Reducing Target Group Bias in Hate Speech Detectors

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Abstract

The ubiquity of offensive and hateful content on online fora necessitates the need for automatic solutions that detect such content competently across target groups. In this paper, we show that text classification models trained on large publicly available datasets despite having a high overall performance, may significantly under-perform on several protected groups. On the Vidgen et al. (2020) dataset, we find the accuracy to be 37% lower on an under-annotated Black Women target group and 12% lower on Immigrants, where hate speech involves a distinct style. To address this, we propose to perform token-level hate sense disambiguation, and utilize tokens’ hate sense representations for detection, modeling more general signals. On two publicly available datasets, we observe that the variance in model accuracy across target groups drops by at least 30%, improving the average target group performance by 4% and worst case performance by 13%.

1 Introduction

The diverse nature of hate speech against distinct target groups makes its automatic detection very challenging. In this paper, we study the impact of training machine learning models on two public hate speech datasets, where the content is organically driven by forum users, making the subsequent corpora unbalanced. While datasets should reflect content produced in the real world, we find models trained on such unbalanced datasets to perform with varying competence across target groups – demographic segmentations, often being poorer for protected groups. For example, a BERT model (Devlin et al., 2019) trained and evaluated on the dataset in Vidgen et al. (2020), has a high variance in detection accuracy across different target groups, significantly underperforming on attacks against Gay Men and Black Women (see Figure 1).

Our analysis of this bias – high variance in detection accuracy across target groups, shows that data distribution in these unbalanced datasets is a critical factor. Hate speech detection on a target group is more challenging with fewer corresponding training data points. Additionally, stylistic differences in hateful and offensive text against different minorities also plays a role in poor performance, as discussed in Section 2.

We propose to address this using a token level hate sense disambiguation approach. Benign tokens like woman and gay can be hateful when targeting a particular group and used in malicious context. To distinguish the hateful application from benign, we implement a token-level model which predicts the hate sense (distribution over class labels) at every time-step while predicting the overall hate speech class. Subsequently, the classifier considers hate sense augmented token representations, allowing a more general detection solution. Experimentally, we show that our approach leads to a more balanced performance with a 30% drop in
| Target Group | Training Data | Word Overlap | Eval Accuracy |
|--------------|---------------|--------------|---------------|
| Women        | 1652          | 0.65         | 0.73          |
| Black        | 1580          | 0.79         | 0.81          |
| Jew          | 891           | 0.70         | 0.83          |
| Muslim       | 779           | 0.66         | 0.79          |
| Transgender  | 640           | 0.64         | 0.75          |
| Gay          | 580           | 0.71         | 0.67          |
| Immigrants   | 545           | 0.58         | 0.66          |
| Refugee      | 376           | 0.57         | 0.77          |
| Disable      | 374           | 0.58         | 0.83          |
| South Asian  | 274           | 0.51         | 0.86          |
| Arab         | 262           | 0.53         | 0.82          |
| Gay Men      | 217           | 0.43         | 0.43          |
| Black Women  | 144           | 0.45         | 0.41          |
| East Asian   | 144           | 0.47         | 0.74          |
| Hispanic     | 57            | 0.15         | 0.60          |

Table 1: Performance of a BERT model on different target groups in Vidgen et al. (2020). Statistics on specific number of training data points and fraction of word overlap are also provided.

variance across target groups and has an at least 4% greater average-across-target groups performance than a BERT-based baseline.

In summary, the contribution of this paper include:
1. We are the first to highlight a crucial problem in NLP models having an unbalanced hate speech detection capabilities across different target groups.
2. We propose a zero-shot token level hate sense disambiguation technique to address this.
3. Our technique leads to an absolute 3% improvement in average target detection accuracy with a significant drop in group-wise performance variance.

2 Motivation and Analysis

In this section, we study the performance of a BERT model trained on Vidgen et al. (2020).

