EECS 498-004: Introduction to Natural Language Processing

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Outline

- Word Senses and Word Relations
- Word Similarity
- Word Sense Disambiguation

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Terminology: lemma and wordform

- A **lemma** or **citation form**
  - Same stem, part of speech, rough semantics
- A **wordform**
  - The inflected word as it appears in text

Wordform	Lemma
banks	bank
sung	sing
duermes	dormir

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Lemmas have senses

- One lemma "bank" can have many meanings:
  - Sense 1: …a **bank**$_1$ can hold the investments in a custodial account…
  - Sense 2: "…as agriculture burgeons on the east **bank**$_2$ the river will shrink even more"
- **Sense** (or **word sense**)
  - A discrete representation of an aspect of a word's meaning.
- The lemma **bank** here has two senses

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Homonymy

Homonyms: words that share a form (spell or sound alike) but have unrelated, distinct meanings:

- bank$_1$: financial institution, bank$_2$: sloping land
- bat$_1$: club for hitting a ball, bat$_2$: nocturnal flying mammal

1. Homographs (bank/bank, bat/bat)
2. Homophones:
   1. Write and right
   2. Piece and peace

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Homonymy causes problems for NLP applications

- Information retrieval
  - "bat care"
- Machine Translation
  - bat: murciélago (animal) or bate (for baseball)
- Text-to-Speech
  - bass (stringed instrument) vs. bass (fish)

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- 1. The **bank** was constructed in 1875 out of local red brick.
- 2. I withdrew the money from the **bank**

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Polysemy

- 1. The **bank** was constructed in 1875 out of local red brick.
- 2. I withdrew the money from the **bank**
- Are those the same sense?
  - Sense 1: "The building belonging to a financial institution"
  - Sense 2: "A financial institution"
- A **polysemous** word has **related** meanings
  - Most non-rare words have multiple meanings

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Metonymy or Systematic Polysemy: A systematic relationship between senses

- Lots of types of polysemy are systematic
  - `School, university, hospital`
  - All can mean the institution or the building.
- A systematic relationship:
  - Building ⟺ Organization
- Other such kinds of systematic polysemy:

Author (`Jane Austen wrote Emma`)
⟺ Works of Author (`I love Jane Austen`)
Tree (`Plums have beautiful blossoms`)
⟺ Fruit (`I ate a preserved plum`)

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How do we know when a word has more than one sense?

- The "zeugma" test: Two senses of `serve`?
  - `Which flights` **`serve`** `breakfast?`
  - `Does Lufthansa` **`serve`** `Philadelphia?`

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How do we know when a word has more than one sense?

- The "zeugma" test: Two senses of `serve`?
  - `Which flights` **`serve`** `breakfast?`
  - `Does Lufthansa` **`serve`** `Philadelphia?`
  - Does Lufthansa serve breakfast and San Jose?
- Since this conjunction sounds weird,
  - we say that these are **two different senses of "serve"**

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Synonyms

- Words that have the same meaning in some or all contexts.
  - filbert / hazelnut
  - couch / sofa
  - big / large
  - automobile / car
  - vomit / throw up
  - Water / H_20
- Two words are synonyms if they can be substituted for each other in all situations (strict/perfect definition).

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Synonyms

- But there are few (or no) examples of perfect synonymy.
  - Even if many aspects of meaning are identical
  - Still may not preserve the acceptability based on notions of politeness, slang, register, genre, etc.
- Example:
  - Water/$H_2 0$
  - Big/large
  - Brave/courageous

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Synonymy is a relation between senses rather than words

- Consider the words *big* and *large*
- Are they synonyms?
  - How **big** is that plane?
  - Would I be flying on a **large** or small plane?

