Fair Hate Speech Detection through Evaluation of Social Group Counterfactuals

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Abstract
Approaches for mitigating bias in supervised models are designed to reduce models’ dependence on specific sensitive features of the input data, e.g., mentioned social groups. However, in the case of hate speech detection, it is not always desirable to equalize the effects of social groups because of their essential role in distinguishing outgroup-derogatory hate, such that particular types of hateful rhetoric carry the intended meaning only when contextualized around certain social group tokens. Counterfactual token fairness for a mentioned social group evaluates the model’s predictions as to whether they are the same for (a) the actual sentence and (b) a counterfactual instance, which is generated by changing the mentioned social group in the sentence. Our approach assures robust model predictions for counterfactuals that imply similar meaning as the actual sentence. To quantify the similarity of a sentence and its counterfactual, we compare their likelihood score calculated by generative language models. By equalizing model behaviors on each sentence and its counterfactuals, we mitigate bias in the proposed model while preserving the overall classification performance.

Introduction

Hate speech classifiers have high false-positive error rates on documents that contain specific social group tokens (SGTs; e.g., Asian, Jew), due in part to the high prevalence of SGTs in instances of hate speech (Wiegand, Ruppenhofer, and Kleinbauer 2019; Mehrabi et al. 2019). This unintended bias (Dixon et al. 2018) is illustrated by the high frequency of “Muslim”, for example, in hate speech-related instances of the train set, and the consequent higher false-positive errors for posts that include the word “Muslim”. Several existing frameworks offer methods for countering unintended bias based on counterfactual fairness. Counterfactual fairness considers the change in model prediction in a counterfactual situation by changing the SGT in the input. Fairness evaluation metrics, e.g., equality of odds and equality of opportunity, require model predictions to be robust in counterfactual situations (Hardt et al. 2016). Satisfying these metrics has motivated data augmentation approaches to balance the data distribution (Dixon et al. 2018; Zhao et al. 2018; Park, Shin, and Fung 2018) or fair input representations to equalize model performance with respect to protected groups (Madras et al. 2018; Zhang, Lemoine, and Mitchell 2018).

However, when SGTs have a definitional contribution to the semantics of a construct, as they do for hate speech, the contribution of the SGT to preserving the meaning of the sentence should be concomitantly considered prior to expecting robust model predictions for counterfactuals (Haas 2012). In fact, social groups are mentioned in specific contexts based on how they are socially perceived and stereotyped (Fiske et al. 2002; Warner and Hirschberg 2012). For instance, if a document includes a stereotype about Muslims (e.g., calling a Muslim terrorist because of their religion), changing the word “Muslim” to “Jew” underscores the interaction of the context and the SGT since the same stereotypes do not hold and are not usually used for Jews. Therefore, robust model behaviors should be restricted to counterfactuals that are similar to the actual sentence.

In this paper, rather than equalizing model behavior for all counterfactuals of a sentence, we restrict counterfactual reasoning to cases where substituting the SGT conveys a similar meaning (e.g., we may not consider substituting “Muslim” with “Jew” in a hateful sentence about terrorism). In doing so, we detect and discard asymmetric counterfactuals, in which the SGT substitution modifies the meaning of the text drastically (Figure 1). To operationalize the meaning modification, we evaluate the decrease in the likelihood of the sentence, calculated by a pre-trained language model, as a result of counterfactual SGT substitution. During train-
ing, we equalize the classifier’s predictions on sentences and their similar counterfactuals (symmetric counterfactuals) by employing a logit pairing approach (Kannan, Kucharikin, and Goodfellow 2018). We show that assuring similar performance on sentences and their symmetric counterfactuals helps pursue counterfactual token fairness (Garg et al. 2019).

