Intra-Processing Methods for Debiasing Neural Networks

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Abstract

As deep learning models become tasked with more and more decisions that impact human lives, such as criminal recidivism, loan repayment, and face recognition for law enforcement, bias is becoming a growing concern. Debiasing algorithms are typically split into three paradigms: pre-processing, in-processing, and post-processing. However, in computer vision or natural language applications, it is common to start with a large generic model and then fine-tune to a specific use-case. Pre- or in-processing methods would require retraining the entire model from scratch, while post-processing methods only have black-box access to the model, so they do not leverage the weights of the trained model. Creating debiasing algorithms specifically for this fine-tuning use-case has largely been neglected.

In this work, we initiate the study of a new paradigm in debiasing research, intra-processing, which sits between in-processing and post-processing methods. Intra-processing methods are designed specifically to debias large models which have been trained on a generic dataset and fine-tuned on a more specific task. We show how to repurpose existing in-processing methods for this use-case, and we also propose three baseline algorithms: random perturbation, layerwise optimization, and adversarial fine-tuning. All of our techniques can be used for all popular group fairness measures such as equalized odds or statistical parity difference. We evaluate these methods across three popular datasets from the AIF360 toolkit, as well as on the CelebA faces dataset. Our code is available at https://github.com/abacusai/intraprocessing_debiasing.

1 Introduction

The last decade has seen a huge increase in applications of machine learning in a wide variety of domains such as credit scoring, fraud detection, hiring decisions, criminal recidivism, loan repayment, face recognition, and so on [43, 8, 46, 4, 36]. The outcome of these algorithms are impacting the lives of people more than ever. There are clear advantages in the automation of classification tasks, as machines can quickly process thousands of datapoints with many features. However, algorithms are susceptible to bias towards individuals or groups of people from a variety of sources [50, 47, 48, 62, 9, 29, 61].

For example, facial recognition algorithms are currently being used by the US government to match application photos from people applying for visas and immigration benefits, to match mugshots, and to match photos as people cross the border into the USA [25]. However, recent studies showed that many of these algorithms exhibit bias based on race and gender [24]. For example, some of the algorithms were 10 or 100 times more likely to have false positives for Asian or Black people, compared to white people. When used for law enforcement, it means that a Black or Asian person is more likely to be arrested and detained for a crime they didn’t commit [2].
Motivated by the discovery of biased models in real-life applications, the last few years has seen a huge growth in the area of fairness in machine learning. Dozens of formal definitions of fairness have been proposed [45], and many algorithmic techniques have been developed for debiasing according to these definitions [60]. Many debiasing algorithms fit into one of three categories: pre-processing, in-processing, or post-processing [14, 6]. Pre-processing techniques make changes to the data itself, in-processing techniques are methods for training machine learning models tailored to making fairer models, and post-processing techniques modify the final predictions outputted by a (biased) model.

However, as datasets become larger and training becomes more computationally intensive, especially in the case of computer vision and natural language processing, it is becoming increasingly more common in applications to start with a very large pretrained model, and then fine-tune for the specific use-case [51, 31, 11, 59]. In fact, PyTorch offers several pretrained models, all of which have been trained for dozens of GPU hours on ImageNet [52]. Pre-, in-, and post-processing debiasing methods are of little help here: pre- and in-processing methods would require retraining the entire model from scratch, and post-processing methods would not make use of the full power of the model.

In this work, we initiate the study of **intra-processing** methods for debiasing neural networks. An intra-processing method is defined as an algorithm which has access to a trained model and a dataset (which typically differs from the original training dataset), and outputs a new model which gives debiased predictions on the target task (typically by updating or augmenting the weights of the original model). To see an overview of all the fairness debiasing algorithm classes, see Figure 1. We propose three different intra-processing baseline algorithms, and we also show how to repurpose a popular in-processing algorithm [64] to the intra-processing setting. All of the algorithms we study work for any group fairness measure and any objective which trades off accuracy with bias.

Our first baseline is a simple random perturbation algorithm, which iteratively adds multiplicative noise to the weights of the neural network and then picks the perturbation which maximizes the chosen objective. Our next baseline optimizes the weights of each layer using GBRT [22]. Finally, we propose adversarial methods for fine-tuning. Adversarial training was recently used as an in-processing method for debiasing [64], by training a critic model to predict the protected attribute of datapoints, to ensure that the predictions are not correlated with the protected attribute. We modify this approach to fit the intra-processing setting, and we also propose a new, more direct approach which trains a critic to **directly measure the bias** of the model weights, which gives us a differentiable proxy for bias, enabling the use of gradient descent for debiasing.

We compare the four above techniques with three post-processing algorithms from prior work: reject option classification [32], equalized odds post-processing [27], and calibrated equalized odds post-processing [53]. We run experiments with three fairness datasets from AIF360 [6], as well as the CelebA dataset [39], with three popular fairness definitions. We show that intra-processing is much more effective than post-processing for the fine-tuning use case. We also show that the difficulty of intra-processing and post-processing debiasing is highly dependent on the initial conditions of the original model. In particular, given a neural network trained to optimize accuracy, the variance in the amount of bias of the trained model is much higher than the variance in the accuracy, with respect to the random seed used for initializing the weights of the original model. Fairness research (and machine learning research as a whole) has seen a huge increase in popularity, and recent papers have highlighted the need for fair and reproducible results [56, 6]. To facilitate best practices, we run our experiments on the AIF360 toolkit [6] and open source all of our code.

