

Word Relations and Word Sense Disambiguation

Slides adapted from Dan Jurafsky, Jim Martin and Chris Manning

Homework Questions? Schedule

- ▶ Next week
 - Finish semantics
 - Begin machine learning for NLP
 - Review for midterm
- ▶ Midterm
 - October 27th
 - Will cover everything through semantics
 - A sample midterm will be posted
 - Includes multiple choice, short answer, problem solving
- ▶ October 29th
 - Bob Coyne and Words Eye: Not to be missed!
- ▶ Class outing to *Where the Wild Things Are*
Either Friday Oct. 23rd or Sunday Oct. 25th. Sign sheet or send email if interested.

Three Perspectives on Meaning

1. Lexical Semantics

- The meanings of individual words

2. Formal Semantics (or Compositional Semantics or Sentential Semantics)

- How those meanings combine to make meanings for individual sentences or utterances

3. Discourse or Pragmatics

- How those meanings combine with each other and with other facts about various kinds of context to make meanings for a **text or discourse**
- **Dialog or Conversation** is often lumped together with Discourse

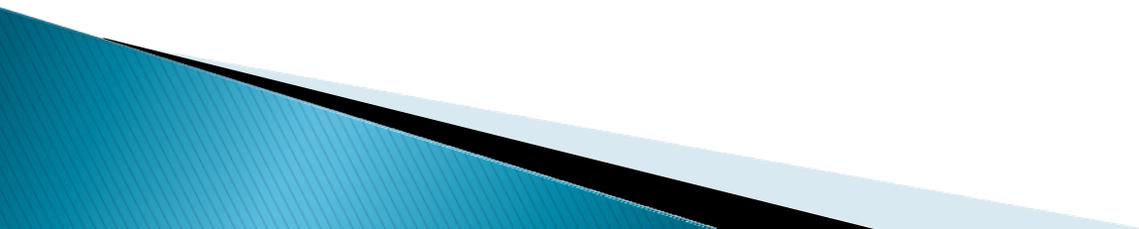
Outline: Comp Lexical Semantics

- ▶ Intro to Lexical Semantics
 - Homonymy, Polysemy, Synonymy
 - Online resources: WordNet
- ▶ Computational Lexical Semantics
 - Word Sense Disambiguation
 - Supervised
 - Semi-supervised
 - Word Similarity
 - Thesaurus-based
 - Distributional

Preliminaries

- ▶ What's a word?
 - Definitions we've used over the class: Types, tokens, stems, roots, inflected forms, etc...
 - **Lexeme**: An entry in a lexicon consisting of a pairing of a form with a single meaning representation
 - **Lexicon**: A collection of lexemes

Relationships between word meanings

- ▶ Homonymy
 - ▶ Polysemy
 - ▶ Synonymy
 - ▶ Antonymy
 - ▶ Hypernymy
 - ▶ Hyponymy
 - ▶ Meronymy
- 

Homonymy

- ▶ Lexemes that share a form
 - Phonological, orthographic or both
- ▶ But have unrelated, distinct meanings
- ▶ Clear example:
 - Bat (wooden stick-like thing) vs
 - Bat (flying scary mammal thing)
 - Or bank (financial institution) versus bank (riverside)
- ▶ Can be homophones, homographs, or both:
 - Homophones:
 - Write and right
 - Piece and peace

Homonymy causes problems for NLP applications

- ▶ Text-to-Speech
 - Same orthographic form but different phonological form
 - bass vs bass
- ▶ Information retrieval
 - Different meanings same orthographic form
 - QUERY: bat care
- ▶ Machine Translation
- ▶ Speech recognition

Polysemy

- ▶ The **bank** is constructed from red brick
I withdrew the money from the **bank**
- ▶ Are those the same sense?
- ▶ Or consider the following WSJ example
 - While some banks furnish sperm only to married women, others are less restrictive
 - Which sense of bank is this?
 - Is it distinct from (homonymous with) the river bank sense?
 - How about the savings bank sense?

Polysemy

- ▶ A single lexeme with multiple **related** meanings (bank the building, bank the financial institution)
- ▶ Most non-rare words have multiple meanings
 - The number of meanings is related to its frequency
 - Verbs tend more to polysemy
 - Distinguishing polysemy from homonymy isn't always easy (or necessary)

Metaphor and Metonymy

- ▶ Specific types of polysemy
- ▶ Metaphor:
 - Germany will pull Slovenia out of its economic slump.
 - I spent 2 hours on that homework.
- ▶ Metonymy
 - The White House announced yesterday.
 - This chapter talks about part-of-speech tagging
 - Bank (building) and bank (financial institution)

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

- ▶ ATIS examples

- Which flights serve breakfast?
- Does America West serve Philadelphia?

