EFFICIENTLY MITIGATING CLASSIFICATION BIAS VIA TRANSFER LEARNING

Xisen Jin§, Francesco Barbieri†, Aida Mostafazadeh Davani§, Brendan Kennedy§, Leonardo Neves†, Xiang Ren§
§University of Southern California
†Snap Research
{xisenjin, mostafaz, btkenned, xiangren}@usc.edu
{fbarbieri, lneves}@snap.com

ABSTRACT

Prediction bias in machine learning models refers to unintended model behaviors that discriminate against inputs mentioning or produced by certain groups; for example, hate speech classifiers predict more false positives for neutral text mentioning specific social groups. Mitigating bias for each task or domain is inefficient, as it requires repetitive model training, data annotation (e.g., demographic information), and evaluation. In pursuit of a more accessible solution, we propose the Upstream Bias Mitigation for Downstream Fine-Tuning (UBM) framework, which mitigate one or multiple bias factors in downstream classifiers by transfer learning from an upstream model. In the upstream bias mitigation stage, explanation regularization and adversarial training are applied to mitigate multiple bias factors. In the downstream fine-tuning stage, the classifier layer of the model is re-initialized, and the entire model is fine-tuned to downstream tasks in potentially novel domains without any further bias mitigation. We expect downstream classifiers to be less biased by transfer learning from de-biased upstream models. We conduct extensive experiments varying the similarity between the source and target data, as well as varying the number of dimensions of bias (e.g., discrimination against specific social groups or dialects). Our results indicate the proposed UBM framework can effectively reduce bias in downstream classifiers.

1 INTRODUCTION

The practice of fine-tuning pretrained language models (PTLMs), such as BERT (Devlin et al., 2019), has efficiently improved prediction performance in a wide range of natural language processing (NLP) tasks. However, fine-tuned models may exhibit biases against protected groups (e.g., gender and ethnic minorities), as models may learn to associate certain features with positive or negative labels (Dixon et al., 2018), or propagate bias encoded in pre-trained models to downstream classifiers (Caliskan et al., 2017; Bolukbasi et al., 2016). Among many examples, Kurita et al. (2019) demonstrates that models trained using BERT embeddings for pronoun resolution are gender-biased, performing more poorly on resolving female pronouns than male pronouns even in a balanced dataset. Additionally, Kennedy et al. (2020) shows that hate speech classifiers fine-tuned from BERT spuriously correlate certain protected groups with hateful language, resulting in false positive model predictions when certain group identifiers (e.g., “muslim”, “black”) are present—e.g., misclassifying non-hate speech text such as “I am a Muslim” as hate speech.

The majority of methods combating bias in NLP tasks try to mitigate bias during fine-tuning PTLMs for a specific downstream task (dataset) (Park et al., 2018; Zhang et al., 2018; Beutel et al., 2017). For example, data augmentation approaches achieve bias mitigation by preventing models from capturing spurious patterns in the original dataset (Dixon et al., 2018; Zhao et al., 2018; Park et al., 2018); adversarial approaches learn to generate debiased data representations that are exclusive to the downstream model (Madras et al., 2018; Zhang et al., 2018). A critical issue with downstream bias mitigation techniques is their inefficiency. For example, hate speech is a recurrent problem.

Link to code and data: https://github.com/INK-USC/bias-mitigation-via-transfer-learning
occurring in myriad domains including various social media platforms; downstream bias mitigation requires that new bias factors are identified in each dataset, and subsequently bias mitigation techniques are applied and evaluated for each. But given the common semantic themes of hate speech, offensive language, and toxicity, as well as the common themes of a given bias factor (Warner & Hirschberg, 2012), repeating this process over every dataset and domain is redundant. Moreover, given the challenges and costs of bias mitigation — model training, definition of fair measures, annotating bias factors (e.g., African American English), and collection of user demographic data — model developers in the areas affected by bias are less likely to perform the process repeatedly. For any model affected by bias, we aim to make bias mitigation more efficient and accessible.

In this paper, we propose the Upstream Bias Mitigation for Downstream Fine-Tuning (UBM) framework for efficient, cross-domain and task bias mitigation for classification models, which can make bias mitigation more accessible in practice. Our framework takes a transfer learning approach: first, in the upstream bias mitigation stage, a PTLM is fine-tuned with bias mitigation objectives on one or several upstream tasks, and subsequently the classification layer is re-initialized; second, in the downstream fine-tuning stage, the de-biased encoder from the PTLM is again fine-tuned on a downstream task without additional bias mitigation steps. Our hypothesis is that the de-biased encoder will maintain a reduction in overall bias with respect to protected groups, to downstream tasks in new datasets. If so, de-biased downstream models would be achievable by de-biasing and transferring one upstream model. This transfer learning approach to mitigating classification bias offers the potential for more widespread application of bias mitigation techniques in model deployment.

