Balancing out Bias: Achieving Fairness Through Training Reweighting

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Abstract

Bias in natural language processing arises primarily from models learning characteristics of the author such as gender and race when modelling tasks such as sentiment and syntactic parsing. This problem manifests as disparities in error rates across author demographics, typically disadvantaging minority groups. Existing methods for mitigating and measuring bias do not directly account for correlations between author demographics and linguistic variables. Moreover, evaluation of bias has been inconsistent in previous work, in terms of dataset balance and evaluation methods. This paper introduces a very simple but highly effective method for countering bias using instance reweighting, based on the frequency of both task labels and author demographics. We extend the method in the form of a gated model which incorporates the author demographic as an input, and show that while it is highly vulnerable to input data bias, it provides debiased predictions through demographic input perturbation, and outperforms all other bias mitigation techniques when combined with instance reweighting.

Introduction

Natural Language Processing (NLP) models have achieved extraordinary gains across a variety of tasks in recent years. However, previous work has shown that naively-trained models often learn spurious correlations with demographics and socio-economic factors (Hendricks et al. 2018; Lu et al. 2018; Bolukbasi et al. 2016; Park, Shin, and Fung 2018), leading to disparities across author demographics in contexts including coreference resolution, sentiment analysis, and hate speech detection (Badjatiya, Gupta, and Varma 2019; Zhao et al. 2018; Li, Baldwin, and Cohn 2018a; Díaz et al. 2018).

Two popular approaches for mitigating such biases are: (1) removing demographic information from textual representations (Li, Baldwin, and Cohn 2018a; Wang et al. 2019; Ravfogel et al. 2020; Han, Baldwin, and Cohn 2021b); and (2) balancing each demographic group in training, either explicitly via sampling (Zhao et al. 2018; Wang et al. 2019) or implicitly via balancing losses for each group (Höfler et al. 2005; Lahoti et al. 2020).

While existing debiasing methods have been shown to be successful, their general applicability varies: they either attempt to remove authors’ demographic attributes from learned representations (Li, Baldwin, and Cohn 2018a; Wang et al. 2019; Ravfogel et al. 2020; Han, Baldwin, and Cohn 2021b), or remove biases based on data filtering/augmentation (Bolukbasi et al. 2016; Zhao et al. 2018; Manzini et al. 2019). Other approaches have largely relied on loss reweighting based on demographics, which has been shown to be detrimental to main task label accuracy (Höfler et al. 2005; Wang et al. 2019). Additionally, such approaches have not been tested extensively over NLP tasks. In this paper, we focus on author bias and adapt several balanced training approaches for model debiasing, and propose novel ways of combining them with demographic information removal approaches.

Conversely, Hovy (2015) showed that explicitly modelling author demographics can enhance text classification performance, due to differences in language use based on variables such as age and gender. There is thus a fine line to be walked in terms of optimising for linguistic variables associated with different demographic groups (potentially boosting overall model accuracy), and ensuring model fairness.

Inspired by work in domain adaptation on learning domain-specific representations that generalise across domains (Bousmalis et al. 2016; Li, Baldwin, and Cohn 2018b), we propose a gated model, which incorporates author demographics as an input to generate group-specific representations but also generalises across demographic groups. Although this richer modelling framework has an increased propensity to replicate and exacerbate training biases, we show that when combined with instance reweighting during training this technique leads to substantial bias reductions over leading debiasing techniques, typically with higher predictive accuracy. We also introduce a second means of bias reduction, through tailoring gating coefficients of the trained model, which allows for fine-tuning of the accuracy–fairness trade-off. Our experiments over two benchmark datasets for language debiasing show that our techniques are competitive with much more complex state-of-the-art methods for debiasing in situations where the demographic attribute is not known at test time, and provide substantial gains over the state-of-the-art when the protected...
attribute is observed.

Related Work

Fairness

Much work on algorithmic fairness has focused on group fairness, i.e., disparities in error rates across groups defined by protected attributes, such as gender, age, or race. Many criteria have been proposed for group fairness, such as statistical parity (Dwork et al. 2012) and equal opportunity (Hardt, Price, and Srebro 2016). Broadly speaking, fairness can be classified into three categories: independence, separation, and sufficiency (Barocas, Hardt, and Narayanan 2019), with most recent work addressing separation criteria, i.e., potential correlations between main task labels and protected attributes. We also focus on separation criteria, as measured by disparities in true positive rate (TPR) and true negative rate (TNR) across groups.

