BiFair: Training Fair Models with Bilevel Optimization

Mustafa Safa Ozdayi  
The University of Texas at Dallas  
mustafa.ozdayi@utdallas.edu

Murat Kantarcioglu  
The University of Texas at Dallas  
muratk@utdallas.edu

Rishabh Iyer  
The University of Texas at Dallas  
rishabh.iyer@utdallas.edu

Abstract

Prior studies have shown that, training machine learning models via empirical loss minimization to maximize a utility metric (e.g., accuracy), might yield models that make discriminatory predictions. To alleviate this issue, we develop a new training algorithm, named BiFair, which jointly minimizes for a utility, and a fairness loss of interest. Crucially, we do so without directly modifying the training objective, e.g., by adding regularization terms. Rather, we learn a set of weights on the training dataset, such that, training on the weighted dataset ensures both good utility, and fairness. The dataset weights are learned in concurrence to the model training, which is done by solving a bilevel optimization problem using a held-out validation dataset. Overall, this approach yields models with better fairness-utility trade-offs. Particularly, we compare our algorithm with three other state-of-the-art fair training algorithms over three real-world datasets, and demonstrate that, BiFair consistently performs better, i.e., we reach to better values of a given fairness metric under same, or higher accuracy. Further, our algorithm is scalable. It is applicable both to simple models, such as logistic regression, as well as more complex models, such as deep neural networks, as evidenced by our experimental analysis.

1 Introduction

Researchers have illustrated that machine learning (ML) models might exhibit discriminatory behavior. For example, in [1], researchers found out many of the commercial face recognition systems tend have higher rates of error on darker skinned people. In another work [2], researchers have analyzed COMPAS, a software used by some of the U.S courts to assess defendants’ likelihood to reoffend, and unveiled that, the software overestimates the likelihood to reoffend for non-white defendants, and underestimates for white defendants. Finally, it was reported that the Amazon had to abandon the use of its ML based recruitment tool, after it was revealed that the tool was disproportionately penalizing the women candidates [3].

The cause of these issues lie in the data on which the models are trained, as well as how the models are trained. Typically, we train models via empirical loss minimization to maximize their utility. For example, for supervised classification tasks, neural networks and logistic regression models are trained by minimizing the cross-entropy loss to maximize the accuracy of the models. This results in models picking up the biases that exist in the data if learning these biases help the model to minimize their loss.

Preprint. Under review.
Figure 1: Learning curves for BiFair, regularized training, and our baseline setting as measured over a biased synthetic dataset for binary classification task via logistic regression. Baseline setting tries to maximize its accuracy by trying to minimize the cross-entropy loss (utility loss). This yields biased models as evidenced by the increasing fairness loss. Regularized training modifies the training objective by adding a fairness loss as a regularization term. Due to this, it jointly minimizes for both utility, and fairness. Similarly, BiFair also minimizes for utility and fairness, however, we do so without directly modifying the training objective. Rather, we assign and learn a set of weights on the training data, such that, training on the weighted data yields models with both good utility, and fairness performance. Learning the weights is done concurrently during the training by solving a bilevel optimization problem with a held-out validation dataset (see Equation 1). Since we do not modify the training objective, our approach provides a higher utility than regularized training. For the setting presented in the figure, averaged over three runs, baseline yields a mean accuracy of 73.1%, and a mean AOD of 41.3% (fairness metric, the lower the better), and BiFair yields a mean accuracy of 69.6%, and a mean AOD of 2.4%. These figures are 69.0%, and 2.4% for the regularized training. The results become more pronounced, in favor of BiFair, as we move the real-world datasets (see Table 3).

In this work, we develop a new training algorithm, named BiFair, that yields models with strong fairness-utility trade-offs. In practice, our algorithm jointly minimizes for a utility, and a fairness loss of interest. Our main novelty, and improvement, stems from the fact that we do so without directly modifying the training objective, such as by adding regularization terms. Rather, we learn a set of weights on the training dataset, such that, training on the weighted dataset results in both good utility, and fairness performance. These weights are learned simultaneously during the training of the model by formulating, and solving, a bilevel optimization problem (see Figure 1 for an overview). This novel approach outperforms several other prominent fair training algorithms.

In particular, we compare our algorithm with three other state-of-the-art fair training algorithms sampled from the literature for supervised classification tasks, and show that, we consistently outperform them, i.e., our algorithm yields fairer models under same or higher values of accuracy. Furthermore, our algorithm is agnostic to the fairness definition. Given a fairness metric of interest, if one can define a differentiable surrogate fairness loss, the fairness loss can be plugged into our algorithm in black-box fashion. Consequently, we can accommodate for a wide range of fairness metrics. Finally, our algorithm is scalable. It is applicable both to simple models, such as logistic regression on tabular data, as well as more complex models, such as deep convolutional neural networks on image data, as evidenced by our experimental analysis.

The rest of the paper is structured as follows: in Section 2, we provide the necessary background to the reader, and discuss some related work. In Section 3, we explicitly formulate the problem we solve, and present our algorithm. In Section 4, we show the empirical performance of our algorithm via experiments. Finally, in Section 5, we discuss some limitations of our work, present ideas for possible future works, and provide some concluding remarks.
2 Background and Related Work

2.1 Fairness in ML

Fairness is a multifaceted concept that has many definitions based on different contexts. Our main focus in this work is supervised classification, and in this domain, group-based fairness definitions, such as statistical parity, equalized odds and equality of opportunity \[4\], are the most prominent in the recent literature. In particular, AIF360 \[5\], a popular toolkit for fairness research, benchmarks its results by using group-based fairness metrics. So in this work, we use group-based fairness metrics in our experimental analysis to be in-line with the recent literature. However, our algorithm is compatible with any fairness metric for which a differentiable loss function can be defined. Consequently, our algorithm might accommodate other fairness notions such as individual fairness \[6\], or Rawls’ min-max fairness \[7\].

