



Chapter 7: Word Sense Disambiguation (WSD)

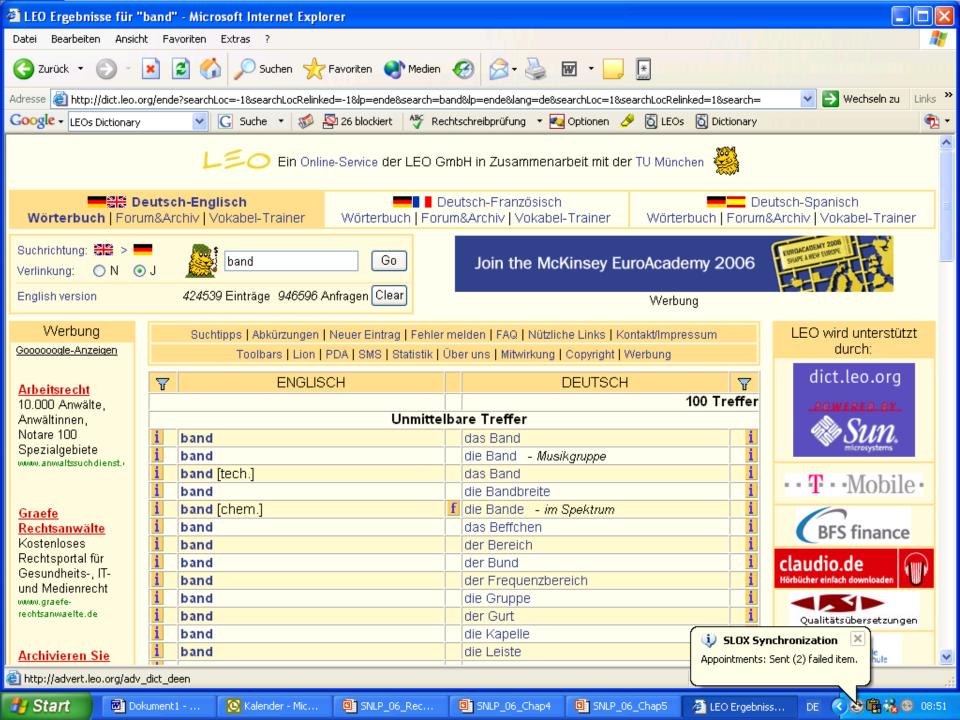
See: Christopher D. Manning and Hinrich Schütze.