**Our contributions.** We summarize our main contributions below.
We initiate the study of intra-processing algorithms for debiasing ML models. This framework sits in between in-processing and post-processing algorithms, and is realistic for many fine-tuning use cases.

We study the nature of intra-processing techniques for debiasing neural networks, showing that the problem is sensitive to the initial conditions of the original model.

We propose three intra-processing algorithms, and we show how to repurpose popular in-processing algorithms into the intra-processing setting. We compare all algorithms across a variety of group fairness constraints and datasets against three post-processing algorithms.

2 Related Work

Debiasing overview. There is a surging body of research on bias and fairness in machine learning. There are dozens of types of bias that can arise [41], and many formal definitions of fairness have been proposed [45]. Popular definitions include statistical parity/demographic parity [18, 35], equal opportunity (a subset of equalized odds) [26], and average absolute odds [6]. For an overview of fairness definitions and techniques, see [6, 60]. Recently, the AIF360 toolkit was established to facilitate best practices in debiasing experiments [6]. A meta-algorithm was also recently developed for in-processing debiasing by reducing fairness measures to convex optimization problems [10]. Another work treats debiasing as an empirical risk minimization problem [16]. Yet another work adds the fairness constraints as regularizers in the machine learning models [7]. A recent work adaptively samples the training dataset during optimization in order to reduce disparate performance [1]. There is also prior work using adversarial learning to debias algorithms [64]. To the best of our knowledge, no prior work has designed an intra-processing algorithm using adversarial learning.
Post-processing methods. Many post-processing debiasing algorithms have been proposed, which all assume black-box access to a biased classifier [33, 39, 26, 53, 32]. We describe a few of these techniques in Section 6. Currently, most of these techniques have only been established for specific fairness measures. In natural language processing, there is recent work which decreases the bias present in pretrained models such as BERT or ELMo [38], however, these techniques were not shown to work on tabular or computer vision datasets.

Debiasing in computer vision. A recent work studied methods for debiasing CelebA with respect to gender [61]. However, the study was limited to in-processing techniques focusing on achieving the highest accuracy in light of distribution shift with respect to correlations present in the data. Another work considered counterfactual sensitivity analysis for detecting bias on the CelebA dataset, using the latent space in GANs [15]. There is also recent work in measuring and mitigating bias in facial recognition software and related computer vision tasks [9, 62, 54, 36].

3 Broader Impact

Deep learning algorithms are more prevalent now than ever before. The technology is becoming integrated into our society, and is being used in high-stakes applications such as criminal recidivism, loan repayment, and hiring decisions [43, 8, 46, 4]. It is also becoming increasingly evident that many of these algorithms are biased from various sources [50, 47, 48]. Using technologies that makes prejudiced decisions for life-changing events will only deepen the divides that already exist in society. The need to address these issues is higher than ever [5, 49].

Our work seeks to decrease the negative effects that biased deep learning algorithms have on society. Intra-processing methods, which work for any group fairness measure, will be applicable to large existing deep learning models, since the networks need not be retrained from scratch. We present simple techniques (random perturbation) as well as more complex and strong techniques (adversarial fine-tuning) that work with most existing deep learning architectures. Our study on the nature of our proposed intra-processing debiasing methods compared to prior work, may also facilitate future work on related debiasing algorithms.

Algorithms to mitigate bias such as the ones in our paper are an important part of creating inclusive and unbiased technology. However, as pointed out in other work [15], bias mitigation techniques must be part of a larger, socially contextualized project to examine the ethical considerations in deploying facial analysis models.

4 Preliminaries

In this section, we give notation and definitions used throughout the paper. Given a dataset split into three parts, $\mathcal{D}_{\text{train}}$, $\mathcal{D}_{\text{valid}}$, $\mathcal{D}_{\text{test}}$, let $(\mathbf{x}_i, Y_i)$ denote one datapoint, where $\mathbf{x}_i \in \mathbb{R}^d$ contains $d$ features including one binary protected attribute $A$ (e.g., identifying as female or not identifying as female), and $Y_i \in \{0, 1\}$ is the label. Denote the value of the protected feature for $\mathbf{x}_i$ as $a_i$. We denote a trained neural network by a function $f_\theta : \mathbb{R}^d \rightarrow [0, 1]$, where $\theta$ denotes the trained weights. We often denote $f_\theta(\mathbf{x}_i) = \hat{Y}_i$, the output predicted probability for datapoint $\mathbf{x}_i$. Finally, we refer to the list of labels in a dataset $\mathcal{D}$ as $\mathcal{Y}$. 
Fairness measures. We now give an overview of group fairness measures used in this work. Given a dataset $\mathcal{D}$ with labels $Y$, protected attribute $A$, and a list of predictions $\hat{Y} = \{f_{\theta}(x_i) | (x_i, Y_i) \in \mathcal{D}\}$ from some neural network $f_{\theta}$, we define the true positive and false positive rates as

$$TPR_{A=a}(\mathcal{D}, \hat{Y}) = \frac{|\{i | \hat{Y}_i = Y_i = 1, a_i = a\}|}{|\{i | Y_i = 1\}|} = P_{(x_i, Y_i) \in \mathcal{D}}(\hat{Y}_i = 1 | a_i = a, Y_i = 1),$$

$$FPR_{A=a}(\mathcal{D}, \hat{Y}) = \frac{|\{i | \hat{Y}_i = 1, Y_i = 0, a_i = a\}|}{|\{i | \hat{Y}_i = 1\}|} = P_{(x_i, Y_i) \in \mathcal{D}}(\hat{Y}_i = 1 | a_i = a, Y_i = 0).$$

