L114 Lexical Semantics

Session 2: Word Sense Disambiguation Algorithms

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Last time: the theory behind word senses

- Homonymy and polysemy
- Tests for ambiguity
- Request to take a look at data: shower

Today:

- Wordnet
- Algorithms for Word Sense Disambiguation (WSD)

Organization of Wordnet

- Wordnet groups words into synsets (synonym sets).
- One synset = one sense; this constitutes the senses's definition.
- Homonyms and polysemous word forms are therefore associated with multiple (different) synsets.
- Senses are indicated by slashes and numbers: interest/1, interest/2...
- Synsets are organized into a hierarchical structure by the use of hyponymy, e.g. a dog is-a pet, pet is-a animal
- Other relations are also recorded: metonymy (part-of), paronymy (same stem, morphological variation)
- Play around with it: `http://wordnetweb.princeton.edu/perl/webwn`

WN example – "interest"

Noun

- S (n) **interest**, involvement (a sense of concern with and curiosity about someone or something) *"an interest in music"*
- S (n) sake, **interest** (a reason for wanting something done) *"for your sake"; "died for the sake of his country"; "in the interest of safety"; "in the common interest"*
- S (n) **interest**, interestingness (the power of attracting or holding one's attention (because it is unusual or exciting etc.)) *"they said nothing of great interest"; "primary colors can add interest to a room"*
- S (n) **interest** (a fixed charge for borrowing money; usually a percentage of the amount borrowed) *"how much interest do you pay on your mortgage?"*
- S (n) **interest**, stake ((law) a right or legal share of something; a financial involvement with something) *"they have interests all over the world"; "a stake in the company's future"*
- S (n) **interest**, interest group (usually plural) a social group whose members control some field of activity and who have common aims) *"the iron interests stepped up production"*
- S (n) pastime, **interest**, pursuit (a diversion that occupies one's time and thoughts (usually pleasantly)) *"sailing is her favorite pastime"; "his main pastime is gambling"; "he counts reading among his interests"; "they criticized the boy for his limited pursuits"*

Verb:

- S (v) **interest** (excite the curiosity of; engage the interest of)
- S (v) concern, **interest**, occupy, worry (be on the mind of) *"I worry about the second Germanic consonant shift"*
- S (v) matter to, **interest** (be of importance or consequence) *"This matters to me!"*

Word Sense Disambiguation: the task

- Helps in various NLP tasks:
  - Machine Translation
  - Question Answering
  - Information Retrieval
  - Text Classification
- What counts as "one sense"?
  - Task-specific senses
  - dictionary-defined senses.
- Sense-tagged corpora exist, e.g., SemCor
  - 186 texts with all open class words WN synset tagged (192,639)
  - 166 texts with all verbs WN synset tagged (41,497)

Types of Algorithms for WSD

- Supervised
- Unsupervised
- Semi-supervised

Supervised: We know the answers for many examples and can use them to learn from their (automatically determinable) characteristics. We then apply the learned model to a comparable set of examples (not the same ones!)

- lexical items occurring near bank/1 and bank/2 (e.g., Decadt et al. 04)

Unsupervised WSD

In unsupervised WSD, we start with no known answers. Instead, we use only unannotated texts to infer underlying relationships using, for instance:

- dictionary glosses (Lesk)
- mutual sense constraints (Barzilay and Elhadad)
- properties of WN-Graph (Navigli and Lapata).

Semi-supervised WSD

In Semi-supervised WSD, we know the answers for some examples, and can gain more examples from the data by finding similar cases and inferring the answers they should have.

- Bootstrapping of context words (Yarowsky)
- Active Learning

Idea behind Original Lesk: Mutual Disambiguation

Typically there is more than one ambiguous word in the sentence.