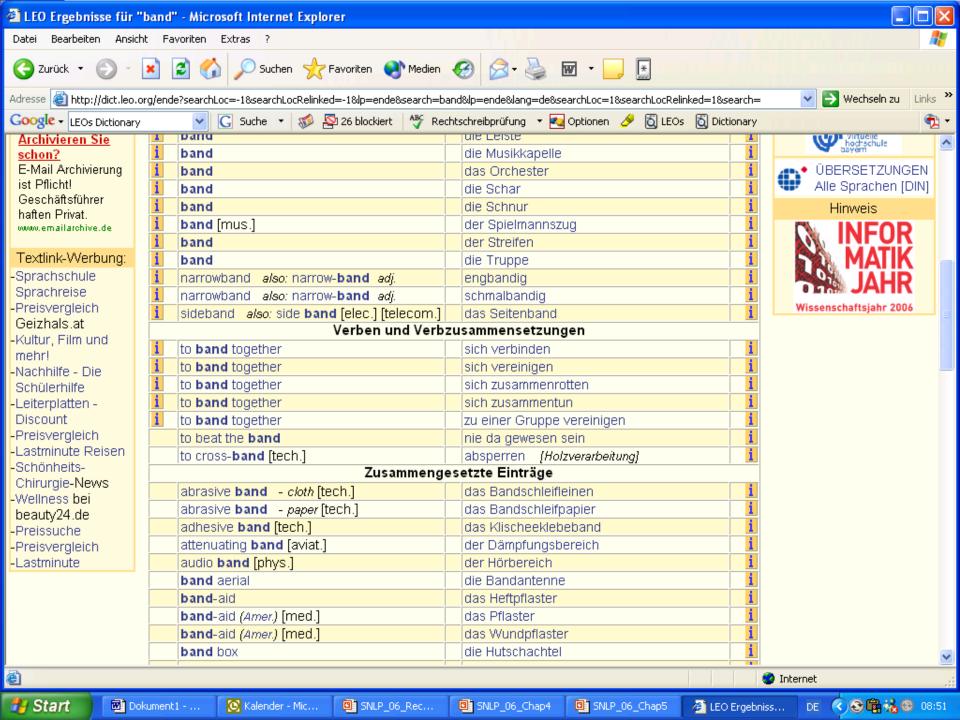
Chapter 7: Word Sense Disambiguation

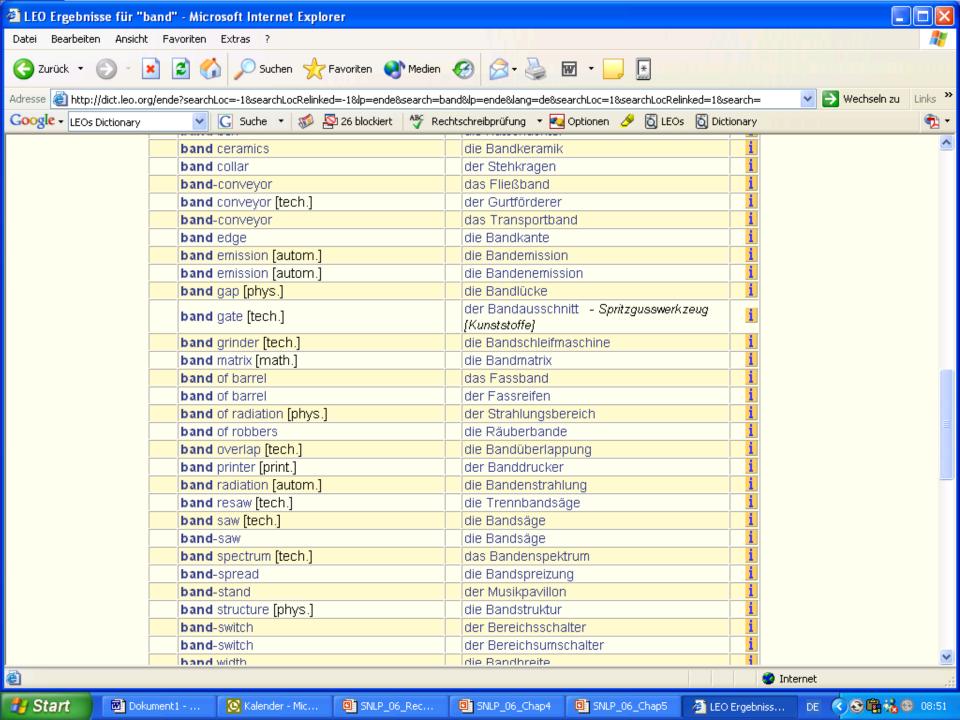




Introduction and Examples: Word Sense Disambiguation













- Many words have several meanings/senses.
- Consider two senses of the word bank
 - The rising ground bordering a lake, river or sea ...
 - An establishment for the custody, loan exchange, or issue of money, for the extension of credit, and for facilitating the transmission or funds
- However, the senses are not always so well defined.



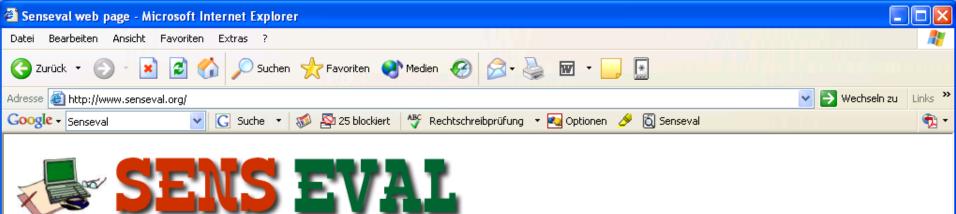


Disambiguation

 To determine which of the senses of an ambiguous word is invoked in a particular use of the word.

