Fairer Machine Learning Software on Multiple Sensitive Attributes With Data Preprocessing

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Abstract—This research seeks to benefit the software engineering society by providing a simple yet effective approach to improve fairness of machine learning software on data with multiple sensitive attributes. Machine learning fairness has attracted increasing attention since machine learning software is increasingly used for high-stakes and high-risk decisions. Amongst all the fairness notations, this work specifically targets “equalized odds”. Equalized odds requires that members of every demographic group do not receive disparate mistreatment. It is one of the most widely accepted fairness notations given its advantage in always allowing perfect classifiers.

Most existing solutions for machine learning fairness do not directly target equalized odds and only affect one sensitive attribute (e.g. sex) at a time. To overcome this shortage, we analyzed the condition of equalized odds and hypothesize that balancing the class distribution of training data across every demographic group will improve equalized odds of the learned model. On four real-world datasets (two of which have multiple sensitive attributes) and three synthetic datasets, our empirical results show that, at low computational overhead, the proposed preprocessing algorithm FairBalance can significantly improve equalized odds without much, if any damage to the prediction performance. FairBalance also outperforms existing state-of-the-art approaches in terms of equalized odds. To facilitate reuse, reproduction, and validation of this work, our scripts and data are available at \texttt{https://github.com/hil-se/FairBalance} under an open-source Apache license (v2.0).

Index Terms—machine learning fairness, ethics in software engineering.

1 INTRODUCTION

Increasingly, machine learning and artificial intelligence software is being used to make decisions that affect people’s lives. This has raised much concern on the fairness of that kind of reasoning. Decision making software can be “biased”; i.e. it gives undue advantage to specifics group of people (where those groups are determined by sex, race, etc.). Such bias in the machine learning software can have serious consequences in deciding whether a patient gets released from the hospital [1], [2], which loan applications are approved [3], which citizens get bail or sentenced to jail [4], who gets admitted/hired by universities/companies [5].

Equalized odds [6] is one of the most widely accepted fairness and discrimination notations. Equalized odds is a simple, interpretable, and easily checkable notion of nondiscrimination with respect to a specified sensitive attribute [6]. More importantly, it always allows for the perfectly accurate solution of $f(X, A) = Y$. This is why equalized odds are almost always applied to evaluate machine learning fairness. However, most existing machine learning fairness solutions do not directly target equalized odds. It is much more common that a fairness solution targets demographic parity, which is achieved if the percentages of the desired outcome are the same across every demographic group. When one group is on average more qualified than the other, demographic parity does not allow the perfectly accurate solution. Therefore, such fairness solutions will not satisfy equalized odds.

In addition, most existing machine learning fairness solutions only affect one sensitive attribute (e.g. sex) at a time. For example, on a dataset with two sensitive attributes sex and race, most existing approaches can learn either a fair model on sex or a fair model on race, but not a fair model on both sex and race [7], [8], [9]. This also hinders the application of the fairness algorithms since a fair machine learning model cannot be biased on any sensitive attribute.

Some in-processing bias mitigation algorithms can tackle multiple sensitive attributes at the same time by optimizing for both prediction performance and specific fairness metrics [10] (including equalized odds). However, such in-processing bias mitigation algorithms are usually very expensive. Magic parameters also need to be decided beforehand to trade off between prediction performance and fairness metrics.

In this paper, we propose a simple yet effective algorithm, FairBalance, to learn a fairer machine learning model directly targeting equalized odds on every sensitive attribute. FairBalance is a preprocessing technique which balances the class distribution of training data across every demographic group. Here, each demographic group is a possible combination of different values from each sensitive attribute.

Overall, the contributions of this paper include:

- We analyzed the conditions of equalized odds and derived two hypotheses for improving equalized odds.
- We proposed two preprocessing algorithms following the hypotheses to directly target equalized odds and work for data with multiple sensitive attributes.
- With empirical results on seven datasets, we tested the two proposed algorithms (and the two hypotheses). Our proposed preprocessing algorithms significantly outper-

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formed existing state-of-the-art machine learning fairness approaches in terms of equalized odds. The proposed algorithms also feature very low computational overhead ($O(n)$).

To facilitate reuse, reproduction, and validation of this work, our scripts and data are available at https://github.com/hil-se/FairBalance.

The rest of this paper is structured as follows. Section 2 provides the background and related work of this paper. Section 3 analyzes the conditions of equalized odds and present two hypotheses for improving equalized odds. Two preprocessing algorithms are then proposed to implement the hypotheses. To test our hypothesis and the proposed algorithms, Section 4 presents the empirical experiment setups on seven datasets while Section 5 shows the experiment results. Followed by discussion of limitations and threats to validity in Section 6 and conclusion in Section 7.

Before all that, we first answer two frequently asked questions about this work:

- Is this really a software engineering (SE) problem?
- Is bias more than just a decision-algorithm problem?

## 1.1 FAQ1: Is this really a SE problem?

We assert that issues of bias in software is such a pressing matter that it is reckless and irresponsible to assume some other community will fix it (e.g. our colleagues from the AI research community). We say this for three reasons.

Firstly, so far the problems of software decision bias have not been fixed. Perhaps this is an "all hands on deck" situation where all communities should lean in to help address a pressing social problem.

Secondly, the distinction between "AI engineering" and "software engineering" is somewhat arbitrary. Sculley et al. argue that most of "AI software" is actually not about AI [11]. They say AI software needs a lot of SE which means our research has much to say about the practicality of AI.

