Language Modeling

VL Sprachliche Informationsverarbeitung

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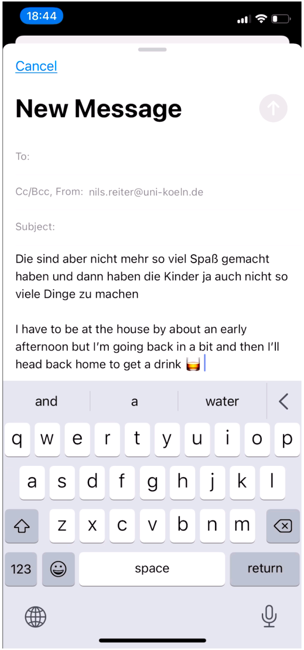
INSTITUT FÜR
DIGITAL HUMANITIES
UNIVERSITÄT ZU KÖLN


18:44
Cancel
New Message
To:
Cc/Bcc, From: nils.reiter@uni-koeln.de
Subject:
Die sind aber nicht mehr so viel Spaß gemacht haben und dann haben die Kinder ja auch nicht so viele Dinge zu machen
I have to be at the house by about an early afternoon but I'm going back in a bit and then I'll head back home to get a drink 🥃
and
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q w e r t y u i o p
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123
space
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Introduction

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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)
  - Bidirectional LM: Previous and following words (context)
- Formally: $p(\text{word}|\text{history})$

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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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- Not all textual histories can be treated individually
  - We couldn't predict anything on completely new histories
  - Chance of a text re-appearing is astronomically slim
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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
  - E.e.: $p(\text{bark}|\text{the dog})$ instead of $p(\text{barks}|\text{The dog})$

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  - Content words like nouns, verbs, adjectives and adverbs
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- Limit history: Only look at the last n words

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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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  - Trigram model: $p(w_3|\langle w_1, w_2\rangle)$
  - 4-gram model: $p(w_4|\langle w_1, w_2, w_3\rangle)$

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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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Example

5-gram model: “swallowed the large green ___”

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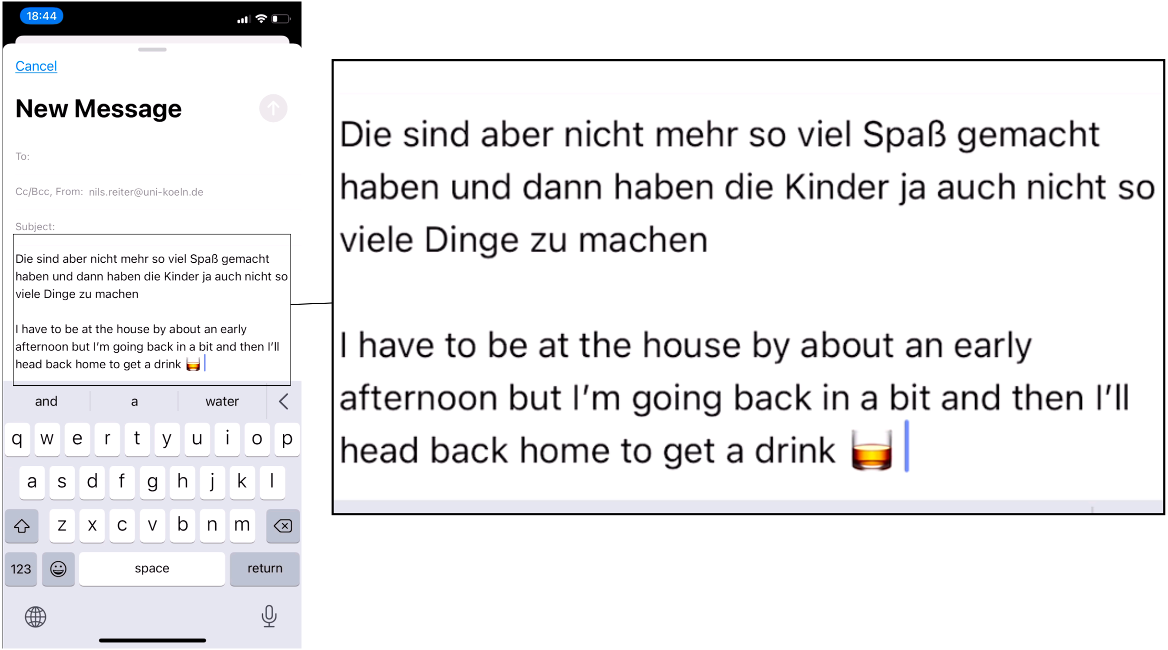
Example

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 (= ca. 50 MB)
  - Trigram model: $20\,000^3 = 8\,000\,000\,000\,000 = 8 \times 10^{12}$ parameters (= ca. 8 GB)
  - 4-gram model: $20\,000^4 = 1.6 \times 10^{17}$ parameters (= ca. 20 PB)

Again, a Compromise

- Longer n-grams would give better predictions
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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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  - Corpora.

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- Training
  - Count frequences of features from data
  - 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)

- Parameters that maximize probability on the training corpus
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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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$$
\begin{aligned}
p(\text{Bier und}) &= \frac{22}{1880232} \\
p(\text{Wein}|\text{Bier und}) &= \frac{p(\text{Bier und Wein})}{p(\text{Bier und})} \\
&= \frac{\frac{4}{1880232}}{\frac{22}{1880232}} \\
&= \frac{4}{1880232} \times \frac{1880232}{22} \\
&= \frac{4}{22} = 0.1818
\end{aligned}
$$

Application

- Training corpus used for estimating probability
- Test/application corpus used for using probability
- Never use the same corpus for training and testing

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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

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

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

- 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)

Smoothing

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- Goal
  - Prevent zero probabilities
  - Reserve some amount of probability mass for OOV words

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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?)

Neural Language Models

- Based on neural networks
- Efficient matrix handling
- Bidirectional
- Use of sub words
- Attention: Not all contextual words are equally important

Summary

- 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