How it is done:

- A word is assumed to have a finite number of discrete senses.
- Look at the context of the word's use to disambiguate.





Evaluation Exercises for the Semantic Analysis of Text - Organized by ACL-SIGLEX -

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There are now many computer programs for automatically determining the sense of a word in context (Word Sense Disambiguation or WSD). The purpose of Senseval is to evaluate the strengths and weaknesses of such programs with respect to different words, different varieties of language, and different languages.

Senseval-1 took place in the summer of 1998 for English, French, and Italian, culminating in a workshop held at Herstmonceux Castle, Sussex, England on September 2-4.

Senseval-2 took place in the summer of 2001, and was followed by a workshop held in July 2001 in Toulouse, in conjunction with ACL 2001. Senseval-2 included tasks for Basque, Chinese, Czech, Danish, Dutch, English, Estonian, Italian, Japanese, Korean, Spanish, Swedish.

Senseval-3 took place in March-April 2004, followed by a workshop held in July 2004 in Barcelona, in conjunction with ACL 2004. Senseval-3 included 14 different tasks for core word sense disambiguation, as well as identification of semantic roles, multilingual annotations, logic forms, subcategorization acquisition.

Semeval-1 / Senseval-4 is currently underway. Check the Semeval-1/Senseval-4 site for more information.

News

- The call for task proposals for Semeval-1/Senseval-4 has been issued. Task proposals are due on July 1 2006. Check the Semeval-1/Senseval-4 site for details.
- All data sets used during the Senseval-3 evaluations are now in the public domain. The Senseval-3 proceedings and panel minutes are also available. Check the Senseval-3 website.

Site maintained by Rada Mihalcea, hosted by University of North Texas



























Examples of Senses of the Word "Band" from SENSEVAL



band 532732 strip n band/2/1 band 532733 stripe n band/2/1.2 band 532734 range n band/2/2 band 532735 group n band/1/2 band 532736 mus n band/1/1 band 532744 brass n brass band band 532745 radio n band/2/2.1 band 532746 vb v band/1/3 band 532747 silver n silver band band 532756 steel n steel band band 532765 big n big_band band 532782 dance n dance band band 532790 elastic n elastic_band band 532806 march n marching_band band 532814 man n oneman_band band 532838 rubber n rubber_band band 532903 ed n band/2/3 band 532949 saw n band saw band 532963 course n band_course band 532979 pl n band/2/4 band 533487 vb2 a band/2/5 band 533495 portion n band/2/1.3 band 533508 waist n waistband band 533520 ring n band/2/1.4 band 533522 sweat n sweat band band 533580 wrist n wristband//1 band 533705 vb3 v band/2/6 band 533706 vb4 v band/2/7





Example 1:

The incidence of accents and rests, permuted through a regular space-time grid, becomes rhythmic in itself as it modifies, defines and enriches the grouping procedure. For example, a traditional American jazz <tag ???? '>band</> was subdivided into a front line (melodic) section, usually led by trumpet, and rhythm section, usually based on drums.





Example 1:

The incidence of accents and rests, permuted through a regular space-time grid, becomes rhythmic in itself as it modifies, defines and enriches the grouping procedure. For example, a traditional American jazz <tag "532736">band</> was subdivided into a front line (melodic) section, usually led by trumpet, and rhythm section, usually based on drums.

band 532736 mus n band/1/1





Example 2:

The headsail wardrobe currently consists of a non-overlapping working jib set on a furler, originally designed to cope with wind speeds between 10 and 35 knots plus. But Mary feels it is too small for the lower wind speeds, so she may introduce an overlapping furler for the 10 to 18 knot >band</>. 7777





Example 2:

The headsail wardrobe currently consists of a non-overlapping working jib set on a furler, originally designed to cope with wind speeds between 10 and 35 knots plus. But Mary feels it is too small for the lower wind speeds, so she may introduce an overlapping furler for the 10 to 18 knot <tag "532734">band</>.

band 532734 range n band/2/2





Example 3:

The Moorsee Lake, on the edge of town, is ideal for swimming. rowing boats are also available for hire. Don't leave without hearing the village brass <tag >band</> which plays three times a week.