Mitigating bias

Many approaches for bias mitigation have been proposed in recent work, including removing protected information from hidden representations (Li, Baldwin, and Cohn 2018a; Wang et al. 2019; Ravfogel et al. 2020; Han, Baldwin, and Cohn 2021a), preprocessing data to remove bias (Zhao et al. 2018; Vanmassenhove, Hardmeier, and Way 2018; Saunders and Byrne 2020), modifying the training algorithm (Badjatya, Gupta, and Varma 2019), and post-hoc correction (Hardt, Price, and Srebro 2016).

In the context of NLP, the best results have been achieved through protected information removal. Iterative nullspace projection (INLPR (Ravfogel et al. 2020)) takes hidden representations and projects them onto the nullspace of the weights of a linear classifier for each protected attribute. The classifier training and projection are carried out over multiple iterations to more comprehensively remove protected information.

Another popular approach is adversarial training, which jointly optimises the removal of sensitive information and main task performance, through the incorporation of adversarial discriminator(s) to identify protected attributes from the hidden representations (Li, Baldwin, and Cohn 2018a; Elazar and Goldberg 2018; Wang et al. 2019). Differentiated adversarial learning (DADV (Han, Baldwin, and Cohn 2021a)) uses an ensemble of adversaries for each protected attribute, subject to an orthogonality constraint.

In this work, we employ INLPR and DADV as our two baseline methods for bias mitigation.

Dataset imbalance

Naively-trained NLP models learn and amplify implicit biases in the training data (Zhao et al. 2017; Garg et al. 2018), such as spurious correlations between gender and occupation in biographies (De-Arteaga et al. 2019). While many methods have been proposed to deal with the closely-related task of classification under class imbalance, such as sampling methods (Kubat and Matwin 1997; Wallace et al. 2011) and loss reweighting (Xie and Manski 1989; Cui et al. 2019), there is relatively little work on their application to protected attributes under similar data conditions. Research which has addressed this include (Wang et al. 2019), who use down-sampling to balance the demographic distribution while retaining the main task distribution, and Lahoti et al. (2020) who extend instance reweighting for structured data to consider the joint distribution between demographic and task labels.

We evaluate balanced-training approaches for NLP debiasing, and their interaction with different debiasing methods.

Methods

Problem Formulation

In this paper, we focus on bias mitigation for NLP classification tasks. Formally, we assume a dataset $D = \{(x_i, y_i, g_i)\}_{i=1}^n$ where $x_i \in X$ is a $d$ dimensional encoded input text representation vector, $y_i \in Y$ denotes the main task label such as happy sentiment, and $g_i \in G$ represents the private attribute associated with $x_i$, e.g., author gender.

A standard model $M_{\text{standard}}$ is trained to predict $Y$ given $X$, while debiasing methods (both most existing methods and our methods) aim to learn a model $M_{\text{debiased}}$ that is fair wrt $G$ by considering $X \times G$ together.

Fairness Measurement As in Barocas, Hardt, and Narayanan (2019), the separation criterion acknowledges the correlation between $G$ and $Y$, and can be satisfied iff $G \perp Y | Y$. A relaxation of the separation criterion known as equality of opportunity is widely used (Hardt, Price, and Srebro 2016; Ravfogel et al. 2020; Han, Baldwin, and Cohn 2021a). Equality of opportunity measures the difference in true positive rate (TPR) across all groups, based on the idea that the positive outcome normally represents ‘advantage’, such as being accepted by a school or getting a loan. Essentially, the difference (gap) in TPR reflects whether different groups have equal opportunity.

Balanced Training

Previous work has used different objectives for balanced training. Zhao et al. (2018) augment the dataset according to the demographic label distribution (making $p(G)$ uniform); Wang et al. (2019) down-sample the majority demographic group within each class, so that on a per-class basis, it does not dominate the minority group ($p(G|Y)$ is uniform for all $Y$); and Lahoti et al. (2020) employ instance reweighting so that each training instance is assigned a weight based on the inverse propensity score of their subgroup and class membership ($p(G|Y)$ is effectively uniform across intersectional groups).

