

Assignment 9, 10 + Word Sense Disambiguation

(SNLP Tutorial 10)

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Assignment 9

- Exercise 1: Feature Engineering, Classification
- Bonus: Support Vector Machines

Exam, Learning Material, Repository

- Exam 23. 6. 2021

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github.com/zouharvi/uds-snlp-tutorial

Word Sense Disambiguation

Apple is full of vitamins.

Apple was struggling last quarter.

Apple was thrown away from the meeting.



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$$f : W \times C \rightarrow S_w$$

$$f(\text{Apple}, * \text{ was thrown away from the meeting}) \in \{\text{fruit, company}\}$$

Word Sense Disambiguation

Machine translation:

- Apfel ist voller Vitamine.
- Apple ist voller Vitamine.
- Apfel hatte im letzten Quartal Probleme.
- Apple hatte im letzten Quartal Probleme.

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- Query: Apple vitamins
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Dialogue systems

Spelling correction

One sense per ...

One sense per discourse

- One meaning per word+document

One sense per ...

One sense per discourse

- One meaning per word+document

One sense per collocation

- Nearby words help determine the sense

Dictionary

- Dictionary/Thesaurus: $\forall w, s \in S_w : D(s) = \text{description of sense } s$
- Context: $\forall w, C(w) = \text{context of word } w \text{ in a specific occurrence}$

Lesk's Algorithm

- Idea: Sense s_i of ambiguous word w is likely to be the correct sense if many of the words used in the dictionary definition of s_i are also used in the definitions of words in the ambiguous word's context.

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

Similarity

$$\frac{2|X \cap Y|}{|X| + |Y|}$$

$$\frac{2|X \cap Y|}{|X \cup Y|}$$

$$\frac{|X \cap Y|}{\sqrt{|X| \cdot |Y|}}$$

- Advantages? Disadvantages?

Simplified Lesk's Algorithm Example

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

Senses

- *bank*¹ Gloss/Defⁿ: a financial institution that accepts deposits and channels the money into lending activities.
e.g.: “She cashed a cheque at the bank”.
- *bank*² Gloss/Defⁿ: sloping land (especially the slope beside a body of water).
e.g.: “They had a picnic on the river bank”.