- ▶ The “zeugma” test:

- ?Does United serve breakfast and San Jose?

Synonyms

- ▶ Word that have the same meaning in some or all contexts.
 - filbert / hazelnut
 - couch / sofa
 - big / large
 - automobile / car
 - vomit / throw up
 - Water / H₂O
- ▶ Two lexemes are synonyms if they can be successfully substituted for each other in all situations
 - If so they have the same propositional meaning

Synonyms

- ▶ But there are few (or no) examples of perfect synonymy.
 - Why should that be?
 - 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** and **H₂O**

Some more terminology

- ▶ Lemmas and wordforms
 - A **lexeme** is an abstract pairing of meaning and form
 - A **lemma** or **citation form** is the grammatical form that is used to represent a lexeme.
 - *Carpet* is the lemma for *carpets*
 - *Dormir* is the lemma for *duermes*.
 - Specific surface forms *carpets*, *sung*, *duermes* are called **wordforms**
- ▶ The lemma *bank* has two senses:
 - Instead, a **bank** can hold the investments in a custodial account in the client's name
 - But as agriculture burgeons on the east **bank**, the river will shrink even more.
- ▶ A **sense** is a discrete representation of one aspect of the meaning of a word

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, for instance, became a kind of **big** sister to Benjamin.
 - ?Miss Nelson, for instance, became a kind of **large** sister to Benjamin.
- ▶ Why?
 - *big* has a sense that means being older, or grown up
 - *large* lacks this sense

Antonyms

- ▶ Senses that are opposites with respect to one feature of their meaning
- ▶ Otherwise, they are very similar!
 - dark / light
 - short / long
 - hot / cold
 - up / down
 - in / out
- ▶ More formally: antonyms can
 - define a binary opposition or at opposite ends of a scale (*long/short, fast/slow*)
 - Be reversives: *rise/fall, up/down*

Hyponymy

- ▶ 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*
 - *dog* is a hyponym of *animal*
 - *mango* is a hyponym of *fruit*
- ▶ Conversely
 - *vehicle* is a hypernym/superordinate of *car*
 - *animal* is a hypernym of *dog*
 - *fruit* is a hypernym of *mango*

superordinate	vehicle	fruit	furniture	mammal
hyponym	car	mango	chair	dog

Hypernymy 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)

II. WordNet

- ▶ A hierarchically organized lexical database
- ▶ On-line thesaurus + aspects of a dictionary
 - Versions for other languages are under development

Category	Unique Forms
Noun	117,097
Verb	11,488
Adjective	22,141
Adverb	4,601

WordNet

- ▶ Where it is:

- <http://wordnetweb.princeton.edu/perl/webwn>

Format of Wordnet Entries

The noun “bass” has 8 senses in WordNet.

1. bass¹ - (the lowest part of the musical range)
2. bass², bass part¹ - (the lowest part in polyphonic music)
3. bass³, basso¹ - (an adult male singer with the lowest voice)
4. sea bass¹, bass⁴ - (the lean flesh of a saltwater fish of the family Serranidae)
5. freshwater bass¹, bass⁵ - (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
6. bass⁶, bass voice¹, basso² - (the lowest adult male singing voice)
7. bass⁷ - (the member with the lowest range of a family of musical instruments)
8. bass⁸ - (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

The adjective “bass” has 1 sense in WordNet.

1. bass¹, deep⁶ - (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 Noun Relations

Relation	Also called	Definition	Example
Hypernym	Superordinate	From concepts to superordinates	<i>breakfast</i> ¹ → <i>meal</i> ¹
Hyponym	Subordinate	From concepts to subtypes	<i>meal</i> ¹ → <i>lunch</i> ¹
Member Meronym	Has-Member	From groups to their members	<i>faculty</i> ² → <i>professor</i> ¹
Has-Instance		From concepts to instances of the concept	<i>composer</i> ¹ → <i>Bach</i> ¹
Instance		From instances to their concepts	<i>Austen</i> ¹ → <i>author</i> ¹
Member Holonym	Member-Of	From members to their groups	<i>copilot</i> ¹ → <i>crew</i> ¹
Part Meronym	Has-Part	From wholes to parts	<i>table</i> ² → <i>leg</i> ³
Part Holonym	Part-Of	From parts to wholes	<i>course</i> ⁷ → <i>meal</i> ¹
Antonym		Opposites	<i>leader</i> ¹ → <i>follower</i> ¹