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Synonymy is a relation between senses rather than words

- Consider the words *big* and *large*
- Are they synonyms?
  - How **big** is that plane?
  - Would I be flying on a **large** or small plane?
- How about here:
  - Miss Nelson became a kind of **big** sister to Benjamin.
  - Miss Nelson became a kind of **large** sister to Benjamin.
- Why?
  - *big* has a sense that means being older, or grown up
  - *large* lacks this sense

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Antonyms

- Senses that are opposites with respect to one feature of meaning
- Otherwise, they are very similar!

```
dark/light   short/long    fast/slow rise/fall
hot/cold       up/down          in/out
```

- More formally: antonyms can
  - define a binary opposition or be at opposite ends of a scale
    - `long/short, fast/slow`
  - Be **reversives**:
    - `rise/fall, up/down`

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Hyponymy and Hypernymy

- One sense is a **hyponym** of another if the first sense is more specific, denoting a subclass of the other
  - *car* is a hyponym of *vehicle*
  - *mango* is a hyponym of *fruit*
- Conversely **hypernym/superordinate** ("hyper is super")
  - *vehicle* is a **hypernym** of *car*
  - *fruit* is a hypernym of *mango*

Superordinate/hypernym	vehicle	fruit	furniture
Subordinate/hyponym	car	mango	chair

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Hyponymy more formally

- Extensional:
  - The class denoted by the superordinate extensionally includes the class denoted by the hyponym
- Entailment:
  - A sense A is a hyponym of sense B if *being an A* entails *being a B*
- Hyponymy is usually transitive
  - (A hypo B and B hypo C entails A hypo C)
- Another name: the **IS-A hierarchy**
  - A IS-A B (or A ISA B)
  - B **subsumes** A

Superordinate/hypernym	vehicle	fruit	furniture
Subordinate/hyponym	car	mango	chair

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Hyponymy more formally

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Applications in textual entailment or reasoning or machine comprehension

- Another name: the **IS-A hierarchy**
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Superordinate/hypernym	vehicle	fruit	furniture
Subordinate/hyponym	car	mango	chair

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Hyponyms and Instances

- An **instance** is an individual, a proper noun that is a unique entity
  - `San Francisco` is an **instance** of `city`
- But `city` is a class
  - `city` is a **hyponym** of `municipality...location...`

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Meronymy

- The part-whole relation
  - A *leg* is part of a *chair*; a *wheel* is part of a *car*.
- *Wheel* is a **meronym** of *car*, and *car* is a **holonym** of *wheel*.

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WordNet 3.0

- A hierarchically organized lexical database
- On-line thesaurus + aspects of a dictionary

Category	Unique Strings
Noun	117,798
Verb	11,529
Adjective	22,479
Adverb	4,481

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EuroWordNet

- WordNets for
  - Dutch
  - Italian
  - Spanish
  - German
  - French
  - Czech
  - Estonian

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Senses of “bass” in Wordnet

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"*

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How is "sense" defined in WordNet?

- **The synset (synonym set),** the set of near-synonyms, instantiates a sense or concept, with a gloss
- Example: chump as a noun with the gloss:
  "a person who is gullible and easy to take advantage of"
- This sense of "chump" is shared by 9 words:
  `chump1, fool2, gull1, mark9, patsy1, fall guy1, sucker1, soft touch1, mug2`
- Each of **these** senses has this same gloss
  - (Not **every** sense; sense 2 of gull is the aquatic bird)

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WordNet Hypernym Hierarchy for "bass"

- S: (n) **bass**, basso (an adult male singer with the lowest voice)
  - *direct hypernym* / ***inherited hypernym*** / *sister term*
    - S: (n) singer, vocalist, vocalizer, vocaliser (a person who sings)
      - S: (n) musician, instrumentalist, player (someone who plays a musical instrument (as a profession))
        - S: (n) performer, performing artist (an entertainer who performs a dramatic or musical work for an audience)
          - S: (n) entertainer (a person who tries to please or amuse)
            - S: (n) person, individual, someone, somebody, mortal, soul (a human being) *"there was too much for one person to do"*
              - S: (n) organism, being (a living thing that has (or can develop) the ability to act or function independently)
                - S: (n) living thing, animate thing (a living (or once living) entity)
                  - S: (n) whole, unit (an assemblage of parts that is regarded as a single entity) *"how big is that part compared to the whole?"; "the team is a unit"*
                    - S: (n) object, physical object (a tangible and visible entity; an entity that can cast a shadow) *"it was full of rackets, balls and other objects"*
                      - S: (n) physical entity (an entity that has physical existence)
                        - S: (n) entity (that which is perceived or known or inferred to have its own distinct existence (living or nonliving))