Thirdly, recently, SE researchers have shown they have much to offer about bias and fairness testing. As evidence of this, the FSE conference made distinguished paper awards in 2017 and 2021 to papers defining and extended the new field of software fairness testing (see Galhotra et al. [12], and Chakraborty et al. [13]). For example, researchers outside of SE lament that removing bias comes at a cost of damaging predictive performance. Berk et al. [14] famously said in 2017 that "It is impossible to achieve fairness and high performance simultaneously (except in trivial cases).". That changed in 2021 when SE researchers showed many of the things done to fix fairness are also the sampling operators widely used in software analytics to improve prediction. Hence, Chakraborty et al. [13] found that their Fair-SMOTE system could improve fairness measures and predictive performance.

We are not alone in saying SE has much to offer to the problem of software decision bias. A keynote address to ICSSP’20 [12]+ commented that

"fairness testing is an inevitable step in the software development life-cycle" – Yuriy Brun [15].

Also, many large organizations like IBM [16], Facebook [17], and Microsoft [18] now build and maintain large open-source libraries that address issues of software fairness. In order to better understand and support those large software initiatives, we need SE research in this area.

## 1.2 FAQ2: Is bias more than just a decision-algorithm problem?

Can software decision bias be treated arithmetically? Or is such bias really about a broader space of social issues that fall outside of computer science and software engineering? For example, it has been argued to us that software is a technology and, as such, it selected to favor the ruling elite [19]. In this view, algorithms are as inherently as bad (racist, sexist, extremist, misinforming) as anything else selected by their social context. Hence there is no point in fixing algorithms until we first fix the society that selects and deploys them.

On this point, we are inspired by Freeman Dyson’s quote:

“Technology without morality is barbarous; morality without technology is impotent.”

That is, our premise is that, to better address the social inequities caused by AI, we must explore both:

- Social forces that lead to marginalization and discrimination [20, 21, 22]; as well as
- The AI tools that can help with part of that problem.

To say that another way, we need a “two-way street” between what we might call the humanities view (which is light on CS knowledge) and the computer science view (which is light on knowledge of the broader social context). For example, Gebru [23] wants regulation that “specifically says that corporations need to show that their technologies are not harmful before they deploy them”. Implementing that requirement, at a company-level scale, would require many things including the fairness testing methods discussed here.

## 2 Background and Related Work

Ethical bias in machine learning models is a well-known and fast-growing topic. It leads to unfair treatments to people belonging to certain groups. Recently, large industries have started putting more and more importance on ethical issues of machine learning model and software. IEEE [24], the European Union [25], and Microsoft [26] have each recently published principles for ethical AI conduct. All three stated that intelligent systems or machine learning software must be fair when used in real-life applications. IBM launched an extensible open-source software toolkit called AI Fairness 360 [16] to help detect and mitigate bias in machine learning models throughout the application life cycle. Microsoft has created a research group called FATE [27] (Fairness, Accountability, Transparency, and Ethics in AI). Facebook announced they developed a tool called Fairness Flow [17] that can determine whether a ML algorithm is biased or not. ASE 2019 has organized first International Workshop on Explainable Software [28] where issues of ethical AI were extensively discussed. Several different fairness notations have been defined to assess whether a trained machine learning model has ethical bias. Most of these fairness notations, e.g. individual fairness, counterfactual fairness, fairness through awareness, and demographic parity, test both bias emerged in the learning process and bias inherited from the training labels. In this work, we focus on mitigating the bias emerged in the learning process and assume that all training labels are perfectly correct. Under this assumption, a perfect predictor $f(X, A) = Y$ should always be fair and
unbiased. This is why we specifically target equalized odds and only include real-world datasets with truth as labels (e.g. income of people, reoffended or not in two years) in the experiments.

2.1 Equalized Odds

As defined by Hardt et al. [6], a predictor \(f(X, A)\) satisfies equalized odds with respect to sensitive attribute \(A\) and outcome \(Y\), if \(f(X)\) and \(A\) are conditionally independent on \(Y\). More specifically, for binary targets \(Y\) and sensitive attributes \(A\), equalized odds is equivalent to:

\[
P(f(X, A) = 1|A = 0, Y = y) = P(f(X, A) = 1|A = 1, Y = y), \quad y \in 0, 1
\]

The above equation also means that the predictor has the same true positive rate and false positive rate across the two demographics \(A = 0\) and \(A = 1\). Equalized odds thus enforces both equal bias and equal accuracy in all demographics, punishing models that perform well only on the majority.

Equalized odds is a widely applied fairness notation since it always allows for the perfectly accurate solution of \(f(X, A) = Y\). More broadly, the criterion of equalized odds is easier to achieve the more accurate the predictor \(f(X, A)\) is, aligning fairness with the central goal in supervised learning of building more accurate predictors. This is why in this paper, we focus on achieving equalized odds for machine learning software.

