Increasing Fairness in Predictions Using Bias Parity Score Based Loss Function
Regularization

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Abstract
Increasing utilization of machine learning based decision support systems emphasizes the need for resulting predictions to be both accurate and fair to all stakeholders. In this work we present a novel approach to increase a Neural Network model’s fairness during training. We introduce a family of fairness enhancing regularization components that we use in conjunction with the traditional binary-cross-entropy based accuracy loss. These loss functions are based on Bias Parity Score (BPS), a score that helps quantify bias in the models with a single number. In the current work we investigate the behavior and effect of these regularization components on bias. We deploy them in the context of a recidivism prediction task as well as on a census-based adult income dataset. The results demonstrate that with a good choice of fairness loss function we can reduce the trained model’s bias without deteriorating accuracy even in unbalanced datasets.

Introduction
The use of automated decision support and decision-making systems (ADM) (Hardt, Price, and Srebro 2016) in applications with direct impact on people's lives has increasingly become a fact of life, e.g. in criminal justice (Kleinberg, Mullainathan, and Raghavan 2016; Jain et al. 2020b; Dresdell and Farid 2018), medical diagnosis (Kleinberg, Mullainathan, and Raghavan 2016; Ahsen, Ayvaci, and Raghunathan 2019), insurance (Baudry and Robert 2019), credit card fraud detection (Dal Pozzolo et al. 2014), electronic health record data (Gianfrancesco et al. 2018), credit scoring (Huang, Chen, and Wang 2007) and many more diverse domains. This, in turn, has lead to an urgent need for study and scrutiny of the bias-magnifying effects of machine learning and Artificial Intelligence algorithms and thus their potential to introduce and emphasize social inequalities and systematic discrimination in our society. Appropriately, much research is being done currently to mitigate bias in AI-based decision support systems (Ahsen, Ayvaci, and Raghunathan 2019; Kleinberg, Mullainathan, and Raghavan 2016; Noriega-Campero et al. 2019; Feldman 2015; Oneto, Donini, and Pontil 2020; Zemel et al. 2013).

Bias in Decision Support Systems. As our increasingly digitized world generates and collects more data, decision makers are increasingly using AI based decision support systems. With this, the need to keep the decisions of these systems fair for people of diverse backgrounds becomes essential. Groups of interest are often characterized by sensitive attributes such as race, gender, affluence level, weight, and age to name a few. While machine learning based decision support systems often do not consider these attributes explicitly, biases in the data sets, coupled with the used performance measures can nevertheless lead to significant discrepancies in the system’s decisions. For example, as many minorities have traditionally not participated in many domains such as loans, education, employment in high paying jobs, receipt of health care, resulting datasets are often highly unbalanced. Similarly, some domains like homeland security, refugee status determination, incarceration, parole, loan repayment etc., may be already riddled with bias against certain subpopulations. Thus human bias seeps into the datasets used for AI based prediction systems which, in turn, amplifies it further. Therefore, as we begin to use AI based decision support systems, it becomes important to ensure fairness for all who are affected by these decisions.

Contributions. We propose a technique that uses Bias Parity Score (BPS) measures to characterize fairness and develop a family of corresponding loss functions that are used as regularizers during training of Neural Networks to enhance fairness of the trained models. The goal here is to permit the system to actively pursue fair solutions during training while maintaining as high a performance on the task as possible. We apply the approach in the context of several fairness measures and investigate multiple loss function formulations and regularization weights in order to study the performance as well as potential drawbacks and deployment considerations. In these experiments we show that, if used with appropriate settings, the technique measurably reduces race-based bias in recidivism prediction, and demonstrate on the gender-based Adult Income dataset that the proposed method can outperform state-of-the-art techniques aimed at more targeted aspects of bias and fairness. In addition, we investigate potential divergence and stability issues that can arise when using these fairness loss functions, in particular when shifting significant weight from accuracy to fairness.
Notation

In this paper we present the proposed approach largely in the context of class prediction tasks with subpopulations indicated by a binary sensitive attribute. However, the approach can easily be extended to multi-class sensitive attributes as well as to regression tasks. For the description of the approach in our primary domain, we use the following notation to describe the classification problem and measures to capture group performance measures to assess prediction bias.

Each element of the dataset, \( D = \{(X, A, Y)\}_i \), is represented by an attribute vector \( (X, A) \), where \( X \in \mathbb{R}^d \) represents its features and \( A \in \{0, 1\} \) is the sensitive attribute indicating the group it belongs to. \( C = c(X, A) \in \{0, 1\} \) indicates the value of the predicted variable, and \( Y \in \{0, 1\} \) is the true value of the target variable.

