Language Modeling

VL Sprachverarbeitung

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Recap

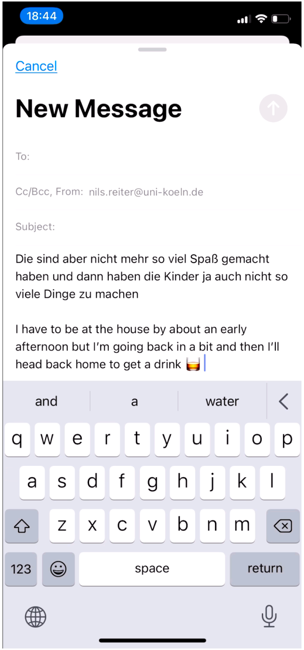
- Statistical significance
  - We expect a certain variation, no clear boundaries
  - How likely is it, that we observe the things we observed under H_0
  - Coin toss: Bernoulli trial
- Application to collocations
  - Not a Bernoulli trial
  - χ^2 test to verify that a potential collocation is statistically significant
- Statistically significant != significant

Glossareintrag

Kollokation

Bei einer Kollokation handelt es sich um die Nebeneinanderstellung zweier oder mehrerer Wörter, die typischerweise miteinander vorkommen. In der Korpuslinguistik definiert sich eine Kollokation außerdem dadurch, dass eine Kollokation eine höhere Wahrscheinlichkeit hat aufzutreten als beide Wörter getrennt.
Ein Beispiel hierfür wäre Substantiv ›Hund‹ und das Verb ›bellen‹, die lediglich zusammen einen Sinn ergeben, da ausschließlich Hunde in der Lage sind zu bellen. Die Wahrscheinlichkeit, dass diese beiden Begriffe in einem Korpus zusammen vorkommen, ist also höher als wenn man beide Begriffe zufällig dem Korpus entnehmen würde.

demo


18:44
Cancel
New Message
To:
Cc/Bcc, From: nils.reiter@uni-koeln.de
Subject:
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  - Long before predictive typing on smart phones became a thing
- Language model (LM) predicts the next word, given previous words (history)
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Reading

Christopher D. Manning/Hinrich Schütze (1999). *Foundations of Statistical Natural Language Processing*. Cambridge, Massachusetts and London, England: MIT Press, Ch. 6.1–6.2. Ilias

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  - We couldn't predict anything on completely new histories
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$$\text{More generalization} \xleftarrow{\text{less}} \text{Equivalence classes} \xrightarrow{\text{more}} \text{More discrimination}$$

Figure: Compromise between generalization and discrimination

Forming Equivalence Classes

Different strategies

- Stemming/lemmatization: Don't look at word forms, look at lemmas or stems
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- Limit history: Only look at the last n words

Markov Assumption

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- n-gram model: Only the last $n-1$ words are looked at to predict the nth word
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Example

Bigram model: »green ___«

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Trigram model: »large green ___«

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4-gram model: »the large green ___«

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5-gram model: »swallowed the large green ___«

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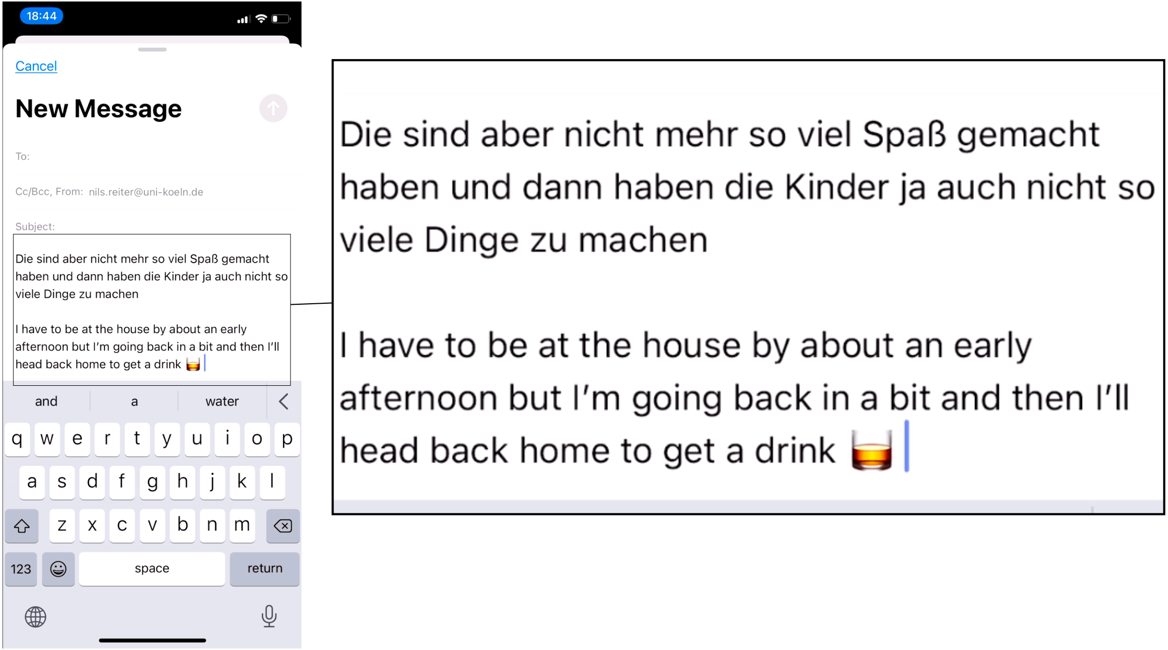
Example