To measure the extent to which a predictor satisfies equalized odds, two important fairness metrics were established:

- **Average Odds Difference (AOD)** [16], [29]: Average of difference in False Positive Rates (FPR) and True Positive Rates (TPR) (2).

\[
AOD = 0.5 \times [(FPR(A = 0) - FPR(A = 1)) + (TPR(A = 0) - TPR(A = 1))]
\]

- **Equal Opportunity Difference (EOD)** [6]: Difference of True Positive Rates (TPR) (3).

\[
EOD = TPR(A = 0) - TPR(A = 1)
\]

Where TPR and FPR are the true positive rate and false positive rate calculated as \[4\] with results from the confusion matrix on a test set (as shown in Table 1).

\[
TPR = TP/(TP + FN) \\
FPR = FP/(FP + TN)
\]

The two fairness metrics AOD and EOD each features a relaxed version of equalized odds. When \(AOD = 0\), the sums of true positive rate and false positive rate are the same across the two demographics \(A = 0\) and \(A = 1\). This metric measures whether the predictor \(f(X, A)\) favors one demographic over the other. When \(EOD = 0\), the true positive rates are the same across the two demographics \(A = 0\) and \(A = 1\). This metric measures a relaxed version of equalized odds called equal opportunity where only true positive rates were considered. When both \(AOD = 0\) and \(EOD = 0\), equalized odds will be achieved.

2.2 Fairness on Multiple Sensitive Attributes

Most machine learning fairness research only considers one sensitive attribute with binary values (such as the definition of equalized odds by Hardt et al. [6]). However, it is very important to extend the fairness notations to multiple sensitive attributes. This is because in many real-world scenarios, multiple sensitive attributes exist and discrimination against any demographic group \(s = (A_1, A_2, \ldots, A_m)\) is not desired. Here, \(s \in S\) where \(S\) is the set of all possible combinations of the sensitive attributes \(A_1, A_2, \ldots, A_m\). For example, when there are two sensitive attributes \(A_1 = \{\text{Male, Female}\}\) and \(A_2 = \{\text{White, Non-White}\}\), the demographic groups are \(S = \{(\text{Male, White}), (\text{Male, Non-White}), (\text{Female, White}), (\text{Female, Non-White})\}\). Following this notation, equalized odds on multiple sensitive attributes is equivalent to:

\[
P(f(X, A) = 1|A = s_i, Y = y) = P(f(X, A) = 1|A = s_j, Y = y), \forall s_i, s_j \in S, y \in 0, 1
\]

As a result, in the rest of this paper, we will use the following two metrics shown in (6) and (7) to evaluate the violation of equalized odds on multiple sensitive attributes:

\[
mAOD = 0.5 \times [\max_{s \in S} (TPR(A = s) + FPR(A = s))] - \min_{s \in S} (TPR(A = s) + FPR(A = s))
\]

\[
mEOD = \max_{s \in S} TPR(A = s) - \min_{s \in S} TPR(A = s)
\]

2.3 Related Work

Prior work on machine learning fairness can be classified into three types depending on when the treatments are applied:

**Pre-processing algorithms.** Training data is preprocessed in such a way that discrimination or bias is reduced before training the model. Kamiran and Calders [7] proposed reweighing method that generates weights for the training examples in each (group, label) combination differently to achieve fairness. Feldman et al. [30] designed disparate impact remover which edits feature values to increase group fairness while preserving rank-ordering within groups. Calmon et al. [31] proposed an optimized pre-processing method which learns a probabilistic transformation that edits the labels and features with individual distortion and group fairness. Another pre-processing technique, learning fair representations, finds a latent representation which encodes the data well but obfuscates information about sensitive attributes [32].

**In-processing algorithms.** This approach adjusts the way a machine learning model is trained to reduce the bias. Zhang et al. [12] proposed Adversarial debiasing method which learns a classifier to increase accuracy and simultaneously reduce an adversary’s ability to determine the sensitive 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. [33] designed a meta algorithm to take the fairness metric as part of the input and return a classifier optimized with respect

| TABLE 1: Confusion Matrix. |
|---------------------------|
| \(f(X, A) = 0\) | \(f(X, A) = 1\) |
| \(Y = 0\) | \(TN\) | \(FP\) |
| \(Y = 1\) | \(FN\) | \(TP\) |
Post-processing algorithms. This approach adjusts the prediction threshold after the model is trained to reduce specific fairness metrics. Kamiran et al. [35] 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 concentrates on the Equal Opportunity Difference (EOD) metric [6], [29].

There are other treatments incorporating multiple steps. For example, Fair-SMOTE [13] first utilizes synthetic minority over-sampling technique (SMOTE) [36] to generate synthetic training data points. The training data is divided into subgroups based on class and the sensitive attributes. Initially, these subgroups are of unequal sizes. Fair-SMOTE synthetically generates new data points for all the subgroups except the subgroup having the maximum number of data points. Fair-SMOTE then applies Fair Situation Testing—a logistic regression model is trained and all the data points are predicted by it. After that, the sensitive attribute value for every data point is flipped (e.g. male to female, white to non-white) and tested again to validate whether model prediction changes or not. If the result changes, that particular data point fails the situation testing and will be removed from the training data.

The limitation of these prior works is that they either does not directly target equalized odds or work on data with multiple sensitive attributes. There is only one exception—FERMI was claimed to directly optimize for equalized odds and has been proven to work effectively on multiple sensitive attributes. We will provide more details about this algorithm and will apply it as a baseline in Section 4.

3 METHODOLOGY

Before we present the proposed methods, we need to first analyze how to achieve equalized odds on multiple sensitive attributes.

3.1 Hypotheses

Achieving equalized odds on multiple sensitive attributes requires both mAOD and mEOD to be zero. First, we analyze mAOD with the following proposition.

**Proposition 3.1.** Average odds difference on multiple sensitive attributes (mAOD) is zero if false positive rate (FPR) equals to false negative rate (FNR) for every demographic group \( s \in S \).