To obtain fairness characteristics, we use parity over statistical performance measures, \( m \), across the two groups indicated by the sensitive attribute, where \( m(A=a) \) indicates the measure for the subpopulation where \( A = a \).

Since this paper will introduce the proposed framework in the context of binary classification, the fairness related performance measures used will center around elements of the confusion matrix, namely false positive, false negative, true positive, and true negative rates. In the notation used here, these metrics and the corresponding measures are:

- **False positive rate (FPR):** \( P(C = 1 \mid Y = 0) \), \( m_{FPR}(A=a) = P(C = 1 \mid Y = 0, A = a) \)
- **False negative rate (FNR):** \( P(C = 0 \mid Y = 1) \), \( m_{FNR}(A=a) = P(C = 0 \mid Y = 1, A = a) \)
- **True positive rate (TPR):** \( P(C = 1 \mid Y = 1) \), \( m_{TPR}(A=a) = P(C = 1 \mid Y = 1, A = a) \)
- **True negative rate (TNR):** \( P(C = 0 \mid Y = 0) \), \( m_{TNR}(A=a) = P(C = 0 \mid Y = 0, A = a) \)

Strict parity in these or similar measures implies that they are identical for both groups, i.e. if \( m(A=0) = m(A=1) \).

Related Work

Some recent works (Ntoutsi et al. 2020; Krasanakis et al. 2018) summarize bias mitigation techniques into three categories: i) preprocessing input data approaches (Calders, Kamiran, and Pechenizky 2009; Feldman et al. 2015; Feldman 2015), ii) in-processing approaches or training under fairness constraint that focuses on the algorithm (Celis et al. 2019; Zafar et al. 2017; Josifidis and Ntoutsi 2020) and, iii) postprocessing approaches that seek to improve the model (Hardt, Price, and Srebro 2016; Mishler, Kennedy, and Chouldechova 2021). Expanding on this, (Orphanou et al. 2021) sums up mitigating algorithmic bias as detection of bias, fairness management, and explainability management. Their "fairness management" step is the same as the aforementioned "bias mitigation techniques" but they added "Auditing" (Fairness formalization) as an additional category.

The first bias mitigation technique involving preprocessing data is built on the premise that disparate impact in training data results in disparate impact in the classifier. Therefore these techniques are comprised of massaging data labels and reweighting tuples. Massaging is altering the class labels that are deemed to be mislabeled due to bias, while reweighting increases weights of some tuples over others in the dataset. Calders et al. (Calders, Kamiran, and Pechenizky 2009) assert that these massaging and reweighting techniques yield a classifier that is less biased than without such a process. They also note that while massaging labels is intrusive and can have legal implications (Barocas and Selbst 2016), reweighting does not have these drawbacks.

The second technique of in-processing fairness under constraint (Celis et al. 2019; Zafar et al. 2017) chooses impact metrics (Josifidis and Ntoutsi 2020; Zafar et al. 2017; Calders et al. 2013), followed by modifying the imposed constraints during classifier training or by adding constraints that steer the model towards the optimization goals (Zafar et al. 2017; Calders et al. 2013; Josifidis and Ntoutsi 2020; Oneto, Donini, and Pontil 2020). Similarly, (Josifidis and Ntoutsi 2020) change the training data distribution and monitor the discriminatory behavior of the learner. When this discriminatory behavior exceeds a threshold, they adjust the decision boundary to prevent discriminatory learning.

The third technique to improve the results involves a postprocessing approach to comply with the fairness constraints. The approach can entail selecting a criterion for unfairness relative to a sensitive attribute while predicting some target. In the presence of the target and the sensitive attribute, (Hardt, Price, and Srebro 2016), shows how to adjust the predictor to eliminate discrimination as per their definition.

Our work uses supervised learning without balancing the dataset. The reason is to avoid issues from massaging labels and the consideration that while reweighting can be effective for simple sensitive attributes and predictions, in general multiple overlapping sensitive attributes and classes could exist, making reweighting complex and potentially impossible. Some work employing unsupervised clustering also seek to maintain the original balance in the dataset (Abbasi, Bhaskara, and Venkatasubramanian 2021; Abraham, Sundaram, and others 2019; Chierichetti et al. 2018).

Definitions of Fairness. Literature contains several concepts of fairness requiring one or more demographic or statistical properties to be constant across subpopulations. Demographic parity (or statistical parity), mandates that decision rates are independent of the sensitive attribute (Noriega-Campero et al. 2019; Louizos et al. 2015; Calders et al. 2013; Iosifidis and Ntoutsi 2020; Oneto, Donini, and Pontil 2020). Similarly, (Josifidis and Ntoutsi 2020) change the training data distribution and monitor the discriminatory behavior of the learner. When this discriminatory behavior exceeds a threshold, they adjust the decision boundary to prevent discriminatory learning.

