# Natural Language Processing

Lecture 13: Lexical Semantics (part II) - Word Representations and Word Embeddings.

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COMS W4705
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## Natural Language Semantics

- Semantics is concerned with the meaning of language.
  - Lexical Semantics: What is the meaning of individual words?
  - Computational Semantics: How do we compute language meaning from word meaning? (next week)
  - How do we represent meaning?

## Two Approaches to Language Meaning

- Usage-based semantics:
  - Distributional / Vector-space semantics. Word embeddings.
  - Core concept: Semantic similarity.
  - History in connectionist approaches (neural networks).
- Formal Semantics:
  - Use formal Meaning Representations for words /sentences / discourse.
  - Based on lexical resources.
  - History in cognitive science (mind as symbol manipulation device).

## Why Natural Language Semantics?

- Meaning representations bridge between linguistic input and extra-linguistic knowledge.
  - Support inference and reasoning.
  - Examples:
    - Answering questions on an exam.
    - Deciding what to order at a restaurant by reading the menu.
    - Learning how to use a device by reading the manual.
    - Finding a joke funny.
    - Following a recipe.

### Syntax and Semantics

- Can we do syntax without semantics?
  - "He read the book with the blue cover"
  - "He saw the hill with the telescope"
  - "Last night I shot an elephant in my pajamas"

 These examples require world knowledge (books have covers, telescopes are used for seeing, elephants are large, ...)

#### Semantics and Machine Translation

L'Avocat général the general avocado en ??

#### Word Senses

 Different word senses of the same word can denote different (more or less related) concepts.

bank (of a river) vs. bank (financial institution) vs. bank (storage facility)

mouse (animal) vs. mouse (computer accessory)

bright [light] vs. bright [idea] vs. bright [student] vs. bright [future]

"Lexeme" - a pairing of a particular word form with its sense.

### Homonymy

- Homonymy is a relation between concepts/senses:
  - Multiple unrelated concepts correspond to the same word form.
  - Examples:
    - bank
    - check
    - kind
    - bass

## Polysemy

- Multiple semantically related concepts correspond to the same word form.
- Examples:
  - wood (material that trees are made of) vs.
     wood (a forested area)

 bank (financial institution) vs. bank (building)

### Metonomy

- A subtype of polysemy.
- Systematic and productive.
- One aspect of a concept is used to refer to other aspects of a concept (or the concept itself).
  - BUILDING <-> ORGANIZATION (bank, school,...)
  - ANIMAL <-> MEAT (the chicken was overcooked, the chicken eats a worm)

## Zeugma

- when a single word is used with two other parts of a sentence but must be understood differently (word sense) in relation to each.
  - Does United serve breakfast and JFK?
  - He lost his gloves and his temper.

#### Semantic Relations

- Synonym / Antonym
- Hypernym / Hyponym (IS-A)
- Meronym / Holonym (part-of relationship)

## Synonyms

- Two lexemes that share a sense.
  - couch/sofa
  - vomit/throw up
  - car/automobile
  - hazelnut/filbert
  - water/H<sub>2</sub>O

Note that even though the sense is the same, there may be differences in politeness, slang, register, genre, etc.

#### Lexical Substitution

- Two lexemes are synonyms if they can be substituted for each other in a sentence, such that the sentence retains its meaning (truth conditions).
- Note that synonymy is not a relationship between words, but between lexemes.

large
How big is that plane?

large (?) She was like a big sister to him.

## Antonyms

- Senses are opposites with respect to one specific feature of their meaning.
- Otherwise, they are very similar!
  - dark / light (level of luminosity)
  - short / long (length)
  - hot / cold (temperature)
  - rise / fall (direction)
  - front / back (relative position)

Antonyms typically describe opposite ends of a scale, or opposite direction/position with respect to some landmark (reversives).

## Hyponymy

- One sense is a hyponym (or subordinate) of another sense if the first sense is more specific, denoting a subclass of the other. (IS-A relationship).
  - dog is a hyponym of mammal.
  - mammal is a hyponym of animal.
  - desk is a hyponym of furniture.
  - sprint is a hyponym of run.
- The inverse relation is called **hypernymy**, so *furniture* is a hypernym (or superordinate) of *desk*.

## Hyponymy

- Can think of Hyponymy as a set relationship.
  - The set of things denoted by the hyponym is a superclass of the set of things denoted by the hypernym.
  - for all x, if x is a mammal, then x is an animal.
- Related to entailment:

The woman ate spaghetti with cheese.