Statistical Parity Difference (SPD), or demographic parity difference [18, 35], measures the difference in the probability of a positive outcome between the protected and unprotected groups. Formally,

$$SPD(\mathcal{D}, \hat{Y}, A) = P_{(x_i, Y_i) \in \mathcal{D}}(\hat{Y}_i = 1 | a_i = 0) - P_{(x_i, Y_i) \in \mathcal{D}}(\hat{Y}_i = 1 | a_i = 1).$$

Equal opportunity difference (EOD) [26] measures the difference in TPR for the protected and unprotected groups. Equal opportunity is identical to equalized odds in the case where the protected feature and labels are binary. Formally, we have

$$EOD(\mathcal{D}, \hat{Y}, A) = TPR_{A=0}(\mathcal{D}, \hat{Y}) - TPR_{A=1}(\mathcal{D}, \hat{Y}).$$

Average Odds Difference (AOD) [6] is defined as the average of the difference in the false positive rates and true positive rates for unprivileged and privileged groups. Formally,

$$AOD(\mathcal{D}, \hat{Y}, A) = \frac{(FPR_{A=0}(\mathcal{D}, \hat{Y}) - FPR_{A=1}(\mathcal{D}, \hat{Y})) + (TPR_{A=0}(\mathcal{D}, \hat{Y}) - TPR_{A=1}(\mathcal{D}, \hat{Y}))}{2}.$$

Optimization techniques. Zeroth order (non-differentiable) optimization is used when the objective function is not differentiable (as is the case for most definitions of group fairness). This is also called black-box optimization. Given an input space $W$ and an objective function $\mu$, zeroth order optimization seeks to compute $w^* = \arg\min_{w \in W} \mu(w)$. Leading methods for zeroth order optimization when function queries are expensive (such as optimizing a deep network) include gradient-boosted regression trees (GBRT) [22, 40] and Bayesian optimization (BO) [55, 21, 57], however BO struggles with high-dimensional data. In contrast, first-order optimization is used when it is possible to take the derivative of the objective function. Gradient descent is an example of a first-order optimization technique.

5 Methodology

In this section, we describe three new intra-processing algorithms for debiasing neural networks. First we give more notation and formally define the different types of debiasing algorithms.

Given a neural network $f_\theta$, where $\theta$ represents the weights, we sometimes drop the subscript $\theta$ when it is clear from context. We denote the last layer of $f$ by $f^{(L)}$, and we assume that
\( f = f^{(l)} \circ f' \), where \( f' \) is all but the last layer of the neural network. One of our three algorithms, layer-wise optimization, assumes that \( f \) is feed-forward, that is, \( f = f^{(l)} \circ \cdots \circ f^{(1)} \) for functions \( f^{(1)}, f^{(2)}, \ldots, f^{(l)} \). The performance of the model is given by a performance measure \( \rho \). For a set of data points \( D \), given the list of true labels \( Y \) and the list of predicted labels \( \hat{Y} = \{ f(x) \mid (x, Y) \in D \} \), the performance is \( \rho(Y, \hat{Y}) \in [0, 1] \). Common performance measures include accuracy, precision, recall, or AUC ROC (area under the ROC curve). In our experiments we use balanced accuracy as our performance measure. The formal definition of balanced accuracy is

\[
\rho(Y, \hat{Y}) = \frac{1}{2} \left( \frac{TPR}{TPR + FNR} + \frac{TNR}{TNR + FPR} \right).
\]

We also define a bias measure \( \mu \), given as \( \mu(D, \hat{Y}, A) \in [0, 1] \), such as one defined in Section 4.

The goal of any debiasing algorithm is to increase the performance \( \rho \), while constraining the bias \( \mu \). Many prior works have observed that fairness comes at the price of accuracy for many datasets, even when using large models such as deep networks [6, 60, 12]. Therefore, a common technique is to maximize the performance subject to a constraint on the bias, e.g., \( \mu < 0.05 \). Concretely, we define an objective function as follows.

\[
\phi_{\mu, \rho, \epsilon}(D, \hat{Y}, A) = \begin{cases} 
\rho & \text{if } \mu < \epsilon, \\
0 & \text{otherwise.}
\end{cases}
\]

An in-processing debiasing algorithm takes as input the training and validation datasets and outputs a model \( f \) which seeks to maximize \( \phi_{\mu, \rho, \epsilon} \). An intra-processing algorithm takes in the validation dataset and a trained model \( f \) with weights \( \theta \) (typically \( f \) was trained to optimize the performance \( \rho \) on the training dataset), and outputs fine-tuned weights \( \theta' \) such that \( f_{\theta'} \) maximizes the objective \( \phi_{\mu, \rho, \epsilon} \). A post-processing debiasing algorithm takes as input the validation dataset as well as a set of predictions \( \hat{Y} \) on the validation dataset (typically coming from a model \( f \) which was optimized for \( \rho \) on the training dataset), and outputs a post-processing function \( h : [0, 1] \rightarrow \{0, 1\} \) which is applied to the final output of the model so that the final predictions optimize \( \phi_{\mu, \rho, \epsilon} \).