We conduct a series of experiments with the proposed UBM framework. These experiments address the overall effectiveness of the transfer learning approach and the scope of our proposed framework. Using datasets with previously recognized bias factors, we train and evaluate models on the ability to detect hate speech and toxicity while monitoring their bias towards social group identifiers and text written in African American Vernacular English. In doing so, we establish the scope of the framework, in particular the various settings in which a downstream user might make use of our framework. (1) In the most straightforward setting, the target data consists of new examples from the same distribution as the source data, which corresponds to fine-tuning a less biased model over emerging new examples; (2) in a more challenging setting, the source and the target data have different distributions (e.g., different datasets); (3) furthermore, we perform multi-task learning to reduce different kinds of bias in the source domain and task, so that fine-tuned classifiers are less biased in term of multiple bias factors. We achieve overall positive empirical results, evidencing the capability of learning less biased models with the proposed framework.

2 RELATED WORKS

Bias, in our setting, refers to undesirable model behaviors, such as correlating mentions of certain group names with labels (Kiritchenko & Mohammad, 2018; Zhang et al., 2020) or differential performance on data produced by different social groups (Shen et al., 2018; Sap et al., 2019) that causes harm to certain social groups. Several recent studies (Mehrabi et al., 2019; Blodgett et al., 2020; Shah et al., 2020) provide taxonomies for machine learning bias. A number of works propose algorithms for mitigating bias in different steps during training a machine learning model (e.g., Park et al., 2018; Zhang et al., 2018).

Mitigating Bias in Representations. One successful approach to mitigate bias is to prevent biased data representations during the training process. (Zhang et al., 2018; Beutel et al., 2017) introduced methods for jointly training a classifier with an adversarial predictor for sensitive attributes, in which data representations are shared within the adversarial learning framework. (Madras et al., 2018) further studied re-usable de-biased data representations by training a new downstream classifier (potentially with a different classification task) using the learned representations. However, since the approach relies on transferring the frozen data representations instead of the model, the framework fails to generate de-biased predictions for new data (e.g., new examples from the same or different domains).

Mitigating Bias in Pretrained Models. Another line of work detects and reduces bias as it appears in pretrained models (e.g., word vectors, BERT) (Zhou et al., 2019; May et al., 2019; Bhardwaj et al., 2020). Many such studies are restricted to measuring bias in the latent semantic space (e.g., operationalizing gender bias as the distance between gendered words from occupational and familial words). Other studies assess the propagation of bias from pretrained models to downstream
classifiers: Zhao et al. (2019) demonstrate that gender-bias propagates from contextualized word embeddings to models for coreference resolution tasks (e.g., by associating gendered pronouns with stereotypical words). Liang et al. (2020), Ravfogel et al. (2020) study algorithms for mitigating bias in pretrained models by de-biasing the learned representations. However, these approaches treat pretrained models as being frozen and do not study whether mitigating bias in PTLMs leads to similarly less biased classifiers after fine-tuning on downstream tasks.

Transferring Learning of Less Biased Classifiers. In contrast to the mentioned approaches, we do not analyze or mitigate latent semantic (representational) bias embedded in PTLMs; rather, we ask whether fine-tuned PTLMs with bias mitigation can subsequently be transferred to downstream domains and tasks, via fine-tuning using the de-biased PTLM encoder. A few previous works have studied related research problems, with significant differences to our work. Schumann et al. (2019) study the transferability of machine learning fairness across domains with theoretical analysis, but assumes simultaneous access of source and target domain data, which does not achieve the goal of separating out bias mitigation from downstream fine-tuning. Shafahi et al. (2020) study transfer learning of robustness to adversarial attacks under fine-tuning, but with no address for bias mitigation. In summary, no previous works provide the capacity for achieving downstream bias mitigation in fine-tuned classifiers from upstream application of bias mitigation techniques.

3 Preliminaries

We first introduce important concepts that are later used in our approach, such as transfer learning, fine-tuning, prediction bias, and downstream bias mitigation algorithms.

3.1 Transfer Learning via Fine-tuning

Fine-tuning is a common transfer learning technique with widespread application in NLP. The most significant advantage of fine-tuning is its simplicity of implementation. Model developers can load pretrained weights of a complicated source model and take advantage of its powerful inductive bias to obtain an efficient model without training them from scratch (Qu et al., 2020).

Formally, fine-tuning requires a neural classification model \( f : \mathbb{R}^m \rightarrow \{0, 1, ..., C\} \), which maps an input sentence \( x \) to a class label \( y \). The model \( f = h \circ g \) is composed of a text encoder \( g : \mathbb{R}^m \rightarrow \mathbb{R}^d \) (e.g., Transformers in RoBERTa (Liu et al., 2019)), which maps an input sentence \( x \) to a hidden representation \( z \in \mathbb{R}^d \) in the representation space; and a classifier head \( h : \mathbb{R}^d \rightarrow \{0, 1, ..., C\} \), which maps the representation \( z \) to the label space. The model is trained on a dataset of examples \( (x, y) \) from a domain \( \mathcal{D} \) for a task \( \mathcal{T} \): the domain describes the input space \( \mathcal{X} \) and its marginal distribution, and the task \( \mathcal{T} \) describes the label space \( \mathcal{Y} \) and the predictive function to learn. To adapt a classification model from a source domain \( \mathcal{D}_s \) (trained for a source task \( \mathcal{T}_s \)) to a target domain \( \mathcal{D}_t \) (for a target task \( \mathcal{T}_t \)), one first trains the model \( f_s = h_s \circ g_s \) in the source data \( (x^s, y^s) \), yielding the source (upstream) model. Then, for transfer learning to \( \mathcal{D}_t \) and implementing the downstream (target) model \( f_t = h_t \circ g_t \) for task \( \mathcal{T}_t \), the upstream encoder \( g_s \) is used to initialize the weights of downstream encoder \( g_t \), while the classifier head \( h_t \) is randomly initialized. The full target model \( f_t \) is then trained on the target data \( (x^t, y^t) \). Note that the upstream model itself can also be obtained via fine-tuning from an upstream source model, for example, PTLMs, which is the practice we apply.