The person consumed pasta with dairy product.

anima

dog

mamma

## Meronymy

- Part-whole relationship.
- A meronym is a part of another concept.
  - leg is a meronym of chair.
  - wheel is a meronym of car.
  - cellulose is a meronym of paper. (substance meronymy)
- The inverse relation is **holonymy**. *Car* is a holonym of *wheel*.

#### WordNet

- WordNet is a lexical database containing English word senses and their relations.
- Represents word sense as synsets, sets of lemmas that have synonymous lexemes in one context.

```
{composition, paper, report, theme}
{newspaper, paper}
{paper}
```

 Version 3.1 Contains synonyms, antonyms, hypernyms, (some) meronyms, and frequency information for about 117.000 nouns, 11.500 verbs, 22.000 adjectives, and 4.500 adverbs.

#### WordNet Senses

each sense comes with a gloss (dictionary definition).

trackball")

```
$ wn mouse -over
Overview of noun mouse
The noun mouse has 4 senses (first 1 from tagged texts)
1. (14) mouse -- (any of numerous small rodents typically resembling
diminutive rats having pointed snouts and small ears on elongated
bodies with slender usually hairless tails)
2. shiner, black eye, mouse -- (a swollen bruise caused by a blow to
the eye)
3. mouse -- (person who is quiet or timid)
```

4. mouse, computer mouse -- (a hand-operated electronic device that

controls the coordinates of a cursor on your computer screen as you

move it around on a pad; on the bottom of the device is a ball that

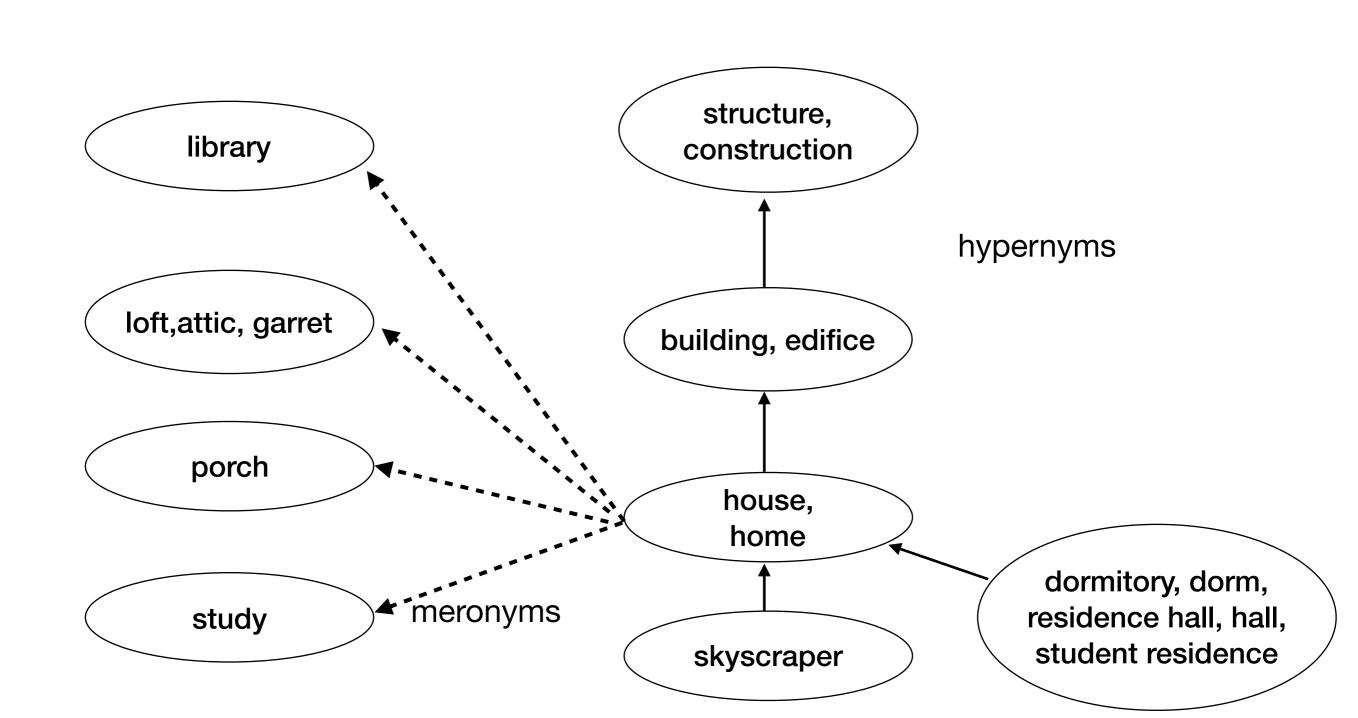
rolls on the surface of the pad; "a mouse takes much more room than a

