HAU at the GermEval 2019 Shared Task on the Identification of Offensive Language in Microposts System Description of Word List, Statistical and Hybrid Approaches

Johannes Schäfer¹, Tom De Smedt², and Sylvia Jaki³

¹ Institute for Information Science and Natural Language Processing, Hildesheim
² Computational Linguistics Research Group, University of Antwerp

³ Department of Translation and Specialized Communication, U. of Hildesheim

Jaivers/zaz

johannes.schaefer@uni-hildesheim.de, tom.desmedt@uantwerpen.be, jakisy@uni-hildesheim.de

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Motivation



Best performing systems from last year:

From our research:

Manually created/annotated word list



 \rightarrow combination possibilities?

POW Lexicon



| 2 Offensive Language Detection Systems | 10 |
|--|----|
| • POW - HAU2 | 10 |
| • RF - HAU3 | 11 |
| • CNN - HAU1 | 12 |
| 3 Results, Conclusion and Outlook | 16 |



| 1 POW Lexicon | 4 |
|--|----|
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| POW - HΔII2 | 10 |

3 Results, Conclusion and Outlook 1

Overview POW List



Profanity and Offensive Words (POW)

- Manually annotated dictionary which allows for the quantitative analysis of hate speech in a dataset
- Decision to work with a dictionary result of GermEval 2018
- List of 2852 words, mainly taken from German Twitter Embeddings (Ruppenhofer, 2018)
- Words either often used tendentiously in political contexts or vulgar/offensive

POW List: Types of Words



Word classes (mostly)

- Nouns (*Lüge, Wesen, Arsch, Firlefanz*), incl. compounds (*Fremdenfeind, Lügenpresse*)
- Also: adjectives (blöd, links-grün) and participles (verblendet)
- Infinitives (hetzen, spucken) and imperatives (lutsch, laber)
- Interjections (mimimi, boah)

Separate entries (tokens)

- Declensions (Dreckschwein, Dreckschweine)
- Conjugations (labern, laber, labert)
- Spelling variations (schreien/schrein, scheiß/scheiss/scheis/chice)

POW List: Annotation

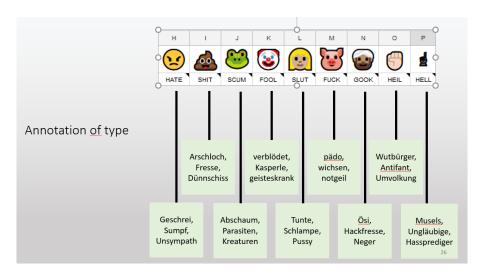


Annotation of intensity

- tendentious (nichtmal, religiös, AfDler, Staub, Übergriffe)
- tendentious, sensational (heulen, unkontrolliert, Extremisten)
- ② demeaning (Schnauze, stupide, Systemparteien, antideutsch)
- **offensive (vulgar, racist)** (verblödet, Dreck, Honk, Lügenpresse)
- offensive (extremely so) (Hure, Untermenschen, Drecksau)

POW List: Annotation of Types





POW List: Difficulties



Context-dependence

- Intensity (honk, verrecken, hurensöhne)
- Polarity (bunt, willkommenskultur, fachkräfte)

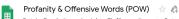
Type

- Lexial ambiguity (geil, sack, fickt, würgen, schwuler, dödel, muschi)
- Grammatical ambiguity (quatsch, blase, leeren, ritze)
- \Rightarrow Pragmatic solution:

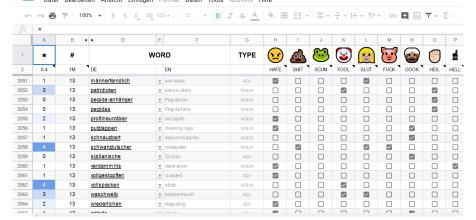
Possibility for contextualisation by direct link to social media

POW List





Datei Bearbeiten Ansicht Einfügen Format Daten Tools Add-ons Hilfe





| 10 |
|----|
| 10 |
| 11 |
| 12 |
| |

Results, Conclusion and Outlook



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- POW HAU2
 - RF HAU3CNN HAU1
- 3 Results, Conclusion and Outlook

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System HAU2: POW List Lookup





Motivation:

Word lists are very explainable (cf. "black boxes") and precise

Method:

- For each message, check if it has words that are also in the POW list
- ullet Compute the sum of the score of those words > threshold \Rightarrow offensive
- Mapping of intensity annotation (0-4 in POW list):

0
$$\rightarrow$$
 0.1, $~$ 1 \rightarrow 0.25, $~$ 2 \rightarrow 0.5, $~$ 3/4 \rightarrow 1.0

