# Evaluation of German NER Tools on Medical Admission Notes

## AP: NER tools for German medical text SoSe 2017

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# Content

# NER in Medical Texts

In comparison to other domains, named entity recognition (NER) on German medical texts is still an almost unexplored research area.
*(Sterlinger 2016)*

# Problem Definition

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- Challenges in German syntax (capitalization, morphology)
- Still just a few cooperations between medical and computer science institutions

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- Occasionally even hand-written
- Sometimes semi-structured
- Contain non-standarized and ambiguous abbreviations
- Varying and sometimes even locally specific terminology

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- Evaluation of these models on medical admission notes
- Assessment of the valuability of these tools for anonymization of medical texts

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- Today we focus on evaluation of this tool on medical admission notes

# Tools

- Python 3 (comfortable handling of UTF-8 text)
- German Stanford NER *(Pado 2010)*
- Stanford PTBTokenizer (Tokenizing the medical texts)
- Bash tools for preprocessing and corpus analysis
- extract_corpus.py (Create new corpus from GermaEval, CoNLL and EP and mixes in medical entities)
- evaluation.py (Evaluation script using Scikit Learn library)
- several converter script, for converting GermEval, CoNLL and European Parliament data into Stanford NER compatible data

# Non-medical Training Data

- Bypassing lack of annotated medical texts by using out-of-domain data

| | |
|---|---|
| LOC | Locations |
| ORG | Organizations |
| PER | Persons |

Table: Named entity classes

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- Combining existing data sets to get larger training sets.
- Two German training corpora typically used in German NER research
- As named entity classes we adapted the classes used in the CoNLL 2003 corpus. (exluding MISC class)

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Table: Named entity classes

# CoNLL 2003

- **German CoNLL 2003**: Selected texts from German newspaper Frankfurter Rundschau
- 206.931 tokens in 12.705 sentences

| LOC | ORG | PER |
|---|---|---|
| 4.363 | 2.427 | 2.773 |

Table: Absolute amount of entity tokens per entity in CoNLL 2003

# GermEval 2014

- **GermEval 2014** data set contains text from German Wikipedia articles and online news texts
- 590.000 tokens in 24.000 sentences

| LOC | ORG | PER |
|---|---|---|
| 12.791 | 9.889 | 12.423 |

Table: Absolute amount of entity tokens per entity in GermEval

In addition we used a small data set (around 20.000 tokens) from the European Parliament annotated by Sebastian Pado.

# MEDICATION Class

- As a sub-task we mixed in a list of drugs often used in cardiology
- Randomly inserted fixed amount of drugs **without semantic context** into the data set and annotated these as 'MEDICATION'

## Example extract with MEDICATION class

| | |
|---|---|
| Barack | LOC |
| Obama | LOC |
| erhält | O |
| Aspirin | MEDICATION |
| Friedensnobelpreis | MISC |
| . | O |

Table: MEDICATION entity token including class label

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Our medical data in this project consists of medical admission notes.

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- Let us have a look at an example

# How does a Medical admission note look like?

Sehr geehrte Kollegen,

wir berichten über Ihre Patientin <PER>, geboren am <DATE>, wh. <LOC>, die sich am <DATE> in unserer Ambulanz vorstellte.

Diagnosen:
Aktuell: Operabilität mit leicht erhöhtem Risiko gegeben

Z.n. 2x Herzkatheter-Untersuchung, zuletzt <DATE> (anamnestisch
Z.n. HWS-Eingriff <DATE> (<LOC>), Versuch der Stabilisierung
Anamnestisch OP bei intracranieller Blutung <DATE>

Anamnese:
Die Vorstellung der Patientin erfolgte zur präoperativen kardiologischen Abklärung vor geplanter HWS-Operation. Die Patientin berichtet von reduzierter körperlicher Belastbarkeit im Alltag (2 Etagen, NYHAII-III) auch beim Bergauflaufen Belastungsdyspnoe, im Verlauf jedoch konstant, keine belastungsinduzierten pectanginösen Beschwerden.

Kardiovaskuläre Risikofaktoren: Arterielle Hypertonie, Nikotin (sistiert vor 20 Jahren, 2PY), Diabetes mellitus Typ 2 (diätetisch eingestellt)

# Medical Data

Following basic structure in majority of notes

- Header

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- Header
    - Addressee

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- Salutation

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- Diagnosis
- Cardiovascular risk factors
- Allergies
- Anamnese
- Physical examination (Körperlicher Untersuchungsbefund)
- Laboratory data (some in tabular structure)
- ECG
- Recommended therapy
- Summary

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Charecteristics of medical admission notes

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- Amount of text varying a lot
- Sometimes free unstructured text, sometimes tables
- Often subsections are titled differently, but contain similar informations
- Concluded by salutation and names of involved physicians.