WordNet Verb Relations

Relation	Definition	Example
Hypernym	From events to superordinate events	<i>fly</i> ⁹ → <i>travel</i> ⁹
Troponym	From a verb (event) to a specific manner elaboration of that verb	<i>walk</i> ¹ → <i>stroll</i> ¹
Entails	From verbs (events) to the verbs (events) they entail	<i>snore</i> ¹ → <i>sleep</i> ¹
Antonym	Opposites	<i>increase</i> ¹ ⇔ <i>decrease</i> ¹

WordNet Hierarchies

Sense 3

bass, basso --

(an adult male singer with the lowest voice)

- => singer, vocalist, vocalizer, vocaliser
- => musician, instrumentalist, player
 - => performer, performing artist
 - => entertainer
 - => person, individual, someone...
 - => organism, being
 - => living thing, animate thing,
 - => whole, unit
 - => object, physical object
 - => physical entity
 - => entity
- => causal agent, cause, causal agency
 - => physical entity
 - => entity

Sense 7

bass --

(the member with the lowest range of a family of musical instruments)

- => musical instrument, instrument
 - => device
 - => instrumentality, instrumentation
 - => artifact, artefact
 - => whole, unit
 - => object, physical object
 - => physical entity
 - => entity

How is “sense” defined in WordNet?

- ▶ The set of near-synonyms for a WordNet sense is called a **synset (synonym set)**; it’s their version of a sense or a concept

- ▶ Example: **chump** as a noun to mean

- ‘a person who is gullible and easy to take advantage of’

{chump¹, fool², gull¹, mark⁹, patsy¹, fall guy¹, sucker¹, soft touch¹, mug²}

- ▶ Each of these senses share this same gloss
- ▶ Thus for WordNet, the meaning of this sense of **chump** is this list.

Word Sense Disambiguation (WSD)

- ▶ Given
 - a word in context,
 - A fixed inventory of potential word senses
- ▶ decide which sense of the word this is.
 - English-to-Spanish MT
 - Inventory is set of Spanish translations
 - Speech Synthesis
 - Inventory is homographs with different pronunciations like *bass* and *bow*
 - Automatic indexing of medical articles
 - MeSH (Medical Subject Headings) thesaurus entries

Two variants of WSD task

- ▶ Lexical Sample task
 - Small pre-selected set of target words
 - And inventory of senses for each word
- ▶ All-words task
 - Every word in an entire text
 - A lexicon with senses for each word
 - Sort of like part-of-speech tagging
 - Except each lemma has its own tagset

Approaches

- ▶ Supervised
- ▶ Semi-supervised
 - Unsupervised
 - Dictionary-based techniques
 - Selectional Association
 - Lightly supervised
 - Bootstrapping
 - Preferred Selectional Association

Supervised Machine Learning Approaches

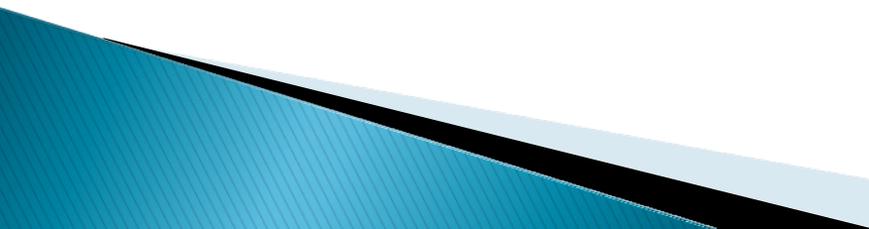
- ▶ Supervised machine learning approach:
 - a **training corpus** of ?
 - used to train a classifier that can tag words in new text
 - Just as we saw for part-of-speech tagging, statistical MT.
- ▶ Summary of what we need:
 - the **tag set** (“sense inventory”)
 - the **training corpus**
 - A set of **features** extracted from the training corpus
 - A **classifier**

Supervised WSD 1: WSD Tags

- ▶ What's a tag?