Let $p$ be the target objective, and $\tilde{p}$ be the empirical probability based on the training dataset. We focus on the following two balancing approaches.

Instance Reweighting: reweight each instance inversely proportional to the frequency of the combination of its main label and demographic label, i.e., $\tilde{p}^{-1}$,

$$\frac{1}{|D|} \sum_{(x, y, g) \in D} \tilde{p}^{-1} \mathcal{X}(y, g),$$
where $X$ is the task loss (e.g. cross entropy), and $\hat{y}_i$ denotes the model prediction given input text $x_i$.

**Corpus Down-sampling:** sub-sample non-minority instances to derive a balanced training dataset, such that $\hat{p} = p$. For instance, assuming $p(g, y)$ is the balancing objective over the demographic and task labels, let $D_{y,g}$ denote a subset of training instances s.t. $D_{y,g} = \{(x_i, y_i, g_i) \mid y_i = y, g_i = g\}_{i=1}^n$. We sample without replacement to get a target subset $D_{y,g}$ such that $|D_{y,g}| = \min\{|D_{y,g}|, \forall y \in Y, g \in G\}$. The sampled subsets are merged to form the sub-sampled balanced training set.

**Gated model**

Ignoring demographic-specific features can lead to bias even when the training data has been balanced (Wang et al. 2019; Lahoti et al. 2020). Our approach to dealing with this is, when the training data has been balanced (Wang et al. 2019; Lahoti et al. 2020). Our approach to dealing with this is, rather than removing demographic information from representations conditioned on the gold protected attribute, $g^*$, with the two encoders weighted by either $\alpha$ and $1 - \alpha$, or $1 - \beta$ and $\beta$, respectively, according to the value of $g^*$. Values of $\alpha, \beta < 0.5$ mean the protected label is (softly) preserved, while values $> 0.5$ mean the label is flipped. In cases where the model is biased towards or against a demographic group, it may be advantageous to use these two additional parameters to correct for this bias, by disproportionately using the other group’s encoder.

**Evaluation Metrics**

Following Ravfogel et al. (2020), we use overall accuracy as the performance metric, and the separation criterion to measure fairness in the form of TPR GAP and TNR GAP: the true positive rate and true negative rate differences between demographic groups. For both GAP metrics, the smaller the better, and a perfectly fair model will achieve 0 across both metrics. For multiclass classification tasks, we follow Ravfogel et al. (2020) in reporting the quadratic mean (RMS) of TPR GAP over all classes. In a binary classification setup, TPR and TNR are equivalent to the TPR of the positive and negative classes, respectively, so we employ the RMS TPR GAP in this case also.

Throughout this paper, we report accuracy and GAP results as mean values ± standard deviation over the test set.
averaged across five independent runs with different random seeds.

In addition to performance and fairness, we are also interested in the efficiency of the different debiasing approaches and report each method’s average training time. Given that the training time is affected by factors such as batch size, hidden size, and learning rate, to perform a fair comparison between different models, we estimate the training time of a model based on hyperparameter tuning results, over a shared search space of base hyperparameters (i.e., the hyperparameters related to the standard model), with any other approach-specific hyperparameters fixed. We present normalised training times relative to the standard method, i.e., the average training time divided by that of the standard model.

Dataset

Following Ravfogel et al. (2020), we conduct experiments over two NLP classification tasks — sentiment analysis and biography classification — using the same dataset splits as prior work.

MOJI This sentiment analysis dataset was collected by Blodgett, Green, and O’Connor (2016), and contains tweets that are either African American English (AAE)-like or Standard American English (SAE)-like. Each tweet is annotated with a binary ‘race’ label (based on language use: either AAE or SAE), and a binary sentiment score determined by (redacted) emoji contained in it.