**Proof.** We have

\[
FPR(A = s) = FNR(A = s) \quad \forall s \in S
\]  

and

\[
FNR = FN/(FN + TP) = 1 - TPR
\]

Applying (8) and (9) to (6) yields

\[
mAOD = 0.5 \times \left[ \max_{s \in S}(1 - FNR(A = s) + FPR(A = s)) - \min_{s \in S}(1 - FNR(A = s) + FPR(A = s)) \right]
\]

\[
= 0.5 \times (1 - 1)
\]

(10)

Given Proposition 3.1 we have the following hypothesis:

**Hypothesis 1.** Average odds difference on multiple sensitive attributes (mAOD) is reduced when classes are balanced by preprocessing for every demographic group \( s \in S \).

The rationale behind Hypothesis [1] is that, fitting a machine learning model is equivalent to minimizing the weighted error:

\[
\min L(f) = \sum_{s \in S} (w(A = s, Y = 0) \times FPR(A = s) + w(A = s, Y = 1) \times FNR(A = s))
\]

Class balancing in preprocessing gives

\[
\frac{w(A = s, Y = 0)}{w(A = s, Y = 1)} = \frac{FN(A = s) + TP(A = s)}{TN(A = s) + FP(A = s)}
\]

Applying (12) to (11) yields

\[
L(f) = \sum_{s \in S} \alpha(A = s)(FPR(A = s) + FNR(A = s))
\]

where

\[
\alpha(A = s) = w(A = s, Y = 0)(TN(A = s) + FP(A = s))
\]

\[
= w(A = s, Y = 1)(FN(A = s) + TP(A = s))
\]

Here, (13) implies that \( FPR(A = s) \) and \( FNR(A = s) \) are of equal importance in the model training for every demographic group \( s \in S \). This helps reduce the difference between \( FPR(A = s) \) and \( FNR(A = s) \) when trading off \( FP(A = s) \) for \( FN(A = s) \). According to Proposition 3.1, this further implies a reduced mAOD. Hypothesis [1] will be tested empirically in Section 4.

Then, we analyze mEOD with the following corollary.

**Corollary 3.2.** Equalized odds is achieved if false positive rate (FPR) equals to false negative rate (FNR) for every demographic group \( s \in S \) and the error rates across every demographic group \( s \in S \) are the same.

**Proof.** We have

\[
ErrorRate = \frac{FP + FN}{FP + FN + TP + TN}
\]

and

\[
ErrorRate(A = s_i) = ErrorRate(A = s_j), \forall s_i, s_j \in S
\]
Applying (8) to (15) yields
\[
\text{Error Rate}(A=s) = \text{FPR}(A=s) = \text{FNR}(A=s) = 1 - \text{TPR}(A=s)
\] (17)
Applying (17) to (16) yields
\[
\text{TPR}(A=s_i) = \text{TPR}(A=s_j), \quad \forall s_i, s_j \in S
\] (18)
Therefore equalized odds is achieved.

Given Corollary 3.2, we have the following hypothesis:

**Hypothesis 2.** Both mAOD and mEOD are reduced when (1) classes are balanced across every demographic group and (2) sizes of each demographic group are balanced.

The rationale is that, on top of Hypothesis 1, the weight \( w \) for each sample is set to also satisfy
\[
w(A = s_i, Y = 0)(\text{TN}(A = s_i) + \text{FP}(A = s_i)) + w(A = s_i, Y = 1)(\text{FN}(A = s_i) + \text{TP}(A = s_i))
\]
w(A = s_i, Y = 0)(\text{TN}(A = s_j) + \text{FP}(A = s_j)) + w(A = s_j, Y = 1)(\text{FN}(A = s_j) + \text{TP}(A = s_j)),
\forall s_i, s_j \in S
\] (19)
Applying (14) to (19) yields
\[
\alpha(A = s_i) = \alpha(A = s_j) = \alpha \quad \forall s_i, s_j \in S
\] (20)
Applying (20) to (13) yields
\[
L(f) = \alpha \sum_{s \in S} (\text{FPR}(A = s) + \text{FNR}(A = s))
\] (21)
This implies that \( \text{FPR}(A = s) \) and \( \text{FNR}(A = s) \) from every demographic group \( s \) are of equal importance in the model fitting process. Thus, the difference between both true positive rates and false positive rates will be reduced and results in reduced mAOD and mEOD. Note that, Hypothesis 2 is less likely to hold than Hypothesis 1 since when training a machine learning model, there are ways to directly trade-off between false negatives and false positives but not between errors from different demographic groups. Hypothesis 2 will be tested empirically in Section 4.

### 3.2 FairBalance

In this section, we will present our proposed fairness preprocessing treatments following the two hypotheses in Section 3.1. As shown in (22), FairBalance implements Hypothesis 1 by assigning different weights to training data samples to balance the classes within each demographic group. FairBalanceVariant implements Hypothesis 2 by further balance the group size of each demographic group with sample weights calculated as (23). Here, we also extend the Reweighing [7] algorithm to multiple sensitive attributes by assigning sample weights as (24). Reweighing is an existing preprocessing treatment very similar to FairBalance and FairBalanceVariant. Therefore we will apply its extended version on multiple sensitive attributes as a baseline in the next section. Table 2 summarizes the difference between FairBalance, FairBalanceVariant, and Reweighing.

\[
w_{FB}(s, y) = \frac{|A = s|}{|A = s \& Y = y|}, \quad \forall s \in S, y \in Y. \quad (22)
\]
\[
w_{FBV}(s, y) = \frac{1}{|A = s \& Y = y|}, \quad \forall s \in S, y \in Y. \quad (23)
\]
\[
w_{RW}(s, y) = \frac{|A = s| |Y = y|}{|A = s \& Y = y|}, \quad \forall s \in S, y \in Y. \quad (24)
\]

