# FairBalance: Mitigating Machine Learning Bias Against Multiple Protected Attributes With Data Balancing

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#### Abstract

This paper aims to improve machine learning fairness on multiple protected attributes. Machine learning fairness has attracted increasing attention since machine learning models are increasingly used for high-stakes and high-risk decisions. Most existing solutions for machine learning fairness only target one protected attribute (e.g. sex) at a time. These solutions cannot generate a machine learning model which is fair against every protected attribute (e.g. both sex and race) at the same time. To solve this problem, we propose FairBalance in this paper to balance the distribution of training data across every protected attribute before training the machine learning models. Our results show that, under the assumption of unbiased ground truth labels, FairBalance can significantly reduce bias metrics (AOD, EOD, and SPD) on every known protected attribute without much, if not any damage to the prediction performance.

# 1 Introduction

With machine learning and artificial intelligence systems increasingly being used to make decisions that affect people's lives, much concern has been raised on the fairness in machine learning. Studies have shown that, sometimes the machine models behave in a biased manner that gives undue advantages to a specific group of people (where those groups are determined by sex, race, etc.). Such bias in the machine learning models can have serious consequences in deciding whether a patient gets released from hospital [Kharpal, 2018, Strickland, 2016], which loan applications are approved [Olson, 2011], which citizens get bail or sentenced to jail [Angwin et al., 2016], who get admitted/hired by universities/companies [Dastin, 2018].

Much research has been done trying to mitigate the ethical bias in the machine learning models. However, to our best knowledge, all existing bias mitigation algorithms target one specific protected attribute at a time. For example, on a dataset with two protected attributes sex and race, the existing approaches can learn a fair model on sex or a fair model on race, but cannot learn a model which is unbiased on both sex and race [Kamiran and Calders, 2012, Calmon et al., 2017b, Zhang et al., 2018]. This hinders the application of bias mitigation algorithms since a fair machine learning model cannot be biased on any protected attribute.

In this paper, we propose FairBalance to learn a fair machine learning model on every protected attribute. FairBalance is a preprocessing technique which balances the training data across every protected group. FairBalance can also balance the class distribution in the meantime. This variant of FairBalance, which we call FairBalanceClass, can be very useful when we care about the model's

prediction performance (e.g. precision, recall, and  $F_1$  score) on a minority class. To validate the usefulness of Fairness, we explore and answer the following research questions with experiments:

**RQ1:** Can FairBalance mitigate machine learning bias against multiple protected attributes? Tested on three widely-used machine learning fairness datasets each with two protected attributes, five commonly applied machine learning models trained on the FairBalance preprocessed training data had reduced biases on every protected attribute while maintaining similar prediction performances.

**RQ2:** Can FairBalance balance classes (FairBalanceClass) as well? With the same experiment setup as RQ1, FairBalanceClass achieved higher F<sub>1</sub> score on the minority class while reducing bias on every protected attribute. This suggests that class balance is effective in FairBalance.

**RQ3:** How does FairBalance perform comparing with the existing state-of-the-art bias mitigation algorithms? With the same experiment setup as RQ1, the performance of FairBalance was compared against other state-of-the-art bias mitigation algorithms. Our result in Section 4 shows that FairBalance almost always achieves similar if not better prediction performance, and performs better in terms of fairness metrics especially on the non-target protected attributes of the other algorithms.

Overall, the contributions of this paper include:

- We propose FairBalance, a preprocessing algorithm which mitigates bias on multiple protected attributes at the same time. Class balance can be performed as well (FairBalanceClass) to achieve better performance on the minority class.
- We show that FairBalance outperforms the existing state-of-the-art bias mitigation algorithms on three widely applied machine learning fairness datasets.
- The source code and data used in our experiments are publicly available on our Github repository<sup>1</sup> to facilitate reuse, reproduction and validation.

The rest of this paper is structured as follows: Section 2 provides the background and related work of this paper. Section 3 introduces our proposed algorithm FairBalance and its variant FairBalanceClass in details. Experiments in Section 4 explore and answer the three research questions. Followed by limitations in Section 5 and conclusions in Section 6.