Example 3:

The Moorsee Lake, on the edge of town, is ideal for swimming. rowing boats are also available for hire. Don't leave without hearing the village brass <tag "532744">band</> which plays three times a week.

band 532744 brass n brass_band





Example 4:

Here, suspended from Lewis's person, were pieces of tubing held on by rubber <ta ???? >bands</>
>bands</>
peg, a bit of cork.





Example 4:

Here, suspended from Lewis's person, were pieces of tubing held on by rubber tag "532838">bands, an old wooden peg, a bit of cork.

band 532838 rubber n rubber band







- Machine Translation
- Information Retrieval
- Dialogue systems
- Spelling correction
- •





How difficult is it?

- Upper bound: human performance
 - 98% correct for words like bank with a clear meaning
 - 65% for highly ambiguous words with overlapping meanings





How difficult is it?

Lower bound: always pick the most likely sense

Word	# different meanings	Fraction most frequent meaning
behavior	3	96%
band	24	73%
slight	8	67%
aware	2	58%
float	28	14%



One sense per discourse, one sense per collocation



- (Yarowsky, 1995)'s Idea: there are constraints between different occurrences of an ambiguous word within a corpus that can be exploited for disambiguation:
 - One sense per discourse: The sense of a target word is highly consistent within any given document.
 - One sense per collocation: nearby words provide strong and consistent clues to the sense of a target word, conditional on relative distance, order and syntactic relationship.





WSD Algorithms: Data available





Methods for Disambiguating

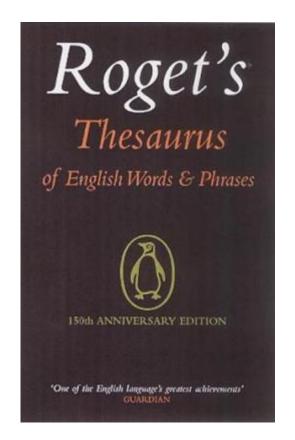
- <u>Dictionary-based</u>: disambiguation based on lexical resources such as dictionaries and thesauri.
- Supervised Disambiguation:
 disambiguation based on a labeled training set.
- Unsupervised Disambiguation:
 disambiguation based on training on an unlabeled text corpora.





Dictionary-Based Disambiguation

 Sense definitions are extracted from existing sources such as dictionaries and thesauri.













Lesk's Algorithm

- Use dictionary descriptions to disambiguate meanings
- Set of meanings: s₁, s₂, ... s_k
- Set of descriptions:
 D(s₁), D(s₂), ... D(s_k)
- Words v_i in context C of ambiguous word
- Lexicon definitions of context words: E(v_j)





Lesk's Algorithm

Classification algorithm

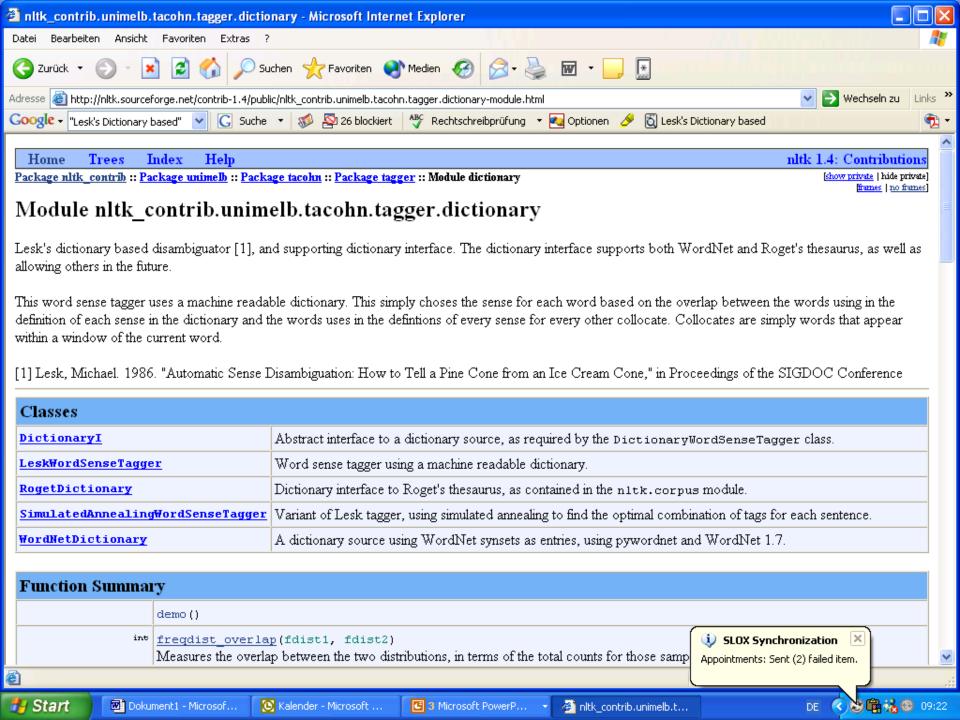
$$s_{opt} = \underset{s_k}{\operatorname{arg max}} \quad sim \left(D(s_k), \bigcup_{v \in C} E(v_j) \right)$$