3.2 Prediction Bias and Downstream Bias Mitigation

Before discussing prediction bias in the context of fine-tuning PTLMs, we first define what we mean by “prediction bias”, and how we measure it based on a model’s behaviors. To evaluate models’ prediction bias, we operationalize equal opportunities (Hardt et al., 2016); a model \( f \) is biased if it yields higher prediction error rates for a certain label over a subset \( S \) of the data. In cases where the subset \( S \) is associated with a specific social group, lack of equal opportunities leads to unfair, biased predictions. We evaluate equal opportunities for various subsets of the data, each associated with a bias factor. We refer to each bias factor \( a^{(j)} \) with its index \( j \in \{0, 1, ..., K\} \); for example, the subset \( S^{(j)} \) may consist of all examples produced by African American English speakers, or all input examples that mention a certain group identifier (e.g., female pronouns). For each sample \( (x_i, y_i) \) in the dataset, we use a binary attribute vector \( a_i \in \{0, 1\}^K \) to indicate its associated subsets, where the \( j \)-th item \( a^{(j)}_i \in \{0, 1\} \) indicates whether \( x_i \) belongs to the set \( S^{(j)} \).
In this paper, we assess equal opportunities regarding false positive error rates, given that positives in our label sets (e.g., spam, offensive, hate speech labels) are considered harmful and an incorrect positive prediction leads to some cost for the instance (e.g., offensive posts can get blocked in a social media platform); however, the framework can effortlessly be applied to other cases, e.g., where false negative rates are also considered as the evidence of bias. For simplicity of notations, we use label $y = 1$ to refer to harmful outcomes (e.g., spam, or hate speech), and $y = 0$ for others. The prediction bias regarding subset $S^{(j)}$ is formally defined as the false positive rate difference (FPRD$^{(j)}$), and is quantified as:

$$
\text{FPRD}^{(j)} = P(\hat{y} = 1|a^{(j)} = 1, y = 0) - P(\hat{y} = 1|a^{(j)} = 0, y = 0),
$$

where $\hat{y}$ is the model prediction for a sample. The term $P(\hat{y} = 1|y = 0, a^{(j)})$ indicates the false positive rate for bias factor $j$ (FPR$^{(j)}$). In other words FPR$^{(j)}$ shows the probability of predicting a label as positive when the ground truth is negative, conditioned on the value of the attribute $a^{(j)}$.

**Downstream Bias Mitigation.** Bias mitigation algorithms have the objective of reducing, and ideally eliminating, bias in machine learning models. For a fine-tuned model, bias is typically addressed for the downstream fine-tuning task $T_t$ with an auxiliary learning task associated with protected groups. Formally, given a labeled dataset with attribute indicators $(x^t, y^t, a^t)$, the model is trained by jointly optimizing a main learning objective $\ell_s(x^t, y^t)$ and a bias mitigation objective $\ell_b(x^t, y^t, a^t)$, which penalizes biased behaviors of models. For example, in adversarial learning, the loss penalizes data representation $z^t = g(x^t)$ that are predictable of the attribute $a^t$. Note that while $x^t$ or $y^t$ can be excluded for computing the bias mitigation objective $\ell_b$, the ground truth attribute indicator $a^t$ is almost always required.

**Limitations.** Downstream bias mitigation is limited in that it require optimizing the task objective and the bias mitigation objective for every dataset (task and domain). Problematically, the requirements of performing bias mitigation might be inaccessible to every task and domain, because attribute indicator $a$ is usually not provided in datasets – e.g., speaker demographics are usually not reported for the hate speech datasets (Bender & Friedman [2018]) – or may be difficult to collect due to privacy concerns. However, amidst the redundancies of exclusively downstream de-biasing there is an opportunity for greater efficiency: de-biasing while fine-tuning an upstream model, and transferring the de-biased encoder to downstream tasks and domains. By taking advantage of the similarities among tasks and domains, and fundamentally from the general representation of bias in models, bias mitigation objectives must be trained and satisfied only during upstream fine-tuning.

### 4 Upstream Bias Mitigation for Downstream Fine-Tuning

We propose to achieve bias mitigation for downstream classifiers by transferring from an de-biased upstream model. We operate in the specific transfer learning setting of PTLM fine-tuning, as outlined in Section 3.1. To this end, we propose the Upstream Bias Mitigation for Downstream Fine-Tuning (UBM) framework. Our proposed approach concurrently attends to several bias factors in the upstream models. Transferring the resulting model to target domain and task suffices for mitigating bias factors in downstream models with no further need for de-biasing algorithms.