Algorithms that train fair models are typically grouped under three categories: pre-processing, in-processing, and post-processing. Pre-processing methods are applied to the data prior to the training. The goal is to transform the training data in a way such that, when a model is later trained on the transformed data, it exhibits good fairness performance \[8, 9, 10, 11\]. The in-processing methods are applied at the training time, for example by adding regularization terms or encoding hard constraints on the training objective \[12, 13, 14, 15, 16, 17\]. Finally, post-processing methods are applied to an already trained model. They try to limit the bias of the model by adjusting the model’s outputs directly, such as by negating its output on certain inputs \[18, 19, 20\]. Our work falls into the category of in-processing methods.

In the in-processing literature, one line of work enforces fairness by encoding linear constraints on the training objective \[17, 15, 16\]. It is not clear to us whether such approaches scale to the deep learning setting: the experimental analysis of the respective papers consider relatively simple models such as logistic regression, SVM, and decision trees on tabular datasets. Compared to these techniques, our algorithm is applicable both to these simple models, as well as more computationally involved deep learning models as evidenced by our experimental analysis.

Another line of work modifies the training objective directly by adding certain regularization terms \[12, 13\]. Our experimental analysis indicate that our approach yields better fairness-utility trade-off in practice compared to these works. Finally, some works \[14, 21\] use adversarial training to debias the models. However, it has been observed that debiasing models via adversarial training usually results in significant accuracy degradation \[22\]. The benchmark results of AIF360 \[5\] also confirm this observation. In contrast, we do not observe a significant drop in accuracy with our method. It seems that the accuracy provided by our algorithm is either on par with, or better than regularization based approaches (see Table 3).

2.2 Bilevel Optimization

A bilevel optimization is type a nested optimization, where optimality of an outer problem is subject to the optimality of an inner problem. A general formulation of the bilevel optimization is given below,

\[
\min_{x,y} f(x, y^*) \text{ subject to } y^* \in \arg\min_y g(x, y).
\]

Here, \( f : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R} \) is referred as the outer problem, and \( g : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R} \) is referred as the inner problem. It is important to note the dependence of the outer problem to the inner problem. Due to this, one cannot solve inner and outer problems simultaneously, but rather, inner problem has to be solved first before one can treat the outer problem.

Recent years have seen the successful application of bilevel optimization to various areas in ML, such as meta-learning with the works like MAML \[23, 24, 25\], or scalable high-dimensional hyperparameter optimization \[26, 27\]. From the recent works that use bilevel optimization, the most similar works to ours are of \[28, 29\]. In both of these works, bilevel optimization is used to learn a set of weights on the training dataset as in our work. In \[28\], the learned weights ensure good training under datasets with severe label imbalance, and/or noisy labels. In \[29\], weights are learned in a way to ensure good generalization of the trained model. Our work primarily differs from these works by the setting which we consider. We are concerned with training fair models, and consequently, we formulate our outer-level problem differently.

3
We consider the problem of binary supervised classification on a dataset where weighted dataset yields good utility, and low bias for the model. We learn the values for $\lambda$ on the weighted training dataset. To achieve this, we introduce a set of weights $w$ on the training dataset, such that training on the weighted dataset yields good utility, and low bias for the model. We learn the values for $\lambda$ on the weighted training dataset. L$_u$ is a loss function that we use to train the model. For example, if its label is $\hat{\mathbf{Y}} = 1$, and the model’s probability of classifying an input favorable, given it is privileged, $Pr[\hat{\mathbf{Y}} = 1 | p]$ is the sensitive feature (e.g., gender) of the $i$th sample. A sample is referred as favorable if its label is 1 (e.g., labeled as ”good credit” for a credit card application setting), and unfavorable otherwise (e.g., labeled as ”bad credit”). Similarly, the samples with a sensitive attribute of 1 are referred as privileged, and unprivileged otherwise. By definition, privileged samples have a higher association with the favorable label, e.g., it could be that 2/3 of privileged samples have the favorable label, where as this association could be 1/3 for unprivileged samples. The sensitive feature $s^{(i)}$ can either be part of the other features $X^{(i)}$, as often the case in tabular data, or it could be a meta-feature that is available to a human observer, but not fed into the model. For example, a human could tell the gender of a person by looking at an image, but the model is fed only the pixels of the image. Our goal is to learn a set of parameters that can predict labels of new samples with high accuracy, while exhibiting low bias with respect to a given fairness definition (see Table 1).

To achieve this, we introduce a set of weights $w$ on the training dataset, such that training on the weighted dataset yields good utility, and low bias for the model. We learn the values for $w$ concurrent to the model training on a held-out validation dataset by solving a bilevel optimization problem. Concretely, let $L_u$ be a loss function that we use to train the model. For example, $L_u$ could be the hinge loss if our model is a SVM, or it could be cross-entropy if it is a neural network. Further, let $L_f$ be a fairness loss that is associated with a fairness metric, such that, by minimizing $L_f$, we can reduce the bias of the model. Then, we can formulate our learning objective as follows,

$$
\begin{align*}
\mathbf{w^*, \theta^*} & \in \arg \min_{\mathbf{w, \theta}} L_u(M_{\theta^*}, D_{\text{val}}) + \lambda \cdot L_f(M_{\theta^*}, D_{\text{val}}), \\
& \text{subject to } \theta^* \in \arg \min_{\theta} L_u(M_{\theta}, D_{tr}, w) \text{ and } \|w\|_1 = 1,
\end{align*}
$$

where $L_u(M_{\theta}, D_{tr}, w) = \sum_i w^{(i)} \cdot L_u(M_{\theta}, D_{tr}^{(i)})$. Here, $D_{tr}$ and $D_{val}$ respectively denote the training, and validation dataset, and the superscript $(i)$ denotes the $i$th sample of the dataset. As is seen, in the inner optimization, we minimize $L_u$ on the weighted training dataset. In the outer optimization, the weights are adjusted to minimize a combination of utility loss, and fairness loss on the validation dataset where $\lambda$ is a scalar hyperparameter to control the trade-off between utility and fairness. Finally, the constraint $\|w\|_1 = 1$ is to stabilize the training, i.e., it prevents weights from becoming arbitrarily large, and cause gradients to explode.

