

CS447: Natural Language Processing

<http://courses.engr.illinois.edu/cs447>

Lecture 20:

Lexical Semantics:

Word Sense

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Part 1: Lexicographic approaches to word meaning

Where we're at

We have looked at how to represent the **meaning of sentences** based on the meaning of their words (using predicate logic).

Now we will get back to the question of how to represent the **meaning of words** (although this won't be in predicate logic)

We will look at **lexical resources** (WordNet)

We will consider two different tasks:

- Computing **word similarities**
- **Word sense disambiguation**



Different approaches to lexical semantics

Lexicographic tradition (today's lecture)

- Use lexicons, thesauri, ontologies
- Assume words have discrete word senses:
bank1 = financial institution; bank2 = river bank, etc.
- May capture explicit relations between word (senses):
“dog” is a “mammal”, etc.

Distributional tradition (earlier lectures)

- Map words to (sparse) vectors that capture corpus statistics
- Contemporary variant: use neural nets to learn dense vector
“embeddings” from very large corpora
(this is a prerequisite for most neural approaches to NLP)
- This line of work often ignores the fact that words have
multiple senses or parts-of-speech

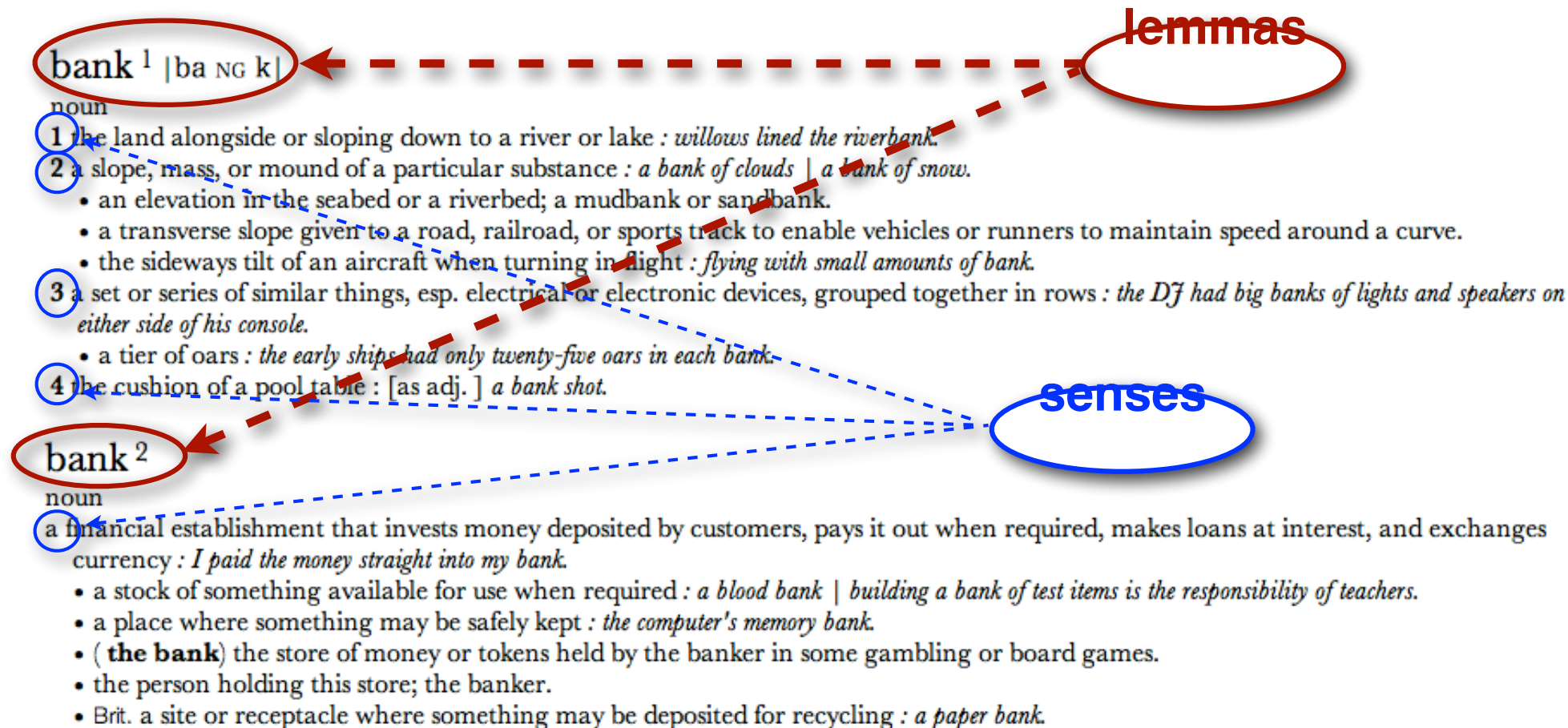
Word senses

What does '*bank*' mean?

- **a financial institution**
(US banks have raised interest rates)
- **a particular branch of a financial institution**
(the bank on Green Street closes at 5pm)
- **the bank of a river**
(In 1927, the bank of the Mississippi flooded)
- **a 'repository'**
(I donate blood to a blood bank)



Lexicon entries



Some terminology

Word forms: *runs, ran, running; good, better, best*

Any, possibly inflected, form of a word
(i.e. what we talked about in morphology)

Lemma (citation/dictionary form): *run*

A basic word form (e.g. infinitive or singular nominative noun) that is used to represent all forms of the same word.
(i.e. the form you'd search for in a dictionary)

Lexeme: RUN(V), GOOD(A), BANK¹(N), BANK²(N)

An abstract representation of a word (and all its forms), with a part-of-speech and a set of related word senses.
(Often just written (or referred to) as the lemma, perhaps in a ***different* FONT**)