Note that intra-processing and post-processing debiasing algorithms are useful in different settings. Post-processing algorithms are useful when there is access to the original model, or when the prediction is over a continuous feature. Now we present three new intra-processing techniques.

**Random perturbation.** Our first intra-processing algorithm is a simple iterative random procedure, random perturbation. In every iteration, each weight in the neural network is multiplied by a Gaussian random variable with mean 1 and standard deviation 0.1. In case the model \( f \) outputs probabilities, we find the threshold \( \tau \) such that \( \hat{Y}_\tau = \{ \hat{Y}_i > \tau \} | \hat{Y}_i \in \hat{Y} \) maximizes \( \phi_{\mu, \rho, \epsilon}(Y, \hat{Y}_\tau, A) \). We run \( T \) iterations and output the perturbed weights that maximize \( \phi_{\mu, \rho, \epsilon} \) on the validation set. See Algorithm 1.

**Layer-wise optimization.** Our next method fine-tunes the model by debiasing individual layers using zeroth order optimization. Intuitively, an optimization procedure will be much more effective
than random perturbations. However, zeroth order optimization can be computationally expensive and does not scale well, so instead we only run the optimization on individual layers. Given a model, assume the model can be decomposed into several functions \( f = f^{(1)} \circ \cdots \circ f^{(L)} \) For example, a feed-forward neural network with \( L \) layers can be decomposed in this way. We denote the trained weights of each component by \( \theta_1, \ldots, \theta_L \). Now assume that we have access to a zeroth order optimizer \( A \), which takes as input a model \( f = f^{(L)} \circ \cdots \circ f^{(1)} \), weights \( \theta = (\theta_1, \ldots, \theta_L) \), dataset \( D_{\text{valid}} \), and an index \( i \). The optimizer returns weights \( \theta_i' \), optimized with respect to \( \phi_{\mu, \rho, \epsilon} \). In Algorithm 2, we set the optimizer to be gradient-boosted regression trees (GBRT) [22, 40], a leading technique for black box optimization which converts shallow regression trees into strong learners. GBRT iteratively constructs a posterior predictive model using the weights to make predictions and uncertainty estimates for each potential set of weights \( \theta' \). To trade off exploration and exploitation, the next set of weights to try is chosen using lower confidence bounds (LCB), a popular acquisition function (e.g., [30]). Formally, \( \phi_{\text{LCB}}(\theta') = \hat{\theta}' - \beta \hat{\sigma} \), in which we assume our model’s posterior predictive density follows a normal distribution with mean \( \hat{\theta}' \) and standard deviation \( \hat{\sigma} \). \( \beta \) is a tradeoff parameter that can be tuned. See Algorithm 2. Note that this algorithm can be easily generalized to optimize multiple layers at once, but this comes at the price of runtime. For example, running GBRT on the entire neural network would be more powerful than the random permutation algorithm but is prohibitively expensive.

**Algorithm 1** Random Perturbation

1: **Input:** Trained model \( f \) with weights \( \theta \), validation dataset \( D_{\text{valid}} \), objective \( \phi_{\mu, \rho, \epsilon} \), parameter \( T \)
2: Set \( \theta^* = \theta \), \( \text{val}^* = -\infty \), and \( \tau^* = 0 \)
3: for \( i = 1 \) to \( T \) do
4: Sample \( q_j \sim \mathcal{N}(1, 0.1) \) for all \( j \in \{1, 2, \ldots, |\theta|\} \)
5: \( \theta'_j = \theta_j \cdot q_j \)
6: Select threshold \( \tau \in [0, 1] \) which maximizes the objective \( \phi_{\mu, \rho, \epsilon} \) on the validation set
7: Set \( \text{val} = \phi_{\mu, \rho, \epsilon}(D_{\text{valid}}, \{1 \{ f_{\theta'}(x) > \tau \} \mid (x, y) \in D_{\text{valid}}, A \}) \)
8: If \( \text{val} > \text{val}^* \), set \( \text{val}^* = \text{val} \), \( \theta^* = \theta' \), and \( \tau^* = \tau \).
9: end for
10: **Output:** \( \theta^* \), \( \tau^* \)