#### 4.1 Problem Formulation

Formally, we consider the problem of reducing one or multiple bias factors in (potentially a large number of) downstream classifiers $f_t = h_t \circ g_t$ in target domains and tasks $\langle D_t, T_t \rangle$ with a dataset of examples $(x^t, y^t)$. The attribute indicators $a^t$ are not available in the target domain. The downstream classifier $f_t$ can be fine-tuned from an upstream model $f_s$ trained in source domains, where it is possible to run bias mitigation algorithms. When dealing with multiple bias factors, the upstream model $f_s$ may be jointly trained on several datasets with domains $D_s^{1:K}$ for tasks $T_s^{1:K}$ (noted as domain-task pairs $\langle D_s, T_s \rangle^{1:K}$). We assume each source domain-task pair $\langle D_s, T_s \rangle$ is dedicated to address a single bias factor $a^{(j)}$, sharing the same superscription. The joint training can be formulated as a multi-task learning problem, where the encoder $g_t$ is shared and the classifier head $h_t$ is specific to each domain-task pair. Specifically, we consider two dimensions of settings, specifying: (1) the similarity between the source and the target domain and the task, and (2) the number of bias factors considered. Settings can vary based on these two dimensions (Figure 1 (left)):
One bias factor

Multiple bias factors

Settings

(\mathcal{D}\!, \mathcal{T})

Source domain / task examples + attributes

(\mathbf{x}_i, y_i, a_i)

Target domain / task examples

(\mathbf{x}_i, y_i)

One bias factor

Different (\mathcal{D}\!, \mathcal{T})

Source domain / task examples + attributes

(\mathbf{x}_i, y_i, a_i)

Figure 1: Proposed settings and the framework of Upstream Bias Mitigation for Downstream Fine-Tuning (UBM). We consider the settings with the same or different source and target domains and tasks, addressing one or more bias factors. Our proposed framework consists of two stages: (1) an upstream (source) model \( f_s = g_s \circ h_t \) is trained with bias mitigation algorithms and (2) the encoder \( g_s \) is transferred to the downstream (target) model \( f_t \) for fine-tuning.

**Same or different source and target domains and tasks.** In the simplest setting, we have \( (\mathcal{D}_i, \mathcal{T}_i) = (\mathcal{D}_s, \mathcal{T}_s) \) for some \( i \). Practically, it corresponds to fine-tuning a de-biased model over emerging new examples from the same domain and task. In a more challenging setting, we have \( (\mathcal{D}_s, \mathcal{T}_s) \notin (\mathcal{D}_i, \mathcal{T}_i)^{1:K} \), which is a more common case in practice.

**Dealing with one or multiple bias factors.** As mentioned above, the upstream model \( f_s \) can be de-biased for either one or multiple bias factors.

## 4.2 Upstream Bias Mitigation for Fine-tuning Method

We propose the Upstream Bias Mitigation for Downstream Fine-tuning (UBM) framework. The framework involves two stages: (1) **Upstream bias mitigation**, in which a source model \( f_s = h_s \circ g_s \) is trained on the source domain and task, with bias mitigation objectives. The encoder \( g_s \) is transferred to a target domain and a task while the classifier head \( h_s \) is discarded. (2) **Downstream fine-tuning**, in which the target model \( f_t = h_t \circ g_t \) utilizes \( g_s \) to initialize the encoder weights and is then fine-tuned to improve target domain prediction performance. Figure 1 (right) illustrates the proposed framework.

We consider two approaches in the bias mitigation stage: explanation regularization (Kennedy et al., 2020) and adversarial de-biasing (Zhang et al., 2018; Madras et al., 2018; Xia et al., 2020). The explanation regularization approach can be applied when the model is overly sensitive to a particular lexicon, associated with the bias factors. For instance, the model may spuriously associate hate speech labels with data that mentions group identifiers, or language that is commonly used by a certain demographic group, resulting in higher FPRDs. The adversarial de-biasing approach is more general and does not require a predefined set of lexicons.

**Explanation Regularization.** For a source domain and task in \( (\mathcal{D}_s, \mathcal{T}_s)^{1:K} \) with training examples \((\mathbf{x}^s, y^s, a^s)\), explanation regularization approaches assign an importance score \( \phi^{(j)}(w, \mathbf{x}^s) \) for each word \( w \) in a predefined lexicon set \( \mathcal{W}^{(j)} \) that is present in the input example \( \mathbf{x}^s \) and indicates an attribute \( a^{(j)} \in a^s \). When training the upstream model \( f_s \) on a set of bias factors, the importance scores are regularized jointly with the main learning objective,

\[
\min_{f_s} \ell_c + \alpha \sum_{j=1}^{K} \sum_{w \in \mathbf{x}^s \cap \mathcal{W}^{(j)}} ||\phi^{(j)}(w, \mathbf{x}^s)||^2
\]

where \( \ell_c \) is the classification loss and \( \alpha ||\phi^{(j)}(w, \mathbf{x}^s)||^2 \) penalizes the importance attributed cumulatively to all \( w \in \mathcal{W}^{(j)} \). \( \alpha \) is a hyperparameter controlling the strength of the regularization. While a variety of explanation algorithms can be applied to measure \( \phi^{(j)}(w, \mathbf{x}^s) \), we focus on the simplest input occlusion algorithm (Zintgraf et al., 2017), where the importance is quantified as the change in model prediction caused by removing \( w \) from the input \( \mathbf{x}^s \).

