

Offensive Comment Classification on German Language Microposts

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Abstract

In this paper, we present two deep-learning based classifier systems for the identification of offensive comments in German Language microposts: A bidirectional LSTM and a CNN model. We compare the performance of our systems with a traditional, machine-learning based SVM classifier and evaluate our approach on Task 1 (binary classification) of the GermEval 2018 shared task where our best model (CNN) is able to reach a F1 score of 91.08%.

1 Introduction

Modern communication devices and social media play an increasingly important role in our daily lives and the Internet has created tremendous opportunities for exchanging information with people from all over the globe in real-time. Unfortunately however, this freedom gets frequently abused, and hate speech and toxic comments are present in virtually all online communities. A 2017 report by Pew Research even came to the conclusion that up to 41% of all adults have personally experienced online harassment (Duggan, 2017).

Automated detection routines to identify and block toxic messages have proven to be viable methods in shielding online communities from harassment (Wulczyn et al., 2017). Training a computer to understand the emotions and opinions expressed in a document is a common task in the area of Natural Language Processing (NLP), and the results from previous publications (Georgakopoulos et al., 2018) as well as a Kaggle competition¹ sponsored by Google Jigsaw have already shown promising

results for the identification of toxic content in online messages.

The intention of this paper at hand is to create a series of deep-learning based neural network models to compete in Task 1 (binary classification) of the GermEval 2018² competition. The GermEval 2018 competition is a shared task for the identification of offensive comments in German language microposts. For our research, we choose a simple Support Vector Machine (SVM) model as a baseline and compare its performance against our implementations of a bidirectional Long Short-Term Memory (LSTM) and a Convolutional Neural Network (CNN) model.

2 Related Works

So far, most of the research in the area of toxic comment classification has been focused on English language, and a variety of machine-learning and deep-learning models have been produced to tackle this problem (Schmidt and Wiegand, 2017). Amongst others, Georgakopoulos et al. (2018) used a deep-learning based CNN model to detect toxic language in online content. Nobata et al. (2016), on the other hand, developed a machine-learning model using a variety of feature classes (N-grams, Syntactic Semantics etc.) and were able to outperform existing deep-learning based approaches. Other research by Razavi et al. (2010) used multi-level classification to detect offensive comments, mainly in Usenet messages.

The identification of toxicity in German language messages has received less attention by the research community so far, and comparable research results are sparse. In the related domain of sentiment analysis for tweets, Cieliebak et al. (2017) created a corpus consisting of 10.000 tweets in German language and provided benchmarks for the classi-

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¹Toxic Comment Classification Challenge
<https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge>

²GermEval 2018 - Shared Task on the Identification of Offensive Language - <https://projects.cai.fbi.h-da.de/iggsa>

fication of these tweets into sentiment classes of either *positive*, *negative* or *neutral* using a CNN.

3 Data

Before training our systems, we first obtain the training set from the GermEval 2018 competition mailing list. The training set contains a total of 5009 messages which have been labeled either *OFFENSE* or *OTHER*. A detailed breakdown of the class distribution in the dataset is presented in Table 1.

Dataset	Offense	Other	Total
Training set	1688	3321	5009

Table 1: Class distribution - GermEval 2018 dataset

The dataset is imbalanced, and the majority of the tweets (66%) belong to the neutral class, whereas the remaining data (34%) belongs to the offensive class. The microposts within the dataset were extracted exclusively from Twitter³ because the conference organizers regarded tweets “as a prototypical type of micropost”².

4 Experimental Setup

We present two classification systems in our research: a bidirectional LSTM model and a CNN model. Both models were implemented in Python and make use of the Keras library (Chollet, 2015) for training the classifier. In addition, we create a SVM classifier using Scikit-learn (Pedregosa et al., 2011) and consider this as a baseline for testing and improving our deep-learning models. The experiments were performed on a workstation running Ubuntu 16.04 with 64 cores and 128 GB of RAM. For this research we use the word vectors published by Deriu et al.(2017). These vectors were trained on a total of 200 million tweets and have a dimensionality of $d = 200$.

Preprocessing: Before extracting features, we first preprocess the data according to the following procedure:

1. Replace URLs, usernames and retweets with replacement tokens *URLTOK*, *USRTOK* and *rt*
2. Convert tweet text to lowercase

3. Convert categorical classification variables into an One-Hot encoded vector
4. Tokenize tweets (using Keras’s builtin Tokenizer) and create a list of word indexes with length $l = 100$ (comments shorter than 100 are padded with 0)

For further reference, a preprocessed tweet is presented in Example 4.1.