![Figure 1: Demonstration of FairBalance and FairBalanceVariant.](image)

Table 2: Characteristics of each treatment.

| Treatment         | Same class distribution for every group | Balanced classes | Balanced group size |
|-------------------|-----------------------------------------|------------------|--------------------|
| None              | ✓                                       | ✓                | ✓                  |
| Reweighing [7]    | ✓                                       | ✓                | ✓                  |
| FairBalance       | ✓                                       | ✓                | ✓                  |
| FairBalanceVariant| ✓                                       | ✓                | ✓                  |

| # Data Points | Male | Female |
|---------------|------|--------|
| White         | T = 50/20 F = 30 | T = 20/10 |
| Non White     | T = 2/30 F = 18 | T = 10/10 |

| Weight       | Male | Female |
|--------------|------|--------|
| White        | T = 1/20 F = 1/30 | T = 1/10 |
| Non White    | T = 1/2 F = 1/18 | T = 1/3 |

4 EXPERIMENTS

4.1 Datasets

For this study, we selected commonly used datasets in machine learning fairness to conduct our experiments. Starting
with datasets seen in recent high-profile papers [10], [13], [41], [42], we selected those with class labels derived from truth, not human decisions. This leads to the selection of the three datasets shown in Table 3. We favor datasets with multiple sensitive attributes but unfortunately, we can only find two of such datasets (Adult Census Income [37] and Compas [38]) each with two sensitive attributes.

Besides the first four real-world datasets, we also generated synthetic hiring data following Lipton et al. [43]. With a little modification to add another sensitive attribute of “age”, the distribution of each attribute in the synthetic hiring data is as follows:

\[
\begin{align*}
\text{sex}_i &\sim \text{Bernoulli}(r) \\
\text{age}_i &\sim \text{Normal}(25, \sigma = 3) \\
\text{hair_length}|\text{sex}_i &\sim 35 \cdot \text{Beta}(2, 2 + 5\text{sex}_i) \\
\text{work_exp}|(\text{sex}_i, \text{age}_i) &\sim \text{Poisson}(\text{age}_i + 6 - l(1 - \text{sex}_i)) - \text{Normal}(20, \sigma = 0.2) \\
y_i|\text{work_exp}_i &\sim \text{Bernoulli}(p_i) \\
\text{where } p_i &\equiv 1/(1 + \exp(25.5 - 2.5\text{work_exp}_i))
\end{align*}
\]

Here, \( r \) is the prevalence of \text{sex}= 1 (Male) and \( l \) affects the difference of average work experience between men and women. The advantage of such synthetic data is that we have full control on it. This data-generating process has the following key properties:

- the historical hiring process was based solely on the number of years of work experience;
- because women on average have fewer years of work experience than men (when \( l > 0 \)), men have been hired at a much higher rate than women;
- women have longer hair than men, a fact that was irrelevant to historical hiring practice;
- older applicants also tend to have longer work experience, thus have been hired at a higher rate than younger applicants; and
- the prevalence of male and female (controlled by the parameter \( r \)) amongst the applicants can vary depending on the job type.

We generated three datasets by each sampling 5,000 observations from the above description with the following parameters:

1. \( l = 0, r = 0.5 \): women on average have the same years of work experience as men (11 years), half of the applicants are women.
2. \( l = 6, r = 0.5 \): women on average have fewer years of work experience as men (5 years vs. 11), half of the applicants are women.
3. \( l = 6, r = 0.95 \): women on average have fewer years of work experience as men (5 years vs. 11), 95 percent of the applicants are men.

Figure 3 shows the class distribution of each demographic group in each dataset. As we can see, classes are highly imbalanced in most datasets except for Heart Health. In addition, Synthetic Hiring Data with \( r = 0.95 \) features a scenario where the prevalence of female samples is extremely low (5%). Therefore, these datasets should be able to test the two hypotheses described in Section 3.1.

### 4.2 Baselines

To test the two hypotheses, FairBalance and FairBalanceVariant will be compared with baselines on the seven datasets. Besides a baseline with no fairness treatment (None) and a baseline of the generalized Reweighing algorithm shown in [24], we will also apply FERMI as a baseline since it
was claimed to directly optimize for equalized odds and can be applied to multiple sensitive attributes. \textsc{FERMI} \cite{FERMI} balances equalized odds and accuracy with a tuneable hyperparameter $\lambda$ by learning the following objective function with stochastic gradient descent:
\begin{equation}
\begin{aligned}
&\min_{\theta} E_{X,C,S} \{L(X,C;\theta)\} + \lambda D_{R}(\hat{C}_\theta(X);S),
\end{aligned}
\end{equation}
where $\hat{C}_\theta(X)$ is the output of the learned model, $D_{R}(\hat{C}_\theta(X);S)$ measures the Exponential Rényi Mutual Information (ERMI) for equalized odds, and $E_{X,C,S} \{L(X,C;\theta)\}$ measures the prediction errors.

As for the specific implementations, \textsc{FERMI} is reproduced with code provided by Lowy et al. \cite{FERMI} at \url{https://github.com/optimization-for-data-driven-science/FERMI}. The rest preprocessing treatments are applied along with logistic regression classifiers implemented by scikit-learn\footnote{1. https://scikit-learn.org}. More details of the implementations can be found at our reproduction package at \url{https://github.com/hil-se/FairBalance}.

