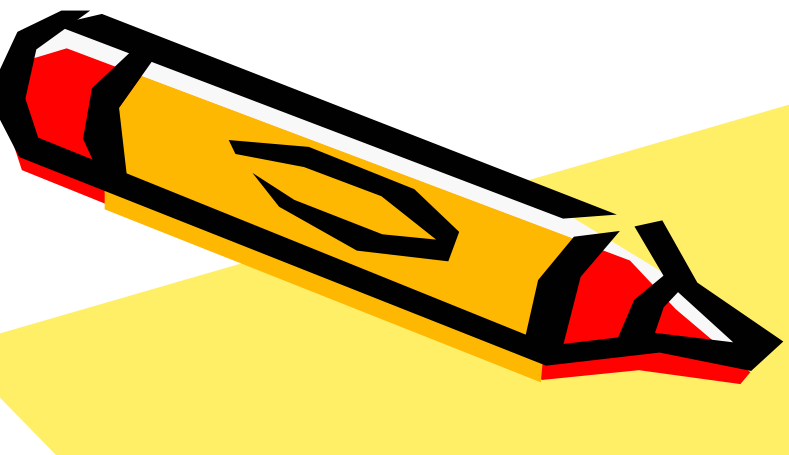
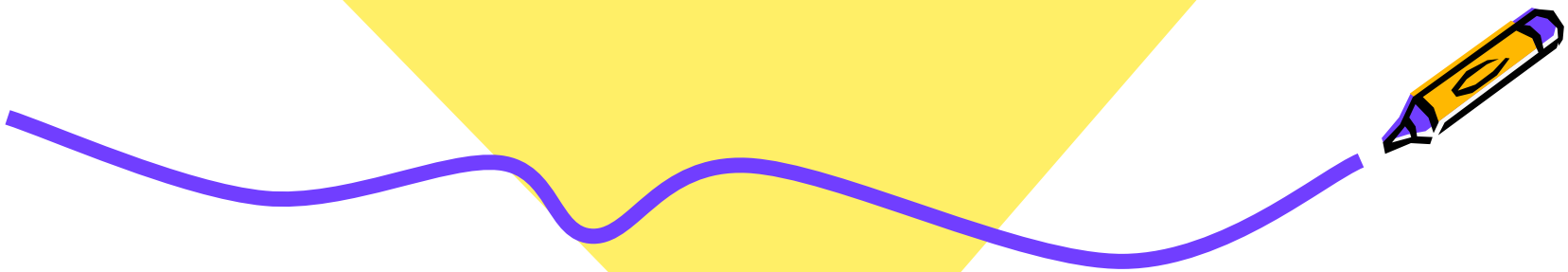


Word Sense Disambiguation

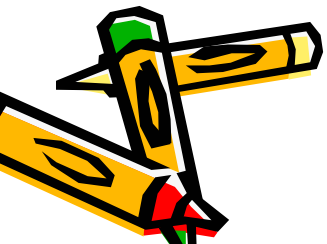
Presented by Jen-Wei Kuo



Reference

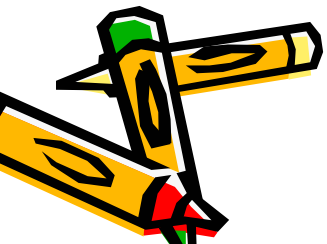
Foundations of Statistical Natural Language Processing,
Chapter 7,
Word Sense Disambiguation

Speech and Language Processing,
Chapter 17.1~17.2,
Word Sense Disambiguation and Information Retrieval



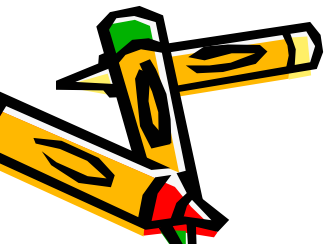
Outline

- Problem
- Task
- Methodological Preliminaries
  - Supervised versus Unsupervised Learning
  - Pseudowords
  - Upper and Lower Bounds on Performance



Outline (cont.)