Table 1: Various group-based fairness metrics that are used to quantify the bias of a model, and corresponding loss functions. Lower values for these metrics indicate lower bias/fairer models. Many group-based fairness definitions can simply be expressed as utility loss difference across groups, and yield differentiable loss functions as can be seen.

| Name                                      | Definition                                                                 | Fairness Loss |
|-------------------------------------------|----------------------------------------------------------------------------|---------------|
| Statistical Parity Difference (SPD)       | $|Pr[\hat{\mathbf{Y}} = 1 | p] - Pr[\hat{\mathbf{Y}} = 1 | up]|$                             | $|L_u^{up} - L_u^{up}|$ |
| Equality of Opportunity Difference (EOD)  | $\frac{TPR_p - TPR_u}{TPR_p + TPR_u}$                                      | $|L_u^{fav} - L_u^{unfav}|$ |
| Average Odds Difference (AOD)             | $0.5 \cdot (|TPR_p - FPR_p| + |TPR_u - FPR_u|)$                          | $|L_u^{fav} - L_u^{unfav}|$ |

| Name                                      | Definition                                                                 | Fairness Loss |
|-------------------------------------------|----------------------------------------------------------------------------|---------------|
| Statistical Parity Difference (SPD)       | $|Pr[\hat{\mathbf{Y}} = 1 | p] - Pr[\hat{\mathbf{Y}} = 1 | up]|$                             | $|L_u^{up} - L_u^{up}|$ |
| Equality of Opportunity Difference (EOD)  | $\frac{TPR_p - TPR_u}{TPR_p + TPR_u}$                                      | $|L_u^{fav} - L_u^{unfav}|$ |
| Average Odds Difference (AOD)             | $0.5 \cdot (|TPR_p - FPR_p| + |TPR_u - FPR_u|)$                          | $|L_u^{fav} - L_u^{unfav}|$ |

FPR, and TPR denote the false positive rate, and true positive rate. The superscripts $p$, and $up$ denote the privileged, and unprivileged groups. Similarly, the superscripts $fav$ and $unfav$ denote the favorable, and the unfavorable label. In contrast to EOD and AOD, SPD does not take ground-truth labels of data into account: it is the difference between model’s probability of classifying an input favorable, given it is privileged, $Pr[\hat{\mathbf{Y}} = 1 | p]$, and the model’s probability of classifying an input favorable, given it is unprivileged, $Pr[\hat{\mathbf{Y}} = 1 | up]$. Therefore, we have to compute the utility loss by setting the target as 1 for SPD, $L_u^{1}$, regardless of the actual label of the input.

3 Problem Formulation and BiFair Algorithm

3.1 Setting and Formulation

We consider the problem of binary supervised classification on a dataset $\{X, y, s\}_{i=1}^n$ with a model $M_{\theta}$ parameterized by $\theta \in \mathbb{R}^d$. Here, $X^{(i)} \in \mathbb{R}^m$ is the set of features, $y^{(i)} \in \{0, 1\}$ is the label, and $s^{(i)} \in \{0, 1\}$ is the sensitive feature (e.g., gender) of the $i$th sample. A sample is referred as favorable if its label is 1 (e.g., labeled as "good credit" for a credit card application setting), and unfavorable otherwise (e.g., labeled as "bad credit"). Similarly, the samples with a sensitive attribute of 1 are referred as privileged, and unprivileged otherwise. By definition, privileged samples have a higher association with the favorable label, e.g., it could be that 2/3 of privileged samples have the favorable label, where as this association could be 1/3 for unprivileged samples. The sensitive feature $s^{(i)}$ can either be part of the other features $X^{(i)}$, as often the case in tabular data, or it could be a meta-feature that is available to a human observer, but not fed into the model. For example, a human could tell the gender of a person by looking at an image, but the model is fed only the pixels of the image. Our goal is to learn a set of parameters that can predict labels of new samples with high accuracy, while exhibiting low bias with respect to a given fairness definition (see Table 1).

To achieve this, we introduce a set of weights $w$ on the training dataset, such that training on the weighted dataset yields good utility, and low bias for the model. We learn the values for $w$ concurrent to the model training on a held-out validation dataset by solving a bilevel optimization problem. Concretely, let $L_u$ be a loss function that we use to train the model. For example, $L_u$ could be the hinge loss if our model is a SVM, or it could be cross-entropy if it is a neural network. Further, let $L_f$ be a fairness loss that is associated with a fairness metric, such that, by minimizing $L_f$, we can reduce the bias of the model. Then, we can formulate our learning objective as follows,
3.2 BiFair Algorithm

Many models of practical interest yield no closed-form solution to the inner problem, but rather, are optimized by iterative methods, e.g., by gradient descent. So, finding an optimal solution to the inner problem formulated in Equation 1 is usually a costly process. One workaround of this, is to relax the inner problem by finding an approximate solution to it as presented in [30]. Briefly, we can approximate the solution to the inner problem by taking a few steps of gradient descent, and then compute the gradient for the outer problem at the approximated solution. We can then update the training data weights using the gradient of the outer problem, and repeat this until the outer level problem converges. This gives us an algorithm that is straightforward to implement with frameworks that provide automatic differentiation such as PyTorch [31] and TensorFlow [32]. The pseudo-code of our algorithm is presented in Algorithm 1. Briefly, the lines 3-9 correspond to approximating the inner problem formulated in Equation 1. Then, we compute the gradient for the outer problem at the approximated solution. We can then update the weights of the training datasets to minimize the sum of utility loss, and fairness loss, of the model. This metric is in-line with the equalized-odds definition of fairness [20]. It further encompasses the equality of odds (EOD), and unlike statistical parity difference (SPD), it takes ground-truth labels of data points into account. For example, even a perfect classifier that correctly classifies every data point might have a high SPD bias, and thus, purposefully mis-classifying data points could be the only way to reduce the SPD. However, a perfect classifier would yield zero AOD.