## WordNet Hypernyms

```
$ wn mouse -hypen
Synonyms/Hypernyms (Ordered by Estimated Frequency) of noun mouse
4 senses of mouse
Sense 1
mouse
 => rodent, gnawer
   => placental, placental mammal, eutherian, eutherian mammal
      => mammal, mammalian
         => vertebrate, craniate
           => chordate
              => animal, animate being, beast, brute, creature, fauna
                 => organism, being
                    => living thing, animate thing
                       => whole, unit
                           => object, physical object
                                => physical entity
                                   => entity
```

### WordNet Meronyms

## Semantic Relations as a Graph



## Word Sense Disambiguation (WSD)

- Given a word token in context, identify its correct word sense (from a list of possible word-senses).
- Why? Machine translation. Question answering. Information Retrieval, Speech Synthesis...
- What set of senses:
  - For MT: Possible translations of a word (e.g. English to Spanish)
  - For Speech Synthesis: Homographs (bass, bread,...)
  - Senses from a dictionary like WordNet

#### Two types of WSD tasks

- Lexical Sample task
  - Small pre-selected set of target words.
  - Inventory of senses for each word.

Largemouth bass are willing to bite a variety of baits.

- All-words task
  - Every word in an entire text.
  - A lexicon with senses for each word.
  - Similar to POS tagging (but specific set of tags for each word).

#### WSD Methods

- Supervised Machine Learning
  - Train a classifier for each word.
  - Requires hand-labeled training data (sense annotations).
- Dictionary Methods
  - No training data. Instead use a sense dictionary (like WordNet).
  - Or exploit sense relations (WordNet graph).
- Semi-supervised learning
  - Use a small hand-annotated data set and generalize ("bootstrapping").

### Supervised WSD

- Given:
  - A sense inventory (for example, WordNet senses).
  - An annotated training corpus.
  - A set of features extracted from the training corpus.
  - A classifier.
- How would you solve this?

#### **Annotated Training Corpus**

- Lexical sample task:
  - SENSEVAL 1 to 3 (1998,2001). Small number of target words (~50), 12.000 to 20.000 instances.
     SemEval 2007.
  - "line, hard, serve" dataset. 4.000 instances each for the words line, hard, and serve.
- All-words task:
  - SENSEVAL 3, SemEval 2007.
  - SemCor ("Semantic concordance"). 234,000 words from Brown Corpus, manually tagged with WordNet senses.

#### Feature Definition - Intuition

"If one examines the words in a book, one at a time as through an opaque mask with a hole in it one word wide, then it is obviously impossible to determine, one at a time, the meaning of the words...

But if one lengthens the slit in the opaque mask, until one can see not only the central word in question but also say N words on either side, then if N is large enough one can unambiguously decide the meaning of the central word...

The practical question is: "What minimum value of N will, at least in a tolerable fraction of cases, lead to the correct choice of meaning for the central word?"

Warren Weaver (1955)

#### Feature Definition

Can you identify the word sense?

bass

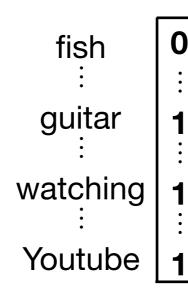
#### Feature Definition

- Approaches for representing context:
  - Collocational features:
    - Take the position of each context word into account.
  - Bag-of-word features:
    - Simply keep the set of all context words.
  - Using word embeddings (or phrase embeddings)

### Bag-of-Words features

He learned how to play guitar and bass watching Youtube videos.