6-gram model: »Sue swallowed the large green ___«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- Storage and training time increases
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  - Bigram model: $20\,000^2 = 400\,000\,000$ parameters
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  - 4-gram model: $20\,000^4 = 1.6 \times 10^{17}$ parameters (= ca. 20 PB)

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- Longer n-grams would give better predictions
- Shorter n-grams would be easier/faster to train and use
- Common: $n = 2$ or $n = 3$
  - Trigrams are surprisingly good at predicting the next word!

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  - Convert them into probabilities, maybe apply mathematical transformations
- Definition of conditional probabilities:

$$p(w_n|\langle w_1, \ldots, w_{n-1}\rangle) = \frac{p(\langle w_1, \ldots, w_n\rangle)}{p(\langle w_1, \ldots, w_{n-1}\rangle)}$$

Maximum Likelihood Estimation (MLE)

- Parameters that maximize probability on the training corpus
- I.e., use the relative frequency from the training corpus as probability

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Maximum Likelihood Estimation (MLE)

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$$\begin{aligned} p(\langle w_1, \ldots, w_n \rangle) &= \frac{c(\langle w_1, \ldots, w_n \rangle)}{N} \\ p(w_n | \langle w_1, \ldots w_{n-1}) &= \frac{p(\langle w_1, \ldots, w_n \rangle)}{p(\langle w_1, \ldots, w_{n-1} \rangle)} \end{aligned}$$

demo

Maximum Likelihood Estimation (MLE)

Example

History	w_n	Count
Bier und	Wein	4
Bier und	Schnaps	3
Bier und	Bratwürsten	1
Bier und	Männerschweiß	1
Bier und	nichtalkoholischen	1
...	...	1
Bier	und	29

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$$
\begin{aligned}
p(\text{Bier und}) &= \frac{22}{1880232} \\
p(\text{Wein}|\text{Bier und}) &= \frac{p(\text{Bier und Wein})}{p(\text{Bier und})} \\
&= \frac{\frac{4}{1880232}}{\frac{22}{1880232}} \\
&= \frac{4}{1880232} \times \frac{1880232}{22} \\
&= \frac{4}{22} = 0.1818
\end{aligned}
$$

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- Training corpus used for estimating probability
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- Training corpus used for estimating probability
- Test/application corpus used for using probability
- Never use the same corpus for training and testing
- After having trained, we can check how probable a new document/corpus is (= test/application)

Example

$$
\begin{aligned}
p(\text{Ich trinke gerne Bier und Wein}) &= p(\text{Ich}|\text{SYM SYM}) \times p(\text{trinke}|\text{Ich SYM}) \\
&\times p(\text{gerne}|\text{Ich trinke}) \times p(\text{Bier}|\text{trinke gerne}) \\
&\times p(\text{und}|\text{gerne Bier}) \times p(\text{Wein}|\text{Bier und})
\end{aligned}
$$

Maximum Likelihood Estimation (MLE)

Drawbacks

- What happens with words not in the training corpus? Zero probability
  - ›out of vocabulary‹ (OOV)
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Drawbacks

- What happens with words not in the training corpus? Zero probability
  - ›out of vocabulary‹ (OOV)
- Because of multiplication, everything will be zero
- There will be OOV words – because Zipf
- MLE conceptually important, but rarely used in NLP

$\Rightarrow$ We need another estimator for the probability

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$$p(\langle w_1, \dots w_n \rangle) = \frac{c(\langle w_1, \dots w_n \rangle) + \lambda}{N + B\lambda}$$

- B: Number of different n-grams (i.e., n-gram types)
- λ: Parameter set to control how much mass remains for OOV words
  - Typical setting: $\lambda = \frac{1}{2}$ (for reasons see MS99, 204)

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  - Prevent zero probabilities
  - Reserve some amount of probability mass for OOV words
- Different strategies
  - Often need for fine-tuning (e.g., what value to we use for λ?)

Section 1

Summary

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- Language modeling
  - Given some history, predict the next word
  - Use cases: Smart phone, ...
  - Maximum Likelihood estimation: Easy, but problematic
  - Lidstone's Law: Smoothing
    - Other smoothing techniques exist
- Different data sets for different purposes
  - Cross validation