WordNet Bass

The noun "bass" has 8 senses 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)
- 

Inventory of sense tags for *bass*

WordNet Sense	Spanish Translation	Roget Category	Target Word in Context
bass ⁴	lubina	FISH/INSECT	... fish as Pacific salmon and striped bass and...
bass ⁴	lubina	FISH/INSECT	... produce filets of smoked bass or sturgeon...
bass ⁷	bajo	MUSIC	... exciting jazz bass player since Ray Brown...
bass ⁷	bajo	MUSIC	... play bass because he doesn't have to solo...

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

Supervised WSD 3: Extract feature vectors

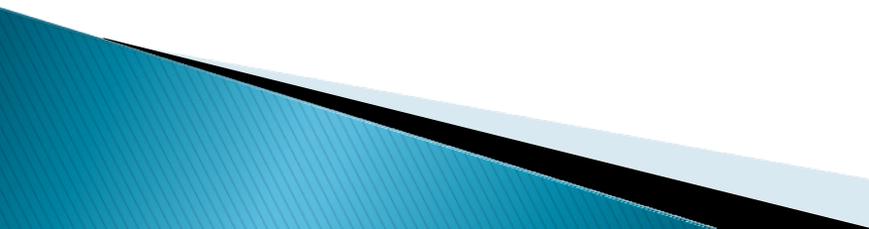
- ▶ Weaver (1955)
- ▶ If one examines the words in a book, one at a time as through an opaque mask with a hole in it one word wide, then it is obviously impossible to determine, one at a time, the meaning of the words. [...] But if one lengthens the slit in the opaque mask, until one can see not only 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?"

▶ dishes

▶ bass

- ▶ washing *dishes*.
- ▶ simple *dishes* including
- ▶ convenient *dishes* to
- ▶ of *dishes* and

- ▶ free *bass* with
- ▶ pound *bass* of
- ▶ and *bass* player
- ▶ his *bass* while

- ▶ “In our house, everybody has a career and none of them **includes washing dishes,**” he **says.**
 - ▶ In her tiny kitchen at home, Ms. Chen works efficiently, stir-frying **several simple dishes, including braised** pig’s ears and chicken livers with green peppers.
 - ▶ Post quick **and convenient dishes to fix** when you’re in a hurry.
 - ▶ Japanese cuisine offers a great **variety of dishes and regional** specialties
- 

- ▶ We need more good teachers – right now, there are only a half a dozen who can play **the free bass** with ease.
- ▶ Though still a far cry from the lake's record **52-pound bass of a** decade ago, “you could fillet these fish again, and that made people very, very happy.” Mr. Paulson says.
- ▶ 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 again.
- ▶ Lowe **caught his bass while fishing** with pro Bill Lee of Killeen, Texas, who is currently in 144th place with two bass weighing 2-09.

Feature vectors

- ▶ A simple representation for each observation (each instance of a target word)
 - Vectors of sets of feature/value pairs
 - I.e. files of comma-separated values
 - These vectors should represent the window of words around the target

How big should that window be?

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

Examples

- ▶ Example text (WSJ)
 - 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
 - Assume a window of $+/- 2$ from the target

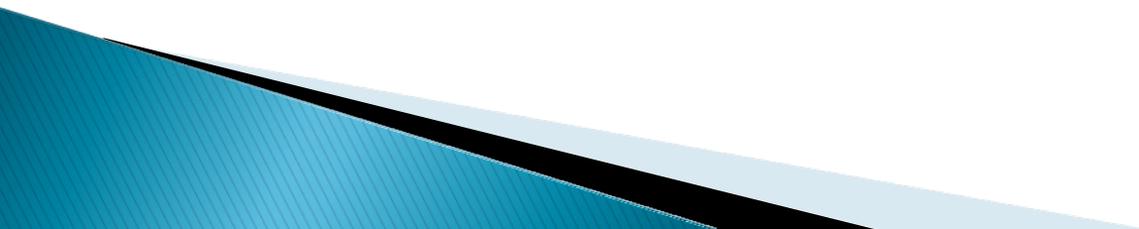
Examples

- ▶ Example text
 - 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
 - Assume a window of ± 2 from the target

Collocational

- ▶ Position-specific information about the words in the window
- ▶ guitar and bass player stand
 - [guitar, NN, and, CC, player, NN, stand, VB]
 - $\text{Word}_{n-2}, \text{POS}_{n-2}, \text{word}_{n-1}, \text{POS}_{n-1}, \text{Word}_{n+1}, \text{POS}_{n+1} \dots$
 - In other words, a vector consisting of
 - [position n word, position n part-of-speech...]

