Word Sense Disambiguation

Natural Language Processing
CSCI 6350
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Word Sense Disambiguation (WSD)

- Given
  - A word in context
  - A fixed inventory of potential word senses
  - Decide which sense of the word this is
- Why? Machine translation, QA, speech synthesis
- What set of senses?
  - English-to-Spanish MT: set of Spanish translations
  - Speech Synthesis: homographs like *bass* and *bow*
  - In general: the senses in a thesaurus like WordNet

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

WSD Methods

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

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**

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).

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)

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

SemCor

<wf pos=PRP>**He**</wf>
<wf pos=VB lemma=recognize wnsn=4 lexsn=2:31:00::>**recognized**</wf>
<wf pos=DT>**the**</wf>
<wf pos=NN lemma=gesture wnsn=1 lexsn=1:04:00::>**gesture**</wf>
<punc>.</punc>

Supervised WSD 3: Extract feature vectors Intuition from Warren 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?"

Feature vectors

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

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

- Assume a window of +/- 2 from the target

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

Collocational features

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

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

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

guitar and

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

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

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]

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 $c \in C$

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" $(d_1, c_1), \ldots, (d_m, c_m)$
- *Output:*
  - a learned classifier $\gamma: d \rightarrow c$

Classification Methods: Supervised Machine Learning

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

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

- Can also generalize to look at other features besides words.
  - Then it would be P(f|c)
    - Conditional probability of a feature given a sense

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

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

	Doc	Words	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	?

Priors:

$P(f) = \frac{3}{4}$

$P(g) = \frac{1}{4}$

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

Choosing a class:

$P(f|d5) \propto 3/4 * 2/14 * 1/14 * (1/14)^2 \approx 0.00003$

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

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

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** from same labeled corpus
- 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 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

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%

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"

Function Words

- Function words (also known as stopwords) are those that have little or ambiguous meaning, but express grammatical relationships among words in a sentence
- The following is a list of the kind of words considered to be function words:
  - articles - the and a, an, etc.
  - pronouns - he, him, she, her, etc.
  - conjunctions - and, or, nor, but, …
  - auxiliary verbs - be, can, do, have, should, will, would, …
  - interjections and expletives

Simplified Lesk Algorithm

function SIMPLIFIED LESK(*word, sentence*) **returns** best sense of *word*

best-sense ← most frequent sense for *word*
max-overlap ← 0
context ← set of words in *sentence*
for each *sense* **in** senses of *word* **do**
  signature ← set of words in the gloss and examples of *sense*
  overlap ← COMPUTEOVERLAP(*signature*, *context*)
  if *overlap* > *max-overlap* **then**
    max-overlap ← *overlap*
    best-sense ← *sense*
end
return(*best-sense*)

The Simplified Lesk Algorithm Example

Choose sense with most word overlap between gloss and context (bank[1])
(disregarding 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
Overlap = 2	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"
Overlap = 0		

The Corpus Lesk algorithm

- Assumes we have some sense-labeled data (like SemCor)
- Take all the sentences with the relevant word sense:

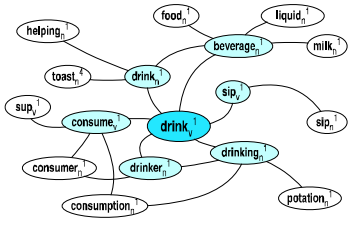
  These short, "streamlined" meetings usually are sponsored by local ***banks[1]****, Chambers of Commerce, trade associations, or other civic organizations.*
- Now add these to the gloss + examples for each sense, call it the "signature" of a sense.
- Choose sense with most word overlap between context and signature.

Corpus Lesk: IDF weighting

- Instead of just removing function words
  - Weigh each word by its `promiscuity' across documents
  - Down-weights words that occur in every `document' (gloss, example, etc)
  - These are generally function words, but is a more fine-grained measure
- Weigh each overlapping word by **inverse document frequency**

Graph-based methods

- First, WordNet can be viewed as a graph
  - senses are nodes
  - relations (hypernymy, meronymy) are edges
  - Also add edge between word and unambiguous gloss words

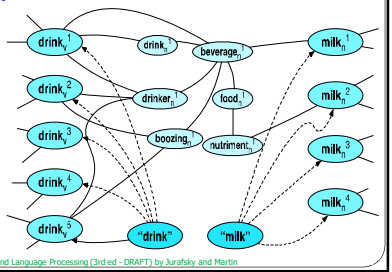


How to use the graph for WSD

- Insert target word and words in its sentential context into the graph, with directed edges to their senses

"She drank some milk"

- Now choose the *most central* sense



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.

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

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.

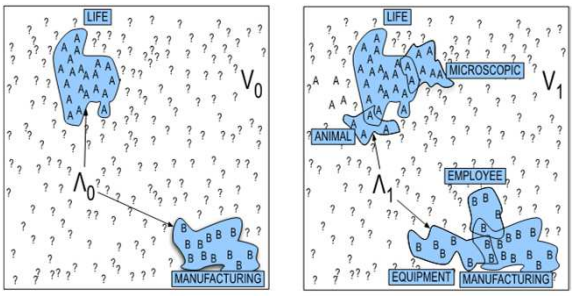
The researchers said the worms spend part of their life cycle in such **fish** as Pacific salmon and striped **bass** and Pacific rockfish or snapper.

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

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)

Stages in Yarowsky bootstrapping algorithm for the word "plant"



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