- Method
  - Supervised Disambiguation
    - Bayesian Classification.
    - An Information-Theoretic Approach.
  - Dictionary-Based Disambiguation
    - Based on Senses Definition
    - Thesaurus-Based Disambiguation
    - Based on Translations in a second-language corpus.
    - One sense per discourse, one sense per collocation.
  - Unsupervised Disambiguation



Problem

- Many words have several meanings or senses.
- There is thus *ambiguity* about how they are to be interpreted.(不同的解釋方式→ambiguity)

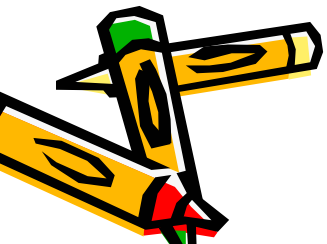
However, the senses are not aloways so well-defined

- For Example：bank
  - The rising ground bordering a lake, river, or sea...(邊坡)
  - As establishment for the custody(保管), loan exchange, or issue of money, for the extension of credit, and for facilitating the transmission of funds.(銀行)

Task

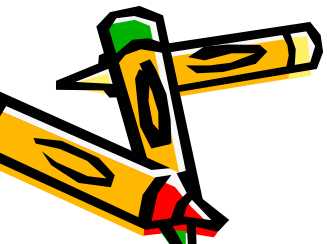
- To determine which of the senses of an ambiguous word is invoked in a particular use of the word.(字義和用法有關)

- How to do：
  - A word is assumed to have a finite number of discrete senses.
  - Look at the context of the word's use.
  - But often the different senses of a word are closely related.



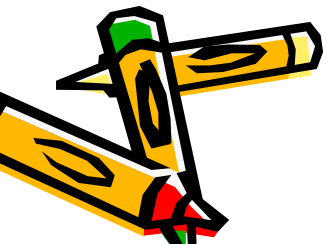
Methodological Preliminaries

- Supervised versus Unsupervised Learing
  - Supervised：
    - Classification task.
    - The sense label of a word is known.
  - Unsupervised：
    - Clustering task.
    - The sense label of a word is unknown.



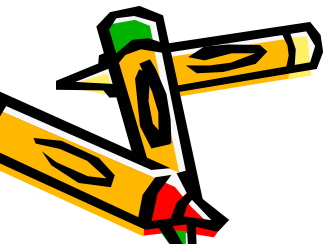
Methodological Preliminaries

- Pseudowords
  - Used to generate artificial evaluation data for comparison and improvements of text-processing alogorithms.
  - Make pseudowords by conflating two or more natural words.
  - For example：Occurrences of banana and door can be replaced by banana-door.
  - The disambiguation algorithm can now be tested on this data to disambiguate the pseudowords.
  - For example：Banana-door into banana and door.



Methodological Preliminaries

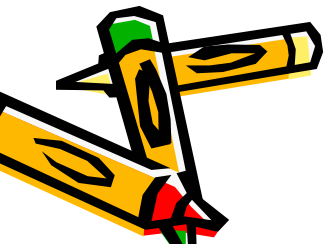
- Upper and Lower Bounds on Performance
  - Used to find out how well an algorithm performs relative to the difficulty of the task.
  - Upper Bounds：
    - Human performance.
  - Lower Bounds：
    - Performance of the simplest (baseline) model.



Method

Supervised Disambiguation

- Training Corpus
  - Each occurrence of the ambiguous word w is annotated with a semantic label (its contextually appropriate sense S_k).
  - Classification problems.
- Approaches
  - Bayesian Classification (Gale et al. 1992)
  - Information Theory (Brown et al. 1991)



Method

Supervised Disambiguation

- Bayesian Classification
  - Bayes Decision Rule：Decide s' if

$$P(s'|c) > P(s_k|c) \quad \text{for } s_k \neq s'$$

  - Look at the words around an ambiguous word in a large context window.
  - Each context word contributes potentially useful information about which sense of the ambiguous word is likely to be used with it.
  - The classifier does no feature selection. Instead, it combines the evidence from all features to choose the class with highest conditional probability.