### 4.3 Evaluation

The two machine learning fairness metrics mAOD and mEOD described in Section 2.2 are applied to evaluate the extend of equalized odds on multiple sensitive attributes. In the meantime, accuracy is applied to evaluate the overall prediction performance:

\begin{equation}
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\end{equation}

Since class balancing is expected to impact the classifiers’ prediction performance by favoring the minority class, we also apply the $F_1$ score on the minority class to reflect the prediction performance on the minority class:

\begin{equation}
F_1(Y = m) = \frac{2 \times TPR(Y = m) \times PPV(Y = m)}{TPR(Y = m) + PPV(Y = m)}
\end{equation}

where $PPV = TP/(TP + FP)$ and $m$ is the minority class.

Each treatment is evaluated 50 times during experiments by each time randomly sampling 50\% of the data as training set and the rest as test set. 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 and a nonparametric effect size testing (Cliff’s delta) 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. Similar to the Scott-Knott test, rankings are also calculated to compare different treatments with nonparametric performance results. For each metric, the treatments are first sorted by their median values in that metric. Then, each pair of treatments is compared with the Mann–Whitney U test ($\rho \geq 0.05$) and Cliff’s delta ($|\delta| < 0.33$) to decide whether they should belong to the same rank. Pseudo code of the ranking algorithm is shown in Algorithm 1.

**Algorithm 1**: Nonparametric ranking.

```
Input : T, performances to rank, a list of list.
Output : R, rankings of the each treatment in T.
1 medians = []
2 for t \in T do
3   asc = argsort(medians)
4   base = T[asc[0]]
5   rank = 0
6   R = []
7   R[asc[0]] = 0
8   for i=1, i<m, i++ do
9     if MannWhitneyU(T[asc[i]], base) < 0.05 &
10     CliffDelta(T[asc[i]], base) > 0.33 then
11       rank = rank + 1
12       base = T[asc[i]]
13     R[asc[i]] = rank
14 return R
```

## 5 RESULTS

In this section, we analyze the empirical results in Table 4 to explore the following research questions.

### RQ1. (Hypothesis 1) Can we reduce average odds difference on multiple sensitive attributes (mAOD) by balancing the classes within each demographic group?

Looking at mAOD in Table 4, FairBalance is always significantly better None except on two datasets (where they rank the same). In Figure 3, the Heart Health data has the most balanced classes in every demographic group. Therefore, it is reasonable that FairBalance did not reduce mAOD significantly on this dataset. On Synthetic Hiring Data ($l = 0$, $r = 0.5$), there is no class difference between Male and Female, the None treatment already achieves a very low mAOD. There is not much room to improve by FairBalance on this dataset. In the meantime, FairBalance always achieves the best rank in terms of mAOD across all seven datasets. Therefore, the empirical results suggest that Hypothesis 1 is valid.

**Answer to RQ1**: Yes. By balancing the classes within each demographic group, FairBalance achieved the lowest mAOD amongst all the tested treatments on seven datasets. It also significantly reduced mAOD on five datasets.

### RQ2. (Hypothesis 2) Can we further reduce equal opportunity difference on multiple sensitive attributes (mEOD) by also balancing the sizes of each demographic group?

Comparing results on Synthetic Hiring Data ($l = 6$, $r = 0.5$) and Synthetic Hiring Data ($l = 6$, $r = 0.95$), the only difference of the two datasets are the prevalence of Female samples. As a result, if Hypothesis 2 holds, FairBalanceVariant should achieve similar mEOD as FairBalance on Synthetic Hiring Data ($l = 6$, $r = 0.5$), and achieve significantly lower mEOD than FairBalance on Synthetic Hiring Data ($l = 6$, $r = 0.95$). However, based on results in Table 4, FairBalanceVariant achieved similar mEOD as FairBalance on Synthetic Hiring Data ($l = 6$, $r = 0.95$). Furthermore, on the Bank Marketing dataset, FairBalanceVariant achieved worse mEOD and mAOD than FairBalance. Overall, FairBalanceVariant does not achieve better mEOD than FairBalance (one win on Bank Marketing and one loss on Compas). Therefore, Hypothesis 2 does not hold according to the empirical results. FairBalanceVariant is also deprecated since it has significantly worse mAOD than FairBalance on Compas dataset.

**Answer to RQ2**: No, mEOD is not further reduced by balancing the sizes of each demographic group.

### RQ3. Does FairBalance outperform the current state-of-the-art baselines in terms of achieving equalized odds on multiple sensitive attributes?

Compared to Reweighing, FairBalance achieved significantly better mEOD on three out of seven datasets and better mEOD on four out of seven datasets. Therefore, FairBalance outperforms Reweighing in terms of equalized odds. Compared to FERMI, FairBalance achieved significantly better mAOD on four out of seven datasets, better mEOD on five out of seven datasets, and worse mEOD on the Bank Marketing dataset. When FERMI outperformed FairBalance on the Bank Marketing dataset, it achieved only slightly lower mEOD in median (0.05 vs 0.07). But on many other datasets, FairBalance outperformed FERMI a lot (e.g. 0.07 vs 0.22 mEOD on the Adult Census Income dataset). Overall, FairBalance outperforms FERMI in terms of equalized odds.

**Answer to RQ3**: Yes. FairBalance outperforms the current state-of-the-art baselines in terms of achieving equalized odds on multiple sensitive attributes.

