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 23. 6. 2021

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- Material: lecture slides, tutorial slides, the book, internet

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github.com/zouharvi/uds-snlp-tutorial

Apple is full of vitamins.

Apple was struggling last quarter.

Apple was thrown away from the meeting.





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 $f: W \times C \to S_w$ $f(\mathsf{Apple}, * \mathsf{was} \mathsf{thrown} \mathsf{away} \mathsf{from} \mathsf{the} \mathsf{meeting}) \in \{\mathsf{fruit}, \mathsf{company}\}$

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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Information retrieval:

- Query: Apple vitamins
- Relevant document: benefits of eating apples

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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: $\forall w, s \in S_w : D_w(s) = \text{description of sense } s$
- Context: $\forall w, C(w) = \text{context of word } w \text{ in a specific occurence}$

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.

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

Similarity

$$\frac{2|X \cap Y|}{|X| + |Y|} \qquad \frac{2|X \cap Y|}{|X \cup Y|} \qquad \frac{|X \cap Y|}{\sqrt{|X| \cdot |Y|}}$$

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

- bank¹ Gloss/Defⁿ: a financial institution that accepts deposits and channels the money into lending activities.
 - e.g.: "She cashed a cheque at the bank".
- bank² 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

$$\hat{s} = \arg \max_{s} p(s|C) = \arg \max_{s} \frac{p(C|s) \cdot (p(s))}{p(C)}$$
$$= \arg \max_{s} p(C|s) \cdot (p(s))$$

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}..., 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: {institution, account, water, land}
 Vector: [0, 1, 0, 0] for given sentence

- 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:

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

- **1** find random partition $P = \{P_1, P_2\}$ of $t_1, ..., t_m$
- while improving I(P;Q) do
- find partition $Q = \{Q_1, Q_2\}$ of $x_1, ..., x_n$ that maximises I(P;Q)
- find partition $P = \{P_1, P_2\}$ of $t_1, ..., t_m$ that maximises I(P;Q)
- end
- t_i: translations of the ambiguous word
- \bullet 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
- Paramaters? $P(v_j|s_k)$ and $P(s_k)$
- Maximise log-likelihood log $\prod_i \sum_k P(c_i|s_k)P(s_k)$
- E step: $h_{ik} = \frac{P(c_i|s_k)}{\sum_{l} P(c_i|s_l)}$
- M step:

$$P(v_j|s_k) = \frac{\sum_i C(v_j \in c_i) \cdot h_{ik}}{\sum_k \sum_i C(v_j \in c_i) \cdot h_{ik}}$$

$$P(s_k) = \frac{\sum_i h_{ik}}{\sum_k \sum_i h_{ik}}$$

• Disambiguation: $s_{opt} = argmax_{s_k} [\log P(s_k) + \sum_{v_j \in C} \log P(v_j | S_k)]$

Semi-Supervised Disambiguation (Yarowsky Algorithm)

- Utilises one sense per discourse and one sense per collocation
- Algorithm:
- 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 abounts in plant life. . .

The classification of plant and animal kingdoms. . .

- ② For each sense of the word $(s_1...s_k)$, 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

- Train on the seed sets (Sense 1, Sense 2).
 - 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.
 - Use one sense per discourse to augment and correct the available data.

e.g.

Sense 1: The company plant is still operational

? \rightarrow Sense 1: The *plant* was shut down due to inflation.

- Repeat (3a) to (3c)
- ullet Hold training parameters constant, and the algorithm will converge on the residual set.
- Apply the classifier to new data or original untagged data.

Resources

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