Lexicon:

A (finite) list of lexemes

Trying to make sense of senses

Polysemy:

A lexeme is polysemous if it has different *related senses*



bank = financial institution or building

Homonyms:

Two lexemes are homonyms if their *senses are unrelated*, but they happen to have the **same spelling and pronunciation**



bank = (financial) bank or (river) bank

Relations between senses

Symmetric relations:

Synonyms: *couch/sofa*

Two lemmas with the **same** sense

Antonyms: *cold/hot, rise/fall, in/out*

Two lemmas with the **opposite** sense

Hierarchical relations:

Hypernyms and **hyponyms:** *pet/dog*

The **hyponym** (*dog*) is **more specific** than the **hypernym** (*pet*)

Holonyms and **meronyms:** *car/wheel*

The **meronym** (*wheel*) is a **part of** the **holonym** (*car*)

WordNet

Very large lexical database of English:

110K nouns, 11K verbs, 22K adjectives, 4.5K adverbs

(WordNets for many other languages exist or are under construction)

Word senses grouped into synonym sets (“synsets”) linked into a conceptual-semantic hierarchy

81K noun synsets, 13K verb synsets, 19K adj. synsets, 3.5K adv synsets

Avg. # of senses: 1.23 nouns, 2.16 verbs, 1.41 adj, 1.24 adverbs

Conceptual-semantic relations: hypernym/hyponym

also holonym/meronym

Also lexical relations, in particular lemmatization

Available at <http://wordnet.princeton.edu>



A WordNet example

WordNet Search - 3.0 - [WordNet home page](#) - [Glossary](#) - [Help](#)

Word to search for:

Display Options:

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations

Noun

- [S: \(n\)](#) **bass** (the lowest part of the musical range)
- [S: \(n\)](#) **bass**, [bass part](#) (the lowest part in polyphonic music)
- [S: \(n\)](#) **bass**, [basso](#) (an adult male singer with the lowest voice)
- [S: \(n\)](#) [sea bass](#), **bass** (the lean flesh of a saltwater fish of the family Serranidae)
- [S: \(n\)](#) [freshwater bass](#), **bass** (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
- [S: \(n\)](#) **bass**, [bass voice](#), [basso](#) (the lowest adult male singing voice)
- [S: \(n\)](#) **bass** (the member with the lowest range of a family of musical instruments)
- [S: \(n\)](#) **bass** (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