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WordNet Noun Relations

Relation	Also Called	Definition	Example
Hypernym	Superordinate	From concepts to superordinates	$breakfast^1 \rightarrow meal^1$
Hyponym	Subordinate	From concepts to subtypes	$meal^1 \rightarrow lunch^1$
Instance Hypernym	Instance	From instances to their concepts	$Austen^1 \rightarrow author^1$
Instance Hyponym	Has-Instance	From concepts to concept instances	$composer^1 \rightarrow Bach^1$
Member Meronym	Has-Member	From groups to their members	$faculty^2 \rightarrow professor^1$
Member Holonym	Member-Of	From members to their groups	$copilot^1 \rightarrow crew^1$
Part Meronym	Has-Part	From wholes to parts	$table^2 \rightarrow leg^3$
Part Holonym	Part-Of	From parts to wholes	$course^7 \rightarrow meal^1$
Substance Meronym		From substances to their subparts	$water^1 \rightarrow oxygen^1$
Substance Holonym		From parts of substances to wholes	$gin^1 \rightarrow martini^1$
Antonym		Semantic opposition between lemmas	$leader^1 \iff follower^1$
Derivationally Related Form		Lemmas w/same morphological root	$destruction^1 \iff destroy^1$

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WordNet Verb Relations

Relation	Definition	Example
Hypernym	From events to superordinate events	$fly^9 \rightarrow travel^5$
Troponym	From events to subordinate event (often via specific manner)	$walk^1 \rightarrow stroll^1$
Entails	From verbs (events) to the verbs (events) they entail	$snore^1 \rightarrow sleep^1$
Antonym	Semantic opposition between lemmas	$increase^1 \iff decrease^1$
Derivationally Related Form	Lemmas with same morphological root	$destroy^1 \iff destruction^1$

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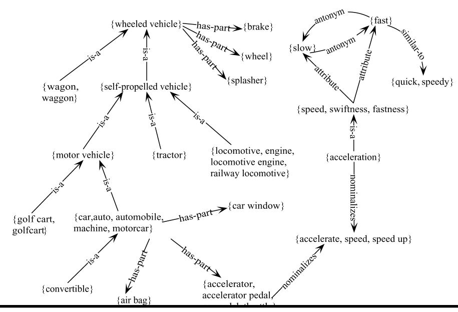
WordNet: Viewed as a graph



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WordNet 3.0

- Where it is:
  - http://wordnetweb.princeton.edu/perl/webwn
- Libraries
  - Python: WordNet from NLTK
    - http://www.nltk.org/Home

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Outline

- Word Senses and Word Relations
- Word Similarity
- Word Sense Disambiguation

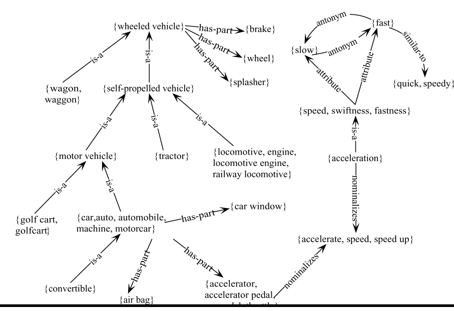
Why word similarity

- A practical component in lots of NLP tasks
  - Question answering
  - Natural language generation
  - Automatic essay grading
  - Plagiarism detection

Word Similarity

- **Synonymy**: a binary relation
  - Two words are either synonymous or not
- **Similarity** (or **distance**): a looser metric (more useful in practice!)
  - Two words are more similar if they share more features of meaning
- Similarity is properly a relation between **senses**
  - Bank^1 is similar to fund^3
  - Bank^2 is similar to slope^5
- But we'll compute similarity over both words and senses

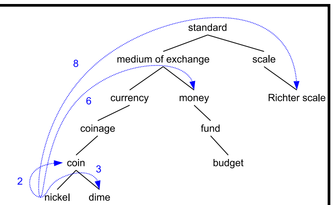
WordNet: Viewed as a graph



Two classes of similarity algorithms

- Thesaurus-based algorithms
  - Are words "nearby" in hypernym hierarchy?
  - Do words have similar glosses (definitions)?
- Distributional algorithms
  - Do words have similar distributional contexts?

