Abstract

Despite recent advances in machine learning based hate speech detection, classifiers still struggle with generalizing knowledge to out-of-domain data samples. In this paper, we investigate the generalization capabilities of deep learning models to different target groups of hate speech under clean experimental settings. Furthermore, we assess the efficacy of three different strategies of unsupervised domain adaptation to improve these capabilities. Given the diversity of hate and its rapid dynamics in the online world (e.g. the evolution of new target groups like virologists during the COVID-19 pandemic), robustly detecting hate aimed at newly identified target groups is a highly relevant research question. We show that naively trained models suffer from a target group specific bias, which can be reduced via domain adaptation. We were able to achieve a relative improvement of the F1-score between 5.8% and 10.7% for out-of-domain target groups of hate speech compared to baseline approaches by utilizing domain adaptation.

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1 Introduction

Current state-of-the-art machine learning approaches for hate speech detection reach F1-scores above 93% (Arango et al., 2019). Despite this progress, in some settings these scores drop to 50% when tested on out-of-domain data (Arango et al., 2019). The lack of generalization capabilities of hate speech detection systems hinders their suitability in real world applications.

Several challenges are faced when trying to generalize knowledge in hate speech detection tasks. Firstly, most benchmark hate speech datasets are focused on certain topics, such as hate speech directed at journalists (Charitidis et al., 2020), refugees and Muslims (Zhang et al., 2018), women only (Basile et al., 2019) or blacks, other races and women (Waseem, 2016). These datasets reflect biases towards different targets of hate, which will usually influence model training and predictive performance. Different target groups are also addressed by different perpetrators in the real world. For example, left-wing hate is frequently aimed against the ‘system’, with police or politicians being targeted, whereas right-wing hate is frequently aimed against Jews or foreigners. Moreover, new target groups can arise due to new phenomena such as the Corona pandemic (Fan et al., 2020). Therefore, being able to adapt models to unknown target groups of hate speech without the need of time consuming labeling of new datasets is crucial. Another challenge for generalizing knowledge across different hate speech datasets is the disagreement over the definition of hate speech (Ross et al., 2017), which is especially problematic for benchmark datasets. These disagreements lead to incompatible annotation of different datasets (MacAvaney et al., 2019; Fortuna et al., 2020), which hinders a proper assessment of the generalization capabilities of the models.

In this work we investigate the generalization and adaptation capabilities of hate speech classifiers to different domains of hate speech while eliminating errors due to incompatible datasets. This is done by conducting our experiments on a single dataset, namely the HateXplain dataset (Mathew et al., 2020), which was annotated following consistent annotation rules. There are many possibilities to categorize hate speech into different domains. For example, hate speech with common topics, hate speech that addresses common target groups, hate speech from common time periods or hate speech from common datasets can be considered as separate domains. In this work, we regard the adaptation capabilities of the
MixUp Regularization. In manifold MixUp, virtual samples and virtual labels are computed by interpolating between the feature representations and corresponding labels (pseudo-labels for unlabeled samples) of data points.

Adversarial Domain Adaptation. The goal of adversarial domain adaptation is to align the feature distributions of source domain samples with feature distributions of target domain data samples.

Curriculum Labeling. After training a model on labeled samples (left), the model predicts pseudo labels (middle) for unlabeled samples from the target domain. Samples which belong to the most confident model predictions are included in the training set, together with their predicted class labels. Finally, the model is retrained from scratch on the augmented dataset (right).

Figure 1: Three different strategies for improving the generalization capabilities of models to different target groups are investigated. These approaches utilize labeled source data samples (colored data points) and unlabeled target domain data samples (grey data points).

models with respect to different target groups of hate speech due to the relevance of the topic for real world applications and the suitability of the HateXplain dataset for this research. An advantage of utilizing the HateXplain dataset for this research is, that target groups were annotated for all samples, not only the hateful ones, which allows us to appropriately select samples that correspond to different domains and therefore to properly investigate the generalization capabilities of our approaches. Adaptation of models to different target groups of hate speech is here investigated by unsupervised domain adaptation methods, namely via manifold MixUp regularization (Fig. 1a), adversarial domain adaptation (Fig. 1b) and curriculum labeling (Fig. 1c).