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metrics that include FPR, FNR, TPR, TNR, and FPR.

Approach

This paper is aimed at providing a framework to allow a deep learning-based prediction system to learn fairer models for known sensitive attributes by actively pursuing improved fairness during training. For this, we first need a quantitative measure of fairness that can be widely addressed. We propose to use Bias Parity Score (BPS) which evaluates the degree to which a common measure in the subpopulations described by the sensitive attribute is the same. Based on this fairness measure we then derive a family of correspondingly differentiable loss functions that can be used as a regularization term in addition to the original task performance loss.

Bias Parity Score (BPS)

In machine learning based predictions, bias is the differential treatment of “similarly situated” individuals. It manifests itself in unfairly benefitting some groups (Jiang and Nachum 2020) [Angwin et al. 2016; Dressel and Farid 2018] [Zeng, Usten, and Rudin 2017] [Jain et al. 2019] [Jain et al. 2020a; Ozkan 2017]. Bias in recidivism, for example, may be observed when prediction yields a symmetric measure for two groups and provides similar bias may be observed when predicting whom to invite for interviews or when making salary decisions, resulting in preferential treatment of one cohort.

To capture this, the relevant property can be encoded as a fairness measure that use the same sensitive attribute and thus denies parole. Similar bias may be observed when predicting whom to invite for interviews or when making salary decisions, resulting in preferential treatment of one cohort.

Although the BPS score of a statistical entity represents a measure of fairness, it does not lend itself directly to training a deep learning system since it is not generally differentiable. To address this, we need to translate the underlying measure into a differentiable form and combine it into a differentiable version of the BPS score that can serve as a training loss function. As we are using FPR, FNR, TPR, and TNR here we first have to define continuous versions of these functions. For this, we build our Neural Network classifiers with a logistic activation function as the output (or a softmax if using multi-attribute predictions), leading, when trained for accuracy using binary cross-entropy to the network output, representing the probability of the positive class, $y = P(Y = 1 | X, A)$. In the experiments we will hold the sensitive attribute and thus $y = P(Y = 1 | X)$. Using this continuous output, we can define a continuous measure approximation $mc_s()$ for FPR, FNR, TPR, and TNR:

$$mc_{FPR}(A = k) = \frac{\sum_{(X,A,Y) : A_i = k, Y = 0} S(y_i - 0.5)}{\sum_{(X,A,Y) : A_i = k} S(y_i - 0.5)}$$

$$mc_{FNR}(A = k) = \frac{\sum_{(X,A,Y) : A_i = k, Y = 1} S(0.5 - y_i)}{\sum_{(X,A,Y) : A_i = k} S(0.5 - y_i)}$$

$$mc_{TPR}(A = k) = \frac{\sum_{(X,A,Y) : A_i = k, Y = 1} S(y_i - 0.5)}{\sum_{(X,A,Y) : A_i = k} S(y_i - 0.5)}$$

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This is not equal to $ms_s()$ as it is sensitive to deviations in the exact prediction probability. For example if the output changes from 0.6 to 0.7 the continuous measure, $mc_s()$, changes while the full measure, $ms_s()$, would not change since both would result in the positive class.

To reduce this discrepancy, we designed a second approximation, $m_{ss_s()}$, that uses a sigmoid function, $S(x) = \frac{1}{1 + e^{-x}}$, to more closely approximate the full statistical measure by reducing intermediate prediction probabilities:

$$ms_{FPR}(A = k) = \sum_{(X,A,Y) : A_i = k, Y = 0} S(y_i - 0.5)$$

$$ms_{FNR}(A = k) = \sum_{(X,A,Y) : A_i = k, Y = 1} S(0.5 - y_i)$$

$$ms_{TPR}(A = k) = \sum_{(X,A,Y) : A_i = k, Y = 1} S(y_i - 0.5)$$

$$ms_{TNR}(A = k) = \sum_{(X,A,Y) : A_i = k, Y = 0} S(0.5 - y_i)$$

Once measures are defined, a continuous approximation for BPS fairness for both measures can be defined as:

$$BPS_{mc} = \frac{\min(ms_{FPR}(A = 1), ms_{FPR}(A = 0))}{\max(ms_{FPR}(A = 1), ms_{FPR}(A = 0))}$$

$$BPS_{ms} = \frac{\min(ms_{FPR}(A = 1), ms_{FPR}(A = 0))}{\max(ms_{FPR}(A = 1), ms_{FPR}(A = 0))}$$

Even though, BPS can be used for many statistical measures as described in (Jain et al. 2020a) we will use it here with FPR, FNR, TPR, TNR as these are often used for classification systems. In addition we will employ it on prediction rate to obtain a BPS equivalent to quantitative statistical parity to facilitate comparisons with previous approaches in the Adult Income domain.