Our contributions are (1) proposing a method for excluding asymmetric counterfactual based on sentence likelihoods; and (2) achieving fair predictions for social group pairs, based on their contextualized similarities. To this end, we first demonstrate the power of sentence likelihoods, calculated by a generative model, in distinguishing the associations of sentences with their mentioned SGTs. We explore documents in a dataset of social media posts each mentioning exactly one social group and show that sentences differ based on whether they are predictive of their mentioned social group. Our results show that in a subset of the dataset, the SGT can exclusively be predicted using the likelihood of the sentence. Then, to apply counterfactual token fairness to hate speech detection, we use sentence likelihoods to differentiate SGTs that can interchangeably appear in a sentence. For each instance of the dataset, we apply counterfactual logit pairing using SGTs that result in the least amount of change in the meaning. Our experiments on two datasets show that our method can better improve fairness, while preserving classification performance, compared to other bias mitigation models.

Related Work

Hate speech detection models have been studied in fairness research in machine learning, given their biases towards SGTs. Dixon et al. (2018) defined unintended bias as differing performance on subsets of the dataset that contain particular SGTs. When biased datasets initiate this issue, approaches for data augmentation are proposed to create a balanced ratio of positive and negative labels for each SGT or prevent biases from propagating to the learned model (Dixon et al. 2018; Zhao et al. 2018; Park, Shin, and Fung 2018).

Other approaches modify training objectives via L2 norms of feature importance (Liu and Avci 2019) or via regularization of post-hoc term-level importance (Kennedy et al. 2020b). Others apply adversarial learning for generating fair representations (Madras et al. 2018; Zhang, Lemoine, and Mitchell 2018) by minimizing predictability of preserved features from input data while maximizing classification accuracy. While fair representations have been applied in different machine learning problems to protect preserved attributes, Elazar and Goldberg (2018) demonstrated that adversarial learning cannot achieve invariant representation of features.

By altering sensitive features of the input and evaluating the changes in the output, counterfactual fairness (Kusner et al. 2017) assesses the bias in machine learning models. Similarly, counterfactual token fairness defines a fair (i.e., unbiased) model as one that behaves consistently across counterfactual sets of instances (Garg et al. 2019).

Dataset

In the present studies, we explore hate speech in a corpus of social media posts from Gab[1]. We downloaded Gab posts from the public dump of the data by Pushshift.io (Gaffney 2018). In the first study, we randomly selected 15 million posts from the Gab corpus, posted from August 2016 to October 2018. We analyze a subset of this dataset; SGT-Gab, which includes all posts that mention one SGT (N = 2M). In the second study, to train hate speech detection models, we used Gab Hate Corpus (GHC; Kennedy et al. 2020a) and Stormfront dataset (Storm, de Gibert et al. 2018), including 27k and 11k social media posts respectively, annotated based on their hate speech content.

The list of SGTs (see Supplementary Materials) is compiled from Dixon et al. (2018) and extended using a Natural Language ToolKit (NLTK; Loper and Bird 2002) function for WordNet synset generation. The resulting list includes 77 specific social group terms.

Analysis of Context-SGT Interaction

As stated by Warner and Hirschberg (2012), hate speech can include language that is offensive to any social group — e.g., call for violence against a group (Kennedy et al. 2020a) — or prejudicial expressions which target individuals and groups based on their social stereotypes (Fiske et al. 2002). Therefore, any attempt for supporting social group fairness in hate speech detection (e.g., counterfactual fairness) requires essential considerations for stereotypical language that is exclusive to particular target groups. In such cases, expecting robust model performance for all counterfactuals of the sentence is not in accordance with fairness objectives. Here, to indicating the extent of stereotypical language in the text, we identify a subset of a corpus of social media posts, in which SGTs can be predicted from their surrounding words. We apply generic language models to evaluate the predictability of a mentioned SGT among possible counterfactuals — e.g., we expect the language model to predict a higher likelihood for a sentence about terrorism when it is paired with “Muslim” versus other SGTs. By doing so, we identify sentences that are significantly different from their counterfactuals. Nadeem, Bethke, and Reddy (2020) show that generative models (e.g., GPT-2) exhibit strong stereotypical biases and therefore, perform well in detecting stereotype content. In this study, we consider all instances of SGT-Gab and construct counterfactuals through the substitution of SGTs.