In summary, we make the following contributions:

• We analyze the influence of data and target group specific bias on hate speech classifiers;
• We investigate the suitability of unsupervised domain adaptation for improving model performances for out-of-domain target groups;
• Our experiments are conducted under clean conditions with properly separated domains and without data incompatibilities during model evaluation.

2 Related Work

Several approaches for machine learning based hate speech detection were investigated in recent years (Badjatiya et al., 2017; Djuric et al., 2015; Mozafari et al., 2019). An active line of research aims at improving generalization capabilities of hate speech detection systems, with most studies focusing on cross-dataset generalization capabilities of models (Bashar et al., 2021; Waseem et al., 2018).

Karan and Šnajder (2018) show the difficulties of hate speech classifier to deal with out-domain datasets. The authors emphasize the importance of in-domain data for their generalization results. They integrated target domain data in their learning procedure using frustratingly easy domain adaptation Daumé III (2007). In contrast to our work, the authors investigated the cross-corpus generalization and adaptation capabilities of linear support vector machines. In this work, we focus
on target group specific domain adaptation of deep learning based hate speech classifiers.

The generalization capabilities of deep learning models from topic generic to topic specific hate speech corpora were investigated by Chiril et al. (2021). The authors showed that models failed to generalize to domain specific corpora, but that the integration of domain specific knowledge improves the classification results in new domains. In contrast to our work, the authors focus on cross dataset generalization, which makes a clean evaluation of target group specific generalization difficult. Faal et al. (2021) suggested exploitation of multi-task learning and domain adaptation for improving the generalization capabilities of hate speech classifiers. After domain adaptive pre-training of a BERT based feature extractor (Devlin et al., 2019), the whole model was trained on multiple tasks by utilizing shared parameters as well as task specific parameters. The authors showed that the reduction of unintended target group specific model bias via multi-task learning successfully boosted generalization. In contrast to our work, they focus on general robustness with respect of target groups rather than a target group specific optimization.

In Bashar et al. (2021), the authors propose to train a language model to learn domain invariant and disentangled feature representation for different hate speech domains. After that, they trained a classifier on top of these feature representations and used it for robustly classifying hate speech from different domains. The authors demonstrated the success of the model in detecting hate speech related to the COVID-19 pandemic. On the other side, Bose et al. (2021) showed that the application of widely used unsupervised domain adaptation approaches can be problematic in the field of hate speech detection. The authors applied various pivot-based and adversarial-based approaches to generalize knowledge across different hate speech corpora. Unlike our work, which focuses on target group specific domain adaptation, these works focus on generalizing on knowledge on the level of hate speech corpora, which introduced previously discussed difficulties in model evaluation and which might be the main reason for bad adaptation results.

3 Methods and Experiments

In this section we describe the dataset, model architecture as well as the training and evaluation strategies used in our experiments.
also experiment with data augmentation. Recently, various techniques for text data augmentation have been proposed (Shorten et al., 2021), such as rule based techniques (Wei and Zou, 2019; Spasic et al., 2020; Karimi et al., 2021), feature space augmentations (Cheung and Yeung, 2020; Khosla et al., 2020) or neural augmentation (Wu et al., 2019). Due to the success of back translation based data augmentation (Xie et al., 2020; Yaseen and Langer, 2021; Corbeil and Abdi Ghadivel, 2020; Sugiyama and Yoshinaga, 2019), we decided to use this approach with pre-trained neural translation models (provided by HuggingFace) in order to create an augmented version of the original HateXplain dataset. Back translation is done with the language pairs English - German, English - French and English - Spanish, resulting in nearly three times the number of instances per class.