**Algorithm 1:** BiFair with automatic differentiation for supervised classification. For each outer iteration, we find an approximate solution to the inner problem (lines 3-9). Then, we compute the sum of utility loss, and fairness loss, $L_{\text{total}}$, on a held-out validation dataset (lines 12-14). Finally, we update the weights of the training datasets to minimize $L_{\text{total}}$ (lines 15-16). Note that, computing $\nabla_w L_{\text{total}}$ requires us to maintain the computation graph of the inner-loop. This computation graph is only freed at line 15, after we compute $\nabla_w L_{\text{total}}$.

4 Experiments

In this section, we evaluate the performance of our algorithm via experiments. First, we illustrate some properties of our algorithm on a synthetic dataset, and then, we compare our algorithm with some other fair training algorithms over real-world datasets.

For all experiments, we use the average odds difference (AOD, see Table 1) to quantify the bias of the model. This metric is in-line with the equalized-odds definition of fairness [20]. It further encompasses the equality of odds (EOD), and unlike statistical parity difference (SPD), it takes ground-truth labels of data points into account. For example, even a perfect classifier that correctly classifies every data point might have a high SPD bias, and thus, purposefully mis-classifying data points could be the only way to reduce the SPD. However, a perfect classifier would yield zero AOD.
To measure utility, we use the balanced accuracy as in [5]. This is because most real-world datasets used in fairness research have label-imbalance, and this makes accuracy a poor metric of choice. Balanced accuracy (BAcc) is equal to the accuracy when there is no label-imbalance, and is defined as follows,

\[
\text{BAcc} = \frac{\text{TNR} + \text{TPR}}{2},
\]

where TNR and TPR stand for true negative rate, and true positive rate, respectively. We implemented all the related code using PyTorch [31] with Higher library [33].

4.1 Synthetic Dataset Experiments

We create a synthetic biased dataset with two features as follows: for points with favorable label \((y = 1)\), we draw the first feature as \(x_1 \sim \mathcal{N}(1, 1)\), and for points with unfavorable label \((y = 0)\), we draw it as \(x_1 \sim \mathcal{N}(0, 1)\). We then designate the second feature \(x_2\) as the sensitive feature, and introduce bias by ensuring 2/3 of favorable labels have \(x_2 = 1\), and ensuring 2/3 of unfavorable labels have \(x_2 = 0\) in the dataset. So, \(x_2 = 1\) has a higher association with the favorable label, and \(x_2 = 0\) has a higher association with the unfavorable label in the dataset. We create a training dataset of size 6000, and a validation and a test dataset of size 2000, where in each partition, we have the same number favorable and unfavorable labels.

In our first experiment, we train a logistic regression model on this dataset by (i) cross-entropy minimization, and by (ii) BiFair. We illustrate the resulting models’ prediction on the test dataset in Figure 2. As is seen, in case (i), the resulting model assigns a high weight to \(x_2\), even higher than the weight of \(x_1\). Consequently, it exhibits high bias. For case (ii), the weight on \(x_2\) is much smaller than of \(x_1\), and this reduces the bias: averaged over three runs, (i) yields a mean accuracy of 73.1%, and a mean AOD of 41.3%, and BiFair yields a mean accuracy of 69.6%, and a mean AOD of 2.4%.

![Figure 2](https://example.com/image.png)

(a) Predictions of \(\sigma(0.99 \cdot x_1 + 1.31 \cdot x_2 - 1.57)\), the model trained with only cross-entropy minimization.

(b) Predictions of \(\sigma(0.65 \cdot x_1 + 0.04 \cdot x_2 - 0.21)\), the model trained with BiFair.

Our code is available at [https://github.com/TinfoilHat0/BiFair](https://github.com/TinfoilHat0/BiFair).
We now compare our algorithm with straightforward regularization based approach, as well as with\textsuperscript{3} \textit{T} with respect to the number of inner iterations taken per outer iteration (\(T_{in}\)). The results are presented in Table 2. As can be seen, even with a single iteration, the bias of the model is significantly reduced. Increasing the value of \(T_{in}\) gives different trade-offs between accuracy and bias until \(T_{in} = 16\), after that point the performance degrades for both metrics as the model begins to overfit on the training data.

| \(T_{in}\) | CE Loss | Fairness Loss | Total Loss | Val. BAcc(\%) | Val. AOD(\%) | Test BAcc(\%) | Test AOD(\%) |
|----------|---------|---------------|------------|---------------|--------------|----------------|--------------|
| Baseline | 0.528 ± 0 | 0.497 ± 0.004 | 1.025 ± 0.004 | 74.2 ± 0 | 41.1 ± 0.1 | 73.1 ± 0 | 41.3 ± 0.1 |
| 1        | 0.022 ± 0.037 | 0.016 ± 0.017 | 0.638 ± 0.032 | 70.9 ± 0.2 | 2.6 ± 0.1 | 70.0 ± 0.3 | 5.8 ± 2.4 |
| 2        | 0.01 ± 0.22 | 0.006 ± 0.004 | 0.616 ± 0.023 | 70.8 ± 0 | 0.5 ± 0.3 | 69.5 ± 0.1 | 3.3 ± 1.1 |
| 4        | 0.589 ± 0.006 | 0.005 ± 0.003 | 0.594 ± 0.003 | 70.8 ± 0.1 | 0.6 ± 0.2 | 69.6 ± 0.1 | 2.7 ± 0.7 |
| 8        | 0.58 ± 0.002 | 0.005 ± 0.001 | 0.585 ± 0 | 70.8 ± 0 | 0.5 ± 0.2 | 69.4 ± 0.1 | 2.9 ± 0.7 |
| 16       | 0.578 ± 0.002 | 0.004 ± 0 | 0.582 ± 0.002 | 70.7 ± 0.1 | 0.5 ± 0.1 | 69.6 ± 0.2 | 2.4 ± 0.3 |
| 32       | 0.579 ± 0.004 | 0.007 ± 0.002 | 0.586 ± 0.005 | 70.8 ± 0 | 0.8 ± 0.4 | 69.2 ± 0.3 | 3.6 ± 1.1 |
| 64       | 0.578 ± 0.005 | 0.021 ± 0.01 | 0.599 ± 0.013 | 70.7 ± 0.1 | 1.6 ± 0.8 | 69.0 ± 0.1 | 2.8 ± 1.5 |
| 128      | 0.005 ± 0.028 | 0.022 ± 0.001 | 0.627 ± 0.033 | 70.8 ± 0.1 | 1.2 ± 0.7 | 69.1 ± 0.6 | 3.0 ± 1.3 |