For an instance $x$ in SGT-Gab with an SGT, $s_i$, and a set of possible SGTs $S$, the set of all counterfactual $\Theta(x)$ is:

$$\{\text{substitute}(s_i, s_j)| y s_j \in S, j \neq i\}$$

To measure SGT predictability across contexts, for a given $x$ and its counterfactual set $\Theta(x)$ we compute the likelihood assigned by a pre-trained language model, specifically GPT-2 (Radford et al. 2019). Notably, GPT-2 has achieved high performance on detecting stereotypes in language (Nadeem, Bethke, and Reddy 2020), and is therefore 

[1]https://files.pushshift.io/gab/

[2]https://gab.com
suitable as a language representations model that embeds stereotypical relations at the sentence level.

For each word \( x_i \) in a sentence, the likelihood of \( x_i \), \( P(x_i|x_0 \ldots x_{i-1}) \), is approximated by the softmax of \( x_i \) with respect to the vocabulary. Therefore, the log-likelihood of a sentence \( x_0, x_1, \ldots x_{n-1} \) is computed with:

\[
\lg P(x) = \sum_{i} \lg P(x_i|x_0, \ldots, x_{i-1})
\]

The log-likelihood of each instance and its counterfactuals were computed for SGT-Gab. The primary outcome was the original instance’s rank in log-likelihood amongst its counterfactuals. Higher rank for a mentioned SGT implies a higher dependence on context and indicates the stereotypical content of the sentence. In SGT-Gab, the aggregated results show that in 2.9% of the sentences, the mentioned SGT achieves the best ranking and in 13.9% of all posts, the mentioned SGT appears in the first 10% rankings.

Moreover, in stereotypical posts (in which the mentioned SGT achieves a high rank), we analyze whether highly ranked SGTs were conceptually related to the mentioned ones by comparing their associated social categories – e.g., race, ethnicity, nationality, and gender. In 86.03% of the posts, where the original SGT is ranked second, the top-ranked SGT is from the same social category. When the original SGT is ranked in the top 10%, 72.46% of SGTs with better ranking are from the same social categories. The results show that the similarity can be in-part explained by SGTs’ common social category. This similarity can be further explored by quantifying social stereotypes regarding different social groups (Fiske et al. 2002). Figure 2 shows the averaged ranking of each SGT among all posts it appears in.

The results show a high variation in averaged ranking among SGTs (\( sd = 15.33 \)), indicating the variation of stereotypical content about each social group in the corpus.

### Asymmetric Counterfactual Filtering

Designing approaches for satisfying the fairness criteria in hate speech classifier models requires specific steps for handling social group biases inherent in stereotyped language. However, we can infer from the results of our first analysis that in stereotype-related settings, substituting the SGT with other tokens potentially creates a counterfactual which should not be constrained to generate the same prediction (as the meaning of the instance has changed). These cases are referred to as asymmetric counterfactuals; here, we propose a method to detect them based on the change in sentence likelihood and ignore them during bias mitigation.

#### Method

We apply counterfactual logit pairing (CLP) to labeled instances and their counterfactuals (Garg et al. 2019). CLP penalizes divergence in output among a given input and its counterfactuals. Rather than simplifying the training process by exclusively training the logit pairing on all counterfactuals of negative instances of hate (Garg et al. 2019), we provide a procedure to identify asymmetric counterfactuals over the entire corpus.

We identify (and filter) counterfactuals based on their likelihood compared to that of the original sentence, calculated by GPT-2. Given a sentence \( x \), which includes an SGT, we generate the set of counterfactuals \( x_{cf} \) with higher log-likelihoods compared with \( x \):

\[
x_{cf} = \{ x|x' \in \Theta(x), P(x) \leq P(x') \}
\]

Consequently, semantically different counterfactuals are not considered for mitigating bias in stereotypical content. Given the generated set of counterfactuals, \( x_{cf} \), a classifier, \( f \), satisfies counterfactual fairness if (Garg et al. 2019):

\[
|f(x) - f(x')| < \epsilon, \forall x \in X, \forall x' \in x_{cf}
\]

where \( X \) contains the whole annotated dataset. The averaged \( |f(x) - f(x')| \) among the predictions of a model is considered as the measurement of counterfactual token fairness (CTF).