BPS-Based Fairness Loss Functions

While the BPS score of a statistical entity represents a measure of fairness, it does not lend itself directly to training a deep learning system since it is not generally differentiable. To address this, we need to translate the underlying measure into a differentiable form and combine it into a differentiable version of the BPS score that can serve as a training loss function. As we are using FPR, FNR, TPR, and TNR here we first have to define continuous versions of these functions. For this, we build our Neural Network classifiers with a logistic activation function as the output (or a softmax if using multi-attribute predictions), leading, when trained for accuracy using binary cross-entropy to the network output, representing the probability of the positive class, $y = P(Y = 1 | X, A)$. In the experiments we will hold the sensitive attribute and thus $y = P(Y = 1 | X)$. Using this continuous output, we can define a continuous measure approximation $mc_s()$ for FPR, FNR, TPR, and TNR:

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$$BPS_{ms} = \frac{\min(ms_{FPR}(A = 1), ms_{FPR}(A = 0))}{\max(ms_{FPR}(A = 1), ms_{FPR}(A = 0))}$$
These, in turn can be inverted into loss functions that can be used during training and further expanded by allowing to weigh small versus large biases by raising the loss to the $k^{th}$ power which depresses the importance of fairness losses close to 0 (i.e. when the system is almost fair).

$$LF_{C(s,k)} = (1 - BPS_{C(s)})^k$$
$$LF_{S(s,k)} = (1 - BPS_{S(s)})^k$$ (5)

These loss functions are continuous and differentiable in all but one point, namely the point where numerator and denominator are equal and thus in the minimum of the loss function. This, however, can be easily addressed in the training algorithm when optimizing the overall loss function.

**Fairness Regularization for Neural Network Training**

The approach in this paper is aimed at training Neural Network deep learning classifiers to obtain more fair results while preserving prediction accuracy. The underlying task is thus maximizing accuracy which is commonly encoded in terms of a binary cross entropy loss function, $L_{BCE}$.

Starting from this, we utilize the fairness loss functions derived in the previous sections as regularization terms resulting in an overall loss function, $LF_C$ and $LF_S$ for continuous and sigmoided fairness losses, respectively:

$$LF_C(\alpha, \tilde{k}) = L_{BCE} + \sum_{s_i} \alpha_i LF_{C(s_i, k_i)}$$
$$LF_S(\alpha, \tilde{k}) = L_{BCE} + \sum_{s_i} \alpha_i LF_{S(s_i, k_i)}$$ (6)

where $\alpha$ is a weight vector determining the contribution of each fairness loss function, $\tilde{k}$ is a vector of powers to be used for each of the fairness losses, and $s$ is the vector of the loss metrics, $<FPR,FNR,TPR,TNR>$. Setting an $\alpha_i$ to 0 effectively removes the corresponding fairness criterion.

These loss function can be used to train a Neural Network classifier where different values for $\alpha$, $\tilde{k}$, and the choice of sigmoided vs continuous loss puts different emphasis on different aspects of the underlying fairness characteristics.

Figure 1 shows an overview of the basic model selection process for the proposed approach. Based on selected fairness criteria and hyperparameter ranges, an architecture is trained in a grid search and the best model is selected.

**Experiments**

To study the applicability of the proposed use of fairness losses as regularization terms, we conducted experiments on three different datasets, two in the recidivism domain and one in the income prediction domain, and analyzed the behavior and effects of different function and weight choices.

**Dataset 1:** This is the main dataset used and is the raw data from the study “Criminal Recidivism in a Large Cohort of Offenders Released from Prison in Florida, 2004-2008 (ICPSR 27781)” (United States Department of Justice 2010) (Bhati and Roman 2014). It contains 156,702 records with a 41:59 recidivist to non-recidivist ratio. This ratio for our two subpopulations is 34:66 for Caucasians and 46:54 for African Americans, making it very unbalanced and leading to significant bias in traditional approaches. In each crime category, the dataset has a higher proportion of non-recidivists Caucasians than African Americans. It covers six crime categories and provides a large range of demographic features, including crime committed, age, time served, gender, etc. We employed one-hot encoding for categorical features and trained to predict recidivism within 3 years.