CE stands for cross-entropy. Results are averaged over three runs, and reported as mean ± std. All losses are measured over the validation data. Excluding the baseline setting, best results are highlighted in bold. Even for the case \(T_{in} = 1\), we improve the fairness of model a lot with a small drop in accuracy. This is also the setting which gives best BAcc value. For AOD, we reach the best value at \(T_{in} = 16\), and performance deteriorates afterwards due to overfitting on the training data. These results suggest that BiFair can work well even for small values of \(T_{in}\), and may improve fairness significantly with relatively modest drops in the accuracy.

In our second experiment, we illustrate how the performance of the model trained by BiFair changes with respect to the number of inner iterations taken per outer iteration (\(T_{in}\) of Algorithm \[1\]). The results are presented in Table 2. As can be seen, even with a single iteration, the bias of the model is significantly reduced. Increasing the value of \(T_{in}\) gives different trade-offs between accuracy and bias until \(T_{in} = 16\), after that point the performance degrades for both metrics as the model begins to overfit on the training data.

### 4.2 Real-world Dataset Experiments

We now compare our algorithm with straightforward regularization based approach, as well as with three other fair training algorithms sampled from the AIF360 toolkit \[5\]. In particular, we have chosen one fair training algorithm for each one of the pre-processing, in-processing, and post-processing categories. When deciding on which particular algorithm to choose, we have taken benchmarks presented in \[5\] into account, and have chosen one of the best performing algorithm in its respective category. When the results between two algorithms were too close to call for a clear winner, we have chosen the algorithm that we deem as simpler to implement. We briefly describe each algorithm we compare against below.

**Regularization** simply corresponds to adding the fairness loss \(L_f\) as a regularization term to the utility loss \(L_u\) in the training objective, i.e., the training objective is to minimize \(L_u + \lambda \cdot L_f\).

**Kamiran Reweighing** \[8\] is a pre-processing technique that aims to ensure statistical independence between the label and the sensitive attribute by assigning weights to data points. Particularly, the technique first computes the expected probability, \(p_{exp}\), for each combination of sensitive attribute and label under the assumption that the sensitive attribute and the label are independent. Then, they measure the observed probability, \(p_{obs}\), for each combination of sensitive attribute and label in the training dataset. Finally, each data point is assigned the weight \(p_{exp}/p_{obs}\) based on the value of their sensitive attribute and their label.

**Prejudice Remover** \[12\] is an in-processing technique that tries to ensure statistical independence between the model’s prediction, and the sensitive attribute. To do so, the empirical mutual information between the model’s prediction and the sensitive attribute is added as a regularization term in the training objective.

**Reject Option Classifier (ROC)** \[18\] is a post-processing technique that aims to reduce bias by modifying the models’ predictions around a symmetric confidence interval of a given decision threshold. For example, let the decision threshold be 0.5, and the confidence interval be 0.1. Then, for a particular point, if the probability of belonging to the favorable label assigned by the model lies in \([0.4, 0.6]\), the prediction for this point is determined based on whether it is privileged, or unprivileged: if it is privileged, it is is predicted as unfavorable, otherwise, as favorable.
As for our datasets, we both use tabular and image data. For tabular setting, we do logistic regression over Adult income prediction \cite{34}, and Compas recidivism datasets \cite{2}. In the Adult dataset, the goal is to predict whether a person’s income is greater than of $50k USD a year, the sensitive feature is gender, and men are privileged. For Compas, the goal is to predict whether a criminal will reoffend, race is the sensitive attribute, and white is the privileged group. For image data, we train a ResNet-18 \cite{35} over a subset of CelebA \cite{36}, a dataset of celebrity faces, for smile detection task where “smiling” is the favorable outcome. Particularly, we randomly sample 40k images from CelebA, designate gender as the sensitive attribute, and to create bias, we ensure a higher association between women and the smiling label, which makes women the privileged group. For each dataset, we ensure a train/validation/test split of 60%/20%/20%. We provide more details on the datasets we use, such as the applied pre-processing techniques and data augmentation methods in the Appendix.

In our experiments, we train every model using Adam optimizer \cite{37}. We also use Adam to update the training dataset weights in case of BiFair. Each model is trained until the validation loss stagnates for 10 epochs, and the decision threshold is adjusted on the validation dataset to maximize BAcc as in \cite{5}.

The general setting of our experiments are as follows: we run each algorithm over a set of hyperparameters using grid-search, and for each algorithm other than BiFair, we report the configuration that minimizes the AOD on the test dataset. For BiFair, we report a configuration in which its AOD is lower than any other fair training algorithm, and its BAcc is either equal or higher, than the fair algorithm with the highest BAcc. The fact that we can find such a configuration for BiFair indicates that it is strictly better than every other fair training algorithm that we compare against. As the results shows, for Compas and CelebA datasets, BiFair improves both BAcc, and AOD, compared to every other fair training algorithm. For Adult dataset, we reduce the bias more than others by maintaining the same accuracy on the average. We provide more details related to our hyperparameter search process, and report the particular configurations in which we obtained the presented results in the Appendix.