3.2 Model Architecture and Training

In our experiments, we use the Structured Self-Attentive Sentence Embedding model (Lin et al., 2017), which provides a good trade-off between model performance and computational costs. The model is visualized in figure 3. The encoder of the model consists of a two layer bidirectional LSTM, followed by an attention module, as proposed by (Lin et al., 2017). The predictor of the model is a linear classifier, consisting of a single linear layer followed by a Softmax activation function. We use WordPiece tokenization (Devlin et al., 2018; Schuster and Nakajima, 2012). The embedding size and the hidden sizes of the LSTMs are 128, the dimension of the attention module 350, and the number of attention heads 30. A domain discriminator is applied in those experiments in which we perform adversarial domain alignment. The input of the domain discriminator is the output of the encoder of the Structured Self-Attentive Sentence Embedding model. The applied discriminator model consists of a gradient reversal layer (Ganin and Lempitsky, 2015), followed by a two layer feed forward neural network with a leaky ReLU activation function at the hidden position and a Sigmoid activation function at the output position.

We use the Adam optimizer (Kingma et al., 2015) with a learning rate of $5e^{-4}$ and beta values of $(0.9, 0.99)$ during our experiments. We apply dropout regularization (Srivastava et al., 2014) with a dropout probability of 0.6 to the LSTM modules to prevent overfitting. All models are trained for a total of 50,000 training iterations with a batch size of 32. Our experiments are implemented using the deep learning framework Pytorch.

3.3 Model Assessment

All models are evaluated using the macro-average F1-score with five-fold cross-validation. During training, we store those model states for which the models achieved the best results on the out-of-fold validation data of the training domains. For these model states, we report the results achieved on the validation data of the other domains, too. We believe that this is a realistic scenario, since we assume that only unlabeled data samples of other domains are available and we therefore need to select our models based on their performances on the source domains, for which labeled data samples are available.

3.4 Zero-Shot Approaches

In the first set of experiments, we investigate the generalization capabilities of models that use only labeled data from one domain and no data from other domains. As we examine the generalization capabilities of the models to target domains that were not present in the training data, we refer to these experiments as zero-shot approaches. In the first, naive zero-shot approach (Zero), models are trained with labeled data from the original HateXplain dataset (Mathew et al., 2020) that belong to a specific target group (e.g. "Race"). The training batches provided to the model in each training itera-

\[2 \text{https://huggingface.co/}\]

\[3 \text{https://pytorch.org/}\]
tion are randomly sampled. In the second zero-shot approach (Zero +), models are trained with target group specific data from the augmented dataset (see Section 3.1). Similar to the first zero-shot learning approach, training batches are sampled randomly. In the last zero-shot learning approach (Zero B+), the training batches are sampled in a balanced manner from the augmented dataset with equal probability per class in each iteration. In all zero-shot approaches, models are evaluated with validation data from the original HateXplain dataset (Mathew et al., 2020), as described in Section 3.3.

### 3.5 Unsupervised Domain Adaptation

Unsupervised single source domain adaptation uses data from two different domains during the training: source data \( X_S = \{(x_i, y_i)\}_{i=1}^N \), which consist of \( N \) labeled samples from a source domain \( D_S = \{X_S, P_S(X_S)\} \), and target data \( X_T = \{x_j\}_{j=1}^M \), which consist of \( M \) unlabeled samples from a target domain \( D_T = \{X_T, P_T(X_T)\} \). \( X = X_S \cup X_T \) is a shared feature space, \( P_S(X_S) \neq P_T(X_T) \) are marginal probability distributions over the feature space, which are similar, but differ. The goal of the learning algorithm is to train a model which achieves a strong performance for a task \( T \) on the target domain although no labeled data points from the target domain are available during the training. For the domain adaptation approaches, we use the same data and sampling strategy as for the last zero-shot learning approach (Zero B+).

The goal in our paper is to cover different research directions in the field of domain adaptation for hate speech detection purposes. The approaches investigated in this paper are typical candidates for their line of research, which consider the problem of domain adaptation from a regularization-based view 3.5.1, a data-based view 3.5.2 and a feature-based view 3.5.3.