Biased Performance The BERT hate speech detection model has a biased performance as seen in Table 1. For instance, model accuracy on the Gay Men target group is 43% which is almost half of 85% on South Asian’s. We hypothesize that these results are due to two factors: (1) Training data available for each target group; (2) Stylistic differences in hate text used across target groups.

Training Data We investigate the impact of training data available for every target group and the corresponding model performance. In particular, we look at the model performance on the Black target group with an increasing number of corresponding training data available. Figure 3 shows that performance on the Black target group improves with an increase in training data.

On the complete dataset we also see that target groups with more training data such as Black, Jew and Muslim target groups (Table 1) have a higher test performance than Gay Men, Black Women and Hispanics target groups which have fewer training data points. However, the size of training data is not the only deciding factor for performance. For instance, the performance on South Asian and Arab target groups is much higher than performance against Immigrant and Women target groups, the latter with far more training data. Overall, training data is an important but not exclusive factor in hate speech detection performance across target groups.

Stylistic Differences Hateful text varies according to the intended target group, hence making such datasets a mixture of unique sub-domains. Such stylistic differences have the potential to cause a variance in performance across target groups. Table 1 reports the token overlap for the most frequent tokens used against different target groups. A higher word overlap for Black, Jew, Women and Muslim target groups corresponds to a high test accuracy, while a lower word overlap for Immigrant, Hispanics and Black Women target groups corresponds to a lower test performance. Performance on Arabs and South Asians target groups with low word overlap is higher than the performance against Gay target group which has a higher word overlap. Overall, the stylistic differences does not explain all the bias but is a strong factor.

3 Towards Unbiased Modeling

In this section, we propose a token-level model which performs sense disambiguation enroute to the overall hate speech prediction. Specifically, we develop our model to detect hate speech re-
Figure 4 shows our model architecture. We consider a Transformer based text encoder $E$ to represent our inputs. For a potential hateful text input $x = \{x_1, x_2, ..., x_n\}$, our model produces representations for every token $E(x) = [E(x_1), E(x_2), ..., E(x_n)]$. The named hate speech classes $C = \{c_1, c_2, ..., c_k\}$ are also represented by using $E$ on their corresponding class names to get $\{E(c_1), E(c_2), ..., E(c_k)\}$ through encoding and subsequent pooling.

Every hidden state $E(x_i)$ in $E(x)$ is attended to the class representations $\{E(c_1), E(c_2), ..., E(c_k)\}$. The hate sense $s_i$ for the hidden state $E(x_i)$ is categorized as token $x_i$’s sense, where:

$$
    s_i = \arg \max_j \frac{\exp(\cos(E(x_i), E(c_j)))}{\sum_{l=1}^k \exp(\cos(E(x_i), E(c_l)))}
$$

(1)

The final prediction, $f(x) = C(E(x))$ with $C$ a Multi-layer Perceptron and Pooling classifier and $E$ the encoder utilize this sense prediction $s$ and attended hidden representations. Specifically, $f(x) = C([E(x_1) + E(c_{s_1}), E(x_2) + E(c_{s_2}), ..., E(x_n) + E(c_{s_n})])$ where a max-pooling and multi-layer perceptron classifier $C$ is applied to the attended representations.

**Optimization** In addition to minimizing the final loss $L(f(x), y)$, we enforce constraints on the token level sense predictions having their consensus match the final hate speech label ($M$ selects the max occurring hateful sense):

$$
    L(M(s_1, s_2, ..., s_n), y)
$$

(2)

We enforce the number of unique hateful senses to be minimized ($U$ selects all unique hateful senses):

$$
    ||U(s_1, s_2, ..., s_n)||_{L_1}
$$

(3)

We hypothesize that our sense prediction approach, implemented through these constraints, models sentence semantics better to allow for a robust hate speech detection.

## 4 Experiments

We report performance across target groups on two public datasets Learning from the Worst LearningWorst (Vidgen et al., 2020) and HateXplain (Mathew et al., 2020). Both these datasets have annotations on the target groups.\(^1\) Tables 2 and 3 list the target groups in the respective datasets.\(^2\)

We consider a BERT document level text-classification model (Devlin et al., 2019) for hate speech detection. We develop our token-level sense disambiguation model on top of this model. The models are implemented using the Huggingface library (Wolf et al., 2019).