Path-based similarity



- Two concepts (senses/synsets) are similar if they are near each other in the thesaurus hierarchy
  - have a short path between them
  - concepts have path 1 to themselves

Refinements to path-based similarity

- pathlen(c_1,c_2) = 1 + number of edges in the **shortest path** in the hypernym graph between sense nodes c_1 and c_2
- ranges from 0 to 1 (identity)
- $\text{simpath}(c_1,c_2) = \dfrac{1}{\text{pathlen}(c_1,c_2)}$
- $\text{wordsim}(w_1,w_2) = \max_{c_1 \in \text{senses}(w_1), c_2 \in \text{senses}(w_2)} \text{sim}(c_1,c_2)$

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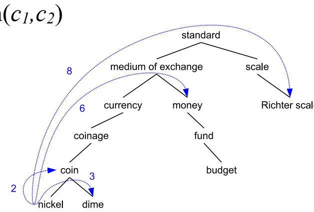
Example: path-based similarity

$\text{simpath}(c_1,c_2) = 1/\text{pathlen}(c_1,c_2)$



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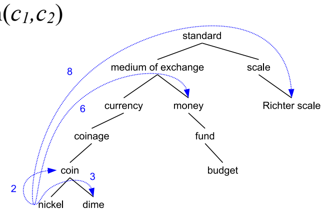
Example: path-based similarity

$\text{simpath}(c_1,c_2) = 1/\text{pathlen}(c_1,c_2)$



simpath(*nickel*,*coin*) = 1/2 = .5

simpath(*fund*,*budget*) = 1/2 = .5

simpath(*nickel*,*currency*) = 1/4 = .25

simpath(*nickel*,*money*) = 1/6 = .17

simpath(*nickel*,*standard*) = 1/6 = .17

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Problem with basic path-based similarity

- Assumes each link represents a uniform distance
  - But *nickel* to *money* seems to us to be closer than *nickel* to *standard*
  - Nodes high in the hierarchy are very abstract
- We instead want a metric that
  - Represents the cost of each edge independently
  - Words connected only through abstract nodes
    - are less similar

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Information content similarity metrics

Resnik 1995

- Let's define P(c) as:
  - The probability that a randomly selected word in a corpus is an instance of concept *c*
  - Formally: there is a distinct random variable, ranging over words, associated with each concept in the hierarchy
    - for a given concept, each observed word is either
      - a member of that concept with probability P(c)
      - not a member of that concept with probability 1-P(c)
  - All words are members of the root node (Entity)
    - P(root)=1 (in practice, it may not be 1)
  - The lower a node in hierarchy, the lower its probability

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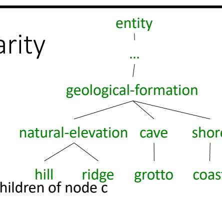
Information content similarity



- Train by counting in a corpus
  - Each instance of `hill` counts toward frequency of *natural elevation*, *geological formation*, *entity*, etc
  - Let words(c) be the set of all words/phrases that are children of node c
    - words("geo-formation") = {hill,ridge,grotto,coast,cave,shore,natural elevation}
    - words("natural elevation") = {hill, ridge}

$$P(c) = \frac{\sum_{w \in words(c)} count(w)}{N}$$

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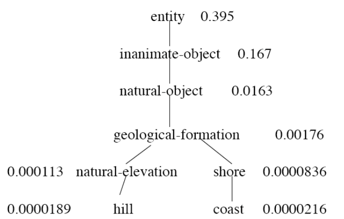
Information content similarity

- WordNet hierarchy augmented with probabilities P(c)

D. Lin. 1998. An Information-Theoretic Definition of Similarity. ICML 1998



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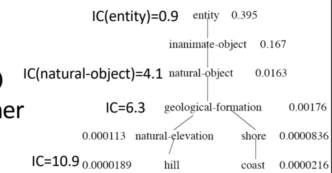
Information content: definitions

- Information content:
  $IC(c) = -\log_e P(c) = -\ln P(c)$
- Most informative subsumer (Lowest common subsumer)
  $LCS(c_1,c_2) =$
  The most informative (lowest) node in the hierarchy subsuming both c_1 and c_2



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Using information content for similarity: the Resnik method

Philip Resnik. 1995. Using Information Content to Evaluate Semantic Similarity in a Taxonomy. IJCAI 1995.
Philip Resnik. 1999. Semantic Similarity in a Taxonomy: An Information-Based Measure and its Application to Problems of Ambiguity in Natural Language. JAIR 11, 95-130.