Adjective

- [S: \(adj\)](#) **bass**, [deep](#) (having or denoting a low vocal or instrumental range) "*a deep voice*"; "*a bass voice is lower than a baritone voice*"; "*a bass clarinet*"

[WordNet home page](#)



Hierarchical synset relations: nouns

Hypernym/hyponym (between concepts)

The more general '*meal*' is a hypernym of the more specific '*breakfast*'

Instance hypernym/hyponym (between concepts and instances)

Austen is an instance hyponym of *author*

Member holonym/meronym (groups and members)

professor is a member meronym of (a university's) *faculty*

Part holonym/meronym (wholes and parts)

wheel is a part meronym of (is a part of) *car*.

Substance meronym/holonym (substances and components)

flour is a substance meronym of (is made of) *bread*

Hierarchical synset relations: verbs

Hypernym/troponym (between events):

travel/fly, walk/stroll

Flying is a troponym of *traveling*:

it denotes **a specific manner** of *traveling*

Entailment (between events):

snore/sleep

Snoring **entails (presupposes)** *sleeping*

WordNet Hypernyms and Hyponyms

- **S: (n) bass** (the lowest part of the musical range)
 - direct hypernym / inherited hypernym / sister term
 - **S: (n) pitch** (the property of sound that varies with variation in the frequency of vibration)
 - **S: (n) sound property** (an attribute of sound)
 - **S: (n) property** (a basic or essential attribute shared by all members of a class) "*a student*"
 - **S: (n) attribute** (an abstraction belonging to or characteristic of an entity)
 - **S: (n) abstraction, abstract entity** (a general concept formed by extracting)
 - **S: (n) entity** (that which is perceived or known or inferred to have)
 - **S: (n) bass, bass part** (the lowest part in polyphonic music)
 - direct hyponym / full hyponym
 - **S: (n) ground bass** (a short melody in the bass that is constantly repeated)
 - **S: (n) figured bass, basso continuo, continuo, thorough bass** (a bass part written out in full and accompanied by other parts)
 - direct hypernym / inherited hypernym / sister term
 - **S: (n) part, voice** (the melody carried by a particular voice or instrument in polyphonic music) "*he*"
 - **S: (n) tune, melody, air, strain, melodic line, line, melodic phrase** (a succession of notes forming a whole)
 - **S: (n) music** (an artistic form of auditory communication incorporating instrumental or vocal elements)
 - **S: (n) auditory communication** (communication that relies on hearing)
 - **S: (n) communication** (something that is communicated by or to or between)
 - **S: (n) abstraction, abstract entity** (a general concept formed by extracting)
 - **S: (n) entity** (that which is perceived or known or inferred to have)