Example 4.1:

Original: @salzmanufaktur @Renft1964 Jetzt bekommt Merkel noch Grüne Untergangs-Beschleuniger dabei!

Preprocessed: USRTOK USRTOK jetzt bekommt merkel noch grüne untergangs-beschleuniger dabei!

5 System Description

After preprocessing, we feed the data into our classification models: a bidirectional LSTM and a CNN model. By using the word vectors from Deriu et al., we create an embedding matrix where we randomly initialize the words that are not in the word embeddings with the arithmetic mean and standard deviation obtained from the embeddings. The resulting embedding matrix has the size of $|\vec{w}_1; \dots; \vec{w}_L| \in \mathbb{R}^{L \times 200}$ with L being the number of unique words in our training set.

While training our models, we try to minimize the binary cross entropy loss on the training set given per the formula below:

$$-\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (1)$$

The final outputs of the models are connected to a softmax regression layer which returns the class $\hat{y} \in [1, K]$ with the largest probability

$$\hat{y} = \arg \max_j P(y = j | \mathbf{x}) = \frac{e^{\mathbf{x}^T \mathbf{w}_j}}{\sum_{k=1}^K e^{\mathbf{x}^T \mathbf{w}_k}} \quad (2)$$

where w_j denotes the weight vector for class j . For the optimization step, we choose the *Adam* optimizer (Kingma and Ba, 2015) with a learning rate $lr = 0.001$, $\beta_1 = 0.99$, $\beta_2 = 0.999$ and $\epsilon = 1^{-8}$.

5.1 LSTM Model

The LSTM model in this research was derived from the works of Hochreiter and Schmidhuber (1997). So far, LSTM networks have been successfully applied in a variety of tasks such as Machine Translation (Sutskever et al., 2014) and Image Captioning

³Twitter social network - <https://twitter.com>

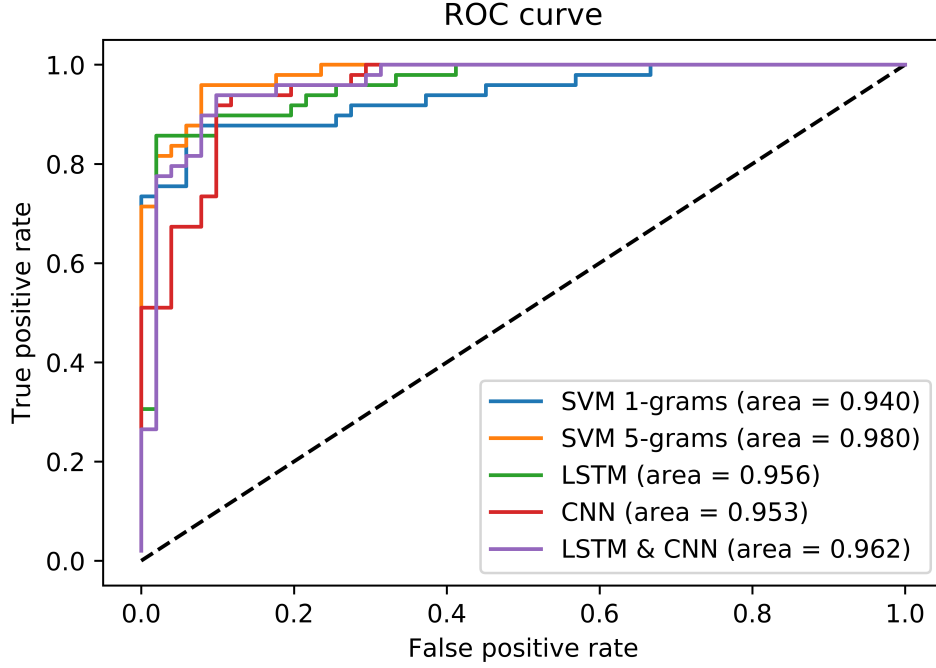


Figure 1: Comparison of ROC metric for our models (PLACEHOLDER)

(Vinyals et al., 2015). Recent research however shows that LSTM models also perform well when applied to NLP tasks such as text classification (Zhang et al., 2015; Zhou et al., 2016).