Bag-of-words

- ▶ Information about the words that occur within the window.
 - ▶ First derive a set of terms to place in the vector.
 - ▶ Then note how often each of those terms occurs in a given window.
- 

Co-Occurrence Example

- ▶ Assume we've settled on a possible vocabulary of 12 words that includes **guitar** and **player** but not **and** and **stand**
- ▶ **guitar and bass player stand**
 - [0,0,0,1,0,0,0,0,0,1,0,0]
 - Which are the counts of words predefined as e.g.,
 - [fish,fishing,viol, guitar, double,cello...

Classifiers

- ▶ Once we cast the WSD problem as a classification problem, then all sorts of techniques are possible
 - Naïve Bayes (the easiest thing to try first)
 - Decision lists
 - Decision trees
 - Neural nets
 - Support vector machines
 - Nearest neighbor methods...

Classifiers

- ▶ The choice of technique, in part, depends on the set of features that have been used
 - Some techniques work better/worse with features with numerical values
 - Some techniques work better/worse with features that have large numbers of possible values
 - For example, the feature **the word to the left** has a fairly large number of possible values

Naïve Bayes

- ▶ $\hat{s} = \arg \max_{s \in S} p(s|V)$, or $\arg \max_{s \in S} \frac{p(V|s)p(s)}{p(V)}$
- ▶ Where s is one of the senses S possible for a word w and V the input vector of feature values for w
- ▶ Assume features *independent*, so probability of V is the product of probabilities of each feature, given s , so $p(V)$ same for any \hat{s}
- ▶
$$p(V|s) = \prod_{j=1}^n p(v_j|s)$$
- ▶ Then
$$\hat{s} = \arg \max_{s \in S} p(s) \prod_{j=1}^n p(v_j|s)$$

- ▶ How do we estimate $p(s)$ and $p(v_j|s)$?
 - $p(s_i)$ is max. likelihood estimate from a sense-tagged corpus ($\text{count}(s_i, w_j) / \text{count}(w_j)$) – how likely is **bank** to mean ‘financial institution’ over all instances of **bank**?
 - $P(v_j|s)$ is max. likelihood of each feature given a candidate sense ($\text{count}(v_j, s) / \text{count}(s)$) – how likely is the previous word to be ‘**river**’ when the sense of **bank** is ‘financial institution’
- ▶ Calculate $\hat{s} = \arg \max_{s \in S} p(s) \prod_{j=1}^n p(v_j|s)$ for each possible sense and take the highest scoring sense as the most likely choice

Naïve Bayes Test

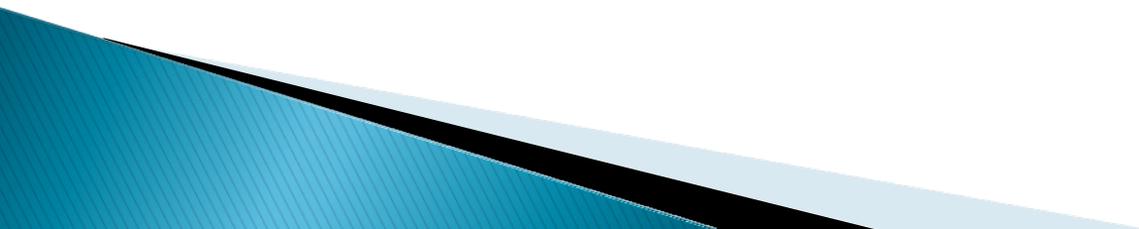
- ▶ On a corpus of examples of uses of the word **line**, naïve Bayes achieved about 73% correct
- ▶ Good?

Decision Lists: another popular method

- ▶ A case statement....

Rule		Sense
<i>fish</i> within window	⇒	bass ¹
<i>striped bass</i>	⇒	bass ¹
<i>guitar</i> within window	⇒	bass ²
<i>bass player</i>	⇒	bass ²
<i>piano</i> within window	⇒	bass ²
<i>tenor</i> within window	⇒	bass ²
<i>sea bass</i>	⇒	bass ¹
<i>play/V bass</i>	⇒	bass ²
<i>river</i> within window	⇒	bass ¹
<i>violin</i> within window	⇒	bass ²
<i>salmon</i> within window	⇒	bass ¹
<i>on bass</i>	⇒	bass ²
<i>bass are</i>	⇒	bass ¹

Learning Decision Lists

- ▶ Restrict the lists to rules that test a single feature (1–decisionlist rules)
 - ▶ Evaluate each possible test and rank them based on how well they work.
 - ▶ Glue the top–N tests together and call that your decision list.
- 

Yarowsky

- ▶ On a binary (homonymy) distinction used the following metric to rank the tests

$$\frac{P(\text{Sense}_1 \mid \text{Feature})}{P(\text{Sense}_2 \mid \text{Feature})}$$

- ▶ This gives about 95% on this test...