#### 3.5.1 MixUp Regularization

We adapt the approach of manifold MixUp regularization proposed by Verma et al. (2019) (Fig. 1a). Given is a deep neural network with an encoder \( e \), which maps an input \( x \in \mathcal{X} \) into hidden representation \( h \in \mathbb{R}^m \), and a predictor \( p \), which computes predictions \( z \in \mathbb{R}^K \) based on the hidden representation \( h \in \mathbb{R}^m \). Manifold MixUp regularization introduces an additional regularization loss based on MixUp feature representations \( \tilde{h} \in \mathbb{R}^m \) and MixUp labels \( \tilde{y} \in \mathbb{R}^K \), which are computed based on hidden representations \( h_1, h_2 \in \mathbb{R}^m \) and corresponding labels \( y_1, y_2 \in \mathbb{R}^K \) of two samples:

\[
\tilde{h} = \alpha \cdot h_1 + (1 - \alpha) \cdot h_2 \tag{1}
\]

\[
\tilde{y} = \alpha \cdot y_1 + (1 - \alpha) \cdot y_2 \tag{2}
\]

Here, \( \alpha \in [0, 1] \) is sampled from a Beta distribution: \( \alpha \sim \text{Beta}(2, 2) \). \( y_1 \) and \( y_2 \) are represented as one-hot encoded class labels for source domain samples and as soft pseudo-labels, which are iteratively computed by the neural network, for target domain samples.

The MixUp features are used for computing the MixUp predictions \( \tilde{z} = p(\tilde{h}) \) based on the predictor of the neural network. The loss between MixUp predictions and MixUp labels is computed as Cross-Entropy loss for source domain samples (\( \tilde{l}_m^s \)) and L1 loss for target domain samples (\( \tilde{l}_m^t \)). The complete MixUp loss \( l_m \) is computed as follows:

\[
l_m = \lambda^s \cdot \tilde{l}_m^s + \lambda^t \cdot \tilde{l}_m^t \tag{3}
\]

We set \( \lambda^s = \lambda^t = 0.1 \) in our experiments.

#### 3.5.2 Curriculum Labeling

In addition to MixUp regularization, we adapt the approach of Cascante-Bonilla et al. (2020), which combines pseudo-labeling with curriculum learning, for domain adaptation purposes (Fig. 1c). Curriculum labeling is done by selecting data points from an unlabeled data pool based on the network’s prediction confidences. The selected data points with corresponding pseudo-labels are iteratively included to the training procedure during the learning epochs. Following Cascante-Bonilla et al. (2020), we select data points based on percentile scores of the prediction confidences. During the training, the percentile threshold for selecting samples corresponding to the most confident predictions is increased from 0% to 100% in increments of 20%. In contrast to Cascante-Bonilla et al. (2020), we select the pseudo-labeled samples based on the model’s prediction confidences independently for each predicted class. This is done to prevent a bias towards the selection of data points from majority classes, which is crucial for hate speech detection tasks. During each iteration (‘curriculum epoch’), the network is re-trained from scratch with both the labeled samples and the pseudo-labeled samples selected by the model trained in the previous curriculum epoch.
### Table 1: Macro average F1 scores achieved by the approaches, averaged over five validation folds and split into target groups, approaches and domains. Improvements over the results, achieved by the best zero-shot approach are marked in green. Violet indicates negative transfer, in which the models achieved worse results than the naive zero-shot learning approach.