**Algorithm 2** Layer-wise optimization

1: **Input:** Trained model \( f = f^{(L)} \circ \cdots \circ f^{(1)} \) with weights \( \theta_1, \ldots, \theta_L \), objective \( \phi_{\mu, \rho, \epsilon} \), black-box optimizer \( A \)
2: Set \( \theta^* = \emptyset \), \( \text{val}^* = -\infty \), and \( \tau^* = 0 \)
3: for \( i = 1 \) to \( L \) do
4: Run optimizer \( A \) to optimize weights \( \theta_i \) to \( \theta_i' \) with respect to \( \phi_{\mu, \rho, \epsilon} \).
5: Select threshold \( \tau \in [0, 1] \) which maximizes objective \( \phi_{\mu, \rho, \epsilon} \)
6: Set \( \text{val} = \phi_{\mu, \rho, \epsilon}(D_{\text{valid}}, \{1 \{ f_{\theta'}(x) > \tau \} \mid (x, y) \in D_{\text{valid}}, A \}) \), where \( \theta' = (\theta_1, \ldots, \theta_i', \ldots, \theta_L) \)
7: If \( \text{val} > \text{val}^* \) set \( \text{val}^* = \text{val} \), \( \theta^* = \theta' \), and \( \tau^* = \tau \).
8: end for
9: **Output:** \( \theta^* \), \( \tau^* \)
**Adversarial fine-tuning.** The previous two methods rely on zeroth order optimization techniques because most group fairness measures such as statistical parity difference and equalized odds are non-differentiable. Our last technique casts the problem of debiasing as first-order optimization by using adversarial learning. The idea behind the adversarial method is that we train a critic model to predict the amount of bias in a minibatch. We sample the datapoints in a minibatch randomly and with replacement. This statistical bootstrapping approach to creating a minibatch means that if the critic can predict the bias in a minibatch accurately, then it can predict the bias in the model with respect to the validation set reasonably well. Therefore, the critic effectively acts as a differentiable proxy for bias, which makes it possible to debias the original model using back-propagation.

The adversarial algorithm works by alternately iterating between training the critic model $g$ using the predictions from $f$, and fine-tuning the predictive model $f$ with respect to a custom function designed to be differentiable while still maximizing the non-differentiable objective function $\phi_{\mu,\rho,\epsilon}$ using the bias proxy $\hat{\mu}$ from $g$. The custom function we use to emulate the objective function while still being differentiable is given by

$$\max\left\{1, \lambda(\left|\hat{\mu} - \epsilon + \delta\right| + 1) \cdot \text{BCELoss}(\hat{y}, \hat{\mu})\right\} \cdot \text{Loss}(y, \hat{y})$$

where $\hat{y}$ is the predicted label, $y$ is the real label, $\lambda, \delta$ are hyperparameters, and BCELoss denotes the standard binary cross-entropy loss. This function multiplies the task specific loss by a coefficient that is 1 if the absolute bias is less than $\epsilon - \delta$, otherwise the coefficient is $\lambda(\left|\hat{\mu} - \epsilon + \delta\right| + 1)$. Intuitively, this custom function optimizes the task specific loss subject to the absolute bias less than $\epsilon - \delta$. The hyperparameter $\lambda$ describes how strict the bias constraint should be, and the hyperparameter $\delta$ describes the margin of error in the bias we want the algorithm to maintain. Note that the $g$ concatenates the examples in the minibatch and returns a single number that estimates the bias of the minibatch as the final output. See Algorithm 3. Note that BCELoss denotes the standard binary cross-entropy loss.

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**Algorithm 3** Adversarial Fine-Tuning

1: **Input:** Trained model $f = f^{(l)} \circ f'$ with weights $\theta$, validation dataset $D_{\text{valid}}$, parameters $\lambda, \epsilon, \delta, n, m, m'$, $T$.
2: Set $g$ as the critic model with weights $\psi$.
3: for $i = 1$ to $n$ do
4:    for $j = 1$ to $m$ do
5:        Sample a minibatch $(X_j, Y_j)$ with replacement from $D_{\text{valid}}$
6:        Evaluate the bias in the minibatch, $\hat{\mu} \leftarrow \mu((X_j, Y_j), f(X_j))$.
7:        Update the critic model $g$ by updating its stochastic gradient
8:        $$\nabla_{\psi}(\hat{\mu} - (g \circ f')(X_j))^2$$
9:    end for
10: for $j = 1$ to $m'$ do
11:    Sample a minibatch $(X_j, Y_j)$ with replacement from $D_{\text{valid}}$
12:    Update the original model by updating its stochastic gradient
13:    $$\nabla_{\theta} \left[ \max\{1, \lambda \cdot (|(g \circ f')(X_j)| - \epsilon + \delta) + 1\} \cdot \text{BCELoss}(Y_j, f(X_j)) \right]$$
14: end for
15: Select threshold $\tau \in [0, 1]$ that minimizes the objective $\phi_{\mu,\rho,\epsilon}$
16: Output: Debiased model $f$, threshold $\tau
Converting in-processing into intra-processing. Since both in-processing and intra-processing algorithms optimize the weights of the neural network while training, it may be possible to convert existing in-processing algorithms into intra-processing algorithms. However, the in-processing algorithm needs to be able to run on a generic neural architecture, and there cannot be any specific weight-initialization step (since it is given a pretrained model as the starting point). Furthermore, the hyperparameters of the in-processing algorithm may need to be modified to better fit the fine-tuning paradigm. For example, the learning rate should be lowered, and the optimizer’s influence on the earlier layers that are unlikely to contribute as much to the final result should be limited.