**Adversarial De-biasing.** For a source domain and task in \( (\mathcal{D}_s, \mathcal{T}_s)^{1:K} \) with training examples \((\mathbf{x}^s, y^s, a^s)\), adversarial de-biasing algorithms reduce the predictability of the attributes \( a^s \) from the intermediate data representations generated by encoder \( g_s \). During training, an adversarial clas-
sifier head \( h^{(j)}_{adv} : \mathbb{R}^d \rightarrow [0, 1] \) is built upon the encoder \( g_s \) for each attribute \( a^{(j)} \in a^i \). The adversarial classifier is trained to predict the attribute \( a^{(j)} \) by optimizing the cross entropy loss \( \ell_{adv}(h^{(j)}_{adv} \circ g_s(x), a^{(j)}) \). A gradient reversal layer [Ganin et al., 2016] is added between the encoder \( g_s \) and \( h^{(j)}_{adv} \), so that the encoder \( g_s \) is optimized to generate representations that do not encode information about the attribute \( a^{(j)} \). The adversarial learning objective is optimized jointly with the classification objective at training. Formally, the optimization problem is written as,

\[
\min_{g_s, h^{(j)}_{adv}} \max_{\Omega(\mathbb{R}^{K})} \ell_c + \sum_{j=1}^{K} \ell_{adv}(h^{(j)}_{adv} \circ g_s(x^t), a^{(j)})
\]

while the adversarial loss \( \ell_{adv} \) can take other forms as in [Madras et al., 2018]. We did not observe meaningful differences empirically.

Next, in the downstream fine-tuning stage, we train a downstream classifier \( f_t = h_t \circ g_t \) in the target domain \( D_t \) for the target task \( T_t \), where \( g_t \) is initialized with \( g_s \), transferred from the source model. While no de-biasing algorithms are applied in this stage, the model is trained by jointly fine-tuning \( g_t \) and \( h_t \); in our main experiments, we employ this simple fine-tuning strategy to obtain the target model \( f_t \). We also consider two approaches aiming at preserving the de-biased encoder for analysis: (1) the encoder \( g_t \) is frozen while only \( h_t \) is trained, and (2) the encoder \( g_t \) is penalized for deviating from \( g_s \) with a regularization term. In the second approach, we use \( \ell^2 \)-sp regularizer [Li et al., 2018], which penalizes the distance between the weights and the initial point of fine-tuning. Formally, let \( w_0 \) be the initial weight of the encoder \( g_t \) before fine-tuning, and \( w \) be the current weight of \( g_t \). The \( \ell^2 \)-sp regularizer is written as \( \Omega(w) = \beta ||w - w_0||_2^2 \), where \( \beta \) is a hyperparameter controlling the strength of the regularization, set to 1 by default.

5 Experiment Setup

In this section we describe the general experimental framework and the evaluation metrics that are reported for each experiment.

5.1 Bias Factors

We consider two bias factors in our study, namely the group identifier bias and the African American English (AAE) dialect bias. Both biases are evaluated in hate speech and toxicity detection tasks.

**Group Identifier Bias.** This bias refers to higher false positive rates of hate speech predictions when dealing with sentences containing group identifiers. This behavior is harmful to certain demographic groups by misclassifying innocuous text mentioning a specific social group (e.g., “I am a Muslim”) as hate speech. We include two datasets for study, namely the Gab Hate Corpus (GHC) [Kennedy et al., 2018] and the Stormfront corpus [de Gibert et al., 2018]. Both datasets contain binary labels for hate and non-hate instances, with differences in the labeling schemas (therefore tasks are not equal). We use the explanation regularization approach with 25 group identifier lexicons provided in [Kennedy et al., 2020].

**AAE Dialect Bias.** Sap et al. [2019] show that offensive and hate speech classifiers yield a higher false positive rate on text written in African American English (AAE). This bias brings significant harm to the community that uses AAE, for example, by leading to the disproportionate removal of the text written AAE in social media platforms, impacting users’ freedom of expressions, and additionally reinforcing negative perceptions of AAE [Blodgett et al., 2020]. We include two datasets for study: FDCL [Founta et al., 2018], which is a four-way classification task for detecting normal, abusive, hateful, and spam language; DWMW [Davidson et al., 2017], which is a three-way classification task for detecting normal, abusive, and hateful language. The models are trained to perform four-way and three-way classification respectively; while to evaluate the prediction bias, we treat abusive, hateful and spam together as harmful outcomes (i.e., false positives for each are harmful). We use an off-the-shelf AAE dialect predictor [Blodgett et al., 2016] to identify examples written in AAE for the bias mitigation stage. We report the results for both explanation regularization and adversarial learning (see Appendix for details of regularization methods).