| Source Domain | Eval. Domain | Target Domain | Race | Rel. | Sex. |
|---------------|--------------|---------------|------|------|------|
| Race          | Target       | Source        | Domain Zero | Zero + | Zero B+ |
| Race          | .56          | .57           | .58       | .52   | .50   |
| Rel.          | .52          | .52           | .52       | .47   | .47   |
| Sex.          | .50          | .50           | .51       | .47   | .47   |

| Source Domain | Eval. Domain | Target Domain | Race | Rel. | Sex. |
|---------------|--------------|---------------|------|------|------|
| Rel.          | Target       | Source        | Domain Zero | Zero + | Zero B+ |
| Race          | .46          | .46           | .48       | .52   | .50   |
| Rel.          | .47          | .48           | .50       | .52   | .50   |
| Sex.          | .47          | .48           | .49       | .52   | .51   |

| Source Domain | Eval. Domain | Target Domain | Race | Rel. | Sex. |
|---------------|--------------|---------------|------|------|------|
| Sex.          | Target       | Source        | Domain Zero | Zero + | Zero B+ |
| Race          | .36          | .37           | .42       | .48   | .42   |
| Rel.          | .39          | .39           | .43       | .46   | .43   |
| Sex.          | .42          | .42           | .46       | .49   | .45   |

Table 2: Average F1-Scores of the investigated approaches and relative improvements compared to the naive zero-shot learning approach with respect to the domains.

| Approach | Source | Target | Other |
|----------|--------|--------|-------|
| Zero     | 0.483  | 0.450  |       |
| Zero +   | 0.490  | 0.455  | +1.4% |
| Zero B+  | 0.513  | 0.475  | +6.2% |
| MixUp    | 0.510  | 0.476  | 0.481 |
| Adv.     | 0.517  | 0.496  | 0.487 |
| Cur.     | 0.525  | 0.498  | 0.488 |

Table 3: Average F1-Scores and its relative improvements over naive zero-shot learning, divided into approaches and classes labels.

| Approach | Normal | Offensive | Hate Speech |
|----------|--------|-----------|-------------|
| Zero     | 0.479  | 0.287     | 0.618       |
| Zero +   | 0.476  | 0.286     | 0.637       |
| Zero B+  | 0.494  | 0.288     | 0.683       |
| MixUp    | 0.490  | 0.281     | 0.690       |
| Adv.     | 0.500  | 0.312     | 0.689       |
| Cur.     | 0.505  | 0.311     | 0.692       |

### 3.5.3 Adversarial Domain Alignment

In order to learn domain invariant feature representations, Ganin et al. (2016) introduced Domain Adversarial Neural Networks (Fig. 1b). Beside the main model, a domain discriminator $D: \mathbb{R}^m \rightarrow \mathbb{R}$ is trained to distinguish between feature representations $h^s \in \mathbb{R}^m$ and $h^t \in \mathbb{R}^m$ for source domain samples $x^s$ and target domain samples $x^t$, computed by encoder $e$. At the same time, the encoder $e$ is trained to confuse the domain discriminator $D$, such that the discriminator is not able to distinguish between these feature representations. To achieve this, an adversarial loss is introduced:

$$
\mathcal{L}_{adv} = \mathbb{E}_{x^s \sim X^s}[\log(D(e(x^s)))] + \mathbb{E}_{x^t \sim X^t}[\log(1 - D(e(x^t)))]
$$

The domain discriminator $D$ is trained to maximize the adversarial loss $\mathcal{L}_{adv}$, while at the same time the encoder $e$ is trained to fool the discriminator and therefore minimize $\mathcal{L}_{adv}$. The theoretical equilibrium is reached when the encoder $e$ produces features which cannot be reliably classified as belonging either to the source or to the target domain by an optimal discriminator.

### 4 Results and Discussion

In this section, we present and discuss the results of our experiments. In table 1, we present macro average F1-scores, achieved by the investigated approaches. The scores are divided into source domain (first column), the domain on which the models were evaluated (second column) and the approaches used. Since the investigated domain adaptation approaches, unlike zero-shot approaches, used unlabeled target domain data...
in addition to labeled source domain data, their results are further subdivided into the target domain that was involved in model training. In Table 2 we present the average F1-scores of the investigated approaches, split by source, target and uninvolved domain. In addition to the average values, relative improvements compared to the naive zero-shot learning approach are also given. Table 3 shows the achieved performances with respect to the class labels "normal", "offensive" and "hate speech". Again, we report the relative improvements of the approaches compared to the naive zero-shot approach. In Table 4, we provide feature visualizations of our models for hate related samples based on lime (Ribeiro et al., 2016). The visualizations are provided for different approaches and combinations of source target and evaluation domains.