- The similarity between two words is related to their common information
- The more two words have in common, the more similar they are
- Resnik: measure common information as:
  - The information content of the lowest common subsumer of the two nodes
  - $sim_{resnik}(c_1,c_2) = IC(LCS(c_1,c_2)) = -\log P(LCS(c_1,c_2))$

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Dekang Lin method

Dekang Lin. 1998. An Information-Theoretic Definition of Similarity. ICML

- Intuition: Similarity between A and B is not just what they have in common
- The more **differences** between A and B, the less similar they are:
  - Commonality: the more A and B have in common, the more similar they are
  - Difference: the more differences between A and B, the less similar

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Dekang Lin similarity theorem

- The similarity between A and B is measured by the ratio between the amount of information needed to state the commonality of A and B and the information needed to fully describe what A and B are

$$sim_{Lin}(A,B) \propto \frac{IC(common(A,B))}{IC(description(A,B))}$$

- Lin (altering Resnik) defines IC(common(A,B)) as 2 x information of the LCS

$$sim_{Lin}(c_1,c_2) = \frac{2\log P(LCS(c_1,c_2))}{\log P(c_1) + \log P(c_2)}$$

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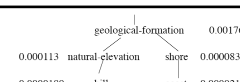
Lin similarity function



$$sim_{Lin}(A,B) = \frac{2\log P(LCS(c_1,c_2))}{\log P(c_1) + \log P(c_2)}$$

$$sim_{Lin}(\text{hill},\text{coast}) = \frac{2\log P(\text{geological-formation})}{\log P(\text{hill}) + \log P(\text{coast})}$$

$$= \frac{2\ln 0.00176}{\ln 0.0000189 + \ln 0.0000216}$$
$$= .59$$

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Libraries for computing thesaurus-based similarity

- NLTK
  - http://nltk.github.com/api/nltk.corpus.reader.html?highlight=similarity - nltk.corpus.reader.WordNetCorpusReader.res_similarity
- WordNet::Similarity
  - http://wn-similarity.sourceforge.net/
  - Web-based interface:
    - http://marimba.d.umn.edu/cgi-bin/similarity/similarity.cgi

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Evaluating similarity

- Extrinsic (task-based, end-to-end) Evaluation:
  - Question answering
  - Spell checking
  - Essay grading
  - Word sense disambiguation

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Evaluating similarity

- Extrinsic (task-based, end-to-end) Evaluation:
  - Question answering
  - Spell checking
  - Essay grading
  - Word sense disambiguation
- Intrinsic Evaluation:
  - Correlation between algorithm and human word similarity ratings (e.g. using Pearson correlation, Spearman correlation)
    - Wordsim353: 353 noun pairs rated 0-10. *sim(plane,car)=5.77*
  - Taking multiple-choice vocabulary tests
    - `Levied is closest in meaning to:`
      `imposed, believed, requested, correlated`

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Lexical Ambiguity

- Most words in natural languages have multiple possible meanings.
  - "pen" (noun)
    - The dog is in the pen.
    - The ink is in the pen.
  - "take" (verb)
    - Take one pill every morning.
    - Take the first right past the stoplight.

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Lexical Ambiguity

- Most words in natural languages have multiple possible meanings.
  - "pen" (noun)
    - The dog is in the pen.
    - The ink is in the pen.
  - "take" (verb)
    - Take one pill every morning.
    - Take the first right past the stoplight.
- Syntax helps distinguish meanings for different parts of speech of an ambiguous word.
  - "conduct" (noun or verb)
    - John's conduct in class is unacceptable.
    - John will conduct the orchestra on Thursday.