Method

Supervised Disambiguation

- Bayesian Classification
  - We want to assign the ambiguous word w to the sense s', given context c, where

$$s' = \arg\max_{s_k} P(s_k \mid c)$$

Baye's Rule

$$= \arg\max_{s_k} \frac{P(c \mid s_k)}{P(c)} P(s_k)$$

$$= \arg\max_{s_k} P(c \mid s_k) P(s_k)$$

log

$$= \arg\max_{s_k} [\log P(c \mid s_k) + \log P(s_k)]$$

Method

Supervised Disambiguation

- Bayesian Classification
  - Naive Bayes Assumption：

The attributes (contextual words) used for description are all conditionally independent.

$$P(c \mid s_k) = P(\{v_j \mid v_j \text{ in } c\} \mid s_k) = \prod_{v_j \text{in } c} P(v_j \mid s_k)$$

  - Consequences of this assumption：
    - ***Bag of Words 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.

Method

Supervised Disambiguation

- Bayesian Classification
  - Decide s' if

$$s' = \arg\max_{s_k} [\log P(s_k) + \sum_{v_j \text{ in } c} \log P(v_j \mid s_k)]$$

  - $P(v_j \mid s_k)$ and $P(s_k)$ are computed from the labeled training corpus, perhaps with appropriate smoothing.

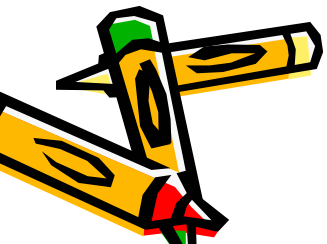
$$P(v_j \mid s_k) = \frac{C(v_j, s_k)}{C(s_k)} \qquad P(s_k) = \frac{C(s_k)}{C(w)}$$

where $C(v_j, s_k)$ is the number of occurrences of v_j in a context of sense s_k in the training corpus, $C(s_k)$ is the number of occurrences of s_k in the training corpus, $C(w)$ is the total number of occurrences of the ambiguous word w.

Method

Supervised Disambiguation

- Information Theoretic Approach
  - **Bayes Classifier** uses information from all words in the context window by using an independence assumption.
  - In the **Information Theoretic Approach** we try to find a single contextual feature that reliably indicates which sense of the ambiguous word is being used.



Method

Supervised Disambiguation

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Ambiguous word	Indicator	Examples: value → sense
prendre	object	*mesure* → *to take* *décision* → *to make*
vouloir	tense	present → *to want* conditional → *to like*
cent	word to the left	*per* → % number → *c.* [money]

Table 7.3 Highly informative indicators for three ambiguous French words.

Method

Supervised Disambiguation

- Information Theoretic Approach
  - Two senses of the word：prendre
    - **Prendre** une measure → **take** a measure
    - **Prendre** une decision → **make** a decision
  - The translations of the ambiguous word $\{t_1,...,t_m\}$ are {take,make} ← meaning
  - The possible indicator words $\{x_1,...,x_m\}$ are {mesure,note,exemple,decision,parole} ← indicate the meaning
  - Find a partition $Q=\{Q_1,Q_2\}$ of $\{x_1,...,x_m\}$ and $P=\{P_1,P_2\}$ of $\{t_1,...,t_m\}$ that maximizes the mutual information：

$$I(P;Q)=\sum_{t\in P}\sum_{x\in Q}p(t,x)\log\frac{p(t,x)}{p(t)p(x)}$$

Method

Supervised Disambiguation

- Information Theoretic Approach

Flip-Flop Algorithm :

find a random partition $P=\{P_1,P_2\}$ for $\{t_1,\ldots, t_m\}$

while (improving) do

find partition $Q=\{Q_1, Q_2\}$ of $\{x_1,\ldots,x_n\}$

that maximizes $I(P;Q)$

find partition $P=\{P_1, P_2\}$ of $\{t_1,\ldots, t_m\}$

that maximizes $I(P;Q)$

end

Method

Supervised Disambiguation

- Information Theoretic Approach
  - Disambiguation：
    - For the occurrence of the ambiguous word, determine the value x_i, of the indicator.
    - 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.

Method

Dictionary-Based Disambiguation

- Concept：
  - Sense definitions are extracted from existing sources such as dictionaries and thesaurus.
- Approaches：
  - Based on Sense Definitions. (Lesk,1986)
  - Thesaurus-Based Disambiguation. (Walker,1987) (Yarowsky, 1992)
  - Based on Translations (Dagan et al. 1991&1994)
  - One Sense per Discourse, One Sense per Collocation (Yarowsky, 1995)

Method

Dictionary-Based Disambiguation

- Disambiguation Based on Sense Definition：
  - A word's dictionary definitions are likely to be good indicators of the senses they define.
  - Express the dictionary sub-definitions of the ambiguous word as sets of bag-of-words and the words occurring in the context of the ambiguous word as single bags-of-words emanating(散發) from its dictionary definitions (all pooled together).
  - Disambiguate the ambiguous word by choosing the sub-definition of the ambiguous word that has the greatest overlap with the words occurring in its context.