OFFENSIVE CONTENT WARNING: The following sections contain examples of hateful content. This is strictly for the purpose of enabling this research. Please be aware that this content could be offensive and cause you distress.

4.1 Model Bias

Although there are cases, in which models show poor generalization abilities to some out-of-domain target groups, all of our models were able to generalize knowledge to other domains to some extent. Best or equal best model performance was achieved when evaluating models against the domain on which they were trained (i.e. source domain) for both the zero-shot approaches (Table 1) as well as after averaging across domain adaptation approaches (Table 2). Data augmentation generally helped to improve the model performances, which shows that the models suffer from a bias due to the low amount of available training data. On average, the class "Hate Speech" benefits most from data augmentation (Table 3), while the performance on the classes "Normal" and "Offensive" is slightly worse compared to the naive zero-shot approach. Models additionally benefit from class balanced data sampling (Zero B+), which on average outperformed the other zero-shot learning approaches on all domains and across all class labels. Despite the improvements due to data augmentation and class balanced sampling, a gap between the performances on source domain and the other domains is still preserved. Moreover, both techniques slightly increased the performance gap between source and other domains (Table 2). We conclude that the models suffer from a target group specific bias, which occurs due to the lack of domain specific knowledge of domains other than the source domain and which cannot be reduced via typical data sampling strategies or data augmentation techniques such as back-translation. Therefore, the integration of domain specific knowledge of the target domain is crucial for reducing the performance gap between source domain and target domain.

Domain adaptation enabled models to learn domain specific features and to produce better model predictions in some instances (see samples a and b, e - h, i and l, Table 4). These results concur with the findings of (Karan and Šnajder (2018)), who highlighted the importance of in-domain knowledge for the generalization capabilities of hate speech classifiers and showed that models trained on domain general hate speech corpora failed to generalize to domain specific hate speech data Chiril et al. (2021). In contrast to our work, the authors investigated the generalization capabilities of models across different datasets, which hinders a clean evaluation due to possible dataset incompatibilities. Our results indicate that the integration of domain specific knowledge via adversarial domain adaptation and curriculum labeling is able to reduce the performance gap and achieve the largest improvements on the target domains, thereby reducing model bias (Table 2).

4.2 Effects of Domain Adaptation Approaches on Model Performance

Domain adaptation was able to improve the performance over all zero-shot learning approaches for each combination of source and target domain (Table 1). Additionally, all domain adaptation approaches achieved better results on average than the zero-shot learning approaches for not only the target domain but also for the third, uninvolved domain (Table 2) and was observable for all three classes (Table 3). Moreover, the adversarial domain adaptation approach and the curriculum labeling approach on average outperformed the zero-shot learning approaches on the source domain. However, in our experiments the choice of the data included in the training procedure had greater impact to the model performances than the chosen domain adaptation approaches themselves. Furthermore, none of our investigated domain adaptation
Table 4: Feature visualization for hate related samples. Words highlighted in red strengthen the model to predict the class "Hate Speech", while words which are highlighted in blue, decrease this prediction confidence.