**Results** Tables 2 and 3 report the results of the baseline BERT method and our debiasing approach on the LearningWorst and HateXplain datasets respectively. Table 2 reports how our method is able

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\(^1\)To the best of our knowledge the performance per target group has not been previously reported.

\(^2\)We consider all target groups with at least 25 data points in the test set.
| Target Group | Baseline Performance | Method Performance |
|--------------|----------------------|---------------------|
| Women        | 0.73                 | 0.71                |
| Black        | 0.81                 | 0.83                |
| Jew          | 0.83                 | 0.85                |
| Muslim       | 0.79                 | 0.82                |
| Transgender  | 0.75                 | 0.78                |
| Gay          | 0.67                 | 0.74                |
| Immigrants   | 0.66                 | 0.69                |
| Refugee      | 0.77                 | 0.77                |
| Disable      | 0.83                 | 0.80                |
| South Asian  | 0.86                 | 0.82                |
| Arab         | 0.82                 | 0.85                |
| Gay Men      | 0.43                 | 0.57                |
| Black Women  | 0.41                 | 0.59                |
| East Asian   | 0.74                 | 0.79                |
| Hispanic     | 0.60                 | 0.56                |

Table 2: Comparison of baseline BERT and token-level classification model on LearningWorst.

| Target Group | Baseline Performance | Method Performance |
|--------------|----------------------|---------------------|
| African      | 0.54                 | 0.75                |
| Jewish       | 0.57                 | 0.79                |
| Islam        | 0.75                 | 0.71                |
| Homosexual   | 0.76                 | 0.73                |
| Women        | 0.63                 | 0.61                |
| Arab         | 0.71                 | 0.74                |

Table 3: Comparison of baseline BERT and token-level classification model on HateXplain.

Our method is effective in reducing the bias by performing better in scenarios with fewer training data points and greater stylistic differences.

5 Related Work

Bias in hate speech Detection The growth of hate and abuse online has inspired the collection of several datasets to study the phenomenon (Waseem and Hovy, 2016; Waseem, 2016; Davidson et al., 2017; Founta et al., 2018; Mandl et al., 2019, 2020; Kumar et al., 2018; Zampieri et al., 2019; Mathew et al., 2020; Toutanova et al., 2021). While these datasets form numerous benchmarks to compare machine learning solutions, several issues have been identified with hate speech training datasets – lack of linguistic variety and annotations (Vidgen et al., 2019a; Poletto et al., 2021). In particular sampling data by searching for keywords can lead to the collection of a biased dataset (Vidgen et al., 2019b; Wiegand et al., 2019). In our work we are identifying a bias in performance across target groups for models trained on hate speech datasets. This work falls in a broader category on fairness and debiasing across various other language tasks (Sun et al., 2019; Chang et al., 2019; Clark et al., 2019; Schuster et al., 2019).

Few Shot Sense Detection Word Sense Detection (Miller et al., 1993) is a long standing task of identifying the meaning of a word in a specific text. Recent methods (Huang et al., 2019; Blevins and Zettlemoyer, 2020; Bevilacqua and Navigli, 2020) have outperformed human performance on sense detection (Navigli, 2009). In scenarios where certain senses are rare, the performance of typical models is not optimal and a BERT based description of the senses helps alleviate the low resource problem (Blevins et al., 2021). In this work, we focus on identifying hateful senses as annotated in the training datasets, using their BERT representations. Despite having no sense annotations, we use the class names to assign token level senses.

6 Discussion

This paper demonstrates that models trained on hate speech datasets may have biased performance across different target groups. Our analysis shows that additional training data related to a target group is beneficial, highlighting the need for a more balanced collection of hateful text. We suggest a sense-based solution to address this issue, leading to a better average performance across different target groups.
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