### RQ4. How did the proposed fairness treatments impact the classifiers’ prediction performance?

The classifiers learned with FairBalance are expected to favor the minority class. The Heart Health dataset has balanced class distribution, as shown in Figure 3, class balancing does not have much impact on the prediction performance. On other datasets, FairBalance is expected to increase the $F_1$ score on the minority class while reducing the accuracy. From Table 4 results on Accuracy and $F_1$ score are as expected on the four real-world datasets. On the three synthetic datasets, FairBalance achieved significantly lower
TABLE 4: Empirical results. Each cell shows (1) the ranking, (2) the median (50th percentile) value, and (3) the IQR value (75th percentile - 25th percentile) of the metric on a certain dataset. Colored cells are the ones with top rank r0.

| Data                     | Treatment         | Accuracy | F1 (Minority) | mEOD | mAOD | Runtime (secs) |
|--------------------------|-------------------|----------|---------------|------|------|----------------|
|                          |                   | r0: 0.85 (0.00) | r2: 0.66 (0.01) | r1: 0.18 (0.06) | r3: 0.13 (0.03) | r4: 1.22 (0.02) |
| Adult Census Income      | None              | r2: 0.84 (0.00) | r4: 0.62 (0.01) | r2: 0.22 (0.05) | r2: 0.11 (0.03) | r4: 25.67 (0.31) |
|                          | FERMI             | r1: 0.84 (0.00) | r3: 0.63 (0.01) | r1: 0.16 (0.04) | r1: 0.07 (0.02) | r1: 1.52 (0.02) |
|                          | Reweighing        | r3: 0.81 (0.00) | r0: 0.68 (0.00) | r0: 0.07 (0.02) | r0: 0.04 (0.03) | r2: 1.55 (0.02) |
|                          | FairBalance       | r4: 0.81 (0.00) | r1: 0.67 (0.00) | r0: 0.07 (0.03) | r0: 0.04 (0.03) | r3: 1.56 (0.03) |
|                          | FairBalanceVariant|         |               |      |      |                |
| Compas                   | None              | r0: 0.67 (0.01) | r2: 0.60 (0.01) | r3: 0.22 (0.03) | r2: 0.30 (0.04) | r0: 0.47 (0.02) |
|                          | FERMI             | r1: 0.66 (0.01) | r3: 0.59 (0.01) | r2: 0.12 (0.05) | r0: 0.07 (0.05) | r2: 5.28 (0.14) |
|                          | Reweighing        | r2: 0.66 (0.01) | r3: 0.59 (0.01) | r1: 0.09 (0.05) | r0: 0.07 (0.03) | r1: 0.52 (0.06) |
|                          | FairBalance       | r3: 0.66 (0.01) | r0: 0.63 (0.01) | r0: 0.06 (0.05) | r0: 0.06 (0.04) | r1: 0.52 (0.06) |
|                          | FairBalanceVariant|         |               |      |      |                |
| Heart Health             | None              | r0: 0.82 (0.03) | r0: 0.80 (0.03) | r1: 0.09 (0.10) | r0: 0.09 (0.07) | r0: 0.02 (0.02) |
|                          | FERMI             | r0: 0.82 (0.03) | r0: 0.81 (0.03) | r0: 0.05 (0.08) | r0: 0.05 (0.06) | r1: 0.23 (0.00) |
|                          | Reweighing        | r0: 0.83 (0.02) | r0: 0.81 (0.03) | r0: 0.06 (0.06) | r0: 0.05 (0.07) | r0: 0.02 (0.02) |
|                          | FairBalance       | r0: 0.82 (0.03) | r0: 0.80 (0.03) | r0: 0.06 (0.08) | r0: 0.06 (0.08) | r0: 0.02 (0.02) |
|                          | FairBalanceVariant|         |               |      |      |                |
| Bank Marketing           | None              | r0: 0.90 (0.00) | r2: 0.45 (0.01) | r3: 0.13 (0.05) | r2: 0.09 (0.03) | r0: 1.29 (0.04) |
|                          | FERMI             | r0: 0.90 (0.00) | r3: 0.44 (0.01) | r0: 0.05 (0.05) | r0: 0.02 (0.03) | r4: 13.13 (2.35) |
|                          | Reweighing        | r0: 0.90 (0.00) | r2: 0.45 (0.01) | r2: 0.09 (0.04) | r1: 0.04 (0.02) | r3: 1.74 (0.37) |
|                          | FairBalance       | r1: 0.84 (0.00) | r0: 0.55 (0.00) | r1: 0.07 (0.04) | r0: 0.01 (0.02) | r1: 1.36 (0.02) |
|                          | FairBalanceVariant|         |               |      |      |                |
| Synthetic Hiring Data \(l = 0, r = 0.5\) | None              | r0: 0.96 (0.00) | r0: 0.96 (0.00) | r1: 0.06 (0.02) | r0: 0.04 (0.02) | r0: 0.19 (0.00) |
|                          | FERMI             | r2: 0.87 (0.01) | r2: 0.86 (0.02) | r2: 0.25 (0.06) | r1: 0.22 (0.03) | r2: 3.62 (0.10) |
|                          | Reweighing        | r1: 0.96 (0.01) | r1: 0.96 (0.01) | r0: 0.04 (0.03) | r0: 0.04 (0.02) | r1: 0.23 (0.00) |
|                          | FairBalance       | r1: 0.96 (0.01) | r1: 0.96 (0.01) | r0: 0.04 (0.02) | r0: 0.05 (0.02) | r1: 0.23 (0.02) |
|                          | FairBalanceVariant|         |               |      |      |                |
| Synthetic Hiring Data \(l = 6, r = 0.5\) | None              | r0: 0.97 (0.01) | r0: 0.95 (0.01) | r2: 0.13 (0.06) | r2: 0.08 (0.04) | r0: 0.19 (0.02) |
|                          | FERMI             | r3: 0.80 (0.01) | r2: 0.74 (0.01) | r3: 0.22 (0.03) | r3: 0.29 (0.02) | r2: 3.69 (0.17) |
|                          | Reweighing        | r1: 0.96 (0.01) | r1: 0.94 (0.01) | r1: 0.09 (0.04) | r1: 0.05 (0.02) | r1: 0.23 (0.02) |
|                          | FairBalance       | r2: 0.96 (0.01) | r1: 0.94 (0.01) | r0: 0.03 (0.02) | r0: 0.04 (0.01) | r1: 0.22 (0.02) |
|                          | FairBalanceVariant|         |               |      |      |                |
| Synthetic Hiring Data \(l = 6, r = 0.95\) | None              | r0: 0.97 (0.01) | r0: 0.96 (0.01) | r1: 0.14 (0.12) | r1: 0.09 (0.07) | r0: 0.19 (0.00) |
|                          | FERMI             | r3: 0.86 (0.01) | r3: 0.86 (0.02) | r2: 0.23 (0.05) | r2: 0.32 (0.07) | r2: 3.62 (0.03) |
|                          | Reweighing        | r1: 0.96 (0.01) | r1: 0.96 (0.01) | r0: 0.07 (0.05) | r0: 0.05 (0.03) | r1: 0.22 (0.02) |
|                          | FairBalance       | r2: 0.96 (0.01) | r2: 0.95 (0.01) | r0: 0.05 (0.05) | r0: 0.05 (0.03) | r1: 0.23 (0.02) |
|                          | FairBalanceVariant|         |               |      |      |                |
performance than None in terms of both accuracy and F1 score on the minority class. This suggests that besides the effect of class balancing, FairBalance does slightly damage the prediction performance by about 1%.

