# The UdS POS Tagging Systems @ EmpiriST 2015

#### Jakob Prange Andrea Horbach Stefan Thater

#### Saarland University, Saarbrücken

#### 3rd NLP4CMC Workshop, KONVENS 2016, Bochum



Projekt Schreibgebrauch Analyse und Instrumentarien zur Beobachtung des Schreibgebrauchs im Deutschen

J. Prange, A. Horbach, S. Thater, Saarland University

## Table of Contents





- Certain phenomena occur over and over in CMC
- Adding in-domain training data will help to cope with them

1st approach: "Retrain" [Horbach et al. 2014, 2015] TIGER + EmpiriST training set + "Schreibgebrauch" project training set



- Certain phenomena occur over and over in CMC
- Adding in-domain training data will help to cope with them

1st approach: "Retrain" [Horbach et al. 2014, 2015] TIGER + EmpiriST training set + "Schreibgebrauch" project training set



- Certain phenomena occur over and over in CMC
- Adding in-domain training data will help to cope with them

#### 1st approach: "Retrain" [Horbach et al. 2014, 2015]

Combine TIGER + EmpiriST training set + "Schreibgebrauch" project training set (boosted 5 times)



### 1st approach: "Retrain" [Horbach et al. 2014, 2015]

 $\label{eq:tight} TIGER + EmpiriST \ training \ set + \ ``Schreibgebrauch'' \ project \ training \ set \ (boosted \ 5 \ times)$ 

Pros

 $\checkmark~$  big performance boost

Cons

- $\times\,$  many words still not in training data
- $\times$  expensive to annotate more data

- unsupervised learning
- profit from large, raw in-domain data set
- assumption: words have the same POS tags as their distributional neighbours



- unsupervised learning
- profit from large, raw in-domain data set
- assumption: words have the same POS tags as their distributional neighbours



- unsupervised learning
- profit from large, raw in-domain data set
- assumption: words have the same POS tags as their distributional neighbours

#### 2nd approach: "Distributional" [Prange et al. 2015]

for each unkown word type:

- generate known candidates based on distributional similarity
- rank POS tags of candidates
- propose highest ranked POS tag(s) to the tagger

#### 2nd approach: "Distributional" [Prange et al. 2015]

for each unkown word type:

- generate known candidates based on distributional similarity
- rank POS tags of candidates
- select highest ranked POS tag(s) to the tagger

## Pros

- $\checkmark\,$  no additional manual annotation
- $\checkmark$  covers more words

### Cons

- $\times\,$  local context not considered
- $\rightarrow\,$  multiple readings of one word cannot be distinguished (only indirectly via off-the-shelf tagging software)

J. Prange, A. Horbach, S. Thater, Saarland University

• assumption: unknown words are often misspellings and similar to their intended forms

#### 3rd approach: "Surface"

for each unkown word type:

• generate candidates based on string-similarity

for each unkown word token:

- rank candidates in context by language model
- replace unknown word with highest ranked candidate

# Revisiting our Submissions

• assumption: unknown words are often misspellings and similar to their intended forms



#### 3rd approach: "Surface"

for each unkown word type:

• generate candidates based on string-similarity

for each unkown word token:

- rank candidates in context by language model
- replace unknown word with highest ranked candidate

## Pros

- $\checkmark\,$  no additional manual annotation
- $\checkmark\,$  local context considered

## Cons

- $\times\,$  very small performance boost, if any
- $\times\,$  "overcorrection": not only typos, but also lexical gaps are replaced



## Afterthoughts and Ideas for the Future

• influence of data vs influence of algorithm

## Afterthoughts and Ideas for the Future

- influence of data vs influence of algorithm
- oracle experiment shows there is room for improvement with an ideally combined system

<ロ> < 団> < 豆> < 豆> < 豆> < 豆 > < 豆 の へ ? 15/16

## Afterthoughts and Ideas for the Future

- influence of data vs influence of algorithm
- oracle experiment shows there is room for improvement with an ideally combined system
- new particle tags are problematic also for humans? Would it help to re-annotate TIGER with STTS 2.0?

<ロ> < 団> < 豆> < 豆> < 豆> < 豆 > < 豆 の へ ? 15/16

## Afterthoughts and Ideas for the Future

- influence of data vs influence of algorithm
- oracle experiment shows there is room for improvement with an ideally combined system
- new particle tags are problematic also for humans? Would it help to re-annotate TIGER with STTS 2.0?
- action words are problematic (morphological) preprocessing? Tokenisation?

< □ > < □ > < Ξ > < Ξ > Ξ · · ○ Q · · 16/16

# Thank you!

software available under http://www.coli.uni-saarland.de/projects/ schreibgebrauch/de/page.php?id=resources