Neural networks at hate speech and offensive language detection with a focus on linguistic features

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Hate Speech (HS) and Offensive Language (OL) Detection

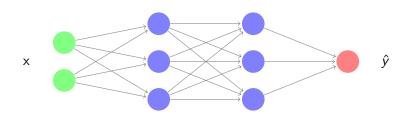


Need for automatic detection in social media posts

- What is offensive and to whom?
- How is OL/HS defined?
 - \rightarrow Not clear (even to humans), complex problem
- Empirical approach:
 - gather (multiple) human assessments of actual data
 - learn model on this data using machine learning
 - automatically find patterns of HS/OL

Why Neural Networks (NNs)?





NNs learn highly **complex** function f: $f(x) = \hat{y}$

- Based on raw input, no predetermined features
 → can learn variety of features/combinations themselves
- Identify helpful input features for the classification task
- Complex combinations of features

Linguistic Features in Neural Networks



Motivation

- NN approaches: purely statistical, processing of signal data
- Linguistic utterances → contain structure
- Support the NN (careful: not predetermined features! only as additional input)
- Basic principle of CL: statistical processing with the inclusion of linguistic knowledge!

Overview

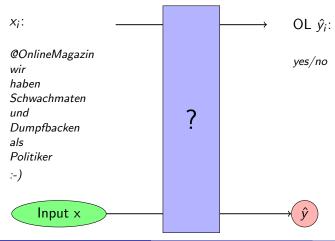


| Methods: Neural Network Systems Extensions using Linguistic Features Future Work: Further Features to detect HS/OL | 6 |
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| | 12 |
| | 14 |

Offensive Language Detection Task

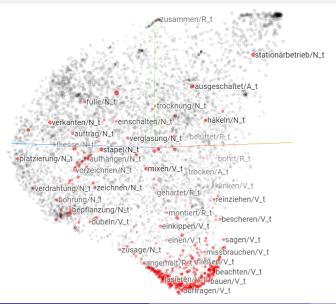
Stillers II

Encoding the Input Sequences (Text)



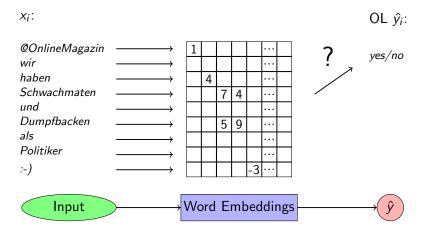
Semantic Representation of Words





Encoding the Semantic Representations

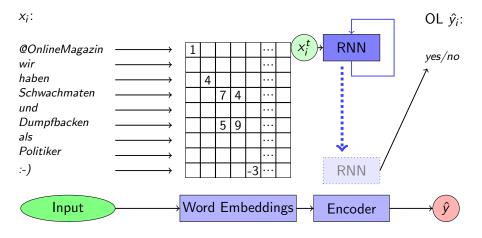








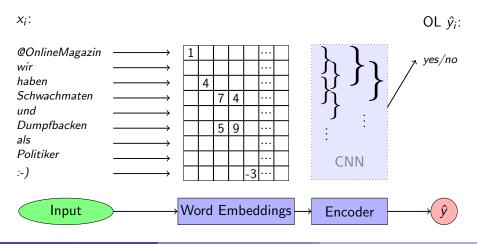
Recurrent Neural Network (RNN) using Long Short-Term Memory (LSTM) cells



Learning on N-Grams

Siversitation of the state of t

Convolutional Neural Network (CNN)



Performance of the Architectures



Results on the GermEval-2018¹ test dataset

- Recurrent NN (RNN) using Long short-term memory (LSTM) units: Learning representations on sequences $F_{1,\text{macro-avg}} = 70.66 \%$
- Convolutional Neural Network: Learning representations as combination of n-grams $F_{1,
 m macro-avg} = 71.14~\%$
- \Rightarrow Usually only part of message offensive \rightarrow trigger

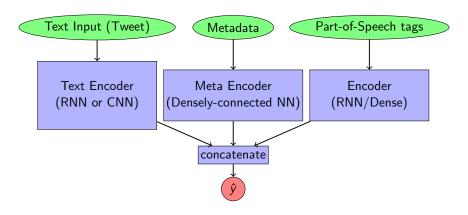
¹https://projects.fzai.h-da.de/iggsa/

Additional sub-networks



Overall NN architecture

extended from Founta et al. 2018



Results:

Metadata sub-network - improvements; minimal with POS tags

Considering Word Components



Motivation

- Pre-trained word embeddings (initial weights)
- OOV words
 (Politidioten, Oberdummzicke, Sozialschmarotzer, Migrantenpack)
- First implementation:
 Handle compounds as seperate words assuming compositionality

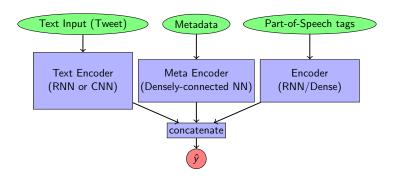
Performance using compound splitting

CNN on word component embeddings:

 $F_{1,\text{macro-avg}} = 73.42 \%$

Where to integrate linguistic features?





Effect of additional features in parallel sub-networks is low

ightarrow Linguistic features directly in the text encoding!





Sophisticated analysis necessary for automatic offensive language and hate speech detection

- Offensive language hidden in words or multi-word constructions
- What NN approaches and linguistic features can be discussed to analyze political discussions in particular?
- Possibilities to include the target/victims (detection of typical groups)

References



- Johannes Schäfer. HIIwiStJS at GermEval-2018: Integrating Linguistic Features in a Neural Network for the Identification of Offensive Language in Micropost, In Proceedings of the Workshop Germeval 2018 – Shared Task on the Identification of Offensive Language. Vienna, Austria. September 21, 2018.
- Michael Wiegand, Melanie Siegel, and Josef Ruppenhofer. Overview of the GermEval 2018 Shared Task on the Identification of Offensive Language. 14th Conference on Natural Language Processing KONVENS 2018. 2018.
 - https://projects.fzai.h-da.de/iggsa/, Results: https://github.com/uds-lsv/GermEval-2018-Data.
- Antigoni-Maria Founta, Despoina Chatzakou, Nicolas Kourtellis, Jeremy Blackburn, Athena Vakali, and Ilias Leontiadis. A unified deep learning architecture for abuse detection. CoRR, abs/1802.00385. 2018.