## 2 Background and Related Work

## 2.1 Scope of This Work

There can be two reasons causing the learned machine learning model to be biased:

- 1. **Biased labels**. Labels in the training data can sometimes be biased already and the model trained on those labels will inherit their bias. This can usually happen in datasets with human decisions as ground truth labels (e.g. predicting whether an HR will hire an applicant).
- 2. **Biased learning process**. Even on labels derived from truth (so that the labels can be 100% fair), machine learning algorithms can learn a biased model.

Some work, e.g. Chakraborty et al. [2020], focuses on removing the biased labels but this direction is not in the scope of this paper. This paper focuses on reducing bias in the learning process. We do not question the fairness of labels in our datasets. As a result, we select datasets with labels derived from truth (e.g. whether a person has income higher than 50K). This paper also assumes that all the protected attributes are known.

Machine learning researchers have defined several different metrics for assessing whether a trained machine learning model has ethical bias. Among these metrics, FairBalance aims to reduce the difference in the treatments each individual from different groups received from the learned model. Such difference in treatments are measured by the following three bias metrics [Bellamy et al., 2018]:

• Statistical Parity Difference (SPD): Difference of probability of being assigned to the positive predicted class (PR) for unprivileged and privileged groups (1).

<sup>1</sup>https://github.com/hil-se/FairBalance

- Equal Opportunity Difference (EOD): Difference of True Positive Rates (TPR) for unprivileged and privileged groups (2).
- Average Odds Difference (AOD): Average of difference in False Positive Rates (FPR) and True Positive Rates (TPR) for unprivileged and privileged groups (3).

Where Table 1 and (4) shows the calculation of PR, TPR, and FPR.

$$SPD = PR_U - PR_P \tag{1}$$

$$EOD = TPR_U - TPR_P \tag{2}$$

$$AOD = [(FPR_U - FPR_P) + (TPR_U - TPR_P)] \times 0.5$$
(3)

$$PR = (TP + FP)/(TP + FP + TN + FN)$$

$$TPR = TP/(TP + FN)$$

$$FPR = FP/(FP + TN)$$
(4)

#### 2.2 Related Work

Prior work in the same scope can be classified into three groups depending on the approach applied to remove ethical bias:

**Pre-processing algorithms.** In this approach, training data is preprocessed in such a way that discrimination or bias is reduced before training the model. Kamiran and Calders [2012] proposed *reweighing* method that generates weights for the training examples in each (group, label) combination differently to achieve fairness. Feldman et al. [2015] designed *disparate impact remover* which edits feature values to increase group fairness while preserving rank-ordering within groups. Calmon et al. [2017a] proposed an *optimized preprocessing* method which learns a probabilistic transformation that edits the labels and features with individual distortion and group fairness. Another preprocessing technique, *learning fair representations*, finds a latent representation which encodes the data well but obfuscates information about protected attributes [Zemel et al., 2013].

**In-processing algorithms.** This approach adjusts the way a machine learning model is trained to reduce the bias. Zhang et al. [2018] proposed *Adversarial debiasing* method which learns a classifier to increase accuracy and simultaneously reduce an adversary's ability to determine the protected attribute from the predictions. This leads to generation of fair classifier because the predictions cannot carry any group discrimination information that the adversary can exploit. Celis et al. [2019] designed a *meta algorithm* to take the fairness metric as part of the input and return a classifier optimized with respect to that fairness metric. Kamishima et al. [2012] developed *Prejudice Remover* technique which adds a discrimination-aware regularization term to the learning objective of the classifier.

**Post-processing algorithms.** This approach adjusts the prediction threshold after the model is trained to reduce specific bias metrics. Kamiran et al. [2018] proposed *Reject option classification* which gives favorable outcomes to unprivileged groups and unfavorable outcomes to privileged groups within a confidence band around the decision boundary with the highest uncertainty. *Equalized odds post-processing* is a technique which particularly concentrate on the Equal Opportunity Difference(EOD) metric [Pleiss et al., 2017, Hardt et al., 2016].

The biggest problem of the existing work is that they all target one specific protected attribute at a time. As a result, these approaches cannot generate a machine learning model which is fair across every protected attributes when multiple protected attributes present in the data.

