Misogyny classification of German newspaper forum comments

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Abstract

This paper presents work on detecting misogyny in the comments of a large Austrian German language newspaper forum. We describe the creation of a corpus of 6600 comments which were annotated with 5 levels of misogyny. The forum moderators were involved as experts in the creation of the annotation guidelines and the annotation of the comments. We also describe the results of training transformer-based classification models for both binarized and original label classification of that corpus.

1 Introduction and Motivation

The ever more widespread use of social media and user-contributed content also causes an increase of toxic or offensive language and other forms of unwanted contributions which may need to get detected and removed. In this paper, we present work aimed at supporting moderators of a large daily Austrian (German language) newspaper which allows registered users to discuss the articles published on its web-site. Users post some 20K to 50K comments per day. An analysis of commenting behaviour has shown that only a third of the users participating in the online discussion are women and that one important reason why women avoid participating in article forum discussions is the presence of sexist comments. The aim therefore was to use automatic classification of sexist/misogynist comments to support moderators in detecting such comments in order to provide a more welcoming and safer climate of discussion especially for female users.

For this, a corpus of 6600 comments was collected and annotated and subsequently used to train a classifier used to flag comments or entire discussion forums with a high number of suspected misogynist comments.

2 Related Work

Together with work on toxic and offensive language classification in recent years, there has also been increasing work on the classification of sexist or misogynist language, sometimes as part of a more general toxic language classification task. Hewitt et al. (2016) give an overview over earlier work and describe a dataset of Tweets containing abusive sexist terms. Anzovino et al. (2018) present work on creating a dataset of tweets, subsequently used as part of IberEval-2018 and EvalIta-2018 challenges (Fersini et al., 2018) for sexism classification. Shushkevich and Cardiff (2019) give an overview over misogyny detection in social media, specifically Twitter.

Waseem and Hovy (2016) describe work on a corpus of 16K tweets for detecting toxic and hate speech including sexist slurs or defending sexism (3383 tweets with sexist content). Frenda et al. (2019) present work on the datasets described in (Fersini et al., 2018) and (Waseem and Hovy, 2016). Sharifirad and Matwin (2019) include some more detailed description of sexist language and is based on another dataset of English language tweets. Parikh et al. (2019) describe work on categorizing accounts of sexism from the Everyday Sexism Project website through fine-grained multilabel classification. Other datasets are described or used in (Chiril et al., 2020a) (12K tweets in French) and (Grosz and Conde-Cespedes, 2020) (tweets, work-related quotes, press quotes and other sources), (Bhattacharya et al., 2020) and (Safi Samghabadi et al., 2020) (Youtube comments in Indian English, Hindi and Bengla), (Rodríguez-Sánchez et al., 2020) (Spanish language tweets) and (Zeinert et al., 2021) (Danish language dataset sampled from several social media sites).

The EXIST task at IberLEF 2021 (Rodríguez-Sánchez et al., 2021) addresses the identification and categorization of sexism in English and Span-
ish language tweets and postings from Gab.com. Most recently, SemEval 2023 Task 10¹ provides an English language corpus of 20000 texts sampled from Gab and Reddit, annotated with 3 hierarchical labels.

3 Corpus Creation

The aim of manual corpus annotation was to reflect the judgement of moderators in their everyday work. For this reason, the manual annotations were carried out by 8 annotators of which 7 were experienced moderators. The 8th annotator is a natural language processing and corpus linguistics expert. One of the annotators is among the authors of this paper. There were 3 male and 5 female annotators.

Since the phenomenon of "sexism"/"misogyny" is complex, guidelines were created to describe the most important kinds of sexism relevant for the annotation task. For this we used the categorization from (Parikh et al., 2019) as inspiration. The guidelines also attempt to clarify some of the difficulties likely to be encountered: how to decide if there is not enough context, what if the sexist remark is aimed at a man or men in general, how to treat "reported sexism" (Chiril et al., 2020b). However, the guidelines follow the aim of providing help for annotating in a way that reflects the daily work of moderators and the newspaper’s editorial concept. They are not meant as an accurate abstract definition of sexism and misogyny. The (German language) guidelines are available online². We will refer to the task as "misogyny classification" in the rest of the paper.

Postings were annotated by assigning one of 5 possible labels 0 . . . 4, corresponding to 0 = absence of misogyny and 4 levels of "severity" of the expressed misogyny as perceived by the individual annotators, with 1 = mild, 2 = present, 3 = strong, 4 = extreme. This was done on the one hand to reflect the personal aspect in the assessment of misogyny, and on the other hand to identify the instances with the biggest disagreements among annotators.