# Medical Data

- Time period: 2004-2016

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- Total amount of tokens: 132 *Million*

# Training and Experiments

- Trained three NER models

| | LOC | ORG | PER | MEDICATION |
|---|---|---|---|---|
| ConLL2003+GermEval+EP | 18.131 | 14.303 | 17.036 | 2.808 |
| GermaEval+EP | 12.892 | 10.061 | 12.541 | 2.808 |
| ConLL2003+EP | 5.340 | 4.414 | 4.613 | 2.808 |

Table: Amount of entity tokens in training set incl. MEDICATION entities

# Evaluation

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| 18 | 25 | 22 | 9 |

Table: Absolute number of tokens per class in test set

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- Used scores are precision and recall with macro average

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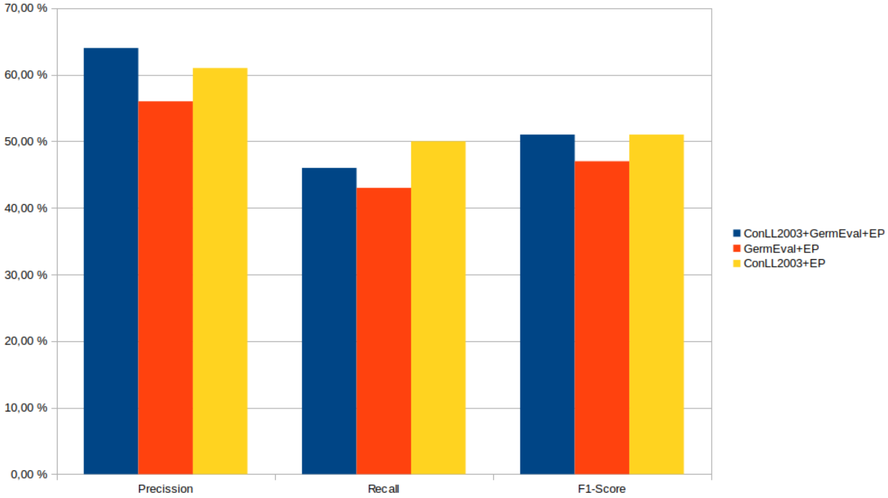
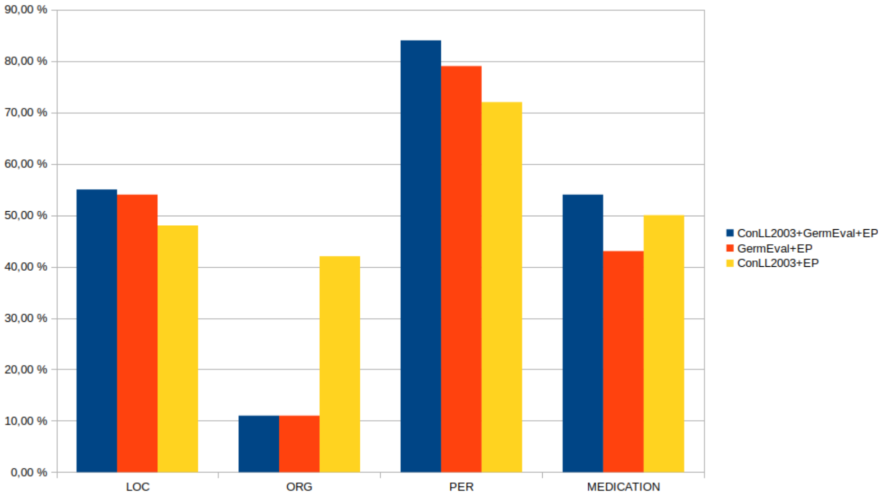
- Evaluation is token-wise not entity-wise, due to limited data

# Evaluation Macro Average



# Evaluation per NE



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- LOC and MEDICATION recognition as well reasonable performance
- ORG recognition score in two data sets very low

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Possible explanations for scores:

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Possible explanations for scores:

- PER entities look similar in test and trainings set
- LOC entities are similar to a lesser extend
- ORG entities have different shape in newspaper texts and medical texts

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# Summary

- Out-of-domain trained NER models have reasonable performance on medical texts
- Further research and annotation work on medical texts is needed
- To do meaningful information extraction data need to be anonymized
- Goal is to keep as much as possible semantic and syntactic structure
- My BA thesis will implement an Anonymizer based on *Yuwono/TouNg* and the NER model trained in this project

# References


- Yuwono, Steven Kester and Ng, Hwee Tou (2016):
  Automated Anonymization as Spelling Variant Detection.
- Starlinger, Johannes and Kittner, Madeleine and Blankenstein, Oliver (2016):
  How to improve information extraction from German medical records.
- Richter-P., Phillip (2017):
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  https://github.com/MaviccPRP/ger_ner_evals/.

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