In this literature review, we looked both papers from GermEval 2021 and elsewhere. We did not constrain our review to papers on German language alone, but extended that to other languages. We will first start with the reviewing approaches taken at GermEval2021 and then review approaches elsewhere.

GermEval2021

In GermEval2021, a hand curated small dataset of online German comments was created, and the task was to categorize it under three categories: toxic comments, fact claiming, and engaging

The majority of the participants used transformers along with other techniques. While some teams in GermEval2021 reported benefits of multi-task learning, other teams reported that there was no benefit in the tasks. Also, the addition of synthetic data, and augmenting data from other sources had mixed results.

Calizzano et. al[[1]](#endnote-1) used XLM-RoBERTa and MT5, both of which are transformers. They pre-trained the transformer on the dataset and that resulted in a 10% improvement in F1-score. They also used data augmentation via two different methods: (1) training on other multi-lingual datasets that include German comments and (2) created a dataset of Facebook comments by classification with a model and keeping the comments classified as toxic or non toxic with a probability of larger than 0.8. However, they found that data augmentation was not very helpful, and in some cases, it actually reduced the accuracy. This could, however, be due to the fact that their method of augmentation relied on another classification network. They reported F1-scores in the ball park of 0.68

Schaefer and Stede [[2]](#endnote-2)used a used BERT encodings and classified them using three techniques: (1) SVM, (2) XGBoost and (3) another Transformer-based classification network. They found that BERT+SVM performed better on the test-set but Bert+Transformers performed better on the evaluation set. They report an F1-score of between 0.69 and 0.736.

Hilderbrandt et al. used ensembles of Logistic Regression and SVM classifiers. For feature extraction, they used a combination of German BERT encodings from a huggingface model and AdHominem[[3]](#endnote-3). They report F1-scores between 0.66 and 0.72.

Tran and Kruschwitz[[4]](#endnote-4) use BERT encodings from XLM-RoBERTa and use an ensemble classifier with majority voting. They also try to translate German text to English and then apply transformers to it before ensembling with majority voting. They also use several BERT based models for classification which are then ensembled by majority voting. Overall, they report F1-scores between 0.68 and 0.76.

Böck et al[[5]](#endnote-5) use a compare mBERT, XLM-R and GottBERT in the task of fact claiming detection and find that GottBERT performs the best. They augment the dataset by using the ClaimBuster dataset. They also augment the dataset further by translating other datasets from English to German. Overall, they report F1-scores in the ball park of 0.74.

Gémes and Recski[[6]](#endnote-6) use Rule-based and hybrid methods for detecting Toxic, engaging and fact-claiming comments. They find that for toxicity detection, if a sentence contains at least two words with at least 4 characters each written in caps, a rule to detect this achieved 91% precision and 4% recall on its own on the validation set. They searched for patterns in toxic comments with unigrams, bigrams of words and lemmas with and without POS tagging for disambiguation. By carefully hand-crafting rules, they were able to achieve F1-scores between 0.79 and 0.82.

Schmidhuber[[7]](#endnote-7) approached GermEval2021 by attempting to generate synthetic data to augment the given data, and classify it using mBERT. It was found that synthetic data actually reduced the performance of the system. Overall F1-scores of 0.618 and 0.615 were reported for the model without and with synthetic data.

Schütz[[8]](#endnote-8) et al. performed toxic comment detection by using BERT and augmenting the data with a set of 1 million tweets. They further enriched BERT encodings with hand-crafted features like word-count, punctuation-count, exclamation-count, questionmark-count, ratios between punctuations, emoji-count, word-emoji ratio etc. They also counted the number of hate-words and hate word count ratio using a list of hate words. They also used a dictionary of words to detect the “sentiment” feature. They were able to achieve an F1-score of 0.74 on the validation data.