- *Several rare ferns grow on the steep banks of the burn where it runs into the lake.*

Ambiguous: *rare, steep, bank, burn, run*

But: humans do not perceive this sentence as ambiguous at all. Hearer selects that combination of lexical readings which leads to the most normal possible utterance-in-context. [Assumption of cooperation in communication, Grice]

Simplified Lesk (Kilgarriff and Rosenzweig; 2000)

```
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 gloss and examples of sense
      overlap := COMPUTE_OVERLAP(signature, context)
      if overlap > max-overlap then
          max-overlap := overlap
          best-sense := sense
      end
  return(best-sense)
```

- Algorithm chooses the sense of target word whose gloss shares most words with sentence
- COMPUTE_OVERLAP returns the number of words in common between two sets, ignoring function words or other words on a stop list.

Example: Disambiguation of *bank*

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

bank/1	(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	(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"*

- Sense *bank/1* has two (non-stop) words overlapping with the context (*deposits* and *mortgage*)
- Sense *bank/2* has zero, so sense *bank/1* is chosen.

Original Lesk (1986) Algorithm

- Instead of comparing a target word's signature with the context words, the target signature is compared with the signatures of each of the context words.
- Example context: *pine cone*

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

cone/3 and *pine/1* are selected:

- overlap for entries *pine/1* and *cone/3* (*evergreen* and *tree*)
- no overlap in other entries

Lesk: Improvements

- Lesk is more complex than Simplified Lesk, but empirically found to be less successful
- Problem with all Lesk Algorithms: dictionary entries for the target words are short $\rightarrow$ often no overlap with context at all
- Possible improvements:
  - Expand the list of words used to include words related to, but not contained in, their individual sense definitions.
  - Apply a weight to each overlapping word. The weight is the inverse document frequency or IDF. IDF measures how many different documents (in this case glosses and examples) a word occurs in.

Supervised Word Sense Disambiguation

- Words are labelled with their senses:
  - She pays 3% interest/INTEREST-MONEY on the loan.
  - He showed a lot of interest/INTEREST-CURIOSITY in the painting.
- Define features that (you hope) will indicate one sense over another
- Train a statistical model that predicts the correct sense given the features, e.g., Naive Bayes
- Classifier is trained for each target word separately
- Unlike situation in Lesk, which is unsupervised, and able to disambiguate all ambiguous words in a text

Features for Supervised WSD

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.*

- Collocational feature: (directly neighbouring words in specific positions)
  [w_{i-2}, POS_{i-2}, w_{i-1}, POS_{i-1}, w_{i+1}, POS_{i+1}, w_{i+2}, POS_{i+2}]
  [guitar, NN, and, CC, player, NN, stand, VB]
- Bag of Words feature: (any content words in a 50 word window)
  12 most frequent content words from *bass* collection: [*fishing, big, sound, player, fly, rod, pound, double, runs, playing, guitar, band*]
  $\rightarrow$ [0,0,0,1,0,0,0,0,0,0,1,0]

Naive Bayes

- Goal: choose the best sense $\hat{s}$ out of the set of possible senses S for an input vector $\vec{F}$:

$$\hat{s} = argmax_{s \in S} P(s|\vec{F})$$

- It is difficult to collect statistics for this equation directly.
- Rewrite it using Bayes' rule:

$$\hat{s} = argmax_{s \in S} = \frac{P(\vec{F}|s)P(s)}{P(\vec{F})}$$

- Drop $P(\vec{F})$ – it is a constant factor in *argmax*
- Assume that F_i are independent:

$$P(\vec{F}|s) \approx \prod_{n}^{j=1} P(F_i|s)$$

Naive Bayesian Classifier

- Naive Bayes Classifier:

$$\widehat{s} = argmax_{s \in S} P(s) \prod_{n}^{j=1} P(F_i|s)$$

- Parameter Estimation (Max. likelihood):
  - How likely is sense s_i for word form w_j?

$$P(s_i) = \frac{count(s_i, w_j)}{count(w_j)}$$

  - How likely is feature f_j given sense s_i?