Table 1: Combined Confusion Matrix for Privileged(P) and Unprivileged(U) Groups.

	Privi	leged	Unprivileged			
	Predicted	Predicted	Predicted	Predicted		
	No	Yes	No	Yes		
Actual No	$TN_P$	$FP_P$	$TN_U$	$FP_U$		
Actual Yes	$FN_P$	$TP_P$	$FN_U$	$TP_U$		

#### 3 FairBalance

Similar to Reweighing<sup>2</sup> [Kamiran and Calders, 2012], FairBalance assign different weights to data from different groups to achieve a balanced training data:

- 1. Training data in each **group** have the same total weight.
- 2. Class distributions are the same across all **groups**.

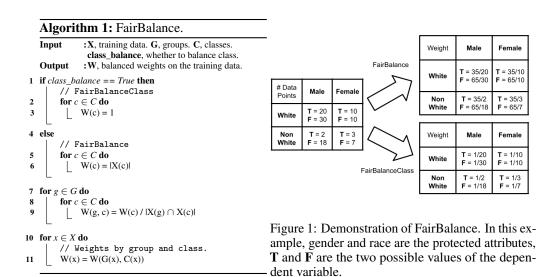
Here, a **group** is a set of data points sharing the same combination of protected attributes. For example, all the data points with *sex=male* and *race=white* form one group.

The intuition behind FairBalance is that, a machine learning model will be most likely biased if the training data it is trained on violates the above two balance criteria. Given that most machine learning algorithms learn to minimize a loss function of misclassification errors, we can analyze the following two violation examples:

- 1. Difference in group sizes:  $|X(g_1)| < |X(g_2)|$ . The cost for misclassifying data points in  $g_1$  will be lower than that in  $g_2$  since data points in  $g_1$  appear less frequently. As a result, the learned model will tend to predict more accurately on data points in  $g_2$  than  $g_1$ . This problem can be resolved by adding higher weight on misclassification errors for  $g_1$ .
- 2. Difference in class distributions:  $|X(g_1,T)|/|X(g_1,F)| < |X(g_2,T)|/|X(g_2,F)|$ . The learned model will tend to predict more as negatives (resulting in fewer false positives but more false negatives) in  $g_1$  than in  $g_2$ , since positive examples appear less frequently in  $g_1$ . This also leads to large SPD, AOD, and EOD. This problem can be resolved by adding higher weight on the positive data points in  $g_1$  and negative data points in  $g_2$ .

In addition to balancing the data for fairness, it is sometimes as important to balance the classes in the training data. This is especially true when we care about the prediction performance on the minority class. As Yan et al. [2020] stressed, machine learning bias may increase after class balancing, due to the process being oblivious of the inherent properties of the datasets. To resolve the class imbalance problem, we propose FairBalanceClass, which is a variant of FairBalance. FairBalanceClass balances the training data for both fairness and class balance. Algorithm 1 shows the pseudo code for the proposed FairBalance (class\_balance = False) and FairBalanceClass (class\_balance = True) algorithms. Figure 1 demonstrates how FairBalance and FairBalanceClass assign weights on an example dataset. Note that, given its simplicity, the computational overhead for FairBalance is negligible (similar to that of Reweighing).

<sup>&</sup>lt;sup>2</sup>FairBalance is equivalent to Reweighing when there is only one protected attribute



# 4 Experiments

In this section, we explore and answer the three research questions listed in Section 1 with experiments.

Table 2: Description of the datasets used for the experiment.

D-44	μъ	4F4	Protecte	ed Attributes	Class Labels		
Dataset	#Kows	#Features	Privileged	Privileged Unprivileged		Majority	
Adult Census	48,842	14	Sex-Male	Sex-Female	Income > 50K	Income $\leq 50$ K	
Income	40,042	14	Race-White	Race-Non-White	11,687	37,155	
Compas	7.214	28	Sex-Female	Sex-Male	Reoffended	Did not Reoffend	
Compas	7,214	20	Race-Caucasian	Race-Not Caucasian	2,483	2,795	
German	1.000	20	Sex-Male	Sex-Female	Bad Credit	Good Credit	
Credit	1,000	20	Age > 25	$Age \leq 25$	300	700	

#### 4.1 Datasets

We selected three commonly used datasets in machine learning fairness to conduct our experiments. To evaluate bias mitigation performance on multiple protected attributes, all three selected datasets have two different protected attributes. Details of the datasets are presented in Table 2,

### 4.2 Experiment Design

We conducted two separate experiments to answer the three research questions.