WordNet-based Word Similarity

WordNet-based word similarity

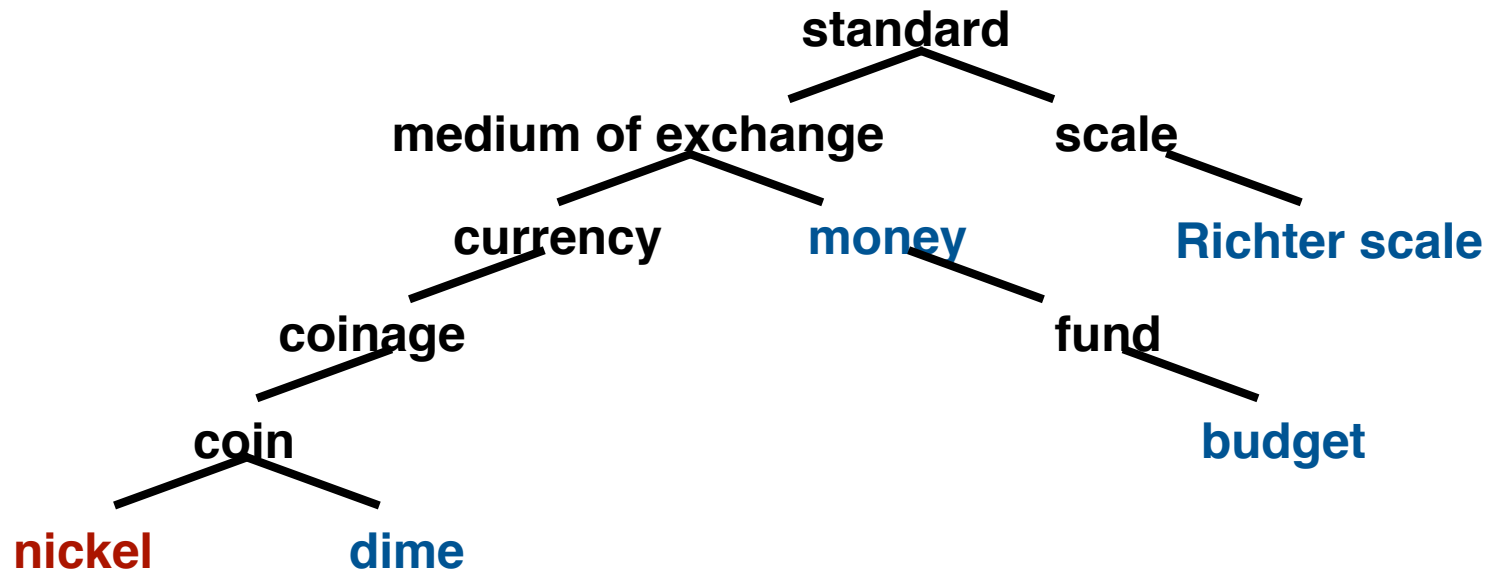
There have been many attempts to exploit resources like WordNet to compute word (sense) similarities.

Classic approaches use the distance (**path length**) between synsets, possibly augmented with corpus statistics.

More recent (neural) approaches aim to learn (non-Euclidean) embeddings that capture the hierarchical structure of WordNet.



WordNet path lengths: examples and problems



Path length is just the distance between synsets

$\text{pathlen}(\text{nickel}, \text{dime}) = 2$ (nickel—coin—dime)

$\text{pathlen}(\text{nickel}, \text{money}) = 5$ (nickel—...—medium of exchange—money)

$\text{pathlen}(\text{nickel}, \text{budget}) = 7$ (nickel—...—medium of exchange—...—budget)

But do we really want the following?

$\text{pathlen}(\text{nickel}, \text{coin}) < \text{pathlen}(\text{nickel}, \text{dime})$

$\text{pathlen}(\text{nickel}, \text{Richter scale}) = \text{pathlen}(\text{nickel}, \text{budget})$

Problems with thesaurus-based similarity

We need to have a thesaurus!
(not available for all languages)

We need to have a thesaurus that contains the words we're interested in.

We need a thesaurus that captures a rich hierarchy of hypernyms and hyponyms.

Most thesaurus-based similarities depend on the specifics of the hierarchy that is implemented in the thesaurus.



Learning hyponym relations

If we don't have a thesaurus, can we learn that Corolla is a kind of car?

Certain **phrases and patterns** indicate hyponym relations:

Hearst(1992) [Hearst patterns]

Enumerations: cars **such as** the Corolla, the Civic, and the Vibe,

Appositives: the Corolla , a popular car...

We can also **learn these patterns** if we have some **seed examples of hyponym relations** (e.g. from WordNet):

1. *Take all hyponym/hypernym pairs from WordNet (e.g. car/vehicle)*
2. *Find all sentences that contain both, and identify patterns*
3. *Apply these patterns to new data to get new hyponym/hypernym pairs*

Word Sense Disambiguation (WSD)



What does this word mean?

This **plant** needs to be watered each day.

⇒ **living plant**

This **plant** manufactures 1000 widgets each day.

⇒ **factory**

Word Sense Disambiguation (WSD):

Identify the sense of content words (nouns, verbs, adjectives) in context (assuming a fixed inventory of word senses).

Presumes the words to classify have a discrete set of senses.