Haak and Engelmann[[9]](#endnote-9) classify for toxicity by extracting features and classifying with Logistic Regression, Support Vector Classification, Linear SVC and multi-layer perceptrons. Their features account for smileys, questions, emojis, caps, short sentences and ellipses. They also Snorkel[[10]](#endnote-10) to determine coverage, overlps, conflicts and empirical accuracy. They find that SVC and Linear Regression perform the best, however, they report F1-scores in the range of 0.51 to 0.57 only. Panda and Levitan[[11]](#endnote-11) generated embeddings using transformers and then experimented with logistic regression and linear classifiers. They found that multi-task learning did not improve the performance of the classifiers. Akomeah et al.[[12]](#endnote-12) build on the work by Hoffman and Kruschtitz[[13]](#endnote-13) used transformer-based encodings and LSTMs and then used these with either SVM or ANN classifiers which were finally ensembled.

Arjun et al.[[14]](#endnote-14) use the embeddings obtained by different methods, and using those embeddings with a classifier to perform all three tasks. They try both embeddings obtained from both Glove and Transformers. As the classifier, they try four different approaches: CNNs, Capsule Networks, RNN/GRU and Ensembles. They also enrich the encodings by hand-crafted features like number of words, urls, punctuations, all-cap words, positive and negative words, moderator mentions and distribution of emojis. They find that ensembles perform the best. They report F1-scores in the range of 0.66 and 0.74.

Gawron and Schmidt[[15]](#endnote-15) compared nine pre-trained transformers and compared the performance, and found that GELECTRA and GBERT perform the best. They also tried to add data from previous GermEvals but that reduced their overall accuracy and F-score.

Morgan et al.[[16]](#endnote-16) used transformer based classifiers and found that multi-task learning yields better results than single-task learning. This may be because the tasks of toxicity detection, fact-claiming detection and engagement detection may rely on similar underlying features, and thus may benefit from multi-task learning. Chan et al.[[17]](#endnote-17) find that pre-training transformers with a larger corpus of similar text can yield better results. They specifically pre-train on the following datasets: OSCAR, OPUS, Wikipedia and OpenLegalData.

Bornheim et al.[[18]](#endnote-18) compared several transformers for all three tasks. They also experimented with different activation functions. They also tried ensemble methods and both mult-label and single-label classifiers. They found that none of these made a significant difference.

Other Sources

We will now review some approaches by sources other than the participants of GermEval2021.

Risch and Krestel[[19]](#endnote-19) explored ensembling Logistic Regression, GRU’s and Syntactic features with Gradient Boosted Decision trees to detect aggression in online text. The same authors also explored bagging the output of BERT based models.[[20]](#endnote-20) In another work, the same authors use up-votes and down-votes to detect engaging comments.[[21]](#endnote-21)

Malmasi and Zampieri[[22]](#endnote-22) have found that it is difficult to distinguish between hate speech and profanity. In a different work, Zampieiri et al.[[23]](#endnote-23) found that Bi-LSTM with CNNs outperformed SVM based models and Bi-LSTMs alone in the task of offensive speech detection.

Ranasinghe et al.[[24]](#endnote-24) compared 7 different deep neural-network approaches (Pooled GRU, Stacked LSTM with attention, LSTM and GRU with attention, 2D convolution with pooling, GRU with Capsule Networks, LSTM with Capsule and Attention, and BERT), and found that BERT based networks performed the best on aggression detection.

Zhao et al.[[25]](#endnote-25) compare the performance of downstream classifiers after applying BERT to the task of toxic comment detection. They find that simple linear neural networks with BERT outperform more complex neural networks (like Bi-LSTM and CNN) with BERT. D’Sa et al.[[26]](#endnote-26) found that BERT models with fine-tuning outperformed FastText when they were combined with simple deep neural networks.

Maslej-Krešňáková[[27]](#endnote-27) did an in-depth comparison of several methods of pre-processing with popular transformer models. They also compare transformer based models with more traditional language models like Bi-LSTM with similar preprocessing techniques.