The first experiment compares FairBalance and its class balancing variant FairBalanceClass against no bias mitigation (None). In this experiment, each dataset is randomly split into 70% training data and 30% test data every time. Five commonly applied classification algorithms are applied to learn from the preprocessed training data and then collect their performances on the test data. This process was repeated for 50 times to enable statistical analysis (described in the next subsection). The five classification algorithms are:

- LR: Logistic Regression Classifier implemented with scikit-learn<sup>3</sup>.
- **SVM:** Linear Support Vector Machine Classifier implemented with scikit-learn<sup>4</sup>.

 $<sup>^3</sup> https://scikit-learn.org/stable/modules/generated/sklearn.linear\_model. LogisticRegression.html$ 

<sup>4</sup>https://scikit-learn.org/stable/modules/generated/sklearn.svm.LinearSVC.html

- **DT:** Decision Tree Classifier implemented with scikit-learn<sup>5</sup>.
- **RF:** Random Forest Classifier implemented with scikit-learn<sup>6</sup>.
- **NB:** Gaussian Naive Bayes Classifier implemented with scikit-learn<sup>7</sup>.

The second experiment compares FairBalance and FairBalanceClass against three selected state-of-the-art bias mitigation algorithms. In this experiment, each dataset is randomly split into 70% training data and 30% test data every time. Logistic regression classifier is applied as the base classifier. This process was repeated for 10 times due to a memory leakage problem of Reject Option Classification in AIF360 [Bellamy et al., 2018]. The three baseline bias mitigation algorithms are selected based on their popularity in each category:

- **Reweighing:** A pre-processing bias mitigation algorithm implemented with AIF360<sup>8</sup> under Apache License 2.0.
- Adversial Debiasing: An in-processing bias mitigation algorithm implemented with AIF3609.
- **Reject Option Classification:** A post-processing bias mitigation algorithm implemented with AIF360<sup>10</sup>.

#### 4.3 Evaluation

The three machine learning bias metrics (AOD, EOD, and SPD) described in Section 2.1 are applied to evaluate how bias each treatment is on every protected attributes. In the meantime, accuracy is applied to evaluate the overall prediction performance and  $F_1$  score is applied to evaluate the prediction performance on the minority class:

$$Accuracy = (TP + TN)/(TP + TN + FP + FN)$$
(5)

$$Precision = TP/(TP + FP)$$

$$F_1 = 2 \times Precision \times TPR/(Precision + TPR)$$
(6)

Here for the  $F_1$  score, the minority class is treated as the target class Yes in the confusion matrix.

Each treatment is evaluated multiple times during experiments as described in the previous subsection. Medians (50th percentile) and IQRs (75th percentile - 25th percentile) are collected for each performance metric since the resulting metrics do not follow a normal distribution. In addition, a nonparametric null-hypothesis significance testing (Mann–Whitney U test [Mann and Whitney, 1947]) and a nonparametric effect size testing (Cliff's delta [Cliff, 1993]) are applied to check if one treatment performs significantly better than another in terms of a specific metric. A set of observations is considered to be significantly different from another set if and only if the null-hypothesis is rejected in the Mann–Whitney U test and the effect size in Cliff's delta is medium or large.