Table 3: Comparison of BiFair with other fair training algorithms over various settings.

| Algorithm                | BAcc(%) | AOD(%) | Algorithm                | BAcc(%) | AOD(%) |
|--------------------------|---------|--------|--------------------------|---------|--------|
| Baseline                 | 62.2 ± 0.5 | 21.5 ± 1.3 | Baseline                 | 81.8 ± 0.1 | 16.8 ± 0.3 |
| Regularization           | 59.6 ± 1.2 | 3.2 ± 0.8  | Regularization           | 79.8 ± 0.2 | 6.8 ± 0.2  |
| Kamiran Reweighing \cite{8} | 61.3 ± 0.4 | 1.5 ± 0.1  | Kamiran Reweighing \cite{8} | 80.5 ± 0.0 | 6.9 ± 0.4  |
| Prejudice Remover \cite{12} | 61.0 ± 0.5 | 2.1 ± 1.1  | Prejudice Remover \cite{12} | 80.7 ± 0.1 | 6.7 ± 0.1  |
| ROC Post-processing \cite{18} | 50.7 ± 0.5 | 1.6 ± 0.8  | ROC Post-processing \cite{18} | 80.7 ± 0.6 | 7.0 ± 0.3  |
| BiFair                   | 62.0 ± 0.4 | 0.9 ± 0.3  | BiFair                   | 80.7 ± 0.1 | 6.3 ± 0.2  |

(c) Results on CelebA dataset with ResNet-18

| Algorithm                | BAcc(%) | AOD(%) |
|--------------------------|---------|--------|
| Baseline                 | 92.8 ± 0.1 | 10.3 ± 0.1 |
| Regularization           | 91.3 ± 0.4 | 3.1 ± 0.2  |
| Kamiran Reweighing \cite{8} | 91.5 ± 0.3 | 3.3 ± 0.4  |
| Prejudice Remover \cite{12} | 91.3 ± 0.1 | 3.0 ± 0.3  |
| ROC Post-processing \cite{18} | 91.4 ± 0.5 | 2.9 ± 0.1  |
| BiFair                   | 91.9 ± 0.2 | 2.5 ± 0.1  |

Results are averaged over three runs, and reported as mean ± std. Baseline corresponds to training with only cross-entropy minimization.

5 Discussion and Conclusion

We briefly discuss a few aspects of our work before concluding the paper. First, as noted before, we have to maintain the computation graph of the inner optimization (lines 3-9 in Algorithm \cite{1}) until gradient of the outer optimization is computed (line 16 in Algorithm \cite{1}). Consequently, the memory usage of our algorithm scales linearly with $T_{in}$. Although we have observed that we get
good performance, even with small values of $T_{in}$ in our experimental evaluation, the high memory requirements could pose a problem for larger models (e.g., ResNet-101 [35]). One straightforward way to reduce the memory usage is due to the truncated backpropagation method presented in [38]. With truncated backpropagation, we maintain the computation graph only for the last few iterations regardless of the value of $T_{in}$. Consequently, this makes memory requirements independent of $T_{in}$. For example, we can take 100 inner iterations, yet maintain the computation graph only for the last 5 steps. This is likely to give a better performance than only taking 5 inner iterations (see experimental analysis of [38]). With respect to computation cost, we see that our algorithm does a forward-backward pass for each inner iteration (line 5 and 7), and then another forward-backward pass at the outer level (line 11 and 15), per iteration. Consequently, this induces a computation overhead factor of $T_{in} + 1$ over the baseline setting, which does a single forward-backward pass per iteration. Approaches such as implicit gradients [25] might be used to reduce the extra computation cost.

In summary, we introduced a new training algorithm that can jointly minimize for a utility, and a fairness loss. This is done by learning a set of weights on the training dataset, such that, training on the weighted dataset minimizes for both losses. Our experimental analysis indicate this gives us better performance than simple regularization based approach, as well as some other state-of-the-art fair training algorithms. Further, our algorithm is compatible with a wide range of fairness metrics, where one can plug an associated differentiable fairness loss to our algorithm in black-box fashion. Finally, we would like to note that, although we focused on supervised classification in this work, one can trivially extend our main formulation given in Equation 1 for other tasks, such as regression, as long as one can define a differentiable utility and fairness loss, for the task and for the fairness metric of interest.

References

[1] Joy Buolamwini and Timnit Gebru. “Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification”. In: Proceedings of the 1st Conference on Fairness, Accountability and Transparency. Ed. by Sorelle A. Friedler and Christo Wilson. Vol. 81. Proceedings of Machine Learning Research. New York, NY, USA: PMLR, 23–24 Feb 2018, pp. 77–91. URL: http://proceedings.mlr.press/v81/buolamwini18a.html.

[2] Lauren Kirchner Jeff Larson Surya Mattu and Julia Angwin. How We Analyzed the COMPAS Recidivism Algorithm. Online; accessed May 14, 2021. URL: https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm.

[3] Jeffrey Dastin. Amazon scraps secret AI recruiting tool that showed bias against women. Online; accessed May 21, 2021.

[4] Moritz Hardt et al. “Equality of Opportunity in Supervised Learning”. In: Advances in Neural Information Processing Systems. Ed. by D. Lee et al. Vol. 29. Curran Associates, Inc., 2016. URL: https://proceedings.neurips.cc/paper/2016/file/9d2682367c935defcb1f9e247a9740d-Paper.pdf.

[5] Rachel K. E. Bellamy et al. AI Fairness 360: An Extensible Toolkit for Detecting, Understanding, and Mitigating Unwanted Algorithmic Bias. Oct. 2018. URL: https://arxiv.org/abs/1810.01943.