As an instructive example, we modify a popular in-processing fairness algorithm [64] to convert it to the intra-processing setting. This algorithm relies on a similar adversarial paradigm to our adversarial fine-tuning algorithm. The fundamental difference between the algorithm of [64] and our Algorithm 3 is that their algorithm uses the critic to predict the protected attribute and not to directly predict the bias for the minibatch. As a result, we modify our adversarial fine-tuning algorithm so the critic predicts the protected attribute, and we change the optimization procedure to the one provided by the original work. Finally we modify the hyperparameters so that they are better suited to the fine-tuning use case. For instance, we use a lower learning rate when fine-tuning the model.

6 Experiments

In this section, we experimentally evaluate the techniques laid out in Section 5 compared to baselines, on four datasets and with multiple fairness measures. To promote reproducibility, we release our code at https://github.com/abacusai/intraprocessing_debiasing and we use datasets from the AIF360 toolkit [6] and a popular image dataset. Each dataset contains one or more binary protected feature(s) and a binary label. We briefly describe them below.

Tabular datasets. The COMPAS dataset is a commonly used dataset in fairness research, consisting of over 10,000 defendants with 402 features [20]. The goal is to predict the recidivism likelihood for an individual [3]. We run separate experiments using race and also gender as protected attributes. The Adult Census Income (ACI) dataset is a binary classification dataset from the 1994 USA Census bureau database in which the goal is to predict whether a person earns above $50,000 [17]. There are over 40,000 data points with 15 features. We use gender and race as the protected attribute. The Bank Marketing (BM) dataset is from the phone marketing campaign of a Portuguese bank. There are over 48,000 datapoints consisting of 17 categorical and quantitative features. The goal is to predict whether a customer will subscribe to a product [42]. The protected feature is whether or not the customer is older than 25.

The CelebA dataset. The CelebA dataset [39] is a popular image dataset used in computer science research. This dataset consists of over 200,000 images of celebrity head-shots, along with binary attributes such as “smiling”, “young”, and “gender”. As pointed out in other papers [15], the binary categorization of attributes such as gender, hair color, and age, does not reflect true human diversity, and is problematic [13]. Furthermore, some binary attributes present in CelebA such as “attractive” and “chubby” involve pejorative judgements which may cause harm [15].

In our experiments on CelebA, we choose to focus on two models. One model predicts whether or not the person is classified as young, and the other predicts whether the person is classified as
smiling. As pointed out in prior work, smiling detection has a host of potential positive applications with limited negative applications [15].

We set the protected attribute to Fitzpatrick skin tones in range [4–6], as done in prior work investigating inequity in computer vision models [62, 54]. The Fitzpatrick skin type scale [19] consists of six types of skin tones, and generally tones 4–6 are darker than 1–3. To label all 200,000 attributes, we used a pretrained classifier [63]. We removed all images which were not predicted as type 1–3 or type 4–6 with at least 70% probability, which left us with roughly 180,000 images. Finally, we manually verified the correct classification of 1000 random images.

The need for neural networks. First, we run a quick experiment to demonstrate the need for neural networks on the tabular datasets above. Deep learning has become a very popular approach in the field of machine learning [37], however, for tabular datasets with fewer than 20 features, it is worth checking whether logistic regression or random forest techniques perform as well as neural networks [44]. We construct a neural network with 10 fully-connected layers, BatchNorm for regularization, and a dropout rate of 0.2, and we compare this to logistic regression and a random forest model on the ACI dataset. We see that a neural network achieves accuracy and area under the receiver operating characteristic curve (AUC ROC) scores which are 2% higher than the other models. See Appendix A for the full results. Therefore, we focus on debiasing the neural network implementation.

Bias sensitivity to initial model conditions. We run experiments to compute the amount of variance in the bias scores of the initial models. Neural networks have a large number of local minima [58]. Hyperparameters such as the optimizer and learning rate, and even the initial random seed, cause the model to converge to different local minima [37]. Techniques such as the Adam optimizer and early stopping with patience have been designed to allow neural networks to consistently reach local minima with high accuracies [34, 23]. However, there is no guarantee on the consistency of bias across the local minima. In particular, the local minima found by neural networks may have large differences in the amount of bias, and therefore, there may be very high variance on the amount of bias exhibited by neural networks just because of the random seed. Every local optima corresponds to a different set of weights. If the weights of the model at a specific local optimum rely heavily on the protected feature, removing the bias from such a model by updating the weights would be harder than removing the bias from a model whose weights do not rely on the protected feature as heavily. We compute the mean and the standard deviation of three fairness bias measures, as well as accuracy, for a neural network trained with 10 different initial random seeds, across three datasets. See Table 1. We see that the standard deviation of the bias score is an order of magnitude higher than the standard deviation of the accuracy. In Appendix A, we also plot the contribution of each individual weight to the bias score, for a neural network. We show that the contribution of the weights to the bias score are sensitive to the initial random seed which means we cannot know the weights that are most likely to contribute to the bias before training the model even if we have another identical model trained using a different seed.