Postings to be annotated were collected from several different sources: (1) a collection of postings which had been reported with a (free text) reporting reason that included a keyword related to sexism/misogyny, (2) postings which were reported with a different reason, (3) postings randomly sampled from all available postings, (4) a subset of postings (2) preclassified with an early version of the binary classifier trained on the first 2800 annotated postings and (5) postings from 24 article forums which have been identified to contain an above-average number of postings considered sexist, preclassified with the same early binary classifier. Preclassified postings were selected from the highest probability label "1" postings (to correct false positives) as well as those label "0" and "1" postings with close to 0.5 probability (to add what may be hard to classify instances).

Postings were given to annotators in batches of 100, by creating a spreadsheet from the posting texts and preparing a selection field for selecting one of the 5 possible labels. The first batch of 100 postings was given to all 8 annotators and then analysed to find postings with the biggest disagreement: for this we calculated a heuristic disagreement score based on all pairwise distances between the labels, where the distance between labels 0 and 1 were defined to be 4, and distances between labels $l_i, l_j > 0$ defined to be $|l_i - l_j|$. Examples with high scores were then discussed among annotators to clarify the annotation guidelines or clear up misunderstandings.

After this, each round of 100 postings was given to a random selection of 3 annotators available at the time. This was done in order to compromise between annotating as many postings as possible given the available time and resources and still get enough annotators for each posting to identify disagreements. In total, 66 rounds with 6600 postings were annotated (20300 annotations). The overall distribution of assigned labels is shown in Table 1.

| Label | %   |
|-------|-----|
| 0     | 66.5|
| 1     | 7.3 |
| 2     | 14.2|
| 3     | 9.4 |
| 4     | 2.6 |
| 1...4 | 33.5|

4 Annotator Agreement and Corpus Analysis

Krippendorff Alpha over all annotations was 0.36 (nominal scale) and 0.64 (ordinal scale). After binarization of the 5 possible annotations into 0 (for no sexism) and 1 (for labels 1 . . . 4), Krippendorff Alpha was 0.60. Overall agreement was 0.65 / 0.83 (binary) if macro averaged over all agreements of

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¹https://codalab.lisn.upsaclay.fr/competitions/7124
²https://ofai.github.io/femdwell/annotation_guidelines_v1.pdf
pairs of users, and 0.66 / 0.82 (binary) if micro averaged over all pairs of annotations. F1.0 macro over all 22300 pairs of annotations was 0.390 / 0.803 (binary). Overall Cohen’s Kappa was 0.39 / 0.63 (binary) if macro averaged over all kappas for pairs of users. This indicates that there was considerable difference of opinion or difficulty in assigning the fine-grained labels.

As shown in Table 1 the overall rate of assigned positive labels (classes 1 . . . 4) was 0.335. Looking at all pairs of annotations in the dataset the relative frequencies of annotation pairs (confusion matrix) is shown in Table 2. This illustrates the large rate of disagreement among annotators, especially on estimating the fine-grained degree of misogyny (labels 1 . . . 4).

Table 2: Relative frequency of annotation pairings

|   | 0   | 1   | 2   | 3   | 4   |
|---|-----|-----|-----|-----|-----|
| 0 | 0.525 | 0.032 | 0.037 | 0.015 | 0.003  |
| 1 | 0.032 | 0.014 | 0.020 | 0.009 | 0.001  |
| 2 | 0.037 | 0.020 | 0.052 | 0.036 | 0.007  |
| 3 | 0.015 | 0.009 | 0.036 | 0.044 | 0.016  |
| 4 | 0.003 | 0.001 | 0.007 | 0.016 | 0.013  |

We deliberately did not decide on a single "best" way to decide on a final single label as the judgement on misogyny may depend on personal opinion and we believe it would be wrong to assume there is a single correct value for each instance. Other instances may have received labels by mistake (e.g. misinterpretation of the text or of the annotation guidelines). For creating a training set we used different strategies to resolve disagreements (see Section 5).

We aim to make the corpus available for academic research, the necessary steps for doing this legally and in accordance with Austrian and EU data protection law are still ongoing.

This is not only the first German language corpus related to misogyny detection but also the first corpus in any language which covers such a wide range of often very subtle ways a comment may express misogyny, and which contains many comments where human annotators will have different opinions on which label is most adequate.

5 Sexism Classification Model

The main purpose of the deployed classification model is to alert moderators both of individual sexist comments and article forums with a high rate of potentially sexist comments. For this reason, our main interest is a binary classifier (original label 0 vs original labels 1 to 4). However we also studied the performance of a model for predicting the original label, both as seen as a multiclass classification task and as an ordinal regression task. Finally, we investigated if combining both the binary and multiclass tasks into a multi-task model would impair or improve the performance of the individual tasks.

All models are based on a transformer architecture (Vaswani et al., 2017) with one or two classification heads on top of the pooling layer. We used the pretrained German BERT models gbert-base and gbert-large (Chan et al., 2020).