#### Collocational Features

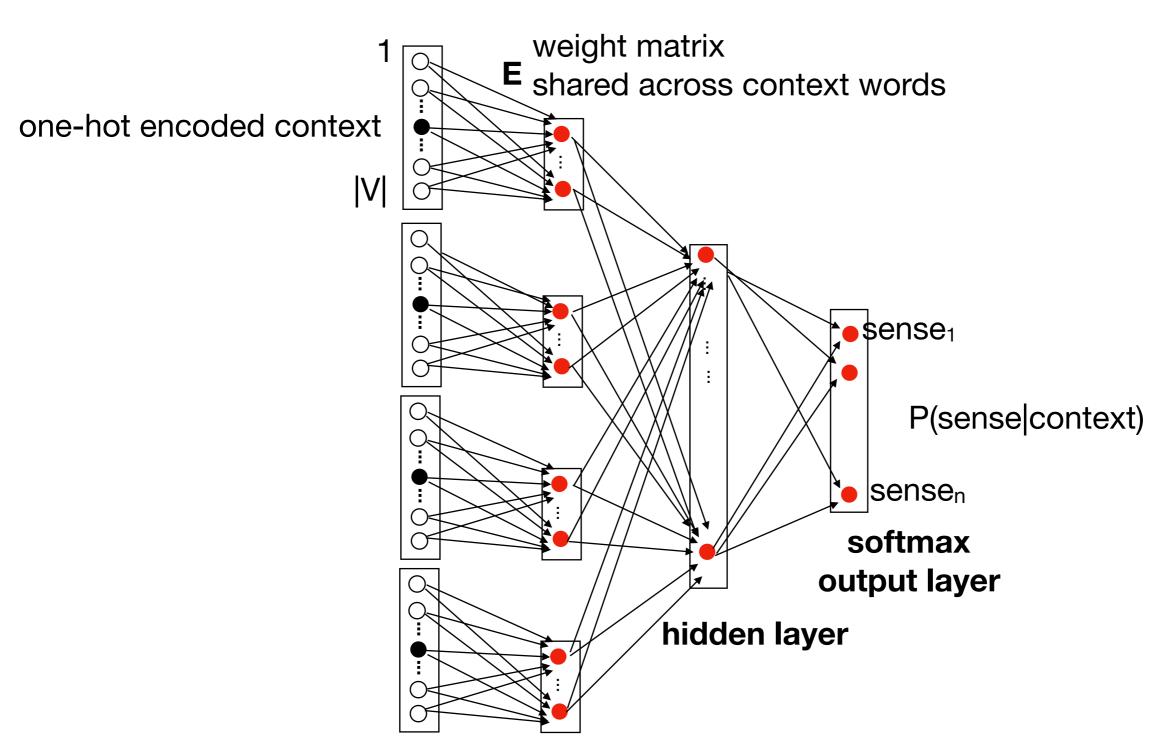
He learned how to play guitar and bass watching Youtube videos.

- Assume feature window: +/- 2 words.
- Position specific information about the words in the window

[guitar, NN, and, CC, watching, VBG, Youtube, NNP]

[word<sub>n-2</sub>, POS<sub>n-2</sub>, word<sub>n-1</sub>, POS<sub>n-1</sub>, word<sub>n+1</sub>, POS<sub>n+1</sub>]

#### Feed-forward NN for WSD



input layer projection layer

#### Dictionary-Based Methods

- Supervised WSD requires a lot of annotated training data.
- Instead, we can use a separate dictionary, such as WordNet:
  - to obtain candidate senses.
  - to obtain information that allows us to identify which of the candidate senses is correct.
- 1. (25) bank sloping land (especially the slope beside a body of water) "they pulled the canoe up on the bank" "he sat on the bank of the river and watched the currents"
- 2. (20) depository financial institution, bank, banking company a financial institution that accepts deposits and channels the money into lending activities
  "he cashed a check at the bank"
- "that bank holds the mortgage on my home"

## Simplified Lesk Algorithm

Use dictionary glosses for each sense.

1. (25) bank

 Choose the sense that has the highest word overlap between gloss and context (ignore function words).

The **bank** can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.

```
sloping land (especially the slope beside a body of water)
"they pulled the canoe up on the bank"
"he sat on the bank of the river and watched the currents"

2. (20) depository financial institution, bank, banking company
a financial institution that accepts deposits and channels the money
into lending activities
"he cashed a check at the bank"
"that bank holds the mortgage on my home"
```

## Extensions to Lesk Algorithm

- Often the available definitions and examples do not provide enough information. Overlap is 0.
- Different approaches to extending definitions:
  - "Corpus-Lesk": Use a sense-tagged-example corpus, add context from example sentences.
  - Extended Gloss Overlap (Banerjee & Pedersen 2003):
     Add glosses from related words (hypernyms, meronyms, ...)
- Use distributional representations for each word in the definition (more on Wednesday). Choose sense with highest average vector similarity to the context.

#### WSD evaluation

- Ideally, we would like to use an extrinsic (task-based) evaluation.
  - Use WSD as a component of some task (for example, MT) and see if the results improve.
- For convenience we often use intrinsic evaluation.
  - Measure sense accuracy (% of correct sense tags).
- What are some good baselines for this task?
  - Most frequent sense (according to some tagged corpus).
  - Lesk often used as a baseline for more elaborate approaches.