Answer to RQ4: Overall, FairBalance will slightly damage the prediction performance by about 1%. It will also increase the F1 score on the minority class and reduce the accuracy given its class balancing property.

RQ5. What is the computational overhead of FairBalance?

From Table 4, the computational overhead of FairBalance is linear to the size of the training data. This validates the analysis in Section 3.2 that the computational complexity of FairBalance is $O(n)$. Compared to FERMI, an in-processing algorithm, the computational overhead of FairBalance is significantly lower.

Answer to RQ5: The computational overhead of FairBalance is linear to the size of the training data. It is significantly lower than the computational overhead of FERMI.

6 Discussion

This work has the following potentially positive impact in the society: our work could improve equalized odds fairness of machine learning software on datasets with multiple sensitive attributes. In addition, the proposed preprocessing algorithm has little potential drawback given its low computational overhead, little if any damage to the prediction performance, and compatibility with most machine learning models. However, scopes and limitations of this work must be considered before applying it to real problems. The results and conclusions of this work are limited to:

- Datasets with unbiased class labels.
- Known sensitive attributes.

One thing especially worth mentioning is that this work targets equalized odds and relies on the mathematical metrics for quantifying fairness (EOD, AOD). Therefore, there is no evidence showing that FairBalance can mitigate bias or discrimination which cannot be detected by these metrics (e.g. biases inherited from the training data labels).

6.1 Threats to validity

Sampling Bias - We have used four real-world and three synthetic datasets in this work. Also, logistic regression model is used as the base classifier for the preprocessing treatments. Conclusions may change a bit if other datasets and classification models are used.

Evaluation Bias - We used only two fairness metrics EOD and AOD to evaluate equalized odds in this work. However, equalized odds is not the only fairness criteria. In future, we will explore more evaluation criteria.

Conclusion Validity - One assumption of evaluating our experiments is that the test data is unbiased. Prior fairness studies also made similar assumption [13], [47]. This assumption is true for the four real-world datasets we used since their class labels were derived from truth. On other datasets with human decisions as class labels, this assumption may fail and we will need other ways to make sure the test data is unbiased.

External Validity - This work focuses on classification problems which are very common in AI software. We are currently working on extending it to regression models. The scope of this work also limits it generalizability to problems with unknown sensitive attributes and potentially biased class labels.

7 Conclusion

This paper proposes FairBalance, a pre-processing technique with low computational overhead for achieving equalized odds fairness on multiple sensitive attributes. Our results show that, within the scope of this paper, FairBalance can significantly improve equalized odds while maintaining the prediction performance. Also, it consistently outperforms other state-of-the-art machine learning fairness algorithms in terms of equalized odds on datasets with multiple sensitive attributes. Note that the scope of this paper also limits the usage of FairBalance—it cannot reduce the bias inherited from biased training labels. Our results also validated the Hypothesis that achieving class balance in each demographic group reduces AOD. On the other hand, Hypothesis is rejected empirically that balancing the size the each demographic group does not help in achieving equalized odds.

To sum up, the best practice suggested in this paper is to apply FairBalance for preprocessing if equalized odds needs to be achieved.

Given the threats to validity discussed in Section 6, future work of this paper will focus on:

- How to detect and mitigate biased ground truth labels. Equalized odds and the fairness metrics utilized in this paper (EOD, AOD) are no longer reliable when ground truth labels can be biased. Other fairness 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 sensitive attributes are unknown or noisy. There are some existing work along this research [48]. However, it remains as a major challenge for machine learning fairness.

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