Method

Dictionary-Based Disambiguation

- Disambiguation Based on Sense Definition：
  - The algorithm:

Given a context c for a word w

For all senses $s_1,\ldots,s_k$ of w do

score (S_k) =

overlap (word set of dictionary definition of sense S_k,

word set of dictionary definition of V_j in context c)

Choose the sense with highest score.

Method

Dictionary-Based Disambiguation

- Disambiguation Based on Sense Definition：
  - Example (Two Senses of *ash*):

Senses		Definition
S_1	tree	a tree of the olive family
S_2	burned stuff	the solid residue left when combustible material is burned

Score		Context
S_1	S_2	
0	1	This cigar burns slowly and creates a stiff ash
1	0	The ash is one of the last trees to com into leaf.

Method

Dictionary-Based Disambiguation

- Thesaurus-Based Disambiguation：
  - This exploits the semantic categorization provided by a thesaurus like Roget's.
  - The semantic categories of the words in a context determine the semantic category of the context as a whole. And this category in turn determines which word senses are used.
  - (Walker,1987)：Each word is assigned one or more subject codes which corresponds to its different meanings.
  - For each subject code, we count the number of words (from the context) having the same subject code.
  - We select the subject code corresponding to the highest count.

Method

Dictionary-Based Disambiguation

- Thesaurus-Based Disambiguation：
  - The algorithm:
    - Given a context c for a word w with senses $s_1,\ldots,s_k$.
    - Find the bags of words corresponding to each sense s_k in the dictionary (s_k bags of words).
    - Compare with the bag of words formed by combining the context word definitions. Pick the sense which gives maximum overlap with this bag.

Method

Dictionary-Based Disambiguation

- Thesaurus-Based Disambiguation：
  - (Yarowsky,1992)：Add new words to a category if they occur more often than chance. For example Navratilova can be added to the sports category.
  - The Bayes classifier is used for both adaptation and disambiguation.
  - Adapted the algorithm for words that do not occur in the thesaurus but that are very informative.
    E.g., Navratilova --> Sports

Method

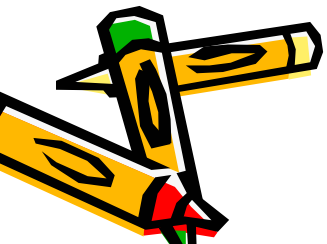
Dictionary-Based Disambiguation

- Disambiguation based on translations in a second-language corpus： (Dagan et al. 1991&1994)
  - Words can be disambiguated by looking at how they are translated in other languages.
  - Example: the word “interest” has two translations in German: 1) “Beteiligung” (legal share--50% a interest in the company) 2) “Interesse” (attention, concern--her interest in Mathematics).
  - To disambiguate the word “interest”, we identify the sentence it occurs in, search a German corpus for instances of the phrase, and assign the meaning associated with the German use of the word in that phrase.
  - Disambiguate words based on translations.
  - Count the number of times a sense translation occurs in a second language corpus along with translations of the context words. Pick the sense with the highest score.

Method

Dictionary-Based Disambiguation

- One Sense per Discourse, One Sense per Collocation：(Yarowsky, 1995)
  - 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.



Method

Unsupervised Disambiguation

- (Schutze,1998)
  - Disambiguate word senses without having resourse 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.
  - The probabilistic model is the same Bayesian model as the one used for supervised classification, but the $P(v_j \mid s_k)$ are estimated using the EM algorithm.