For all models, accuracy and F1.0-macro metrics where estimated using 5-fold cross-validation with class-stratified folds. 10% of the training set were used as dev-set and this split was class-stratified as well. Hyper-parameters where selected in a step-wise process where manually chosen values for a few hyper-parameters were evaluated using grid search. For many parameters, however, there was no clear best selection as the range of F1.0-macro estimation results introduced by different random seeds was larger or comparable to the changes in F1.0-macro estimation for different parameter values. In such cases we chose an intermediate value among those with similar estimates. The final set of hyper-parameters used for all models described below was: BERT maximum sequence length 192, batch size 8, gradient accumulation: 1 batch, learning rate 7.5e-06, language model dropout rate 0.1 and no layer-wise learning rate adjustment. The AdamW optimizer with weight decay 0.01 and linear warm-up during 200 training steps was used. For all classification heads we used an addition layer with 768 hidden units, ReLU and no dropout before the actual output layer.

We evaluated the following single-head models: Bin (binary classification), Multi (multiclass classification), Coral (multiclass classification using an implementation of the CORAL ordinal regression model (Cao et al., 2020)); and the following dual-head models: BinMulti (binary and multiclass heads combined), BinCoral (binary and CORAL heads combined). For each of these 5 models

3 https://huggingface.co/deepset/gbert-base/tree/main
4 https://huggingface.co/deepset/gbert-large/tree/main
we evaluated a variant based on the bert-base model (\textit{/B}) and one based on the bert-large model (\textit{/L}).

Table 3 shows the estimation results (accuracy and F1.0-macro) on a training set where the original and binarized targets were selected as the most frequently assigned labels, falling back to the highest most frequently assigned label or the maximum assigned label. For dual-head multitask models there are two lines, showing the binary model as head 1 (:1) and the multiclass model as head 2 (:2).

Table 3: Accuracy and F1.0 macro estimates (± standard deviation) for models trained on the most frequent original (coral, multi) and binarized (bin) sexism label.

| Model          | Accuracy | F1.0 macro |
|----------------|----------|------------|
| Bin/B          | 0.763 ± 0.012 | 0.735 ± 0.007 |
| Bin/L          | 0.757 ± 0.050 | 0.685 ± 0.159 |
| Multi/B        | 0.608 ± 0.026 | 0.305 ± 0.013 |
| Multi/L        | 0.640 ± 0.043 | 0.262 ± 0.093 |
| Coral/B        | 0.651 ± 0.019 | 0.281 ± 0.011 |
| Coral/L        | 0.662 ± 0.017 | 0.250 ± 0.082 |
| BinMulti/B:1   | 0.757 ± 0.017 | 0.729 ± 0.018 |
| BinMulti/B:2   | 0.612 ± 0.015 | 0.293 ± 0.016 |
| BinMulti/L:1   | 0.733 ± 0.059 | 0.666 ± 0.153 |
| BinMulti/L:2   | 0.506 ± 0.213 | 0.255 ± 0.121 |
| BinCoral/B:1   | 0.756 ± 0.012 | 0.729 ± 0.008 |
| BinCoral/B:2   | 0.656 ± 0.013 | 0.269 ± 0.016 |
| BinCoral/L:1   | 0.788 ± 0.015 | 0.763 ± 0.017 |
| BinCoral/L:2   | 0.658 ± 0.009 | 0.281 ± 0.013 |

The dual-head model combining binary and CORAL ordinal regression heads shows the best accuracy estimates both for the binary and the multiclass tasks, and also the best F1.0-macro for the binary tasks while the performance of the base single-head multiclass model shows best F1.0-macro for the multiclass task. Interestingly, the models based on bert-large did not always perform better than those based on bert-base.

We also trained the same set of models on a training corpus where both the binary and multiclass target was always selected as the highest label assigned by any annotator ("when in doubt, treat it as misogynist"). The results for this experiment are shown in Table 4. On this data, the single-head binary model performed best both with respect to accuracy and F1.0-macro, while the single-head multiclass classification model performed best on the multiclass task with respect to F1.0-macro.

In order to get an impression for how a binary model could be used to indicate forums where moderator intervention may be necessary because of a high number of misogynist postings, moderators selected 6 forums of which 3 have been found to have a high observed rate of misogynist postings and 3 without. The model BinCoral/L:1 from Table 3 assigned a rate of 0.23, 0.17, and 0.27 of postings in each of the first 3 forums to the misogyny class but only a rate of 0.01, 0.02 and 0.07 of the second 3 forums, thus giving a good indication of which of the forums moderators should prioritize. Looking at the actual postings labeled to be misogynist shows that in addition to many postings which were correctly identified, there was also a high number of false positives. However, many of these false positives are texts which are related to topics often raised in misogynist comments. In future work, the corpus will be expanded by providing manual annotations for the false positives detected in those evaluation runs. The code for all experiments is based on the FARM library\footnote{https://github.com/deepset-ai/FARM} and is available online\footnote{URL withheld for anonymous review}.

Additional future work will analyse the performance of the different classification models on comments based on source, annotator disagreement or the kind of misogyny and improve the approach both by further improving and extending the corpus and the models used for training.
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