#### WSD Performance

- Varies widely depending on how difficult the disambiguation task is.
- Accuracies of over 90% are commonly reported on some of the classic, often fairly easy, WSD tasks ("pike, star, interest" data).
- Senseval brought careful evaluation of difficult WSD (many senses, different POS)
- Senseval 1: more fine grained senses, wider range of types:
  - Overall: about 75% accuracy
  - Nouns: about 80% accuracy
  - Verbs: about 70% accuracy

### Upper Bound

- How well do people do on this task?
- Inter-annotator agreement:
  - Compare multiple human annotations on the same data, given the same annotations guidelines.
- Human agreement on all-words task with WordNet senses:
  - 75%-80%

## Semi-Supervised WSD

- What if we only have a few labeled training examples.
- Idea: Bootstrapping. Generalize from a small handlabeled dataset. Yarowsky, 1995
- "One sense per collocation" rule
  - A word reoccurring in collocation with the same word will almost surely have the same sense.
  - Example:
    - the word play occurs with the music sense of bass
    - the word fish occurs with the fish sense of bass

#### Extracting New Sentences

 Using a few keywords and the "One sense per collocation" we can label new sentences for the known senses.

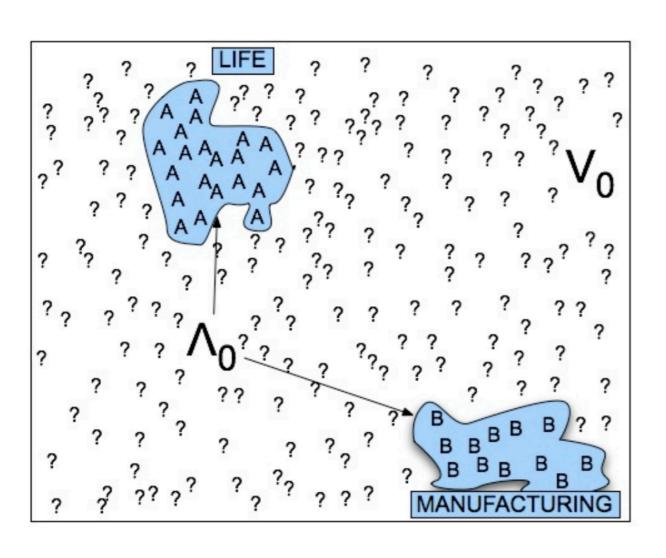
We need more good teachers – right now, there are only a half a dozen who can play the free **bass** with ease.

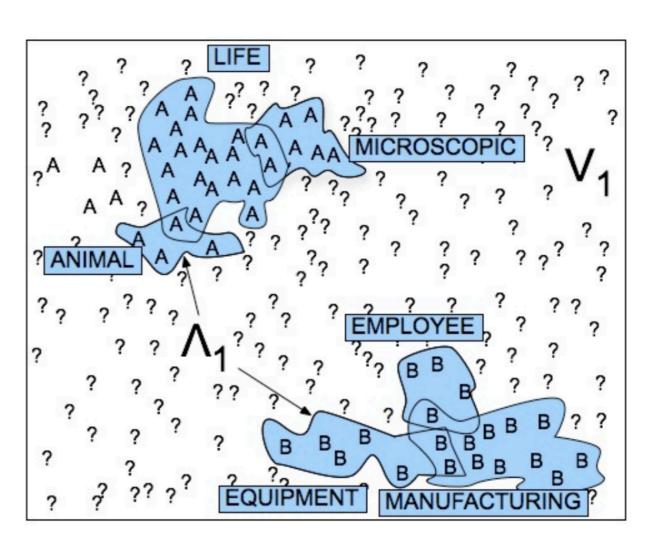
An electric guitar and **bass** player stand off to one side, not really part of the scene, just as a sort of nod to gringo expectations perhaps

The researchers said the worms spend part of their life cycle in such **fish** as Pacific salmon and striped **bass** and Pacific rockfish or snapper.

And it all started when **fish**ermen decided the striped **bass** in Lake Mead were too skinny.

## Stages in Yarowsky's Bootstrapping Algorithm





#### A Lexical Substitution Task

- Instead of identifying word sense
  - find a substitute for the target word, such that the meaning is preserved.

He was bright and independent and proud.

Snow covered areas appear bright blue in the image which was taken in early spring.

... an institution that nurtures the best and brightest young musicians.

How would you solve this task?

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