WSD Evaluations and baselines

- ▶ *In vivo* versus *in vitro* evaluation
- ▶ In vitro evaluation is most common now
 - Exact match accuracy
 - % of words tagged identically with manual sense tags
 - Usually evaluate using held-out data from same labeled corpus
 - Problems?
 - Why do we do it anyhow?
- ▶ Baselines
 - Most frequent sense
 - The Lesk algorithm

Most Frequent Sense

- ▶ Wordnet senses are ordered in frequency order
- ▶ So “most frequent sense” in wordnet = “take the first sense”
- ▶ Sense frequencies come from SemCor

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

Ceiling

- ▶ Human inter-annotator agreement
 - Compare annotations of two humans
 - On same data
 - Given same tagging guidelines
- ▶ Human agreements on all-words corpora with Wordnet style senses
 - 75%–80%

Unsupervised Methods

WSD: Dictionary/Thesaurus methods

- ▶ The Lesk Algorithm
- ▶ Selectional Restrictions

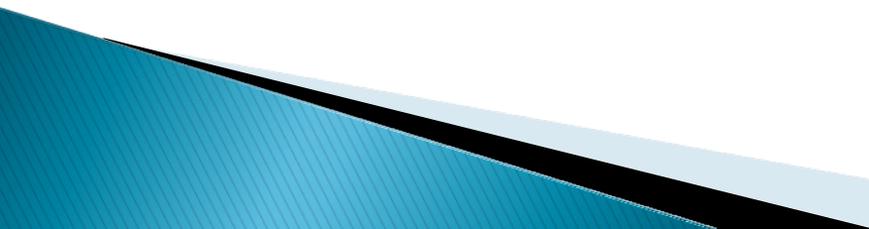
Simplified Lesk

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: Examples:	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”
bank ²	Gloss: Examples:	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”

Original Lesk: pine cone

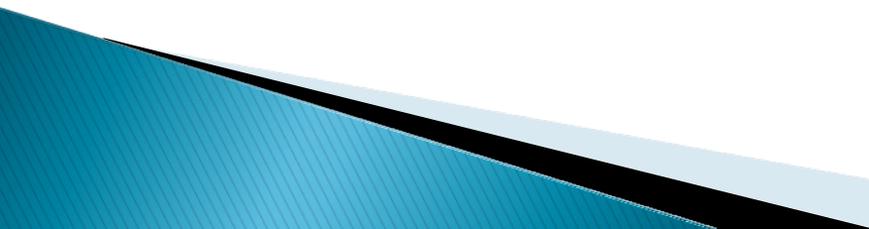
- pine
- 1 kinds of evergreen tree with needle-shaped leaves
 - 2 waste away through sorrow or illness
- cone
- 1 solid body which narrows to a point
 - 2 something of this shape whether solid or hollow
 - 3 fruit of certain evergreen trees
- 

Corpus Lesk

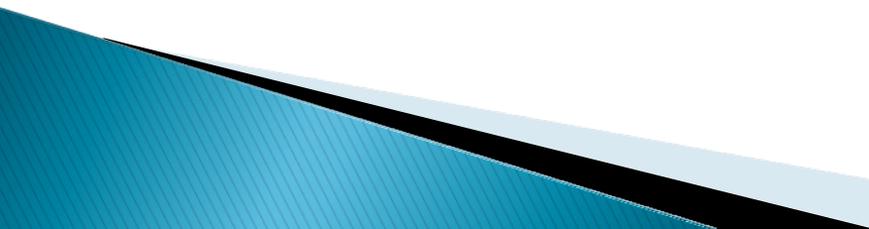
- ▶ Add corpus examples to glosses and examples
- ▶ The best performing variant