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Motivation for Word Sense Disambiguation (WSD)

- Many tasks in natural language processing require disambiguation of ambiguous words.
  - Question Answering
  - Information Retrieval
  - Machine Translation
  - Text Mining
  - Phone Help Systems

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Senses Based on Needs of Translation

- Only distinguish senses that are translated to different words in some other language.
  - play: tocar vs. jugar
  - know: conocer vs. saber
  - be: ser vs. estar
  - leave: salir vs dejar
  - take: llevar vs. tomar vs. sacar
- May still require overly fine-grained senses
  - river in French is either:
    - fleuve: flows into the ocean
    - rivière: does not flow into the ocean

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Word Sense Disambiguation (WSD)

- Given
  - A word in context (*The dog is in the pen*)
  - A fixed inventory of potential word senses (*pen^1, pen^2*)
  - Decide which sense of the word this is
- What set of senses?
  - In general: the senses in a thesaurus like WordNet
  - English-to-Spanish MT: set of Spanish translations
  - Speech Synthesis: homographs like *bass* and *bow*

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Two variants of WSD task

- Lexical Sample task
  - Small pre-selected set of target words (*line, plant*)
  - And inventory of senses for each word
  - **Supervised machine learning: train a classifier for each word**
- All-words task
  - Every word in an entire text
  - A lexicon with senses for each word
  - Data sparseness: can't train word-specific classifiers

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WSD Methods

- Supervised Machine Learning
- Thesaurus/Dictionary Methods
- Semi-Supervised Learning

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Supervised Machine Learning Approaches

- Supervised machine learning approach:
  - a training corpus of words tagged in context with their sense
  - used to train a classifier that can tag words in new text
- Summary of what we need:
  - the **tag set** ("sense inventory")
  - the **training corpus**
  - A set of **features** extracted from the training corpus
  - A **classifier**

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Supervised WSD 1: WSD Tags

- What's a tag?
  - A dictionary sense?
- For example, for WordNet an instance of "bass" in a text has 8 possible tags or labels (bass1 through bass8, as noun).

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8 senses of "bass" in WordNet

1. bass - (the lowest part of the musical range)
2. bass, bass part - (the lowest part in polyphonic music)
3. bass, basso - (an adult male singer with the lowest voice)
4. sea bass, bass - (flesh of lean-fleshed saltwater fish of the family Serranidae)
5. freshwater bass, bass - (any of various North American lean-fleshed freshwater fishes especially of the genus Micropterus)
6. bass, bass voice, basso - (the lowest adult male singing voice)
7. bass - (the member with the lowest range of a family of musical instruments)
8. bass - (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

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Supervised WSD 2: Get a corpus

- Lexical sample task:
  - *Line-hard-serve* corpus - 4000 examples of each
  - *Interest* corpus - 2369 sense-tagged examples
- All words:
  - **Semantic concordance**: a corpus in which each open-class word is labeled with a sense from a specific dictionary/thesaurus.
    - **SemCor**: 234,000 words from Brown Corpus, manually tagged with WordNet senses
    - **SENSEVAL**-3 competition corpora - 2081 tagged word tokens

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Supervised WSD 3: Extract feature vectors

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Feature vectors

- A simple representation for each observation
  (each instance of a target word)
  - **Vectors** of sets of feature/value pairs
  - Represented as an ordered list of values
  - These vectors represent, e.g., context---the window of words around the target

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Lexical Ambiguity

- Most words in natural languages have multiple possible meanings.
  - "pen" (noun)
    - The dog is in the pen.
    - The ink is in the pen.
  - "take" (verb)
    - Take one pill every morning.
    - Take the first right past the stoplight.