• For example:

"Ungebildetes, kulturloses Gesindel führt Deutschland vor!" \rightarrow ungebildet (0.5) + gesindel (1.0) = 1.5 > 0.95 \Rightarrow offensive

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Results:

Low recall for OFFENSE: 37.11% (lexicon should be expanded)



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- POW HAU2 • RF - HAU3
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System HAU3: Random Forest



- Motivation:
 - among last year's best systems, use as comparative baseline
- Python algorithm: https://github.com/textgain/grasp
- **Features**: character trigrams + word unigrams
- 100 trees, each with a random subset of 750 features



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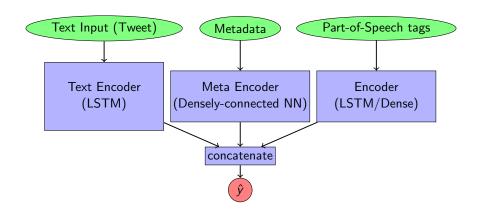
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Starting Point: NN Architecture

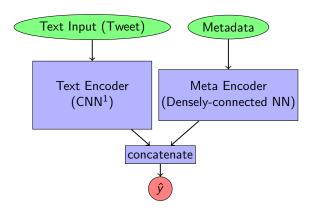
Schäfer (2018) at GermEval 2018; extended from Founta et al. (2018)



Our Basic NN Architecture for GermEval 2019



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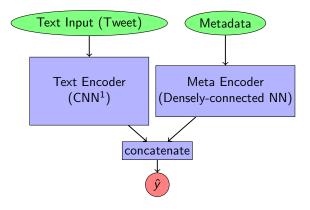
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¹CNN configuration as described in Schäfer and Burtenshaw (2019)

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Our Basic NN Architecture for GermEval 2019



ML improvements: early stopping; class weights

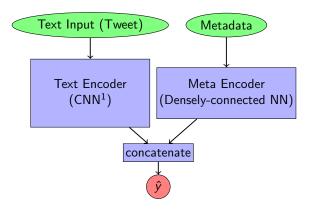
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Our Basic NN Architecture for GermEval 2019



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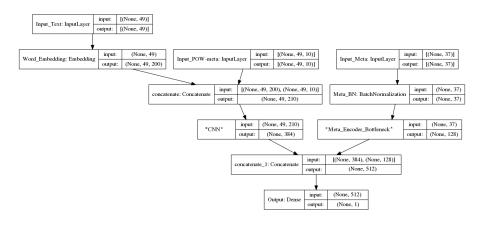


- ML improvements: early stopping; class weights
- → POW list features?

¹CNN configuration as described in Schäfer and Burtenshaw (2019)

HAU1: CNN + POW List Model





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Results on the GermEval Training Dataset

Average scores from 3-fold cross validation (values in %):

| System configuration | Accuracy | | F ₁ -score | |
|--------------------------|----------|-------|-----------------------|-------|
| | | OTHER | OFFENSE | mavg. |
| CNN | 76.25 | 83.02 | 60.47 | 71.98 |
| CNN + meta | 76.10 | 82.23 | 63.43 | 72.84 |
| $CNN + meta_{POW}$ | 78.15 | 83.77 | 66.56 | 75.17 |
| $CNN_{POW} + meta$ | 76.67 | 82.62 | 64.45 | 73.56 |
| $CNN_{POW} + meta_{POW}$ | 78.87 | 84.62 | 66.21 | 75.46 |



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- _

Results, Conclusion and Outlook

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Overview System Runs HAU1-3 for Tasks 1-3



F₁-scores on the GermEval 2019 test dataset

Subtask I (OL detection):

| HAU2 (POW list lookup) | 68.13% |
|-------------------------------|--------|
| HAU3 (random forest) | 69.75% |
| HAU1 (CNN+meta including POW) | 70.46% |

Subtask II (fine-grained OL detection):

| HAU3 (random forest) | 40.80% |
|-------------------------------|--------|
| HAU1 (CNN+meta including POW) | 45.34% |

Subtask III (implicit/explicit):

HAU1 (CNN+meta including POW) 69.3%

Conclusion



Based on our results:

- Simple word list lookup approach is not that bad!
- Statistical ML approaches (CNN here) improve considerably when combining it with word list

Outlook



Future Work:

- Normalization
- Other neural approaches, e.g. contextualized character embeddings
- Linguistic features
- Outlook: further collaboration in EU-project DeTACT (Detect Then ACT: Taking Direct Action against Online Hate Speech by Turning Bystanders into Upstanders)

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