Disambiguation via Selectional Restrictions

- ▶ “Verbs are known by the company they keep”
 - Different verbs **select for** different **thematic roles**
 - wash the *dishes*** (takes washable-thing as patient)
 - serve delicious *dishes*** (takes food-type as patient)
- ▶ Method: another semantic attachment in grammar
 - Semantic attachment rules are applied as sentences are syntactically parsed, e.g.
 - VP --> V NP
 - V → serve <theme> {theme:food-type}
 - Selectional restriction violation: no parse

- ▶ But this means we must:
 - Write selectional restrictions for each sense of each predicate – or use FrameNet
 - Serve alone has 15 verb senses
 - Obtain hierarchical type information about each argument (using WordNet)
 - How many hypernyms does dish have?
 - How many words are hyponyms of dish?
 - ▶ But also:
 - Sometimes selectional restrictions don't restrict enough (**Which dishes do you like?**)
 - Sometimes they restrict too much (**Eat dirt, worm! I'll eat my hat!**)
 - ▶ Can we take a statistical approach?
- 

Semi-supervised Bootstrapping

- ▶ What if you don't have enough data to train a system...
 - ▶ Bootstrap
 - Pick a word that you as an analyst think will co-occur with your target word in particular sense
 - Grep through your corpus for your target word and the hypothesized word
 - Assume that the target tag is the right one
- 

Bootstrapping

- ▶ For **bass**
 - Assume **play** occurs with the music sense and **fish** occurs with the fish sense

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 player** stand off to one side, not really part of the scene, just as a sort of nod to gringo expectations perhaps.

When the New Jersey Jazz Society, in a fund-raiser for the American Jazz Hall of Fame, honors this historic night next Saturday, Harry Goodman, Mr. Goodman’s brother and **bass player** at the original concert, will be in the audience with other family members.

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.

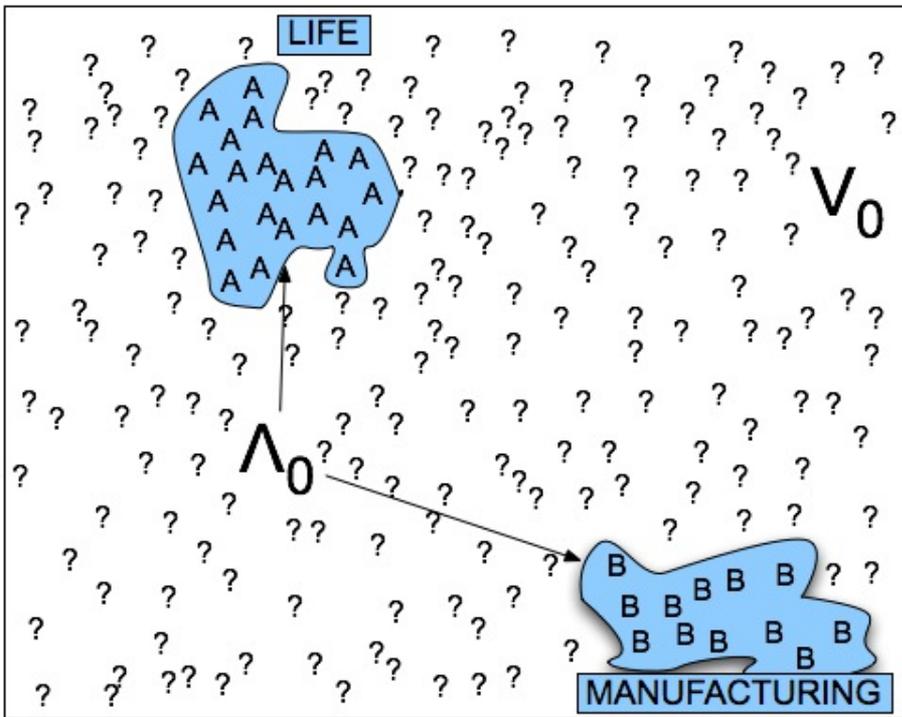
And it all started when **fishermen** decided the striped **bass** in Lake Mead were too skinny.

Though still a far cry from the lake’s record 52-pound **bass** of a decade ago, “you could fillet these **fish** again, and that made people very, very happy,” Mr. Paulson says.