#### 4.4 Results

**RQ1:** Can FairBalance mitigate machine learning bias against multiple protected attributes? Table 3 shows the results of the first experiment. Comparing the performance of FairBalance with None, we observe:

 $<sup>^{5}</sup> https://scikit-learn.org/stable/modules/generated/sklearn.tree. \\ DecisionTreeClassifier.html$ 

 $<sup>^6</sup> https://scikit-learn.org/stable/modules/generated/sklearn.ensemble. \\ RandomForestClassifier.html$ 

<sup>&</sup>lt;sup>7</sup>https://scikit-learn.org/stable/modules/generated/sklearn.naive\_bayes.GaussianNB.html

 $<sup>{\</sup>rm ^8https://github.com/Trusted-AI/AIF360/blob/master/aif360/algorithms/preprocessing/reweighing.py}$ 

https://github.com/Trusted-AI/AIF360/blob/master/aif360/algorithms/inprocessing/adversarial\_debiasing.py

<sup>&</sup>lt;sup>10</sup>https://github.com/Trusted-AI/AIF360/blob/master/aif360/algorithms/postprocessing/reject\_option\_classification.py

Table 3: Comparisons of performances before and after FairBalance. Each dataset has two protected attributes. The second protected attribute is "Age" for the German dataset and "Race" for the other two. Medians (IQRs) are reported for 50 repeats. Colored cells represent whether they are significantly better than the chosen baseline (None) with effect size of small, medium, or large or significantly worse than the chosen baseline (None) with effect size of small, medium, or large.