We use the train, dev, and test splits from Han, Baldwin, and Cohn (2021b) of 100k/8k/8k instances, respectively. This training dataset has been artificially balanced according to demographic and task labels, but artificially skewed in terms of race–sentiment combinations, as follows: AAE—happy = 40%, SAE—happy = 10%, AAE—sad = 10%, and SAE—sad = 40%.

BIOS The second task is biography classification (De-Arteaga et al. 2019, Ravfogel et al. 2020), where biographies were scraped from the web, and annotated for binary gender and 28 classes of profession. Since the data is not directly available, in order to construct the dataset, we use the scraping scripts of Ravfogel et al. (2020), leading to a dataset with 396k biographies.

Following Ravfogel et al. (2020), we randomly split the dataset into train (65%), dev (10%), and test (25%).

Models

We first implement a “STANDARD” model on each dataset, without explicit debiasing. On the MOJI dataset, we follow Ravfogel et al. (2020); Han, Baldwin, and Cohn (2021b) in using DeepMoji (Felbo et al. 2017) as the encoder to get 2304d representations of input texts. The DeepMoji model contains 22.4 million parameters and was pretrained over 1246 million tweets to predict one of 64 common emojis. Ravfogel et al. (2020) and Subramanian et al. (2021) used uncased BERT-base (Devlin et al. 2019) as their STANDARD model for the BIOS dataset, taking the ‘CLS’ token as the source of a fixed text representation, without further fine-tuning. However, we found that taking the average of all contextualised token embeddings led to an accuracy improvement of 1.4% and GAP fairness improvement of 2.4%. Given this, we use 768d ‘AVG’ representations extracted from the pretrained uncased BERT-base model.

For INLP (Ravfogel et al. 2020), we take the fixed STANDARD model for the given dataset, and iteratively train a linear classifier and perform nullspace projection over the learned representation. For the other baseline models — ADV and and DADV— we jointly train the adversarial discriminators and classifier. In order to ensure a fair comparison, we follow Han, Baldwin, and Cohn (2021a) in using a model consisting of the fixed-parameter encoder followed by a trainable 3-layer MLP.

Hyperparameter Tuning

All approaches proposed in this paper share the same hyperparameters as the standard model. Hyperparameters are tuned using grid-search, in order to maximise accuracy for the standard model, and to minimise the fairness GAP for debiasing methods, subject to the accuracy exceeding a given threshold. The accuracy threshold is chosen to ensure the selected model achieves comparable performance to baseline methods, defined as up to 2% less than best baseline accuracy. Taking RW as an example, the best baseline accuracy on the BIOS development dataset is 75.7% and accordingly the (development) accuracy threshold is set to 73.7%; among models in the hyperparameter search space that exceed this threshold, we take the model with minimum GAP. We report test results for the selected models.

In terms of the baseline models, both DADV and INLP have additional hyperparameters: for DADV these are the weight of the adversarial loss, which controls the performance–fairness trade-off; the number of sub-adversaries; and the weight of the difference loss, to better remove demographic information; while INLP also has a trade-off hyperparameter, the number of null-space projection iterations, and other hyperparameters related to linear attackers and classifiers.

The trade-off hyperparameter makes such models more flexible in performing model selection. However, it also requires manual selection for better trade-offs, and different strategies have been introduced. For example, INLP manually selects the model at a iteration where the accuracy is minimally damaged while the fairness improves greatly. Similar manual selection for better trade-offs is also required for ADV and DADV, but the strategies proposed in the original papers are slightly different to one another, and are also task-specific.

In order to reproduce previous methods, we follow the original paper in setting the accuracy threshold, and then tuning hyperparameters for the best fairness.

For the ADV and DADV models, following the work of Han, Baldwin, and Cohn (2021b), we tune extra hyper-
parameters separately, such as the trade-off hyperparameter, while using the same shared hyperparameters to the selected base models. Similarly, the number of iterations for the INLP model is tuned once other hyperparameters have been fixed.

Training Details
We conduct all our experiments on a Windows server with a 16-core CPU (ACM Ryzen Threadripper PRO 3955WX), two NVIDIA GeForce RTX 3090s with NVLink, and 256GB RAM.