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Two kinds of features in the vectors

- **Collocational** features and **bag-of-words** features
  - **Collocational**
    - Features about words at **specific** positions near target word
      - Often limited to just word identity and POS
  - **Bag-of-words**
    - Features about words that occur anywhere in the window (regardless of position)
      - Typically limited to frequency counts

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Examples

- Example text (WSJ):
  An electric guitar and **bass** player stand off to one side not really part of the scene
- Assume a window of +/- 2 from the target

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Examples

- Example text (WSJ)
  An electric guitar and **bass** player stand off to one side not really part of the scene,
- Assume a window of +/- 2 from the target

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Collocational features

- Position-specific information about the words and collocations in window
- guitar and bass player stand

$$[w_{i-2}, \mathrm{POS}_{i-2}, w_{i-1}, \mathrm{POS}_{i-1}, w_{i+1}, \mathrm{POS}_{i+1}, w_{i+2}, \mathrm{POS}_{i+2}, w_{i-2}^{i-1}, w_{i+1}^{i+2}]$$

```
[guitar, NN, and, CC, player, NN, stand, VB, and guitar, player stand]
```

- word 1,2,3 grams in window of ±3 is common

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Bag-of-words features

- "an unordered set of words" – position ignored
- Counts of words occur within the window.
- First choose a vocabulary
- Then count how often each of those terms occurs in a given window
  - sometimes just a binary "indicator" 1 or 0

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Co-Occurrence Example

- Assume we've settled on a possible vocabulary of 12 words in "bass" sentences:

[*fishing, big, sound, player, fly, rod, pound, double, runs, playing, guitar, band*]

- The vector for:
  guitar and bass player stand
  [0,0,0,1,0,0,0,0,0,0,1,0]

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Syntactic Relations
(Ambiguous Verbs)

- For an ambiguous verb, it is very useful to know its direct object.
  - 1-"**played** the game"
  - 2-"**played** the guitar"
  - 3-"**played** the risky and long-lasting card game"
  - 4-"**played** the beautiful and expensive guitar"
  - 5-"**played** the big brass tuba at the football game"
  - 6-"**played** the game listening to the drums and the tubas"
- May also be useful to know its subject:
  - "The game was **played** while the band **played**."
  - "The game that included a drum and a tuba was **played** on Friday."

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Syntactic Relations
(Ambiguous Nouns)

- For an ambiguous noun, it is useful to know what verb it is an object of:
  - "**played** the piano and the **horn**"
  - "**wounded** by the rhinoceros' **horn**"
- May also be useful to know what verb it is the subject of:
  - "the **bank** near the river **loaned** him $100"
  - "the **bank** is **eroding** and the **bank** has **given** the city the money to repair it"

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Syntactic Relations
(Ambiguous Adjectives)

- For an ambiguous adjective, it useful to know the noun it is modifying.
  - "a **brilliant** young **man**"
  - "a **brilliant** yellow **light**"
  - "a **wooden** writing **desk**"
  - "a **wooden** acting **performance**"

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Classification: definition

- *Input*:
  - a word w and some features *f*
  - a fixed set of classes $C = \{c_1, c_2,\ldots, c_J\}$
- *Output*: a predicted class $c \in C$

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Classification Methods:
Supervised Machine Learning

- *Input:*
  - a word *w in a text window d (which we'll call a "document")*
  - a fixed set of classes $C = \{c_1, c_2,\ldots, c_J\}$
  - A training set of *m* hand-labeled text windows again called "documents" $(d_1,y_1),\ldots,(d_m,y_m)$, y_m *is in C*
- *Output:*
  - a learned classifier $\gamma{:}d \rightarrow c$

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Classification Methods:
Supervised Machine Learning

- Any kind of classifier
  - Naive Bayes
  - Logistic regression
  - Neural Networks
  - Support-vector machines
  - k-Nearest Neighbors
  - …

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Applying Naive Bayes to WSD

- P(c) is the prior probability of that sense
  - Counting in a labeled training set.
- P(w|c) conditional probability of a word given a particular sense
  - P(w|c) = count(w,c)/count(c)
- We get both of these from a tagged corpus like SemCor

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$$\hat{P}(c) = \frac{N_c}{N}$$

$$\hat{P}(w \mid c) = \frac{count(w,c)+1}{count(c)+|V|}$$

	Doc	Words (context of "bass")	Class
Training	1	fish smoked fish	f
	2	fish line	f
	3	fish haul smoked	f
	4	guitar jazz line	g
Test	5	line guitar jazz jazz	?