Algorithm	Dataset	Treatment	$F_1$	Accuracy		Sex	CDD	Race / Age		
		None	(2 (1)	_	AOD	EOD	SPD	AOD	EOD 25 (5)	SPD
	compas		62 (1) 61 (2)	66 (1) 65 (1)	18 (4) 6 (5)	22 (7) 6 (6)	22 (3) 11 (5)	21 (4)	23 (3)	25 (4) 2 (5)
	Compas	FairBalanceClass	64 (1)	64 (1)	5 (5)	5 (7)	9 (6)	10 (7)	10 (8)	14 (7)
		None	48 (0)	80 (0)	-28 (0)	-45 (1)	-21 (0)	-10(1)	-16 (2)	-9 (0)
LR	adult	FairBalance	50 (1)	78 (0)	0(3)	0 (5)	-6 (2)	1(1)	3 (3)	-3 (1)
		FairBalanceClass	54 (0)	74 (0)	1(1)	0(3)	-7 ( <del>0</del> )	-1 (1)	0(2)	-6(1)
		None	21 (5)	70 (3)	15 (8)	24 (10)	13 (7)	40 (25)	50 (25)	40 (23)
	german	FairBalance	0 (4)	69 (2)	0 (0)	0(0)	0(1)	0(1)	0 (3)	0 (1)
		FairBalanceClass	50 (5)	61 (3)	4 (8)	3 (15)	5 (6)	7 (7)	5 (10)	12 (8)
		None	62 (1)	66 (0)	19 (5)	24 (7)	22 (4)	22 (6)	27 (7)	25 (5)
	compas		62 (1)	65 (1)	6 (5)	7 (7)	10 (5)	1 (6)	4 (7)	5 (6)
		FairBalanceClass	63 (1)	65 (1)	4 (9)	3 (9)	8 (9)	0 (4)	2 (5)	2 (4)
CVIVA	1.14	None	48 (1)	80 (0)	-27 (0)	-44 (1)	-20 (0)	-10(1)	-16 (2)	-9 (0)
SVM	adult	FairBalance	49 (8)	79 (0)		-13 (12)		2 (6)	3 (11)	-2 (4)
		FairBalanceClass None	55 (1) 17 (17)	73 (1) 70 (3)	-1 (5) 14 (17)	-2 (6) 21 (29)	-9 (4) 12 (14)	-2 (2)	-1 (4) 36 (47)	-6 (1) 26 (30)
	german	FairBalance	1 (6)	70 (3)	0(1)	0 (0)	0(1)	0 (1)	0(3)	0 (1)
	german	FairBalanceClass	50 (4)	60 (3)	1 (5)	0 (12)	4 (6)	6 (10)	× /	11 (10)
		None	61 (2)	65 (1)	14 (5)	18 (8)	18 (5)	19 (4)	22 (6)	22 (4)
	compas	FairBalance	60 (2)	64 (1)	4 (6)	5 (5)	7 (7)	5 (9)	10 (8)	9 (10)
		FairBalanceClass	62 (2)	64 (0)	2(8)	3 (9)	6 (8)	-1 (6)	1 (8)	1 (6)
		None	48 (1)	80 (0)	-28 (1)	-45 (1)	-21 (1)	-10(1)	-16 (2)	-9 (1)
DT	adult	FairBalance	42 (1)	78 (0)	8(2)	13 (3)	0(1)	1(2)	2(5)	-2(1)
		FairBalanceClass	53 (0)	71 (0)	2 (5)	1 (6)	-5 (4)	4 (6)	5 (7)	-1 (6)
	german	None	24 (7)	70 (2)	17 (8)	25 (11)	14 (7)	36 (7)	50 (12)	34 (8)
		FairBalance	19 (12)	68 (2)	12 (15)	15 (23)	10 (13)	24 (22)	30 (28)	
		FairBalanceClass	49 (4)	57 (2)	8 (12)	9 (13)	10 (12)	-8 (12)	-8 (18)	-5 (11)
	compas	None	61 (1)	66 (1)	13 (8)	16 (10)	16 (7)	19 (4)	22 (7)	23 (5)
		FairBalance	61 (2)	65 (1)	3 (4)	4 (7)	7 (5)	7 (7)		11 (7)
		FairBalanceClass	62 (2)	64 (1)	5 (9)	7 (9)	7 (8)	-3 (6)	0 (8)	0 (6)
DE		None	49 (2)	80 (0)	-28 (2)	-46 (4)	-21 (2)	-11 (2)	-16 (4)	-10(1)
RF	adult	FairBalance	42 (1) 54 (0)	78 (0) 71 (1)	8 (1)	12 (3) 0 (5)	0(1)	0 (7)	2 (11)	-2 (4) 5 (2)
		FairBalanceClass None	24 (6)	69 (3)	1 (4) 16 (7)	24 (11)	-6 (4) 14 (6)	1 (4) 35 (8)	3 (5) 49 (10)	-5 (3) 33 (10)
	german	FairBalance	24 (0)	68 (2)	13 (18)	18 (27)	12 (16)		37 (31)	
	german	FairBalanceClass	49 (3)	59 (3)	7 (12)	10 (14)	7 (11)		-9 (18)	-6 (11)
		None	64 (1)	65 (0)	36 (3)	40 (5)	39 (3)	27 (3)	30 (4)	30 (2)
NB	compas	FairBalance	63 (1)	64 (1)	9 (3)	9 (6)	12 (2)	17 (2)	16 (3)	20 (2)
		FairBalanceClass	63 (2)	64 (1)	10 (3)	11 (5)	13 (3)	16 (3)	17 (4)	20 (3)
	adult	None	50 (0)	56 (0)	-6(1)	-5 (1)	-14 (1)	-4(2)	-3 (2)	-8 (4)
		FairBalance	48 (0)	53 (0)	0(1)	0(1)	-5 (1)	-1 (1)	-1 (1)	-4(1)
		FairBalanceClass		52 (6)	1(1)	1 (1)	-3 (3)	-1 (1)	-1 (1)	-4 (1)
		None	48 (4)	62 (4)	18 (16)	20 (19)	19 (14)	25 (16)	27 (20)	28 (14)
	german	FairBalance	49 (5)	61 (3)	4 (8)	5 (13)	6 (6)	12 (8)	14 (9)	15 (7)
		FairBalanceClass	50 (4)	61 (3)	6 (9)	7 (15)	6 (8)	11 (9)	10 (13)	16 (7)

- F<sub>1</sub> score of FairBalance is usually comparable to that of None, except for the german dataset. Accuracy of FairBalance is significantly worse than None in 10 out of 15 settings. However, when comparing the median values of accuracy, FairBalance is just slightly worse than None.
- In every setting, the bias metrics (AOD, EOD, and SPD) for every protected attributes are significantly reduced after applying FairBalance.

The above two observations suggest that FairBalance can reduce bias on every protected attribute while maintaining similar prediction performances.