Dictionary-based methods

We often don't have a labeled corpus, but we might have a **dictionary/thesaurus** that contains **glosses** and **examples**:

bank₁

Gloss: a financial institution that accepts deposits and channels the money into lending activities

Examples: *“he cashed the check at the bank”,
“that bank holds the mortgage on my home”*

bank₂

Gloss: sloping land (especially the slope beside a body of water)

Examples: *“they pulled the canoe up on the bank”,
“he sat on the bank of the river and watched the current”*

The Lesk algorithm

Simple, dictionary-based baseline for WSD

Basic idea: Compare the context with the dictionary definition of the sense.

Assign the dictionary sense whose gloss and examples are most similar to the context in which the word occurs.

Compare the **signature of a word in context** with the **signatures of its senses in the dictionary**

Assign the sense that is **most similar** to the context

Signature = set of content words
(in examples/gloss or in context)

Similarity = size of intersection of context signature and sense signature



Lesk algorithm

bank1:

Gloss: a financial institution that accepts deposits and channels the money into lending activities

Examples: “he *cash*ed the *check* at the *bank*”, “that *bank* *hold*s the *mortgage* on my *home*”

Signature(bank1) = {*financial, institution, accept, deposit, channel, money, lend, activity, cash, check, hold, mortgage, home*}

bank2:

Gloss: sloping land (especially the slope beside a body of water)

Examples: “they *pull*ed the *canoe* up on the *bank*”, “he *sat* on the *bank* of the *river* and *watch*ed the *current*”

Signature(bank2) = {*slope, land, body, water, pull, canoe, sit, river, watch, current*}

Target sentence: “The *bank* refused to give me a loan.”

Original signature: words in context {*refuse, give, loan*}

Augmented signature: add signatures of words in context (all senses) {*refuse, reject, request, ... , give, gift, donate, ... loan, money, borrow, ...*}

Lesk algorithm: Pick the sense whose signature has greatest overlap to (augmented) signature of the target word

WSD as a learning problem

Supervised:

- You have a (large) **corpus annotated with word senses**
- Here, WSD is a **standard supervised learning** task:
predict 1 of k senses for each occurrence of a word
(depending on its context)

Semi-supervised (bootstrapping) approaches:

- You only have **very little annotated data**
(and a lot of raw text)
- Here, WSD is a **semi-supervised learning** task
- Yarowsky algorithm: very influential early semi-supervised algorithm.



Implementing a WSD classifier

Basic insight: The **sense of a word** in a context depends on the **words in its context**.

Features:

- **Which words in context:** all words, all/some content words
- **How large is the context?** sentence, prev/following 5 words
- Do we represent context as **bag of words** (unordered set of words) or do we care about the **position** of words (preceding/following word)?
- Do we care about **POS tags**?
- Do we represent words as they occur in the text or as their **lemma** (dictionary form)?

Yarowsky's weakly-supervised algorithm

1. Initialization:

- Label a few seed examples (*that's one form of supervision*)
- Train an initial classifier on these seed examples

2. Relabel:

- Label all unlabeled examples with the current classifier.
- Add all examples that are labeled with high confidence to the labeled data set.
- Apply **one-sense-per-discourse heuristic** to correct mistakes and get additional labeled examples (*that's another form of supervision*)
[Assume all occurrences of the same token (e.g. *plant*) in the same document have the same sense — this is true often enough that it can be very helpful, since it may be easy to label one occurrence correctly, and then you get the other labeled instances for free]

3. Retrain:

- Train a new classifier on the new labeled data set.

4. Repeat 2. and 3. until convergence.

<https://www.aclweb.org/anthology/P95-1026.pdf>



Problems with word sense

Words can take on new meanings

Metaphors: *bigger **fish** to fry*

Metonymy: *The **SUV** honked at me*

[i.e. the SUV driver honked at me]

Word senses can be *modulated*

to identify different aspects of meaning:

She oiled her bike [bike = bike chain]

She dried off her bike. [bike = bike frame]

Her bike goes like the wind [bike = the bike's motion]

Kilgariff: I don't believe in Word Senses

https://www.sketchengine.eu/wp-content/uploads/I_dont_believe_1997.pdf