#### Experiment and Results

We compare three BiLSTM (Schuster and Paliwal 1997) classifiers with CLP, one trained based on our approach for excluding asymmetric counterfactuals (CLP+ASY), one based on (Garg et al. 2019)’s counterfactual generation (CLP+NEG), which attempts to remove asymmetric counterfactuals by considering all counterfactuals for negative instances of hate. To evaluate alternative strategies for CLP, the third model generates counterfactuals based on social categories (CLP+SC). E.g., for a sentence mentioning a racial group, we only consider counterfactuals that mention racial groups. We also compare the accuracy and fairness of these models with a BiLSTM baseline with no bias mitigation (BiLSTM), and a BiLSTM model that masks the SGTs.
Table 1: Vanilla BiLSTM model, BiLSTM model with masking SGTs, baseline CLP, CLP method based on social categories, and our CLP method with asymmetric detection, trained in 5-fold cross validation and tested on 20% of Storm. Fairness evaluations include true positive (TP) and true negative (TN) as the metrics for equality of odds, and counterfactual token fairness (CTF) over two datasets of counterfactuals.

| Model                  | Acc | Predicting Hate | Precision | Recall | F1 | Equality of odds | TP | TN | CTF |
|------------------------|-----|-----------------|-----------|--------|----|-----------------|----|----|-----|
| BiLSTM                 | 85.67 | 45.74 | 64.39 | 53.38 | 21.25±32.4 | 17.82±33.9 | 67.05 | 46.83 | 21.80±31.5 | 0.04 0.04 |
| BiLSTM+Mask            | 84.73 | 41.28 | 66.09 | 50.63 | 34.07±37.9 | 79.32±31.1 | 67.50±40.8 | 0.07 0.09 |
| CLP+NEG                | 84.19 | 36.26 | 66.84 | 46.76 | 25.30±27.8 | 67.50±40.8 | 0.07 0.09 |
| CLP+SC                 | 83.48 | 36.19 | 67.05 | 46.83 | 21.80±31.5 | 82.22±26.4 | 0.04 0.04 |
| CLP+ASY               | 84.38 | 41.50 | 63.02 | 49.60 | 21.80±31.5 | 82.22±26.4 | 0.04 0.04 |

(BiLSTM+Mask). Table 1 shows the results of analyzing these five models on Storm dataset. The results of comparing these methods on GHC is included in the Appendix.

Once a model achieves baseline accuracy scores on the hate recognition task, fairness scores are reported based on fairness criteria. First, we evaluate the measurements for equality of odds. Namely, we compare the averaged rate of true positive (TP) and true negative (TN) results for predicting the hate speech label associated with each SGT in the preserved test set (20% of the dataset). We then compute counterfactual token fairness (CTF) – averaged \(|f(x) - f(x')|\) for sentences and their counterfactuals – for two datasets of symmetric counterfactuals (Dixon et al. 2018) and asymmetric counterfactuals (Nadeem, Bethke, and Reddy 2020).

Symmetric counterfactuals (SYM) from Dixon et al. (2018) include synthetic instances based on templates (<You are a ADJ SGT>, and <Being SGT is ADJ>). In such instances, the context is explicitly dis-aggregated from the SGT, and the model prediction should solely depend on the ADJs. Therefore, we expect smaller values of CTF for fair models. Asymmetric counterfactuals (ASYM) from Nadeem, Bethke, and Reddy (2020) include stereotypical sentences and their counterfactuals which we generated by substituting the SGTs. Since all these instances are stereotypical, we expect all counterfactuals to be asymmetric, and CTF to be higher for this dataset.

**Conclusion**

We show that the textual context can be variably associated with the social groups they mention. While stereotypical sentences include semantic clues of what social group they mention, other sentences imply the same meaning when paired with different social group tokens. We used this information to apply counterfactual reasoning for evaluating models’ robust predictions upon a change in the social group token. Our method treats social groups equally according to the context, by applying logit pairing on a restricted set of counterfactuals for each instance. By doing so, counterfactual token fairness improved while the general accuracy and other fairness metrics were maintained. Future work will explore alternative techniques for measuring asymmetry in social group counterfactuals and other domains for which our methods can be applied. By considering asymmetric counterfactuals in the method, we can formally model social group differentiation along with similarities, which can shed light on the textual associations of hate speech and stereotype.

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