Possible similarity measures

$$sim(X,Y) = \frac{2|X \cap Y|}{|X| + |Y|}$$

$$sim(X,Y) = \frac{2|X \cap Y|}{|X \cup Y|}$$

$$sim(X,Y) = \frac{|X \cap Y|}{\sqrt{|X| |Y|}}$$









- Simple to implement
- No training data needed
- Relatively bad results





Supervised Disambiguation

- Training corpus:
 - Each occurrence of the ambiguous word w is annotated with a semantic label (its contextually appropriate sense s_k).
- Supervised disambiguation is a classification task.
- We will look at:
 - Bayesian classification (Gale et al. 1992).
 - Information-theoretic approach (Brown et al. 1991)





Bayesian Classification

Bayes Decision rule:

Decide s' if $P(s'|C) > P(s_k|C)$ for all $s_k \neq s'$. (C is the context)

- Bayes decision rule is optimal because it minimizes the probability of error.
- Choose the class (or sense) with the highest conditional probability
- \mapsto smallest error rate.





Applying Bayes Decision Rule

- Choose a large context window around the ambiguous word.
- Combine the evidence from all features to choose the class with highest conditional probability.



Computing Posterior Probability for Bayes Classification



 Assign the ambiguous word w to the sense s', given context C, where:

$$s' = \arg \max_{s_k} P(s_k|C)$$

$$s' = \arg \max_{s_k} \frac{P(C|s_k)}{P(C)} P(s_k)$$

$$s' = \arg \max_{s_k} P(C|s_k) P(s_k)$$

$$s' = \arg \max_{s_k} [\log P(C|s_k) + \log P(s_k)]$$





Naive Bayes (Gale et al. 1992)

Naive Bayes assumption:

 contextual words used for description are all conditionally independent:

$$P(C \mid s_k) = \prod_{v_i \in C} P(v_j \mid s_k)$$
 C: context
v_j: j-th word in C

- Consequences of this assumption:
 - <u>Bag of words</u> model: the structure and linear ordering of words within the context is ignored.
 - The presence of one word in the bag is independent of another.





Decision Rule for Naive Bayes

- Decide s' if $s'= arg \max_{sk} [log \ P(s_k) + \sum_{vj \ in \ C} log \ P(v_j \ | s_k)]$
- P(v_j |s_k) and P(s_k) are computed via Maximum-Likelihood Estimation:

$$P(v_j|s_k) = \frac{N(v_j, s_k)}{\sum_t N(v_t, s_k)} \qquad P(s_k) = \frac{N(s_k)}{N}$$

Here: N are counts

Use your favorite smoothing technique





WSD Algorithms:

No or little or only proxy data available



WORD-SENSE DISAMBIGUATION USING STATISTICAL METHODS



Peter F. Brown, Stephen A. Della Pietra, Vincent J. Della Pietra, and Robert L. Mercer

IBM Thomas J. Watson Research Center P.O. Box 704 Yorktown Heights, NY 10598

We describe a statistical technique for assigning senses to words. An instance of a word is assigned a sense by asking a question about the context in which the word appears. The question is constructed to have high mutual information with the translation of that instance in another language. When we incorporated this method of assigning senses into our statistical machine translation system, the error rate of the system decreased by thirteen percent.