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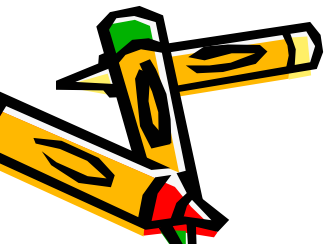


Method

Unsupervised Disambiguation

- EM algorithm
  - Initialize $p(v_j \mid s_k) \rightarrow$ random
  - Compute likelihood $l(C \mid \mu)$

$$l(C \mid \mu) = \log \prod_{i=1}^{I} \sum_{k=1}^{K} p(c_i \mid s_k) p(s_k) = \sum_{i=1}^{I} \log \sum_{k=1}^{K} p(c_i \mid s_k) p(s_k)$$

  - While $l(C \mid \mu)$ is improving repeat:

$$p(c_i \mid s_k) = \prod_{v_j \in c_i} p(v_j \mid s_k)$$

  - E step :

$$h_{i,k} = \frac{p(c_i \mid s_k)}{\sum_{k=1}^{K} p(c_i \mid s_k)}$$

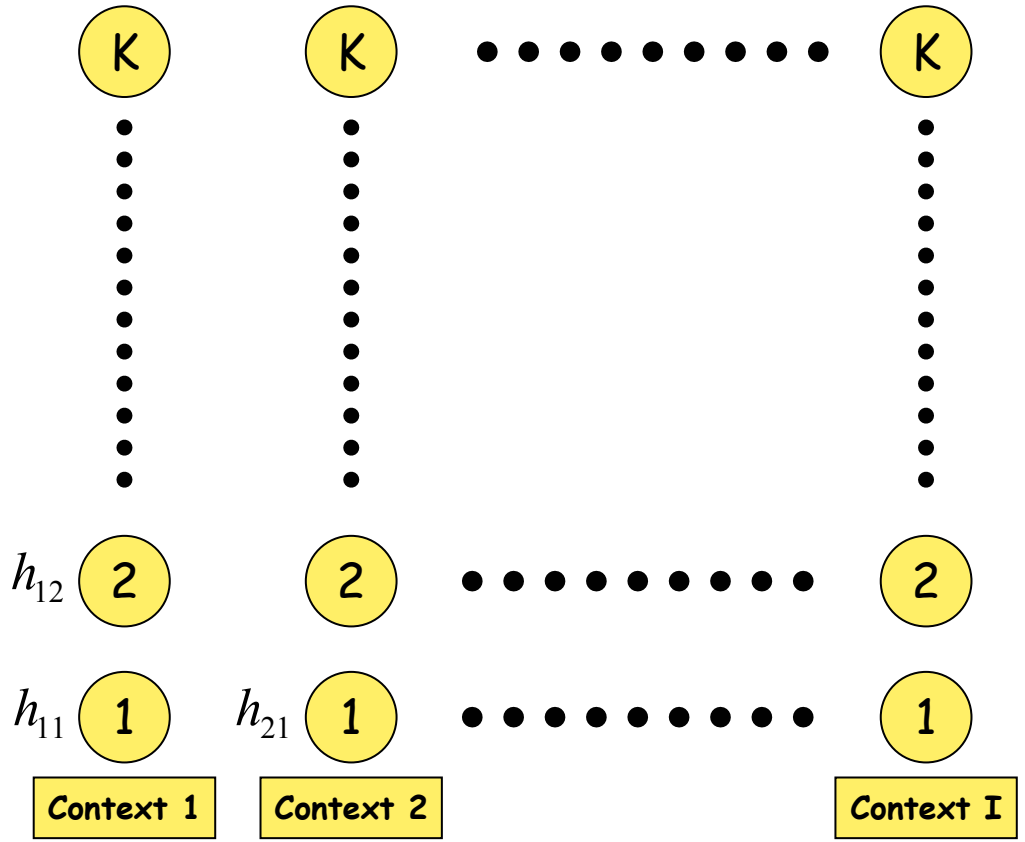
  - M step : Re-estimate

$$p(v_j \mid s_k) = \frac{\sum_{\{c_i : v_j \in c_i\}} h_{i,k}}{\sum_{k=1}^{K} \sum_{\{c_i : v_j \in c_i\}} h_{i,k}} \quad p(s_k) = \frac{\sum_{i=1}^{I} h_{i,k}}{\sum_{k=1}^{K} \sum_{i=1}^{I} h_{i,k}}$$

Method

Unsupervised Disambiguation

- Diagram :



Application

- Tagging
- Information Retrieval

An Application of Word Sense Disambiguation to Information Retrieval (1999) Jason M. Whaley

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