MOJI For all baseline models, we follow the method of Han, Baldwin, and Cohn (2021b). Specifically, we train the STANDARD model for 100 epochs with the Adam optimizer (Kingma and Ba 2015), learning rate of $3 \times 10^{-5}$, and batch size of 1024. For Adv, the main model is jointly trained together with adversaries which are implemented as 3-layer MLP, and the weight of adversarial loss is 0.8. For each iteration (epoch) of the main model, an adversary is trained for 60 epochs, keeping the checkpoint model that performs best on the dev set. Three sub-adversaries are employed by the DADV, with the difference loss weight of $10^{-2.7}$. For INLP, logistic regression models are used for both identifying null-space to the demographic information at each iteration, and making the final predictions given de-biased hidden representations. Since the number of iterations in INLP is highly affected by the random seed at each run, we re-select it at each iteration.

As for our models, the DS model is trained with the learning rate of $10^{-5}$ and batch size of 512; the RW is trained with the learning rate of $10^{-4}$ and batch size of 1024; and the GATE is trained with the the set of hyperparameters to the base model.

BIOS Models are trained with similar hyperparameters as models on the MOJI dataset. We thus only report main differences for each of them: the STANDARD model is trained with the batch size of 512 and learning rate of $3 \times 10^{-4}$; DS models are trained with the batch size of 128 and learning rate of $10^{-3}$, and RW models are trained with the batch of 256 and learning rate of $3 \times 10^{-5}$.

We train the ADV model with the adversarial loss weight of $10^{-2.3}$, learning rare for adversarial training of $10^{-1}$, learning rate of $10^{-3}$, and batch size of 128. The DADV is trained with same setting as the ADV, excepting the difference loss weight of $10^2$. For details of the assignment of other hyperparameters and hyperparameter searching space, refer to Supplementary Materials.

Balanced Training Approaches
Since the MOJI dataset has been artificially balanced for main task labels and demographic labels, balanced training corresponding to $p(g)$ makes no difference, and moreover, the results for $p(g|y)$ and $p(g, y)$ will be identical. Given this, we focus on the BIOS dataset for comparing different balanced training approaches.

Table 1 shows the results of the naively-trained MLP model (“STANDARD”) and six balanced-training methods, all based on the same MLP model architecture as STANDARD. Corpus down-sampling (“DS”) removes instances from majority groups and thus leads to less training data and overall lower accuracy than instance reweighting (“RW”).

When using $p(g)$ as the objective, both RW and DS perform similarly to the STANDARD model, as the overall gender distribution is quite balanced, which can also be seen in the size of the training data for DS + $p(g)$. Both $RW + p(g, y)$ and $DS + p(g, y)$ reduce bias and performance, but $RW + p(g, y)$ outperforms $RW + p(g, y)$ in terms of the performance–fairness trade-off, in that $RW + p(g, y)$ achieves similar performance but substantially better fairness (6.6% absolute improvement in GAP). However, $p(g, y)$ is not as effective as $p(g|y)$ when combined with DS, due to the big drop in the volume of training data. Based on these results, hereafter we only report $RW + p(g, y)$ and $DS + p(g|y)$, and denote them simply as “RW” and “DS”, respectively, for simplicity.

We report results over the sentiment analysis and biography classification tasks in Table 2, which includes the “Trade-off”, a single metric to incorporate accuracy and GAP into a single figure of merit, for ease of comparison between approaches. We calculate this by: (1) normalising each of accuracy and GAP, by dividing by the best result for the given dataset (i.e., highest accuracy, lowest GAP); (2) converting GAP to 1 − GAP (higher is better; optimal 1 − GAP = 1); and (3) calculating the Euclidean distance to the point (1, 1), which represents the (hypothetical) system which achieves highest accuracy and lowest GAP for the dataset. Lower is better for this statistic, with a value of 0 indicating that the given model performed best for both accuracy and GAP on the given dataset.