**RQ2:** Can FairBalance balance classes (FairBalanceClass) as well? Comparing the performance of FairBalanceClass with None and FairBalance, we observe:

- F<sub>1</sub> score of FairBalanceClass is significantly higher than that of None and FairBalance in every setting. Accuracy of FairBalanceClass is significantly lower than that of FairBalance. This suggests that class balancing in FairBalanceClass works perfectly in trading accuracy for higher F<sub>1</sub> score (on the minority class).
- In every setting, the bias metrics (AOD, EOD, and SPD) for every protected attributes are significantly reduced after applying FairBalanceClass.

The above two observations suggest that FairBalanceClass can reduce bias on every protected attribute while increasing the prediction performance on the minority class (when data is imbalanced).

**RQ3:** How does FairBalance perform comparing with the existing state-of-the-art bias mitigation algorithms? Table 4 shows the results of the second experiment. Comparing the performance of FairBalance with baseline bias mitigation algorithms, we observe:

- Except for german, F<sub>1</sub> score of FairBalance is similar to other baseline algorithms (4 wins, 2 losses, and 6 ties), and accuracy is also similar (2 wins, 5 losses, and 5 ties).
- Except for german, FairBalance almost always achieves lower or similar bias metrics when comparing to the baseline algorithms, especially when the baseline algorithm is not targeting the protected attribute. This suggests that FairBalance outperforms the existing baselines in mitigating bias on multiple protected attributes.
- On german dataset, FairBalance achieves a 0 F<sub>1</sub> score but the highest accuracy (69% in median). This result illustrates the necessity for class balancing in FairBalance.
- The median results of each bias metric from FairBalance and FairBalanceClass are all below 0.10 on all three datasets. This suggests that applying either FairBalance or FairBalanceClass can reduce the machine learning bias to a very low level.

The above observations show that FairBalance almost always achieves similar if not better prediction performance, and performs better in terms of the fairness metrics especially on the non-target protected attributes of the other state-of-the-art bias mitigation algorithms. In addition, it is better to apply FairBalanceClass on heavily imbalance datasets like german.

#### 5 Limitations

The scope of this work assumes that:

- 1. Ground truth labels are always fair, and
- 2. The protected attributes are already known and correctly labeled.

As a result, this work cannot be applied to datasets violating the above two assumptions.

In the meantime, this work evaluates machine learning fairness with three group-based fairness metrics (AOD, EOD, and SPD). Whether this work is able to reduce other bias metrics remains a question.

#### 6 Conclusion

This paper proposes FairBalance, a preprocessing technique with negligible computational overhead for mitigating machine learning bias on multiple protected attributes. Our results show that, within the scope of this paper, FairBalance can significantly reduce machine learning bias while maintaining the prediction performance. Also, it consistently outperforms other state-of-the-art bias mitigation algorithms on datasets with multiple protected attributes. Note that the scope of this paper also limits the usage of FairBalance—it cannot reduce the bias inherited from biased training labels.

To sum up, the best practice suggested in this paper is to apply FairBalance when the dataset has unbiased labels and multiple known protected attributes, and to apply FairBalanceClass if the dataset is imbalance as well.

Table 4: Comparisons of different bias removal algorithms with logistic regression classifier. Medians (IQRs) are reported for 10 repeats. Colored cells represent whether they are significantly better than the chosen baseline (FairBalance) with effect size of small, medium, or large or significantly worse than the chosen baseline (FairBalance) with effect size of small, medium, or large.