Safaya et al.[[28]](#endnote-28) find that BERT when combined with CNN performs better than BERT alone when trying to detect offensive speech in Arabic.

Song et al.[[29]](#endnote-29) found that model-fusion of several transformers with a fusion of BCE-loss and Focal-loss functions performs best at toxic text detection when there is data imbalance.

Hu et al.[[30]](#endnote-30) discover that while models trained on English approach human levels on many classification tasks, models trained on cross-lingual datasets lag behind.

Compound Words (Komposita)

Both English and German have compound words. In English compound words are separated by a hyphen, for example, father-in-law is one such word. In german, the hyphen is not used. For example, ‘hundemüde,’ in German means dog-tired.

In NLP tasks, sometimes splitting compound words can help. In the case of sentiment analysis and toxic comment detection, this might be most useful.

Marco[[31]](#endnote-31) proposed a frequency based approach with form-to-lemma mappings to split compound words in German. Their method is an extension of the work by Koehn and Knight[[32]](#endnote-32). Given many possible splits of a word, Koehn and Knight pick up the split with the highest geometric mean of frequencies of the individual words of the split occurring in a given corpus. Koehn and Knight’s algorithm is tuned for translation tasks where it is possible to refer to the corpus of another language. Bay et al.[[33]](#endnote-33) have used abbreviation detection via TF/IDF and FastText followed by compound splitting with FastText and found this helpful in processing medical text. Krotova et al.[[34]](#endnote-34) use a deep learning based approach to splitting German compound words. Ma et. al.[[35]](#endnote-35) use a Conditional Random Field model to predict a label for each letter in a compound word to indicate whether the letter is the beginning of a word (B), end of a word (E), an intermediate letter of a word (M), or a letter in a single-letter word (S). The sequence of B-M-E-S labels can then be used to split the word.

However, we were unable to find any library which performed this task reliably, and hence compound word splitting was not done in this assignment.

Sarcasm Detection

Detection of Sarcasm may be key to sentiment and emotion detection. Chauhan et al.[[36]](#endnote-36) manually annotated the MUStARD dataset with both sentiment and emotion classes, and then proposed a novel attention mechanism that can perform well on multi-task learning that involves sentiment and emotion analysis, sarcasm detection. Barnes et al.[[37]](#endnote-37) deem that detection negation is necessary for sentiment analysis, and they find that multi-task learning performs better at detection of negation. They use a combination of a Bi-LSTM network along with a CRF-tagger.

Discussion

In all the papers reviewed here, some tasks were commonly performed – these tasks include tokenization, stop-word removal, removal of punctuations, parts-of-speech tagging, lemmatization/stemming, hyperlink removal, conversion of smileys to text, removal of named entities, replacement of abbreviations with full forms, replacement of numbers with a specific text to indicate the presence of a number, removal of symbols etc.

1. XLM-RoBERTa and MT5, both of which are transformers. They pre-trained the transformer on the dataset and that resulted in a 10% improvement in F1-score. They also used data augmentation via two different methods: (1) training on other multi-lingual datasets that include German comments and (2) created a dataset of Facebook comments by classification with a model and keeping the comments classified as toxic or non toxic with a probability of larger than 0.8. However, [↑](#endnote-ref-1)
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7. Schmidhuber, M. (2021, September). Universität Regensburg MaxS at GermEval 2021 Task 1: Synthetic Data in Toxic Comment Classification. In *Proceedings of the GermEval 2021 Shared Task on the Identification of Toxic, Engaging, and Fact-Claiming Comments* (pp. 62-68). [↑](#endnote-ref-7)
8. Schütz, M., Demus, C., Pitz, J., Probol, N., Siegel, M., & Labudde, D. (2021, September). DeTox at GermEval 2021: Toxic Comment Classification. In *Proceedings of the GermEval 2021 Shared Task on the Identification of Toxic, Engaging, and Fact-Claiming Comments* (pp. 54-61). [↑](#endnote-ref-8)
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