The baseline models are: STANDARD, which is a naively-trained MLP classifier; INLP (Ravfogel et al. 2020), which removes demographic information from text representations through iterative nullspace projection; ADV (Li, Baldwin, and Cohn 2018a, Wang et al. 2019), which performs protected information removal through adversarial training with a single discriminator; and DADV (Han, Baldwin, and Cohn 2021b), which also uses adversarial training but with multiple adversaries subject to an orthogonality constraint, and represents the current state-of-the-art (SOTA).

| Model     | Size | Accuracy↑ | GAP ↓ |
|-----------|------|-----------|-------|
| STANDARD  | 257k | 82.3 ± 0.0 | 16.0 ± 0.5 |
| RW + $p(g)$ | 257k | 82.3 ± 0.0 | 15.6 ± 0.2 |
| RW + $p(g|y)$ | 257k | 75.7 ± 0.2 | 13.9 ± 0.4 |
| RW + $p(g, y)$ | 257k | 74.7 ± 0.3 | 7.4 ± 0.3 |
| DS + $p(g)$ | 237k | 82.1 ± 0.1 | 15.9 ± 0.3 |
| DS + $p(g|y)$ | 37k | 79.4 ± 0.1 | 9.7 ± 0.6 |
| DS + $p(g, y)$ | 5k | 66.1 ± 0.1 | 10.9 ± 0.4 |

Table 1: Results for balanced training methods on the BIOS test set. “RW” = balancing through instance reweighting; “DS” = balancing through dataset down-sampling; and “Size” = the number of instances in the training dataset.
perform better than DS across all metrics. Although balancing DS and RW simultaneously increase main task accuracy, category. Training time is reported relative to S

Table 2: Results over the sentiment analysis (MOJI) and biography classification (BIOS) tasks. Trade-offs are measured by the normalized Euclidean distance between each model and the ideal model, and lower is better. Bold = best trade-off within category. Training time is reported relative to STANDARD, which takes 35 secs and 16 mins for MOJI and BIOS, respectively.

| Method   | Model  | MOJI             | BIOS             |
|----------|--------|------------------|------------------|
|          |        | Accuracy↑ | GAP ↓ | Trade-off↓ | Time↓ | Accuracy↑ | GAP ↓ | Trade-off↓ | Time↓ |
| Baselines|        |           |        |            |       |           |        |            |       |
|          | STANDARD | 71.6±0.1 | 31.0±0.3 | 0.261 | 1.0 | 82.3±0.0 | 16.0±0.5 | 0.110 | 1.0 |
|          | INLP    | 68.5±1.1 | 33.8±3.9 | 0.300 | 14.0 | 70.5±0.5 | 6.7±0.9  | 0.145 | 6.3 |
|          | ADV     | 74.3±0.4 | 22.2±3.7 | 0.163 | 36.1 | 81.1±0.1 | 12.7±0.3 | 0.077 | 1.3 |
|          | DADV    | 74.5±0.3 | 18.5±2.0 | 0.123 | 109.4 | 81.1±0.1 | 12.6±0.3 | 0.076 | 2.4 |
|          |         |           |        |            |       |           |        |            |       |
| Balance  | DS      | 71.9±0.1 | 23.2±0.2 | 0.178 | 0.5 | 79.4±0.1 | 9.7±0.6  | 0.057 | 0.3 |
|          | RW      | 74.0±0.2 | 21.5±0.4 | 0.155 | 1.0 | 74.7±0.3 | 7.4±0.3  | 0.095 | 1.0 |
|          | Gate    | 64.8±0.1 | 65.2±0.9  | 0.640 | 1.0 | 82.4±0.1 | 19.2±0.3 | 0.144 | 1.0 |
|          | GATE + DS | 72.5±0.0 | 16.3±0.7  | 0.104 | 0.6 | 79.4±0.1 | 9.2±0.2  | 0.053 | 0.3 |
|          | GATE + RW | 74.9±0.2 | 13.8±0.3  | 0.072 | 1.1 | 74.9±0.2 | 7.1±0.2  | 0.092 | 1.0 |
|          | GATE soft 0.5 | 72.7±0.2 | 30.2±0.3  | 0.250 | 1.0 | 80.8±0.1 | 11.6±0.3 | 0.066 | 1.0 |
|          | GATE soft Acc | 74.8±0.2 | 20.3±0.3  | 0.142 | 1.0 | 81.1±0.1 | 19.8±0.4 | 0.151 | 1.0 |
|          | GATE soft RMS | 73.5±0.2 | 7.1±0.3   | 0.019 | 1.0 | 80.5±0.1 | 11.1±0.3 | 0.063 | 1.0 |
|          | DADV + DS | 72.2±0.2 | 14.3±0.2  | 0.085 | 72.1 | 79.3±0.1 | 9.9±0.2  | 0.059 | 2.3 |
|          | INLP + DS | 72.1±1.6 | 18.4±3.1  | 0.127 | 6.3 | 73.2±0.6 | 5.9±0.8  | 0.112 | 1.3 |
|          | DADV + RW | 74.6±0.1 | 18.9±0.3  | 0.127 | 108.2 | 74.1±0.2 | 7.2±0.4  | 0.102 | 3.0 |
|          | INLP + RW | 72.3±1.9 | 15.7±3.1  | 0.099 | 13.9 | 73.6±0.6 | 5.6±0.7  | 0.107 | 6.3 |