Dataset	Treatment		F <sub>1</sub>	Aggurgay	Sex			Race / Age		
Dataset				Accuracy	AOD	EOD	SPD	AOD	EOD	SPD
	Reweighing S	sex	62 (1)	66 (0)	5 (8)	8 (7)	8 (8)	22 (2)	26 (3)	26 (2)
	Reweighing r	race	62 (1)	65 (0)	24 (4)	28 (6)	26 (3)	0 (4)	5 (6)	5 (4)
	Adversial s	sex	63 (2)	66 (1)	33 (10)	40 (16)	36 (9)	25 (10)	28 (9)	29 (9)
	Debiasing r	race	62 (2)	64 (1)	21 (6)	25 (10)	24 (4)	-1 (26)	0 (27)	2 (24)
compas	Reject Option s	sex	61 (1)	64 (1)	0 (9)	4 (9)	1 (9)	24 (4)	27 (4)	27 (4)
	Classification r	race	63 (0)	65 (1)	22 (3)	22 (6)	25 (2)	3 (2)	6 (4)	6 (3)
	FairBalanceClass		63 (1)	64 (0)	4 (8)	4 (10)	8 (8)	7 (11)	10 (8)	10 (11)
	FairBalance		62 (0)	65 (1)	6 (3)	5 (5)	10(4)	-2 (4)	0 (6)	1 (3)
	Payaighing S	sex	49 (0)	79 (0)	0(1)	0(2)	-6 (0)	-20 (11)	-32 (19)	-15 (5)
	Reweighing r	race	48 (0)	80 (0)	-29 (0)	-46 (0)	-22 (0)	0 (0)	1(1)	-4 (0)
	Adversial s	sex	50 (0)	79 (0)	-2 (2)	-4 (4)	-8 (1)	-14 (3)	-20 (5)	-13 (2)
adult	Debiasing r	race	49 (0)	80 (0)	-28 (0)	-46 (1)	-21 (0)	1(2)	3 (5)	-3 (1)
auuit	Reject Option s		53 (0)	69 (0)	4 (0)	3 (0)	-3 (0)	-15 (1)	-14 (2)	-21 (1)
	Classification r	race	57 (0)	72 (0)	-34 (2)	-38 (1)	-39 (2)	2(1)	3 (3)	-3 (2)
	FairBalanceClas	SS	54 (1)	74 (0)	1(1)	1(1)	-7 (0)	0(1)	0(3)	-5 (1)
	FairBalance		50 (0)	78 (0)	0(8)	0 (12)	-6 (4)	0(1)	1(2)	-4 (1)
	Reweighing S	sex	10 (8)	68 (1)	-5 (4)	-6 (6)	-4 (3)	21 (12)	19 (14)	22 (12)
german	Reweighing	age	5 (7)	69 (2)	2 (4)	6 (8)	1 (3)	-1 (2)	0 (4)	0(1)
	Adversial s	sex	35 (14)	62 (16)	-30 (90)	-35 (103)	-28 (85)	4 (53)	7 (53)	8 (54)
	Debiasing a	age	34 (15)	59 (37)	-3 (34)	-1 (45)	-2 (34)	-28 (151)	-32 (156)	-26 (150)
	Reject Option s	sex	54 (3)	60 (2)	-1 (9)	-3 (9)	2 (8)	20 (14)	17 (12)	23 (14)
	Classification a	age	47 (4)	55 (3)	8 (2)	4 (10)	12 (5)	2 (10)	1 (8)	7 (11)
	FairBalanceClas	SS	52 (4)	61 (3)	3 (10)	2 (10)	3 (14)	5 (10)	3 (13)	10 (9)
	FairBalance		0(3)	69 (2)	0(2)	0 (0)	0(2)	0(1)	0(2)	0(1)

Given the limitations discussed in Section 5, future work of this paper will focus on:

- How to detect and mitigate biased ground truth labels. The bias metrics utilized in this paper (EOD, AOD, SPD) are no longer reliable when ground truth labels can be biased. Other bias metrics which do not depend on a set of reliable ground truth labels (e.g. individual fairness metric) are required to evaluate fairness in such data.
- How to mitigate potential ethical bias when the protected attributes are unknown or noisy. There are some existing work along this research [Wang et al., 2020], However, it remains as a major challenge for machine learning fairness.

## **Broader Impact**

This work has the following potentially positive impact in the society: our work could enable machine learning fairness on datasets with multiple protected attributes, which most existing works are incapable of.

For machine learning problems with multiple known protected attributes, we argue that applying the proposed algorithm in preprocessing has little potential drawback given its negligible computational overhead, little if any damage to the prediction performance, and compatibility with most machine learning models. However, scopes and limitations of this work, as discussed in Section 5 must be considered before applying it to real problems. One thing especially worth mentioning is that this work relies on the mathematical metrics for quantifying fairness (EOD, AOD, SPD). Therefore, there is no evidence showing that FairBalance can mitigate biases which cannot be detected by these metrics (e.g. biases inherited from the training data labels).

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