5.2 Evaluation Metrics

We aim to train models that maintain their in-domain classification performance yet reduce FPRD with respect to specified bias factors. To evaluate the in-domain classification performance, we
Table 1: Cross-domain and task transfer learning of less biased models with GHC and Stormfront as target domains, where source domains are noted before arrow (→). In-domain FPRD, IPTTS FPRD and NYT Accuracy (Acc.) measures prediction bias. The preferred outcomes for each metric are marked with arrows. We see UBM maintains in-domain prediction performance and overall reduces bias.

As we see from Table 1, GHC and Stormfront both show significant improvements in bias mitigation compared to the Vanilla baseline. However, UBM further reduces bias across all domains, achieving the lowest FPRD across all datasets. The differences in bias mitigation across the domains are also highlighted, with GHC performing better in single-domain settings and Stormfront in cross-domain settings. The overall false positive rate (FPR) is also reduced, indicating a more accurate prediction of hate speech.

5.3 Evaluated Models

For comparison, we report the results when (1) the downstream classifier is directly trained in the target domain without any bias mitigation (noted as Vanilla); and (2) the downstream classifier is trained in the target domain with explanation regularization or adversarial de-biasing (noted as Expl. Reg. or Adv. Learning). We also report (3) a model fine-tuned from the Vanilla model (noted as Van-Transfer); and finally, we report the results of the proposed UBM, where we note the bias mitigation applied in the source domains in the subscriptions (e.g., UBMBReg, UBMBAdv). When multiple source datasets are used for debiasing, the subscriptions show which bias mitigation algorithms are applied for each dataset (e.g., UBMBReg+Adv). We expect that our framework achieves a similar in-domain performance (reported as In-domain F1 or In-domain Accuracy), and less bias (lower FPRD in the in-domain test sets and IPTTS; higher accuracy on NYT Acc and BROD Acc) compared to Vanilla and Van-Transfer. It should be noted that we do not expect UBM to achieve a lower bias compared to directly mitigating bias in target domain (Expl. Reg and Adv. Learning); the focus of our study is to reduce bias when bias mitigation is not practical in the target domain.
In-domain Acc. (\%)

| Method / Datasets | DWMW | FDCL (Half-)B |
|-------------------|------|---------------|
| Metrics           | In-domain | BROD Acc. (\%) |
| Single dataset    |      |               |
| Vanilla           | 91.46 ± 0.1 | 78.77 ± 0.3 |
| Expl. Reg.        | 91.38 ± 0.1 | 76.61 ± 1.5 |
| Adv. Learning     | 91.11 ± 0.3 | 77.53 ± 0.9 |
| FDCL → DWMW      |      |               |
| Van-Transfer      | 91.27 ± 0.2 | 79.98 ± 1.1 |
| UBMM_{Reg}        | 91.39 ± 0.0 | 80.27 ± 0.2 |
| UBMM_{Adv}        | 91.60 ± 0.1 | 79.98 ± 1.7 |
| GHC + FDCL → DWMW |      |               |
| Van-Transfer      | 91.65 ± 0.1 | 80.98 ± 0.4 |
| UBMM_{Reg+,Reg}   | 91.79 ± 0.4 | 81.36 ± 0.8 |
| UBMM_{Reg+,Adv}   | 91.33 ± 0.1 | 81.09 ± 0.4 |
| Sft. + FDCL → DWMW |      |               |
| Van-Transfer      | 91.64 ± 0.2 | 81.12 ± 0.1 |
| UBMM_{Reg+,Reg}   | 91.66 ± 0.2 | 80.05 ± 0.5 |
| UBMM_{Reg+,Adv}   | 91.55 ± 0.2 | 81.14 ± 1.5 |

Table 2: Cross-domain and task transfer with DWMW as the target domain.

Table 3: Same-domain and task transfer with the second half of FDCL as the target domain.

6 RESULTS

We run our experiments with different problem formulations and report the results for each setting. We use RoBERTa-base as our text encoder (i.e., the model in the bias mitigation stage itself is fine-tuned from RoBERTa-base). See Appendix for more implementation details.

6.1 CROSS-DOMAIN AND TASK TRANSFER LEARNING OF LESS BIASED MODELS.

As one of the main settings for our experiments, we first show the results when the source and the target domain-task pairs are different. We use \( \langle D_s, T_s \rangle \rightarrow \langle D_t, T_t \rangle \) as the transfer notation, in which source and target datasets are respectively represented in the left and right-hand side of the arrow. For hate speech classification, we perform transfer learning from GHC to Stormfront (GHC → Stf.); from Stormfront to GHC (Stf. → GHC); and for toxicity classification, we perform transfer learning from FDCL to DWMW (FDCL → DWMW). We do not use DWMW as the source domain since a great portion (~ 97%) of AAE posts are labeled as offensive language in this dataset, and bias mitigation algorithms only make a marginal effect even when they are directly applied to the dataset — which is also observed by Xia et al. (2020). Tables 1 and 2 show the results of the cross-domain and task transfer between GHC and Stormfront and from FDCL to DWMW.