| Text Source | Target Evaluation | Prediction |
|-------------|-------------------|------------|
| a) this little k**e is a good little donkey american | Race | Rel. | Rel. | Hate Speech |
| b) good job scamming you fu***ng fa**ot | Race | Rel. | Sex. | Hate Speech |
| c) y' all n***as is hoes | Sex. | Race | Race | Offensive |
| d) are yall n***as retarded | Sex. | Race | Race | Offensive |
| e) enjoy being a childless fu**er | Rel. | Race | Race | Hate Speech |
| f) deport that be**er sp**k to mexico | Sex. | Race | Race | Hate Speech |
| g) like pick a struggle fa**ot | Rel. | Race | Sex. | Hate Speech |
| h) kill yourself fa**ot | Rel. | Race | Sex. | Hate Speech |
| i) started as trash ending as worthless n****r trash | Rel. | Race | Race | Hate Speech |
| j) those fa**ots off queer eye hate jews | Rel. | Race | Sex. | Hate Speech |
| k) i fu***ng hate jews | Race | Rel. | Rel. | Offensive |
| l) kill yourself fa**ot | Rel. | Race | Sex. | Hate Speech |

4.3 Data Dependency of the Performance

In our experiments, the choice of the training data had the greatest impact on the model performances. Models trained on the source domain "Race" yielded the best results in general with F1 scores ranging from .50 and .58. Models, trained on the source domain "Sexual Orientation" performed worst overall and achieved F1 scores be-
Models, trained on the source domain "Religion" achieved F1 scores between .46 and .52. A similar pattern was observed for unlabeled data from the target domain. The largest improvements via domain adaptation were achieved by utilizing unlabeled data from the target domain "Race", whereas utilizing unlabeled data from the target domain "Sexual Orientation" yielded the lowest improvements. We attribute these observations to the number of training samples available in each class. The best performances were achieved with the largest amount of labeled training data (source domain "Race"), the worst performances were achieved with the lowest amount of labeled training data (source domain "Sexual Orientation"). Additionally, the largest improvements were achieved by incorporating the largest amount of unlabeled data (target domain "Race"), the smallest improvements were achieved with the lowest amount of unlabeled data (target domain "Sexual Orientation"). Since the domain adaptation performance on the target domain depends on the performance achieved on the source domain (Zhang and Harada, 2019), this observation also holds true for the investigated domain adaptation approaches.

5 Conclusion

The goal of this work was to analyze the generalization capabilities of hate speech classifiers to different target groups of hate under clean experimental conditions. Furthermore, we aimed to investigate the suitability of unsupervised domain adaptation to improve these generalization capabilities. Our results indicate that naively trained hate speech classifiers suffer from a target group specific bias and that unsupervised domain adaptation is able to improve the generalization capabilities of models across different target groups of hate. In contrast to previous works, which mainly focus on the generalization capabilities of hate speech classifiers in cross dataset settings, we investigated the generalization capabilities of hate speech classifiers to new hate targets on a single dataset, the HateXplain dataset. This enabled us to strictly separate target groups across all class labels and therefore allowed a clean analysis of the abilities of models to generalize to different target groups of hate, while avoiding the risk of inconsistencies over the definition of hate speech between datasets. We observed a gap of the model performances on the source domains and the model performances on the target domains. While data augmentation and balanced data sampling was able to generally improve the model performances, these methods tend to preserve these gaps. The integration of domain specific knowledge via domain adaptation was able to improve the generalization capabilities of models to other target groups, whereby the number of the involved labeled and unlabeled training samples strongly influenced the results of the approaches. However, our study does not allow a clear conclusion about which domain adaptation approach is best in which constellation of available data, which makes the choice of the appropriate approach difficult in real world situations. In total, there is still potential to improve the prediction quality of the models, especially when it comes to real world applications. Failures to detect hate speech, which contain threats, may lead to life-threatening situations for people, for example. In such scenarios, the achieved model performances are not good enough to reliably support law enforcement agencies. Improvements could be made with more advanced model architectures and a larger amount of available training data, which is a limitation of our work. We also analyzed generalization capabilities for only three target groups of hate, namely "race," "religion," and "sexual orientation." These limitations should be addressed in future works, for which we suggest investigating the generalization capabilities to new targets of hate in settings with a greater amount of data, higher diversity of target groups and with more advanced models like transformer based models. Moreover, the limitations of each of the domain adaptation methods can be further investigated in order gain insight into when and why some methods might fail.

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