Example of Classification based on Information-Theoretic Approach



- Two senses of a word:
 - Prendre une mesure <-> take a measure
 - Prendre une décision <-> make a decision
- The translations of the ambiguous word {t₁,...,t_m} are {take, make, rise, speak}
- The possible indicator words {xf₁,...,xf_n} are {mesure, note, exemple, décision, parole}
- Find a partition Q={Q₁, Q₂} of {xf₁,...,xf_n} and P={P₁, P₂}
 of {t₁,...,t_m} that maximizes the mutual information:

$$I(P;Q) = \sum_{xf \in O} \sum_{t \in P} p(xf,t) \log p(xf,t) / (p(xf)p(t))$$



Flip-Flop Algorithm (Brown et al., 1991)



- Categorize the informant (contextual word) as to which sense it indicates.
- 1. find a random partition $P=\{P_1, P_2\}$ for $\{t_1,...,t_m\}$
- 2. while (improving) do
 - find partition Q={Q₁, Q₂} of {xf₁,...,xf_n}
 - that maximizes I(P;Q)
 - find partition $P=\{P_1, P_2\}$ of $\{t_1, \dots, t_m\}$
 - that maximizes I(P;Q)
- 3. end



Disambiguation using the Information-Theoretic Approach



- 1. For the occurrence of the ambiguous word, determine the value x_i of the indicator.
- 2. If x_i is in Q_1 , assign the occurrence to sense 1, if x_i is in Q_2 , assign the occurrence to sense 2.





Unsupervised Disambiguation

- <u>Idea:</u> disambiguate word senses without having recourse to supporting tools such as dictionaries and thesauri and in the absence of labeled text. Simply cluster the contexts of an ambiguous word into a number of groups and discriminate between these groups without labeling them.
- (Schutze, 1998): The probabilistic model is the same Bayesian model as the one used for supervised classification, but P(v_j | s_k) and P(s_k) are estimated using the EM algorithm.





EM algorithm

- Initialize the parameters μ of model. These are $P(v_i|s_k)$ and $P(s_k)$, j=1,2,...J, k=1,2,...K.
- compute the log likelihood of corpus C given the model μ : $I(C|\mu) = log \Pi_i \Sigma_k P(c_i | s_k) P(s_k)$
- while I(C|μ) increases repeat:
 - **E-step:** $h_{ik} = P(c_i | s_k) P(s_k) / \Sigma_l P(c_i | s_l) P(s_l)$ (use Naive Bayes to compute $P(c_i | s_k)$)
 - M-step: re-estimate the parameters P(v_j |s_k) and P(s_k) by MLE:

$$P(v_j|s_k) = \frac{\sum_i N(v_j \, in \, c_i) \cdot h_{ik}}{Z_k}$$
 where the sum is over all contexts c_i and $Z_k = \sum_j \sum_i N(v_j \, in \, c_i) \cdot h_{ik}$ is a normalizing constant.

$$P(s_k) = \sum_i h_{ik} / Z'_k$$
 with $Z'_k = \sum_k \sum_i h_{ik}$





Disambiguation

- Once the model parameters have been estimated, a word w can be disambiguated by computing the probability of each sense given the words v_j in the context.
- Again we use the Naïve Bayes assumption:

Decide s'=argmax $_{sk}$ [log P(s_k)+ $\Sigma_{vj \text{ in C}}$ log P($v_j \mid s_k$)]



Performance of Unsupervised Disambiguation



- Is capable of identifying minute difference in senses, e.g. a bank in physical sense and in abstract sense.
- Usually the clusters obtained are not identical with dictionary senses.
- Results of unsupervised disambiguation (Schütze 1998)

word	sense Mean accuracy				
suit	lawsuit	95			
	garment	96			
motion	physical movement	85			
	proposal for action	88			
train	Line of railroad cars	79			
	teach	55			