UBM reduces bias compared to fine-tuning in target domains and tasks without bias mitigation. The results of cross-domain and task transfer learning (i.e., Stf.→GHC, GHC→Stf., FDCL→DWMW), show downstream bias is mitigated compared to Vanilla (directly training without bias mitigation in the target domain) when transferring from a less biased model (UBM_{Reg} and UBMM_{Adv}). Meanwhile, the in-domain classification performance has also increased (on GHC and Stormfront) or preserved (on DWMW). It is notable that directly mitigating bias (Expl. Reg., Adv. Learning) on DWMW is not effective; while transferring from FDCL improves BROD Acc. The in-domain FPRD on Stormfront is the only exception that does not show an improvement; however, as discussed in our metrics section, the in-domain FPRD is computed over a much smaller set of examples compared to NYT and IPTTS datasets, which makes the score less reliable.

Transfer learning itself reduces bias, while mitigating bias in the upstream model further reduces bias. Comparing Vanilla and Van-Transfer models, we notice that transfer learning has an overall positive impact on reducing bias in it alone. The observation aligns with Tu et al. (2020), where the authors show that multi-task learning improves models’ robustness to spurious correlations. Our results show that this effect extends to bias mitigation in transfer learning. Nevertheless, UBM almost always further reduces the bias compared to Van-Transfer.

6.2 DEALING WITH MULTIPLE BIAS FACTORS

We also show the results where we include more than one dataset and simultaneously reduce both the group identifier bias and the AAE dialect bias in the source domain with two different datasets. We train the source model with the combination of GHC and FDCL (GHC + FDCL) or Stormfront and FDCL (Stf. + FDCL), and fine-tune the model on Gab, Stormfront, or DWMW. The results are
shown in Table 1 under the rows Stf. + FDCL → GHC and GHC + FDCL → Stf., and in Table 2 under the rows Stf. + FDCL → DWMW, GHC + FDCL → DWMW.

**Transfer learning following bias mitigation on GHC + FDCL reduces both bias factors.** The results show that $\text{UBM}_{\text{Reg+Reg}}$ and $\text{UBM}_{\text{Reg+Adv}}$ (trained on GHC + FDCL) reduce bias in Stormfront and FDCL, compared to both Vanilla and Van-Transfer (measured with IPTTS and NYT).

**Transfer learning following bias mitigation on Stf. + FDCL does not further improve Van-Transfer.** Similarly, fine-tuning from vanilla models trained on Stormfront and FDCL (Van-Transfer) improves bias metrics compared to vanilla training on GHC or FDCL. However, we notice that bias mitigation in source models does not bring further improvements. The results imply that different tasks may interfere with each other when applied for mitigating bias in upstream models. We leave the exploration of this interference to future work.

### 6.3 Transfer Learning with the Same Source and Target Domains and Tasks

We further show the results when the target dataset consists of new, unseen samples from the same data distribution as the source dataset, which is a simpler setting compared to the cross-domain and task setup. By controlling the challenges of domain and task differences, these experiments solely focus on whether bias mitigation, as learned in the upstream model, is preserved during fine-tuning. We set up the experiments by partitioning GHC, Stormfront and FDCL to two subsets with equal sizes, noted as subsets A and B of corresponding datasets, regarded as the source and the target datasets respectively.

**Similar source and target domains and tasks lead to improved transfer learning following bias mitigation.** Tables 3 and 5 (in Appendix) represent the results on Gab, Stormfront, and FDCL. We see a clearer effect of mitigating bias in the source model compared to the cross-domain and task transfer learning setup. The observation is consistent when multiple bias factors are included.

In the experiments above, we have shown that mitigating bias in the source model provides inductive bias to target model that is preserved during simple fine-tuning. Next, we study whether freezing the encoders or discouraging their weight changes improves bias mitigation in the target domain.

### 6.4 Freezing or Regularizing Model Weights

As discussed in Section 4.2, the downstream classification training can vary based on different levels of weight freezing for the transferred encoder. Intuitively, freezing the weights of the encoder may help to retain information from the bias mitigation in the bias mitigation stage, further reducing bias in the target domain. However, we show a counter-intuitive result: freezing or discouraging weight changes typically does not contribute to downstream bias mitigation (while also decreasing the in-domain classification performance). Table 4 shows the results when we keep the weights frozen (Freeze), regularized from changing ($\ell_2$, sp), or unregularized at fine-tuning (fine-tune) In Stf. → GHC, freezing the weights contributed to reducing the bias, while $\ell_2$-sp failed to help. We applied other values of regularization strength $\beta$ but did not observe any improvements in the results. In GHC → Stf and FDCL → DWMW, freezing the weights and $\ell_2$-sp both increased the bias. A possible reason is that by freezing the encoder, we restrict data representation to static values learned from the source model; this reduces the classifier head to a simple linear model that can only rely on numeric clues in the input that may spuriously correlate with the labels.