$$P(F_j|s_i) = \frac{count(s_i, F_j)}{count(s_i)}$$

Intrinsic Evaluation

- Sense accuracy: percentage of words tagged identical with hand-tagged in test set
- How can we get annotated material cheaply?
  - Pseudo-words
    - create artificial corpus by conflating unrelated words
    - example: replace all occurrences of *banana* and *door* with *banana-door*
  - Multi-lingual parallel corpora
    - translated texts aligned at the sentence level
    - translation indicates sense
- SENSEVAL competition
  - bi-annual competition on WSD
  - provides annotated corpora in many languages
  - "Lexical Sample" Task for supervised WSD
  - "All-word" Task for unsupervised WSD (SemCor corpus)

Baselines for supervised WSD

- First (most frequent) sense
- LeskCorpus (Simplified, weighted Lesk, with all the words in the labeled SEMEVAL corpus sentences for a word sense added to the signature for that sense).
- LeskCorpus is the best-performing of all the Lesk variants (Kilgarriff and Rosenzweig, 2000; Vasilescu et al., 2004)

Semi-supervised WSD by Bootstrapping

Yarowsky's (1995) algorithm uses two powerful heuristics for WSD:

- **One sense per collocation:** nearby words provide clues to the sense of the target word, conditional on distance, order, syntactic relationship.
- **One sense per discourse:** the sense of a target words is consistent within a given document.

The Yarowsky algorithm is a **bootstrapping** algorithm, i.e., it requires a small amount of annotated data.

- It starts with a small seed set, trains a classifier on it, and then applies it to the whole data set (bootstrapping);
- Reliable examples are kept, and the classifier is re-trained.

Figures and tables in this section from Yarowsky (1995).

Seed Set

Step 1: Extract all instances of a polysemous or homonymous word.

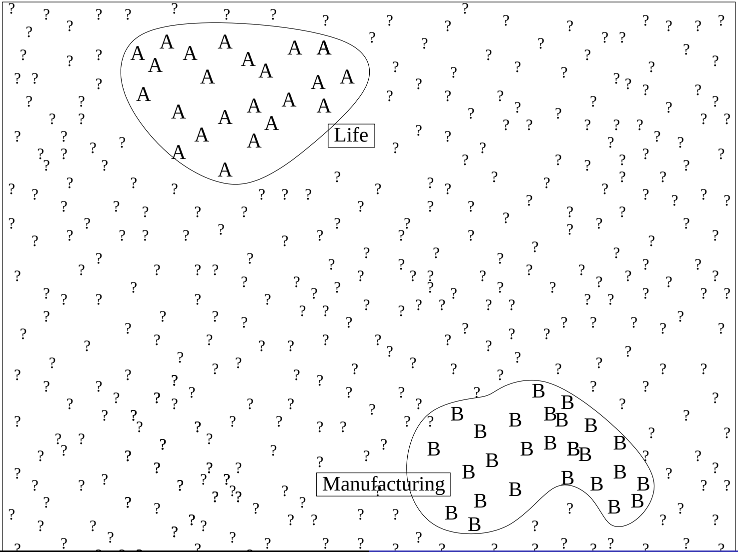
Step 2: Generate a seed set of labeled examples:

- either by manually labeling them;
- or by using a reliable heuristic.

Example: target word *plant*: As seed set take all instances of

- *plant life* (sense A) and
- *manufacturing plant* (sense B).

Seed Set



Classification

Step 3a: Train classifier on the seed set.

Step 3b: Apply classifier to the entire sample set. Add those examples that are classified reliably (probability above a threshold) to the seed set.

Yarowsky uses a **decision list** classifier:

- rules of the form: collocation $\rightarrow$ sense
- rules are ordered by log-likelihood:

$$\log \frac{P(sense_A | collocation_i)}{P(sense_B | collocation_i)}$$

- Classification is based on the first rule that applies.