Learning Problems



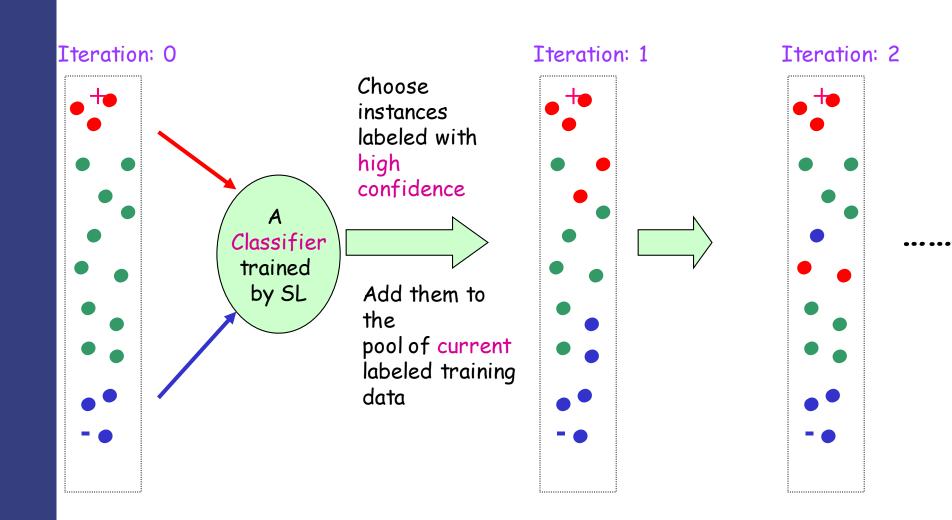
- Supervised learning:
 - Given a sample consisting of object-label pairs (x_i, y_i) , find the predictive relationship between objects and labels.
- Un-supervised learning:
 - Given a sample consisting of only objects, look for interesting structures in the data, and group similar objects.
- What is Semi-supervised learning?
 - Supervised learning + additional unlabeled data
 - Unsupervised learning + additional labeled data



The Yarowsky Algorithm



(Yarowsky 1995)







Results from Yarowsky 95

UNSUPERVISED WORD SENSE DISAMBIGUATION RIVALING SUPERVISED METHODS

David Yarowsky
Department of Computer and Information Science
University of Pennsylvania
Philadelphia, PA 19104, USA
yarowsky@unagi.cis.upenn.edu

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<u> </u>			%		Seed Training Options		ptions	(7) + OSPD		
		Samp.	Major	Supvsd	Two	Dict.	Top	End	Each	Schütze
Word	Senses	Size	Sense	Algrtm	Words	Defn.	Colls.	only	Iter.	Algrthm
plant	living/factory	7538	53.1	97.7	97.1	97.3	97.6	98.3	98.6	92
space	volume/outer	5745	50.7	93.9	89.1	92.3	93.5	93.3	93.6	90
tank	vehicle/container	11420	58.2	97.1	94.2	94.6	95.8	96.1	96.5	95
motion	legal/physical	11968	57.5	98.0	93.5	97.4	97.4	97.8	97.9	92
bass	fish/music	1859	56.1	97.8	96.6	97.2	97.7	98.5	98.8	_
palm	tree/hand	1572	74.9	96.5	93.9	94.7	95.8	95.5	95.9	_
poach	steal/boil	585	84.6	97.1	96.6	97.2	97.7	98.4	98.5	-
axes	grid/tools	1344	71.8	95.5	94.0	94.3	94.7	96.8	97.0	
duty	tax/obligation	1280	50.0	93.7	90.4	92.1	93.2	93.9	94.1	_
drug	medicine/narcotic	1380	50.0	93.0	90.4	91.4	92.6	93.3	93.9	_
sake	benefit/drink	407	82.8	96.3	59.6	95.8	96.1	96.1	97.5] - '
crane	bird/machine	2145	78.0	96.6	92.3	93.6	94.2	95.4	95.5	
AVG		3936	63.9	96.1	90.6	94.8	95.5	96.1	96.5	92.2

→ better than unsupervised algorithm by Schütze







- Determine meaning of a word
- Approaches:
 - Thesaurus based
 - Supervised (→ text classification)
 - Unsupervised
 - Semi supervised (Yarowsky)