[6] Cynthia Dwork et al. “Fairness through Awareness”. In: Proceedings of the 3rd Innovations in Theoretical Computer Science Conference. ITCS ’12. Cambridge, Massachusetts: Association for Computing Machinery, 2012, pp. 214–226. ISBN: 9781450311151. DOI: 10.1145/2090236.2090255. URL: https://doi.org/10.1145/2090236.2090255.

[7] John Rawls. Justice as fairness: A restatement. Harvard University Press, 2001.

[8] Faisal Kamiran and Toon Calders. “Data preprocessing techniques for classification without discrimination”. In: Knowledge and Information Systems 33.1 (2012), pp. 1–33.

[9] Michael Feldman et al. “Certifying and Removing Disparate Impact”. In: Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. KDD ’15. Sydney, NSW, Australia: Association for Computing Machinery, 2015, pp. 259–268. ISBN: 9781450336642. DOI: 10.1145/2783258.2783311.URL: https://doi.org/10.1145/2783258.2783311.

[10] Rich Zemel et al. “Learning fair representations”. In: International conference on machine learning. PMLR. 2013, pp. 325–333.
[11] Flavio P Calmon et al. “Optimized pre-processing for discrimination prevention”. In: Proceedings of the 31st International Conference on Neural Information Processing Systems. 2017, pp. 3995–4004.

[12] Toshihiro Kamishima et al. “Fairness-aware classifier with prejudice remover regularizer”. In: Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Springer. 2012, pp. 35–50.

[13] Yahav Bechavod and Katrina Ligett. “Learning fair classifiers: A regularization-inspired approach”. In: arXiv preprint arXiv:1707.00044 (2017), pp. 1733–1782.

[14] Brian Hu Zhang, Blake Lemoine, and Margaret Mitchell. “Mitigating unwanted biases with adversarial learning”. In: Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society. 2018, pp. 335–340.

[15] Alekh Agarwal et al. “A Reductions Approach to Fair Classification”. In: Proceedings of the 35th International Conference on Machine Learning. Ed. by Jennifer Dy and Andreas Krause. Vol. 80. Proceedings of Machine Learning Research. PMLR, Oct. 2018, pp. 60–69. URL: http://proceedings.mlr.press/v80/agarwal18a.html

[16] L Elisa Celis et al. “Classification with fairness constraints: A meta-algorithm with provable guarantees”. In: Proceedings of the conference on fairness, accountability, and transparency. 2019, pp. 319–328.

[17] Michele Donini et al. “Empirical risk minimization under fairness constraints”. In: arXiv preprint arXiv:1802.08626 (2018).

[18] Faisal Kamiran, Asim Karim, and Xiangliang Zhang. “Decision theory for discrimination-aware classification”. In: 2012 IEEE 12th International Conference on Data Mining. IEEE. 2012, pp. 924–929.

[19] Geoff Pleiss et al. “On fairness and calibration”. In: arXiv preprint arXiv:1709.02012 (2017).

[20] Moritz Hardt, Eric Price, and Nathan Srebro. “Equality of Opportunity in Supervised Learning”. In: Proceedings of the 30th International Conference on Neural Information Processing Systems. NIPS’16. Barcelona, Spain: Curran Associates Inc., 2016, pp. 3323–3331. ISBN: 9781510838819.

[21] Preethi Lahoti et al. “Fairness without demographics through adversarially reweighted learning”. In: arXiv preprint arXiv:2006.13114 (2020).

[22] Yan Zhou, Murat Kantarcioglu, and Chris Clifton. “Improving Fairness of AI Systems with Lossless De-biasing”. In: arXiv preprint arXiv:2105.04534 (2021).

[23] Chelsea Finn, Pieter Abbeel, and Sergey Levine. “Model-agnostic meta-learning for fast adaptation of deep networks”. In: International Conference on Machine Learning. PMLR. 2017, pp. 1126–1135.

[24] Alex Nichol, Joshua Achiam, and John Schulman. “On first-order meta-learning algorithms”. In: arXiv preprint arXiv:1803.02999 (2018).

[25] Aravind Rajeswaran et al. “Meta-learning with implicit gradients”. In: arXiv preprint arXiv:1909.04630 (2019).

[26] Jonathan Lorraine, Paul Vicol, and David Duvenaud. “Optimizing millions of hyperparameters by implicit differentiation”. In: International Conference on Artificial Intelligence and Statistics. PMLR. 2020, pp. 1540–1552.

[27] Luca Franceschi et al. “Bilevel programming for hyperparameter optimization and meta-learning”. In: International Conference on Machine Learning. PMLR. 2018, pp. 1568–1577.

[28] Mengye Ren et al. “Learning to reweight examples for robust deep learning”. In: International Conference on Machine Learning. PMLR. 2018, pp. 4334–4343.

[29] Simon Jenni and Paolo Favaro. “Deep bilevel learning”. In: Proceedings of the European conference on computer vision (ECCV). 2018, pp. 618–633.

[30] Justin Domke. “Generic Methods for Optimization-Based Modeling”. In: Proceedings of the Fifteenth International Conference on Artificial Intelligence and Statistics. Ed. by Neil D. Lawrence and Mark Girolami. Vol. 22. Proceedings of Machine Learning Research. La Palma, Canary Islands: PMLR. 21–23 Apr 2012, pp. 318–326. URL: http://proceedings.mlr.press/v22/domke12.html
Appendices

A Datasets

For Adult [34], and Compas datasets [2], we used the interface provided by the AIF360 toolkit [5] to access the pre-processed versions. More details can be at [https://aif360.readthedocs.io/en/latest/modules/datasets.html#module-aif360.datasets](https://aif360.readthedocs.io/en/latest/modules/datasets.html#module-aif360.datasets). For Adult, we designated gender as the sensitive attribute, and for Compas, we designated race as the sensitive attribute.

