e.g., is coin a hyponym of both metal and money?
- what does the top of the hierarchy look like?

Other semantic relations

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Classical relations:
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Meronomy: PART-OF e.g., arm is a meronym of body, steering wheel is a meronym of car (piece vs part)

Synonymy e.g., aubergine/eggplant.

Antonymy e.g., big/little

Also:

Near-synonymy/similarity e.g., exciting/thrilling e.g., slim/slender/thin/skinny

WordNet

- large scale, open source resource for English
- hand-constructed
- wordnets being built for other languages
- organized into synsets: synonym sets (near-synonyms)

Overview of adj red:

```
1. (43) red, reddish, ruddy, blood-red, carmine, cerise, cherry, cherry-red, crimson, ruby, ruby-red, scarlet - (having any of numerous bright or strong colors reminiscent of the color of blood or cherries or tomatoes or rubies)
2. (8) red, reddish - ((used of hair or fur) of a reddish brown color; "red deer"; reddish hair")
```

Hyponymy in WordNet

```
Sense 6
big cat, cat
       => leopard, Panthera pardus
           => leopardess
           => panther
       => snow leopard, ounce, Panthera uncia
       => iaquar, panther, Panthera onca,
                                    Felis onca
       => lion, king of beasts, Panthera leo
           => lioness
           => lionet
       => tiger, Panthera tigris
           => Bengal tiger
           => tigress
```

Polysemy

- homonymy: unrelated word senses. bank (raised land) vs bank (financial institution)
- bank (financial institution) vs bank (in a casino): related but distinct senses.
- bank (N) (raised land) vs bank (V) (to create some raised land): regular polysemy. Compare pile, heap etc
- vagueness: bank (river vs snow vs cloud)?

No clearcut distinctions.

Dictionaries are not consistent.

Needed for many applications, problematic for large domains. Assumes that we have a standard set of word senses (e.g., WordNet)

- frequency: e.g., diet: the food sense (or senses) is much more frequent than the parliament sense (Diet of Wurms)
- collocations: e.g. striped bass (the fish) vs bass guitar. syntactically related or in a window of words (latter sometimes called 'cooccurrence'). Generally 'one sense per collocation'.
- selectional restrictions/preferences (e.g., Kim eats bass, must refer to fish

WSD techniques

- supervised learning: cf. POS tagging from lecture 3. But sense-tagged corpora are difficult to construct, algorithms need far more data than POS tagging
- unsupervised learning (see below)
- Machine readable dictionaries (MRDs): e.g., look at overlap with words in definitions and example sentences
- selectional preferences: don't work very well by themselves, useful in combination with other techniques

WSD by (almost) unsupervised learning

Disambiguating *plant* (factory vs vegetation senses):

Find contexts in training corpus:			
sense	training example		
?	company said that the <i>plant</i> is still operating		
?	although thousands of plant and animal species		
?	zonal distribution of plant life		
?	company manufacturing plant is in Orlando		
	etc		

Yarowsky (1995): schematically

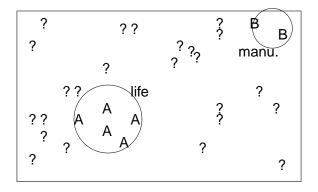
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2. Identify some seeds to disambiguate a few uses. e.g., 'plant life' for vegetation use (A) 'manufacturing plant' for factory use (B):

sense	training example
? ? A B	company said that the <i>plant</i> is still operating although thousands of <i>plant</i> and animal species zonal distribution of <i>plant</i> life company manufacturing <i>plant</i> is in Orlando etc

Seeds



3. Train a decision list classifier on the Sense A/Sense B examples.

reliability	criterion	sense
8.10	plant life	Α
7.58	manufacturing <i>plant</i>	В
6.27	animal within 10 words of plant	Α
	etc	

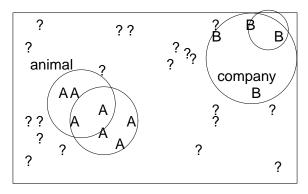
Decision list classifier: automatically trained if/then statements. Experimenter decides on classes of test by providing definitions of features of interest: system builds specific tests and provides reliability metrics.

4. Apply the classifier to the training set and add reliable examples to A and B sets.

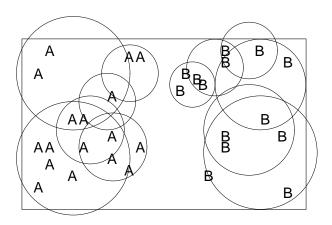
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Α	although thousands of plant and animal species
Α	zonal distribution of plant life
В	company manufacturing <i>plant</i> is in Orlando
	etc

5. Iterate the previous steps 3 and 4 until convergence

Iterating:



Final:



- 6. Apply the classifier to the unseen test data
- 'one sense per discourse': can be used as an additional refinement
- e.g., once you've disambiguated *plant* one way in a particular text/section of text, you can assign all the instances of *plant* to that sense

Evaluation of WSD

- SENSEVAL competitions
- evaluate against WordNet
- baseline: pick most frequent sense hard to beat (but don't always know most frequent sense)
- human ceiling varies with words
- MT task: more objective but sometimes doesn't correspond to polysemy in source language