V = {fish, smoked, line, haul, guitar, jazz}

Priors:
P(f)=
P(g)=

Choosing a class:
P(f|d5)

P(g|d5)

Conditional Probabilities:
P(line|*f*) =
P(guitar|*f*) =
P(jazz|*f*) =
P(line|*g*) =
P(guitar|*g*) =
P(jazz|*g*) =

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$$\hat{P}(c) = \frac{N_c}{N}$$

$$\hat{P}(w \mid c) = \frac{count(w,c)+1}{count(c)+|V|}$$

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V = {fish, smoked, line, haul, guitar, jazz}

Priors:
P(f)= $\frac{3}{4}$
P(g)= $\frac{1}{4}$

Choosing a class:
P(f|d5) $\propto$ 3/4 * 2/14 * $(1/14)^2$ * 1/14
≈ 0.00003

Conditional Probabilities:
P(line|*f*) = (1+1) / (8+6) = 2/14
P(guitar|*f*) = (0+1) / (8+6) = 1/14
P(jazz|*f*) = (0+1) / (8+6) = 1/14
P(line|*g*) = (1+1) / (3+6) = 2/9
P(guitar|*g*) = (1+1) / (3+6) = 2/9
P(jazz|*g*) = (1+1) / (3+6) = 2/9

P(g|d5) $\propto$ 1/4 * 2/9 * $(2/9)^2$ * 2/9
≈ 0.0006

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WSD Evaluations and baselines

- Best evaluation: **extrinsic ('end-to-end', `task-based') evaluation**
  - Embed WSD algorithm in a task and see if you can do the task better!
- What we often do for convenience: **intrinsic evaluation**
  - Exact match **sense accuracy**
    - % of words tagged identically with the human-manual sense tags
  - Usually evaluate using **held-out data/test data** from same labeled corpus

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- Baselines
  - Most frequent sense
  - The Lesk algorithm

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Most Frequent Sense

- WordNet senses are ordered in frequency order
- So "most frequent sense" in WordNet = "take the first sense"
- Sense frequencies come from the *SemCor* corpus

Freq	Synset	Gloss
338	plant^1, works, industrial plant	buildings for carrying on industrial labor
207	plant^2, flora, plant life	a living organism lacking the power of locomotion
2	plant^3	something planted secretly for discovery by another
0	plant^4	an actor situated in the audience whose acting is rehearsed but seems spontaneous to the audience

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The Simplified Lesk algorithm

- Let's disambiguate "**bank**" in this sentence:
  The **bank** can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.
- given the following two WordNet senses:

$bank^1$	Gloss:	a financial institution that accepts deposits and channels the money into lending activities
	Examples:	"he cashed a check at the bank", "that bank holds the mortgage on my home"
$bank^2$	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 currents"

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The Simplified Lesk algorithm

Choose sense with most word overlap between gloss and context
(not counting function words)

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

$bank^1$	Gloss:	a financial institution that accepts deposits and channels the money into lending activities
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	Examples:	"they pulled the canoe up on the bank", "he sat on the bank of the river and watched the currents"

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Semi-Supervised Learning

Problem: supervised and dictionary-based approaches require large hand-built resources

What if you don't have so much training data?

Solution: Bootstrapping

Generalize from a very small hand-labeled seed-set.

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Bootstrapping

- For `bass`
  - Rely on "One sense per collocation" rule
    - A word reoccurring in collocation with the same word will almost surely have the same sense.
  - the word `play` occurs with the music sense of bass
  - the word `fish` occurs with the fish sense of bass

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Sentences extracting using "fish" and "play"

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 play**er 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.

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Summary: generating seeds

1) Hand labeling
2) "One sense per collocation":
   - A word reoccurring in collocation with the same word will almost surely have the same sense.
3) "One sense per discourse":
   - The sense of a word is highly consistent within a document - Yarowsky (1995)
   - (At least for non-function words, and especially topic-specific words)

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Summary

- Word Sense Disambiguation: choosing correct sense in context
- Applications: MT, QA, etc.
- Three classes of Methods
  - Supervised Machine Learning: Naive Bayes classifier
  - Thesaurus/Dictionary Methods
  - Semi-Supervised Learning
- Main intuition
  - There is lots of information in a word's context
  - Simple algorithms based just on word counts can be surprisingly good

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