Classification

LogL	Collocation	Sense
8.10	*plant* life	→ A
7.58	manufacturing *plant*	→ B
7.39	life (within +-2-10 words)	→ A
7.20	manufacturing (in +- 2-10 words)	→ B
6.27	animal (within +-2-10 words)	→ A
4.70	equipment (within +-2-10 words)	→ B
4.39	employee (within +-2-10 words)	→ B
4.30	assembly *plant*	→ B
4.10	*plant* closure	→ B
3.52	*plant* species	→ A
3.48	automate (within +-2-10 words)	→ B
3.45	microscopic *plant*	→ A
	...	

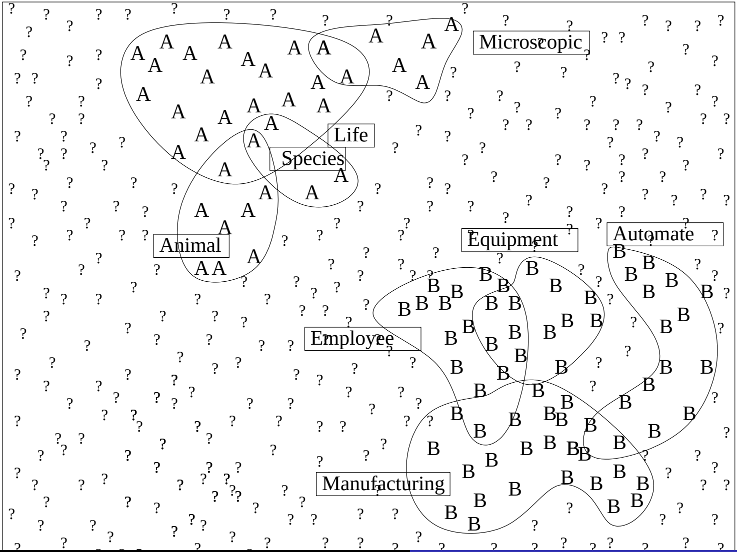
Classification

Step 3c: Use one-sense-per-discourse constraint to filter newly classified examples:

- If several examples in one document have already been annotated as sense A, then extend this to all examples of the word in the rest of the document.
- This can bring in new collocations, and even correct erroneously labeled examples.

Step 3d: repeat Steps 3a–d.

Classification



Generalization

Step 4: Algorithm converges on a stable residual set (remaining unlabeled instances):

- most training examples will now exhibit multiple collocations indicative of the same sense;
- decision list procedure uses only the most reliable rule, not a combination of rules.

Step 5: The final classifier can now be applied to unseen data.

Discussion

Strengths:

- simple algorithm that uses only minimal features (words in the context of the target word);
- minimal effort required to create seed set;
- does not rely on dictionary or other external knowledge.

Weaknesses:

- uses very simple classifier (but could replace it with a more state-of-the-art one);
- not fully unsupervised: requires seed data;
- does not make use of the structure of a possibly existing dictionary (the sense inventory).

Alternative: Exploit the structure of the sense inventory for WSD:

- Graph-based (Navigli and Lapata)

Graph-Based WSD (Navigli and Lapata (2010)

- The internal structure of sense inventories can be exploited even further.
- Represent Wordnet as a graph whose nodes are synsets and whose edges are relations between synsets.
- The edges are not labeled, i.e., the type of relation between the nodes is ignored.

Figures and tables in this section from Navigli and Lapata (2010).

Example

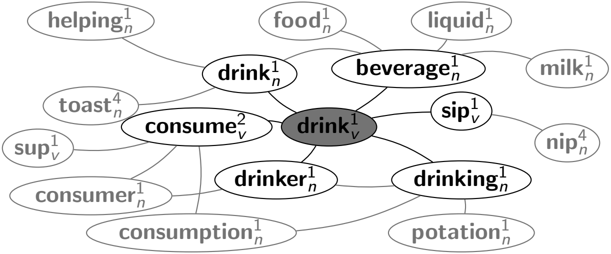
Wordnet Synsets (senses) of drink/v:

- {**drink**$_v^1$, *imbibe*$_v^3$} (take in liquids)
- {**drink**$_v^2$, *booze*$_v^1$, *fuddle*$_v^2$} (consume alcohol)
- {*toast*$_v^2$, **drink**$_v^3$, *pledge*$_v^2$, *salute*$_v^1$, *wassail*$_v^2$} (propose a toast)
- {*drink in*$_v^1$, **drink**$_v^4$} (be fascinated, pay close attention)
- {**drink**$_v^5$, *tope*$_v^1$} (be an alcoholic)

Wordnet Synsets (senses) of milk/n:

- {**milk**$_n^1$} (a white nutritious liquid secreted by mammals and used as food by human beings)
- {**milk**$_n^2$} (produced by mammary glands of female mammals for feeding their young)
- {**Milk**$_n^3$, *Milk River*$_n^1$} (a river that rises in the Rockies in northwestern Montana and flows eastward to become a tributary of the Missouri River)
- {**milk**$_n^4$} (any of several nutritive milklike liquids)

Graph for first sense of *drink*



Graph Construction

Disambiguation algorithm:

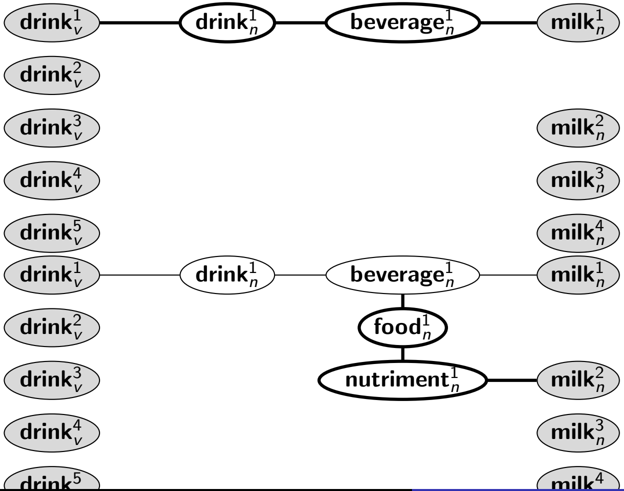
1. Use the Wordnet graph to construct a graph that incorporates each content word in the sentence to be disambiguated;
2. Rank each node in the sentence graph according to its importance using **graph connectivity measures;**
    - **Local measures:** give a connectivity score to an individual node in the graph; use this directly to select a sense;
    - **Global measures:** assign a connectivity score the to the graph as a whole; apply the measure to each interpretation and select the highest scoring one.

Graph Construction

- Given a word sequence $\sigma = (w_1, w_2, \ldots, w_n)$, find all possible word senses of all words; call this set V_σ.
- Perform a depth-first search of the Wordnet graph: every time we encounter a node $v' \in V_\sigma$ $(v' \neq v)$ along a path $v \rightarrow v_1 \rightarrow \cdots \rightarrow v_k \rightarrow v'$ of length L, we add all intermediate nodes and edges on the path from v to v' to the graph G.
- For tractability, we set the maximum path length to 6.

Graph Construction

Example: graph for *drink milk*.



Summary

- The **Lesk** algorithm uses overlap between context and glosses.
- **Supervised WSD** uses context and bag-of-words features and machine learning.
- The **Yarowsky** algorithm uses bootstrapping and two key heuristics:
  - one sense per collocation;
  - one sense per discourse;
- WSD and **Lexical Chain** construction use mutual constraints to pick the best senses.
- **Unsupervised graph-based WSD** finds the most connected nodes (senses) in a graph that represents all possible interpretations of a sentence.

Essential Reading

- Jurasfky and Martin, chapter 20.1-20.4.
- Barzilay and Elhadad (1997)
- Navigli and Lapata (2010)

References

Lesk (1986): Automatic sense disambiguation using machine readable dictionaries: how to tell a pine cone from an ice cream cone. In SIGDOC '86, ACM.

Yarowsky (1995): Unsupervised Word Sense Disambiguation rivaling Supervised Methods. Proceedings of the ACL.

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