In this paper, we employ a bidirectional LSTM model with 64 units. The output is passed to two fully connected layers with 64 and 2 units respectively. To prevent our model from overfitting, we apply the early-stopping technique (Prechelt, 1998) in combination with a dropout of $d = 0.5$ after the first dense layer as well as on the recurrent input signal of the LSTM units (Gal and Ghahramani, 2016). We furthermore use Rectified Linear Unit (RELU) as the activation function of the first hidden layer (Srivastava et al., 2014; Glorot et al., 2011).

5.2 CNN Model

The CNN model used in this research builds on the work of Kim (2014) who proposed to use a 2 layered CNN to perform sentence classification in NLP tasks. We create our model by using 1 convolutional layer with 64 filters (one layer consists of a convolution and a pooling layer). The output of the convolutional layers is then fed into one dense layer of 64 units. As in the previous model, we again make use of the RELU function for the activation of the layer and apply early-stopping in combination with a dropout of $d = 0.5$.

5.3 Ensemble

To further improve the overall performance, we create an ensemble by combining the results from the LSTM and the CNN model. To create the ensemble, we average the probability outputs from both models and apply the *argmax* function to obtain the binary outputs. We then use these predictions for the final submission run of the GermEval 2018 task.

5.4 SVM Model

As a baseline for the evaluation of our results, we use a simple SVM classifier trained on Term-Frequency times Inverse Document-Frequency (TF-IDF) vectors (Ramos, 2003) of the tweets in the dataset. The TF-IDF scores were calculated by using the count matrices of 1-grams and 5-grams where the tweet texts serve as input tokens. The classifier uses Stochastic Gradient Descent (SGD) with the logistic regression loss function where we multiply the regularization term with a constant $\alpha = 1^{-5}$.

6 Results

Since the official test set will only be published by the task organizers on July 17, 2018, the authors of this paper used a sample set with size $n = 100$ obtained from the conference website to conduct their preliminary experiments. Once the official test

data is published, this section will be updated and the final results will be submitted to the shared task.

For the evaluation of our models, we use the script provided by the competition organizers to calculate the F1-score on the test set (size $n = 100$). In Table 2, we present the F1-scores for each category. We further marked the best result in bold face.

The CNN model achieved best results on the given dataset (F1 score of 91.08), followed by the LSTM and SVM model using 5-grams (both reach a F1-score of 90.49). In comparison to that, the ensemble (with a F1-score of 88.46) performs poorly in comparison to the SVM classifiers. We consider this result surprising, since we were actually able to create pretty good classifiers by just calculating the TF-IDF vectors on n-grams obtained from the tweet texts.

	Offense	Other	Average
SVM (1-grams)	85.71	88.07	87.33
SVM (5-grams)	88.89	90.91	90.49
LSTM	88.89	90.91	90.49
CNN	91.09	90.01	91.08
LSTM & CNN	86.67	89.09	88.46

Table 2: F1-Scores per Category

To evaluate the output of our classifiers, we further included a Receiver Operating Characteristic (ROC) curve metric in Figure 1 where we calculated the Area Under Curve (AUC) score for each of our classifiers. As we can see, the SVM model trained on 5-grams generally outperforms our collection of deep-learning based classifiers. The ensemble, created from the LSTM and CNN classifiers, achieves the second-best AUC score, followed by the SVM where we used 1-grams.

Overall, and given the current excitement about the use of deep-learning based classifiers for NLP tasks, we consider these results surprising. Even though we provided the SVM classifier with only one feature (TF-IDF), it was able to achieve very promising results and outperformed our deep-learning systems.

Once the official test data is released, we will update this section with an in-depth discussion of the results.

7 Conclusion

The objective of our participation in the GermEval 2018 shared task was to evaluate the performance of deep-learning based models on the classification of offensive language in German microposts. While using a SVM classifier as a baseline, we presented two deep-learning based systems and evaluated their results on the given dataset: a bidirectional LSTM model and a CNN model. As a result from this research, we have shown that our CNN model outperforms the LSTM model on the given GermEval dataset.

We hope that online social network platforms can use our results to build systems that can successfully detect and combat toxicity in online conversations. Services such as the Perspective API ⁴ are taking a step into the right direction, and we expect to see more fascinating research for making the Internet a more friendlier and welcoming place.

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⁴Perspective API - <https://www.perspectiveapi.com/>

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