On the MOJI dataset, compared to the STANDARD model, both DS and RW simultaneously increase main task accuracy and mitigate bias, leading to results competitive with ADV and better than INLP. Furthermore, RW consistently performs better than DS across all metrics. Although balanced training methods do not outperform the SOTA DADV, they lead to performance–fairness trade-offs that are competitive with the other debiasing methods.

On the BIOS dataset, two balanced training methods again lead to performance–fairness trade-offs that outperform the baseline methods. However, different to the MOJI dataset, RW is not as effective as DS, increasing fairness by 2.3% absolute at a cost of 3.7% in accuracy, implying that the effectiveness of the balanced approach depends on properties of the dataset. We return to discuss this effect at the end of the paper.

In terms of training time, existing debiasing methods (esp. DADV on MOJI) incur a substantial overhead, while balanced training is much more frugal: the training time for RW is the same as for the STANDARD model, and DS is around 2 times faster (because of the reduction in training data volume).

Gated Model
In addition to evaluating the standard gated model (GATE), we also combine the method with balanced training (GATE + DS and GATE + RW).

On both datasets, the GATE model amplifies bias: as it uses demographic information directly to make predictions, it is highly vulnerable to bias in the training dataset. However, when combined with balanced training, GATE + DS and GATE + RW achieve a better performance–fairness balance, as shown in Table 2. Indeed, the GATE + RW outperforms the SOTA DADV on the MOJI dataset, and GATE + DS achieves the best trade-off on the BIOS dataset.

Intuitively, the only objective of GATE model training is standard cross-entropy loss, which has been shown to lead to bias amplification under imbalanced training without regularization. The gate components explicitly rely on demographic information, and thus become a strong indicator of main label predictions due to spurious correlations between the main task label and demographic labels in the training set. The balanced training approaches act as a regularizer in preventing the model from learning and amplifying spurious correlations in the training set.

Soft Averaging
We next look to the Bayesian “soft averaging” approach to gating, as a means of both dealing with test instances where we do not have access to protected attributes (the case of $\alpha = \beta = 0.5$), and mitigating bias at inference time. Note that this does not involve retraining the model, as the soft averaging happens at test time. We first evaluate the effectiveness of using a uniform averaging in gated model predictions, where $\alpha = \beta = 0.5$. We label this method “GATE soft 0.5”, and present results in Table 2. The method results in a much better performance–fairness tradeoff that the standard GATE, and for the BIOS dataset its results are competitive with the best debiasing methods.

We next take the demographic labels into consideration, and search for the best gating coefficients for each group. Figure 2 shows accuracy and GAP results from tuning the coefficients on development data, for the basic GATE model. The results show that $\alpha = \beta = 0.5$ is a reasonable default setting, however small gains may be possible for non-uniform parameter settings.
The baseline methods INLP and DA optimise the performance–fairness trade-off when optimising for GAP, ATE and test datasets. As a result, the accuracy-optimised model IOS outperforms both the standalone demographic removal methods and balanced training approaches, without extra training time cost. That is, demographic information removal and balanced training appear to be complementary.