6.1 Intra-processing debiasing experiments

Now we present our main experimental study by comparing four intra-processing and three post-processing debiasing methods across four datasets and three fairness measures. This includes one
Figure 2: Results for tabular datasets over 5 trials. We plot the mean bias with std error bars (top), and the median value of the objective function in Equation 1 (bottom). Note that we report the median because Equation 1 has a large discontinuity.
Table 1: Bias and accuracy of a neural network.

|              | AOD   | EOD   | SPD   | accuracy    |
|--------------|-------|-------|-------|-------------|
| ACI (gender) | -0.084 ± 0.012 | -0.082 ± 0.017 | -0.198 ± 0.011 | 0.855±0.002 |
| BM (age)     | 0.011 ± 0.027  | -0.009 ± 0.051  | 0.047 ± 0.015  | 0.901±0.002 |
| COMPAS (race)| 0.138 ± 0.017  | 0.194 ± 0.027   | 0.168 ± 0.016  | 0.669±0.006 |

Figure 3: Probability of smiling on the CelebA dataset, before and after debiasing w.r.t. race. The adversarial fine-tuning method was used to debias.

in-processing algorithm that we have adapted to the intra-processing setting. First we briefly describe the baseline post-processing algorithms that we tested.

The reject option classification post-processing algorithm [32] defines a critical region of points in the protected group whose predicted probability is near 0.5, and flips these labels. This algorithm is designed to minimize statistical parity difference. The equalized odds post-processing algorithm [26] defines a convex hull based on the bias rates of different groups, and then flips the label of data points that fall inside the convex hull. This algorithm is designed to minimize equal opportunity difference. The calibrated equalized odds post-processing algorithm [53] defines a base rate of bias for each group, and then adds randomness based on the group into the classifier until the bias rates converge. This algorithm is also designed to minimize equal opportunity difference. For these algorithms, we use the implementations in the AIF360 repository [6].

Now we explain the experimental setup for the tabular datasets. Our initial model consists of a feed-forward neural network with 10 fully-connected layers of size 32, with a BatchNorm layer between each fully-connected layer, and a dropout fraction of 0.2. The model is trained with the Adam optimizer and an early-stopping patience of 100 epochs. The loss function is the binary cross-entropy loss. We use the validation data as the input for the intra-processing methods, with the objective function set to Equation 1 with $\epsilon = 0.05$. We modified the hyperparameters so that each method took roughly 30 minutes. We run each algorithm on 5 neural networks initialized with different random seeds and aggregate the results. We publish the median objective scores for the tabular datasets as the mean would not accurately portray the expected results since some runs may return an objective score of 0.0. We also publish the mean and std error bars for the bias scores. We limit the plots to those for which the default biased algorithm did not achieve a positive objective score. See Figure 2.

Finally, we run experiments on the CelebA dataset. We use a ResNet18 architecture [28] pretrained on ImageNet from the PyTorch library [52] as our initial model. Then we run 10 epochs of fine-tuning the architecture to predict the “young” attribute (or the “smiling” attribute) from the CelebA dataset using 40,000 random images. To perform fine-tuning, we freeze all of the convolutional layers, only updating the final fully-connected layers. Then we run each of the debiasing algorithms.
Table 2: Results on the CelebA datasets for a pretrained ResNet with three initial random seeds. Results are the balanced accuracy scores after fine-tuning for the task of classifying whether the person in the image should be classified as young. The crossed out scores are those that did not have biases lower than 0.05.

|     | Default | ROC   | EqOdds | CalibEqOdds | Random | LayerwiseOpt | Adversarial |
|-----|---------|-------|--------|-------------|--------|--------------|-------------|
| 1   | 0.819   | 0.840 | 0.978  | 0.837       | 0.784  | 0.762        | 0.914       |
| 2   | 0.823   | 0.833 | 0.978  | 0.804       | 0.777  | 0.889        | 0.917       |
| 3   | 0.830   | 0.852 | 0.977  | 0.837       | 0.801  | 0.750        | 0.905       |

We consider the default model, as well as the three post-processing algorithms and the three novel intra-processing algorithms. As in the previous section, we set the objective function to Equation 1 with $\epsilon = 0.05$. See Table 2. In order to give a qualitative comparison, we also publish a series of images along with the predicted probability that the celebrity is smiling before and after applying the adversarial fine-tuning model. See Figure 3.

Discussion. We see that the intra-processing methods significantly outperform the post-processing methods, sometimes even on the fairness metric for which the post-processing method was designed. We note that there are two caveats. First, the three intra-processing methods had access to the objective function in Equation 1, while the post-processing methods are only designed to minimize their respective fairness measures. However, as seen in Figure 2, sometimes the intra-processing methods simultaneously achieve higher objective scores and lower bias compared to the post-processing methods, making the intra-processing methods dominate them pareto-optimally. Second, intra-processing methods are more powerful than post-processing methods, since post-processing methods do not modify the weights of the original model. Post-processing methods are more appropriate when the model weights are unavailable or when computation time is constrained, and intra-processing methods are more appropriate when higher performance is desired. We find that all the intra-processing algorithms tend to do well on the tabular datasets. However making sure that their bias scores remain below the threshold on the test is not as easy as there were not enough rows. Using regularization techniques helped to ensure that the scores remained consistent even over the test set. We find that when the dataset and the model become more complex as is the case with the CelebA dataset and the ResNet model the more complex algorithms like adversarial fine-tuning tend to perform better than the random perturbation and layerwise optimization algorithm. This indicates that when dealing with more complex datasets and models, using complex intra-processing models like adversarial fine-tuning may be a better fit for the problem.