For CelebA, we do smile classification where “smiling” is considered to be the favorable label, and gender is designated as the sensitive attribute. We sample a subset of size 40k from the whole dataset, and set the women as privileged by ensuring the following statistics on the dataset: 22% of the dataset is women, and has the favorable label, 11% of the dataset is women and has the unfavorable label, 11% of the dataset is men, and has the favorable label, 56% of the dataset is men, and has the unfavorable label. As for data augmentation, we downscale each image to 80x80, and take random crops of size 64x64, and also apply horizontal flipping on the training dataset.

B Hyperparameters

We did grid-search over the following set of hyperparameters. For every other parameter related to the optimizer, such as learning rate, and momentum, we use the default values that come with PyTorch 1.8.1 for the Adam optimizer.

- Batch size (bs): \{128, 256, 512\}
- Weight Decay Multiplier (wd): \{0, 1e-4, 1e-3\}
- $\eta$ to scale the mutual information term in Prejudice Remover (see Equation 7 of [12]): \{0.5, 1, 2, 4\}
- $\lambda$ to scale $L_f$ in regularization and BiFair: \{0.5, 1, 2, 4\}
- $T_{in}$ for BiFair (see Algorithm [1]): \{1, 5, 10, 25, 50\}
- $|w|$ length of the weight vector on training dataset for BiFair: \{4, 8, 16, $|D_{tr}|$\}

We increased weight decay multiplier by multiples of 10, until it became too high so that learning becomes infeasible on some datasets. It was cut at 1e-3. Similarly, we increased $\eta$ by multiples of 11.
two, until it did not increase either the accuracy, nor the fairness metric, and it was cut at 4. We set the \( \lambda \) to the same set as \( \eta \) for convenience. Finally, for some settings, we have observed having one weight per training instance does not perform good in practice for BiFair. Therefore, we opted to cluster the data points based on their sensitive attribute, label, and the probability assigned by the model during training. For example, when we have \( |w| = 4 \), we cluster points into combinations of sensitive attribute and label, and assign one weight per cluster. For \( |w| = 8 \), we first cluster points based on the probabilities assigned by the model: higher than 0.5, and lower than 0.5. We then cluster each group further into the combinations of sensitive attribute and label. In general, with \( |w| = 2^K \), we first partition the probability interval \([0, 1]\) to \(2^{K-2}\) portions of equal length. Then for each portion, we further group the points for each combination of the sensitive attribute, and the label. Finally, when \( |w| = D_{tr} \), we have one weight per training data point. We repeat the results reported in Table 3 with their hyperparameter configurations below.

Table 4: Comparison of BiFair with other fair training algorithms over various settings with hyperparameters.

(a) Results on Compas dataset with logistic regression

| Algorithm                  | BAcc(%)     | AOD(%)    | Hyperparameters     |
|----------------------------|-------------|-----------|---------------------|
| Baseline                   | 62.2 ± 0.5  | 21.5 ± 1.3 | \(bs=128, wd=0\)   |
| Regularization             | 59.6 ± 1.2  | 3.2 ± 0.8  | \(bs=256, wd=1e-3, \lambda = 4\) |
| Kamiran Reweighing [8]     | 61.3 ± 0.4  | 1.5 ± 0.1  | \(bs=256, wd=0\)   |
| Prejudice Remover [12]     | 61.0 ± 0.5  | 2.1 ± 1.1  | \(bs=512, wd=1e-3, \eta = 4\) |
| ROC Post-processing [18]   | 59.7 ± 0.5  | 1.6 ± 0.8  | \(bs=512, wd=0\)   |
| BiFair                     | **62.0 ± 0.4** | **0.9 ± 0.3** | \(bs=256, wd=1e-3, \lambda = 1, T_{in} = 50, |w| = 16\) |

(b) Results on Adult dataset with logistic regression

| Algorithm                  | BAcc(%)     | AOD(%)    | Hyperparameters     |
|----------------------------|-------------|-----------|---------------------|
| Baseline                   | 81.8 ± 0.1  | 16.8 ± 0.3 | \(bs=256, wd=0\)   |
| Regularization             | 79.8 ± 0.2  | 6.8 ± 0.2  | \(bs=512, wd=1e-4, \lambda = 4\) |
| Kamiran Reweighing [8]     | 80.5 ± 0    | 6.9 ± 0.4  | \(bs=256, wd=1e-4\) |
| Prejudice Remover [12]     | 80.7 ± 0.1  | 6.7 ± 0.1  | \(bs=512, wd=1e-4, \eta = 2\) |
| ROC Post-processing [18]   | 80.7 ± 0.6  | 7.0 ± 0.3  | \(bs=256, wd=1e-4\) |
| BiFair                     | **80.7 ± 0.1** | **6.3 ± 0.2** | \(bs=256, wd=0, \lambda = 1, T_{in} = 25, |w| = |D_{tr}|\) |

(c) Results on CelebA dataset with ResNet-18

| Algorithm                  | BAcc(%)     | AOD(%)    | Hyperparameters     |
|----------------------------|-------------|-----------|---------------------|
| Baseline                   | 92.8 ± 0.1  | 10.3 ± 0.1 | \(bs=128, wd=0\)   |
| Regularization             | 91.3 ± 0.4  | 3.1 ± 0.2  | \(bs=256, wd=0, \lambda = 2\) |
| Kamiran Reweighing [8]     | 91.5 ± 0.3  | 3.3 ± 0.4  | \(bs=256, wd=1e-4\) |
| Prejudice Remover [12]     | 91.3 ± 0.1  | 3.0 ± 0.3  | \(bs=256, wd=1e-4, \eta = 2\) |
| ROC Post-processing [18]   | 91.4 ± 0.5  | 2.9 ± 0.1  | \(bs=128, wd=1e-3\) |
| BiFair                     | **91.9 ± 0.2** | **2.5 ± 0.1** | \(bs=256, wd=0, \lambda = 4, T_{in} = 1, |w| = 4\) |

Results are averaged over three runs, and reported as mean ± std. Baseline corresponds to training with only cross-entropy minimization.