Table 4: Transferring from explanation regularized models (GHC, Stf) or adversarially debiased models (FDCL) while keeping the encoder frozen (Freeze), fine-tuning with $\ell_2$-sp regularizer, or vanilla fine-tuning (Fine-tune). We see weight freezing and $\ell_2$-sp overall do not improve over simple fine-tuning.
6.5 Discussion

We further look into one of the reasons why fine-tuning from a de-biased upstream model remains less biased during fine-tuning while no weight freezing or bias mitigation is applied. We argue from the perspective of gradient of importance attributed to the words \( w \) related to bias factors (e.g., group identifiers) by the input occlusion algorithm. A large importance attribution usually induces bias in model predictions. Figure 2 show the importance attribution of group identifiers \( \phi(w, x) \) and the norm of its gradient w.r.t. parameters \( \theta \) of the encoder \( g \), noted as \( ||\nabla_{\theta} \phi(w, x)||_2 \). We plot the change of two values during the downstream fine-tuning process for Van-Transfer and UBM\(_{\text{reg}}\), averaged over all validation set examples. We use the same random initialization of the linear classifier head for two methods and average the results over three runs. We summarize our analysis below.

**Upstream bias mitigation reduces the gradient of** \( \phi(w, x) \), **so that** \( \phi(w, x) \) **is less likely to change during downstream fine-tuning.** Figure 2 shows that at the beginning of the training, the gradient norm w.r.t. importance \( ||\nabla_{\theta} \phi(w, x)||_2 \) is much smaller for UBM\(_{\text{reg}}\), which prevents the importance from increasing even when no bias mitigation is applied. Given that the two methods share the same random initialization of the linear classifier head and that the encoder \( g \) comes from the upstream model, the result attributes to the reduced gradient norm \( ||\nabla_{\theta} \phi(w, x)||_2 \) of encoder parameters w.r.t. importance attribution in the upstream model (shown in cross-marks in Fig 2). It implies the upstream bias mitigation has not only reduced \( \phi(w, x) \) (which is included in the learning objective of explanation regularization as Eq. 2), but also the norm of its gradient \( ||\nabla_{\theta} \phi(w, x)||_2 \) as a side effect.

We further note that when the loss in Eq. 2 is minimized, the gradient \( \nabla_{\theta} \phi(w, x) \) has the same norm but the opposite direction as the main downstream classification objective \( \nabla_{\theta} \ell_c \). It implies whether the upstream model converges at the point where gradients w.r.t both objectives are small (i.e., the optimal where both objectives agree) can be an important indicator of the success of UBM.

The figure also shows that the gradient and the value of \( \phi(w, x) \) remain small for UBM\(_{\text{reg}}\) over the whole training process. We leave more study into the training dynamics of UBM as future works.

7 Conclusion

In this paper, we show how bias mitigation can be transferred from upstream de-biased models to downstream fine-tuning. Our experiments show that upstream models that were de-biased with respect to multiple bias factors remained less biased upon transfer to downstream models in new domains and across similar but different tasks. As we hypothesized, the effects of bias mitigation persisted through transfer, such that multiple applications of bias mitigation for similar tasks is no longer necessary. That these effects were positive for transfer to new domains is evidence that models are learning robust reductions of bias.

Moreso than previous work, our cross-domain, cross-task, multi-bias-factor framework offers model developers an accessible way to de-bias models in production without additional data, such as labels of protected groups for the source domain, or additional bias mitigation training. This is a key step for the wider adoption of bias mitigation. Though we test our framework for hate speech and toxicity classification, other families of tasks might similarly benefit, in which models’ bias towards protected groups is a critical consideration, which is one key task for the future work.
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Table 5: Same-domain transfer with the second half of GHC and Stormfront as the target domain.

A IMPLEMENTATION DETAILS

Training. In the bias mitigation phase, the models are trained with a learning rate $1e^{-5}$, and the checkpoint with the best validation F1 or accuracy score is provided to the fine-tuning phase. We train Gab, FDCL, and DWMW for maximum 5 epochs and Stormfront for maximum 10 epochs. In the fine-tuning phase, we try the learning rate $1e^{-5}$ and $5e^{-6}$, and report the results with a higher validation F1 or accuracy.

Bias mitigation algorithms. For explanation regularization algorithm, we set the regularization strength $\alpha$ as 0.03 for Gab and Stormfront experiments, and 0.1 for FDCL and DWMW experiments. We regularize importance score on 25 group identifiers in Kennedy et al. (2018) for Gab and Stormfront. These group identifiers the ones that have the largest coefficient in a bag-of-words linear classifier. For FDCL, we extract 50 words with largest coefficient in the bag-of-words linear classifier with a AAE dialect probability higher than 60% (given by the off-the-shelf AAE dialect predictor Blodgett et al. (2016)) on its own. For adversarial de-biasing, the adversarial loss term has the same weight as the classification loss term.

B COMPLETE ANALYSIS OF SAME-DOMAIN TRANSFER

Table 5 show the results of same-domain transfer with the second half of GHC and Stormfront datasets as the target domain. Similar to the cross-domain setup, UBMOverall reduces the bias compared to Vanilla and Vanilla-Transfer. We find the NYT accuracy on Stormfront is an exception, which is not improved even when we directly run explanation regularization in the target domain. We reason that the Half-Stormfront dataset is small and the average length of the sentences are quite different between Stormfront and NYT, so that a model trained on Stormfront hardly generalizes to NYT.