7 Conclusion

In this work, we initiate the study of a new paradigm in debiasing research, \textit{intra-processing}, which sits between in-processing and post-processing methods, and is designed for fairly fine-tuning large models. We define three new intra-processing algorithms: random perturbation, adversarial fine-tuning, and layer-wise optimization, and we repurpose a popular in-processing algorithm to work for intra-processing. In our experimental study, first we show that the amount of bias is sensitive
to the initial conditions of the original neural network. Then we give an extensive comparison of four intra-processing methods and three post-processing methods across three tabular datasets, one image dataset, and three popular fairness measures. We show that the intra-processing algorithms outperform the post-processing methods.
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### Table 3: Comparison between models. mean ± standard deviation

|        | logistic regression | neural network | random forest |
|--------|---------------------|----------------|---------------|
| ACI    | accuracy            | 0.852 ± 0.000  | 0.855 ± 0.002 | 0.844 ± 0.002 |
|        | roc_auc             | 0.904 ± 0.000  | 0.908 ± 0.001 | 0.889 ± 0.000 |
| BM     | accuracy            | **0.901 ± 0.000** | 0.901 ± 0.002 | 0.899 ± 0.001 |
|        | roc_auc             | 0.930 ± 0.000  | **0.934 ± 0.001** | 0.932 ± 0.001 |
| COMPAS | accuracy            | **0.677 ± 0.000** | 0.641 ± 0.061 | 0.652 ± 0.006 |
|        | roc_auc             | **0.725 ± 0.000** | 0.679 ± 0.088 | 0.695 ± 0.002 |

**A Additional Experiments and Details**

In this section, we give additional details from the experiments in Section 6, as well as additional experiments.

**The need for neural networks.** We start by comparing the performance of neural networks to logistic regression and gradient-boosted regression trees (GBRT) on the datasets we used, to demonstrate the need for neural networks. This experiment is described at the start of Section 6. For convenience, we restate the details here. We construct a neural network with 10 fully-connected layers of size 32, BatchNorm for regularization, and a dropout rate of 0.2, and we compare this to logistic regression and GBRT on the ACI, BM, and COMPAS datasets. See Table 3. We see that the neural network achieves better accuracy and ROC AUC on all datasets except COMPAS, which is within one standard deviation of the optimal performance.

**Bias sensitivity to initial model conditions.** Next, we study the sensitivity of bias to initial model conditions. Recall that in Table 1, we computed the mean and standard deviation of three fairness measures, as well as accuracy, for training a neural network with respect to different initial random seeds. We see that standard deviation of the bias is an order of magnitude higher than the standard deviation of the accuracy. Now we run more experiments to show that the contribution of the weights to the bias score are sensitive to the initial random seed.

For this experiment, we train 10 neural networks with the same architecture as described in Section 6. We want to identify which parameters of the network contribute most to the bias. To identify these parameters, we create 1000 random delta vectors with mean 1 and standard deviation 0.1 for each of the neural networks. We then take the Hadamard product of each random delta vector with the parameters of the corresponding network. We then evaluate the statistical parity difference (SPD) on the test set for the networks with the new perturbed parameters. To identify which parameters contribute most to the bias, we train a linear model for each of the 10 neural networks to predict the bias from the random delta vectors, and then we analyze the coefficients of the corresponding linear models. The linear models are successfully able to predict the bias based on the random delta vectors with an $R^2$ score of 0.861 ± 0.090. Figure 4 (left) shows that only a small fraction of the parameters contribute to the majority of the bias.

Now we want to identify how similar the coefficients of the linear models are across all 10 neural networks. To identify this, we stack the normalized coefficients for the linear models and decomposed
the stacked matrix with singular value decomposition. The singular values of the matrix measure the degree of linear independence between the coefficients for the 10 linear models. As we see from Figure 4 (right), the singular values are all close to 1. This indicates that the coefficients are all relatively different from one another. This means that the parameters of the 10 neural networks that correspond to the bias are different for each network indicating that each time we train a model, even if it has the same architecture, the parameters that contribute to bias are different.

**Tabular Intra-Processing Debiasing Experiments.** Now we give more results for the intra-processing debiasing experiments from Section 6. The experimental setting is the same as in the tabular data experiments from Section 6 (Figure 2). We give even more combinations of dataset, bias measures, and protected attributes. See Figure 5. Note that the results in this figure are a superset of the results from Figure 2. These additional results show that different debiasing measures work better in different situations.
Figure 5: A continuation of the results from Figure 2, with even more combinations of dataset, bias measure, and protected attribute. Over 5 runs with different seeds, we report mean bias with std error bars (top) and the median of the objective function in Equation 1 (bottom). Note that we report the median because Equation 1 has a large discontinuity.