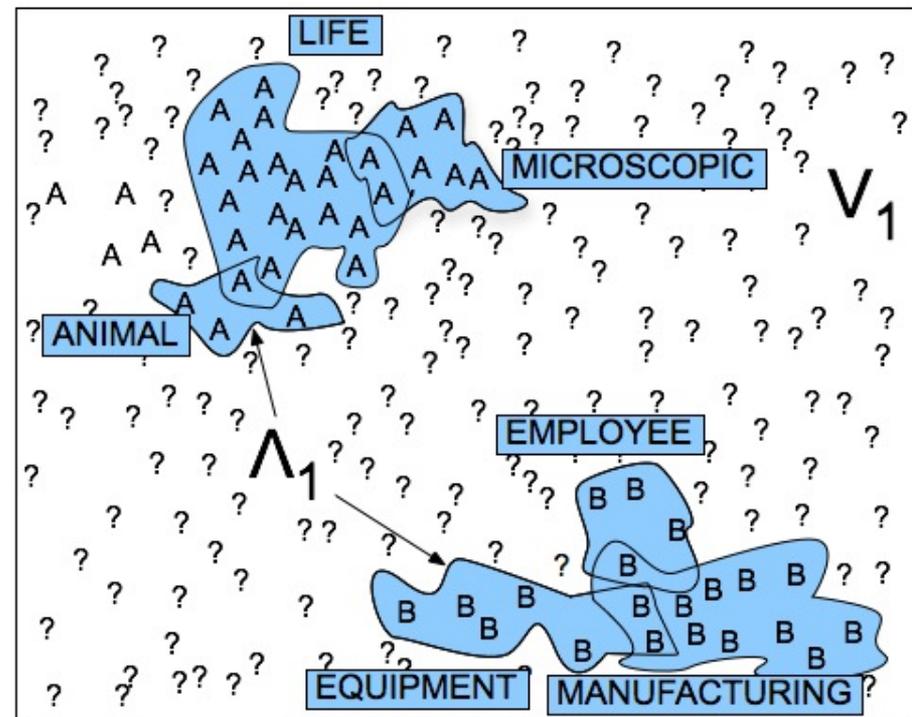
Where do the seeds come from?

- 1) Hand labeling
- 2) “One sense per discourse”:
 - The sense of a word is highly consistent within a document – Yarowsky (1995)
 - True for topic dependent words
 - Not so true for other POS like adjectives and verbs, e.g. make, take
 - Krovetz (1998) “More than one sense per discourse” argues it isn’t true at all once you move to fine-grained senses
- 3) One sense per collocation:
 - A word reoccurring in collocation with the same word will almost surely have the same sense.

Stages in the Yarowsky bootstrapping algorithm



(a)

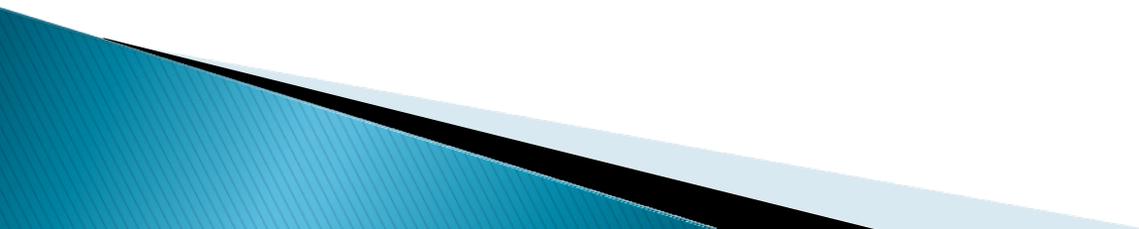


(b)

Problems

- ▶ Given these general ML approaches, how many classifiers do I need to perform WSD robustly
 - One for each ambiguous word in the language
- ▶ How do you decide what set of tags/labels/senses to use for a given word?
 - Depends on the application

WordNet Bass

- ▶ Tagging with this set of senses is an impossibly hard task that's probably overkill for any realistic application
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)
- 

Senseval History

- ▶ ACL–SIGLEX workshop (1997)
 - Yarowsky and Resnik paper
- ▶ SENSEVAL–I (1998)
 - Lexical Sample for English, French, and Italian
- ▶ SENSEVAL–II (Toulouse, 2001)
 - Lexical Sample and All Words
 - Organization: Kilgarriff (Brighton)
- ▶ SENSEVAL–III (2004)
- ▶ SENSEVAL–IV → SEMEVAL (2007)

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)
- ▶ 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

Summary

- ▶ Lexical Semantics
 - Homonymy, Polysemy, Synonymy
 - Thematic roles
- ▶ Computational resource for lexical semantics
 - WordNet
- ▶ Task
 - Word sense disambiguation