Balancing toward anti-stereotyping As shown in Table 2 ("Combination"), and indicate that the combined methods appreciably outperform both the standalone demographic removal methods and balanced training approaches, without extra training time cost. To combine RW with DA, we modify the training objective such that the cross-entropy term is scaled by $\tilde{p}^{-1}$, while leaving the adversarial term unmodified, i.e., solve for $\min_f \max_A \sum_{(x,y,g) \in D} \tilde{p}^{-1} \mathcal{L}(y, \hat{y}) - \lambda_{adv} \mathcal{A}(g, \hat{g})$. For INLP, we simply train an RW model, and then iteratively perform the INLP linear model training and nullspace projection over the learned representations.

Results are presented in the final section of Table 2, even with DS or RW balancing, the model still shows biases in its predictions. We conduct preliminary experiments on M0JI with RW and DS, while controlling for stereotyping skew in training using values for 0.8 to 0.2. In standard rebalancing we use as target 0.5, which describes a balanced situation. A larger skew > 0.5 will amplifying stereotyping, and < 0.5 describes a different type of stereotyping operating in the opposite direction. Balancing towards a 0.4 training skew leads to the best test results, with an accuracy of 71.7% and GAP of 11.8% for DS, and accuracy of 74.5% and GAP of 11.3% for RW. Comparing to the corresponding values in Table 2 (rows Balance DS and RW, for M0JI), both results show a substantial reduction in GAP.

To demonstrate the power of adjusting these parameters, we take the trained GATE model, and then optimise $\alpha$ and $\beta$ over the development set, and report the corresponding results on the test set. We select the parameter values that achieve either: (1) the highest development accuracy; or (2) the lowest development GAP, provided accuracy is above a threshold. The results are reported in Table 2 under GATE soft Acc and GATE soft RMS, respectively. On the M0JI dataset, our results show that GATE with soft averaging can consistently outperform the STANDARD and GATE models without balanced training. In terms of GAP, the model is substantially better than all other models, while remaining competitive in terms of accuracy. The BIOS dataset is noisier, meaning there are bigger discrepancies between the development and test datasets. As a result, the accuracy-optimised model is actually below the standard GATE model in terms of both performance and fairness. However, we achieve a good performance–fairness trade-off when optimising for GAP, at a level comparable to the much more complex INLP and DADV models.

Combining balanced training with benchmark methods The baseline methods INLP and DADV as presented above were used in a manner consistent with their original formulation, i.e., without balanced training. An important question is whether balanced training might also benefit these methods. It is trivial to combine DS with INLP and DADV, as the method simply prunes the training dataset, but does not impact on the training objective. To combine RW with DADV, we modify the training objective such that the cross-entropy term is scaled by $\tilde{p}^{-1}$, while leaving the adversarial term unmodified, i.e., solve for $\min_f \max_A \sum_{(x,y,g) \in D} \tilde{p}^{-1} \mathcal{L}(y, \hat{y}) - \lambda_{adv} \mathcal{A}(g, \hat{g})$. For INLP, we simply train an RW model, and then iteratively perform the INLP linear model training and nullspace projection over the learned representations.

Figure 2: Accuracy and GAP of $\alpha$ and $\beta$ settings for M0JI and BIOS. The axes refer to the propensity to change the gold group in gating the encoder components, and the bottom left point $\alpha = \beta = 0$ is the GATE model using true demographic inputs. Lighter shading denotes better performance.

This idea is related to existing reweighting approaches in long-tail learning. For example, (Cui et al., 2019) infer the effective number of samples which group each instance with its neighbours within a small region instead of using all data points, and reweight the loss of each class inversely proportional to the effective number of samples. We leave this further exploration of this line of research to future work.

We also experiment with GATE +RW and GATE +DS with a 0.4 training skew, however, the gated model does not show the same behaviour, as it just amplifies the training biases. This implies that, for the gated model, balanced training can help remove spurious correlations between protected attributes and main task labels, which is similar in nature to the effects of adversarial training.

Conclusions

This paper proposed the adoption of two simple balanced training approaches to mitigate bias, and demonstrated their effectiveness relative to existing methods, as well as their ability to further enhance existing methods. We also proposed a gated model based on demographic attributes as an input, and showed that while the simple version was highly biased, with a simple Bayesian extension at inference time, the method was highly effective at mitigating bias.
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