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```
from nltk.corpus import senseval
hard, interest, line, serve = senseval.fileids()
line_instances = senseval.instances(line)
```

- Improvements include weighting by measures like IDF

Supervised Disambiguation

Bayes Decision

$$\begin{aligned}\hat{s} &= \arg \max_s p(s|C) = \arg \max_s \frac{p(C|s) \cdot (p(s))}{p(C)} \\ &= \arg \max_s p(C|s) \cdot (p(s))\end{aligned}$$

Naïve Bayes

$$p(C|s) = \prod_{x \in C} p(x|s)$$

- Estimate by MLE counts (+ smoothing)
- Independence within context
- Position in context does not matter
- Advantages? Disadvantages?
- What kind of feature vectors can exist?

Supervised Disambiguation Features Example

Sentence: Transactions on a deposit account of the *bank* are recorded in books, and the resulting balance is recorded as its liability.

- Collocational features:

$[w_{i-3}, POS_{i-3}, w_{i-2}, POS_{i-2}, \dots, w_{i+3}, POS_{i+3}]$

[account, NN, of, PP, the, DT, ...]

$[w_{i-2}, w_{i-1}, w_{i+1}]$

- Bag of Word Features

Let $V : \{\text{institution, account, water, land}\}$

Vector: $[0, 1, 0, 0]$ for given sentence

Flip-Flop Algorithm

- Machine translation is able to choose the right sense (assuming different senses have different translations)
- Apple was struggling last quarter.
Apple hatte im letzten Quartal Probleme.
- Apple is full of vitamins.
Apfel ist voller Vitamine.
- Translations (in German): {Apfel, Äpfel, Apple}
- Indicator words: {struggling, quarter, full, vitamins} (stopwords removed)

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Partition translated words ($\{Q_1, Q_2\}$) and indicator words ($\{P_1, P_2\}$) to maximize:

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

Flip-Flop Algorithm

- ① find random partition $P = \{P_1, P_2\}$ of t_1, \dots, t_m
 - ② while improving $I(P;Q)$ do
 - ③ ▶ find partition $Q = \{Q_1, Q_2\}$ of x_1, \dots, x_n that maximises $I(P;Q)$
 - ④ ▶ find partition $P = \{P_1, P_2\}$ of t_1, \dots, t_m that maximises $I(P;Q)$
 - ⑤ end
- t_i : translations of the ambiguous word
 - x_i : indicator words
 - $I(P;Q)$ monotonically increases until convergence

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- Disambiguation

Determine x_i

if $x_i \in Q_1$ assign sense 1

if $x_i \in Q_2$ assign sense 2

Unsupervised Disambiguation (EM Algorithm)

- Idea: Random initialisation followed by parameter estimation
- Parameters? $P(v_j|s_k)$ and $P(s_k)$
- Maximise log-likelihood $\log \prod_i \sum_k P(c_i|s_k)P(s_k)$
- E step: $h_{ik} = \frac{P(c_i|s_k)P(s_k)}{\sum_l P(c_i|s_l)P(s_l)}$
- M step: $P(v_j|s_k) = \frac{\sum_i C(v_j \in c_i) \cdot h_{ik}}{\sum_j \sum_i C(v_j \in c_i) \cdot h_{ik}}$
 $P(s_k) = \frac{\sum_i h_{ik}}{\sum_k \sum_i h_{ik}}$
- Disambiguation: $s_{opt} = \operatorname{argmax}_{s_k} [\log P(s_k) + \sum_{v_j \in C} \log P(v_j|s_k)]$

Semi-Supervised Disambiguation (Yarowsky Algorithm)

- Utilises one sense per discourse and one sense per collocation
- Algorithm:

- 1 In a large corpus, identify all examples of a polysemous word, and store their contexts as an untagged training set.

e.g.

The company *plant* is still operational. . .

The region abounds in *plant* life. . .

The classification of *plant* and animal kingdoms. . .

- 2 For each sense of the word ($s_1 \dots s_k$), identify collocations representative of the sense, and tag all the sentences from (1) which contain the seed collocation with the respective label.

e.g.

Sense 1: The company *plant* is still operational

Sense 2: The region abounds in *plant* life. . .

Sense 2: The classification of *plant* and animal kingdoms

Yarowsky Algorithm

- 3
 - a) Train on the seed sets (Sense 1, Sense 2).
 - b) Apply the obtained classifier on the entire sample set. Only retain those tags that are above a certain probability threshold. Add these examples to the seed set.
 - c) Use one sense per discourse to augment and correct the available data.
e.g.
Sense 1: The company *plant* is still operational
? → Sense 1: The *plant* was shut down due to inflation.
 - d) Repeat (3a) to (3c)
- 4 Hold training parameters constant, and the algorithm will converge on the residual set.
- 5 Apply the classifier to new data or original untagged data.

Resources

- ① UdS SNLP Class, WSD: <https://teaching.lsv.uni-saarland.de/snlp/>
- ② Classical Statistical WSD: <https://www.aclweb.org/anthology/P91-1034.pdf>
- ③ WSD: <https://www.cs.toronto.edu/~frank/csc2501/Lectures/8%20Word%20sense%20disambiguation.pdf>
- ④ Lesk Algorithm: <https://www.c-sharpcorner.com/article/lesk-algorithm-in-python-to-remove-word-ambiguity/>
- ⑤ Yarowsky Algorithm: https://www.coli.uni-saarland.de/courses/comsem-10/material/Victor_Santos_Yarowsky.pdf
- ⑥ <https://www.aclweb.org/anthology/P95-1026.pdf>
- ⑦ <https://web.stanford.edu/~jurafsky/slp3/slides/Chapter18.wsd.pdf>