**Dataset 2:** This is a secondary dataset to validate results. This dataset ensued from the “Recidivism of Prisoners Released in 1994” study (United States Department of Justice 2014). It contains data from 38,624 offenders that were released in 1994 from one of 15 states in the USA, with each record containing up to 99 pre and post 1994 criminal history records, treatments and courses taken by offenders. As described in Jain et al. 2020b, Jain et al. 2020a, each record was split to create one record per arrest cycle, resulting in approximately 442,000 records that use demographic and history information to predict recidivism. This dataset is significantly more balanced, allowing to verify effects from Dataset 1 in data with different characteristics.

**Dataset 3:** This is the commonly used “Adult Income Data Set” (Kohavi and others 1996) from the UCI repository (Dua and Graff 2017) that was extracted from 1994 Census data. The dataset has 48,842 records, each representing an individual over 16 who had an income greater than $100. The dataset holds socioeconomic status, education, and job information pertaining to the individual and is thus largely demographic, just like Dataset 1, but in a different domain. Unlike Datasets 1 and 2, where race is the sensitive attribute, gender is the sensitive attribute in Dataset 3 with the goal of predicting a salary higher than $50K. This dataset is here mainly used to verify that effects translate to other domains and to permit comparisons with state-of-the-art techniques.

**Constructing Neural Networks**

For the recidivism datasets we trained networks with 2 hidden layers with 41 units each. Each hidden layer used ReLU activation and 10% dropout (Srivastava et al. 2014), followed by Batch Normalization (Santurkar et al. 2018). The output layer had 1 logistic unit as indicated previously. We tuned various hyper parameters to select a batch size of 256 and 100 epochs and trained using the Adam (Kingma and Ba 2014) optimizer. The hyperparameters were chosen based...
on previous experience with the datasets. (Jain et al. 2020b Jain et al. 2020a Jain et al. 2019).

Evaluation Study
To evaluate the characteristics of fairness loss regularization in recidivism prediction, we conducted experiments with 6 measures for both continuous and sigmoided loss functions, employed 4 different exponents for the continuous case, and ran experiments for 10 different weight settings. In particular, we used the 4 statistics individually as well as FPR and FNR or TPR and TNR simultaneously with equal weights. A grid search varied weights $\alpha$ between 0.1 and 1 in steps of 0.1, and for continuous loss used powers of 1, 2, 3, and 4. The goal was to compare the effects of different settings on the behavior of the system in terms of accuracy, fairness, and stability. The Baseline used no fairness regularization.

To capture variance, Monte Carlos cross validation with 10 iterations was used and the means of the metrics are reported. Stability was evaluated using the variance.

Results and Discussion
The goal of these experiments is to evaluate whether the proposed approach can achieve the desired goal and to evaluate the effect of different loss function and regularization weight choices on the performance both in terms of accuracy and fairness. To perform this study we utilized mainly Dataset 1 due to its higher imbalance and studied the effect of different aspects of the loss function design. We then used Dataset 2 to validate some of the results on a more balanced dataset.

Measuring Bias in Results: After conducting the experiments, we investigated the effect of the loss functions on residual bias measured by Bias Parity Score for FPR, FNR, TPR, and TNR, as well as Accuracy. In addition we recorded Accuracy as well as the values for BCE loss and for each of the fairness loss functions used in the respective experiment.

Applicability and Effect of Regularization Weight To study the basic performance we analyzed the experiments for the six continuous fairness measures in the linear case (i.e. with a power of 1). As indicated, the regularization weight was increased step-wise, starting from the Baseline with no regularization ($\alpha = 0$) to equal contributions of BCE and fairness ($\alpha = 1$). Figure 2 shows the average accuracy (solid grey line), BPS scores (solid lines), and loss function values (corresponding dashed lines) as a function of the regularization weight, $\alpha$. Only results for $FNR$, $FPR$, and $FNR+FPR$-based regularization are shown. Behavior for $TNR$, $TPR$, and $TNR+TPR$ was similar.

These graphs show that introducing fairness regularization immediately increases the corresponding BPS score, and thus fairness, while only gradually decreasing accuracy. This demonstrates the viability of the technique. Moreover, in this case, regularization for one statistic also yields improvement in other statistics, which can be explained with the close relation of FPR, FNR, TPR, and TNR.

However, the experiments also show some differences that give information regarding important considerations for regularization weights. In particular, while the experiments with $LFc(FNR,1)$ and $LFc(FNR,1) + LFc(FPR,1)$ show a relatively steady increase in fairness, the case of $LFc(FPR,1)$ shows that after an initial strong increase, the active fairness measure, $BPSc_{FPR}$, starts to decrease once $\alpha$ exceeds 0.2. At the same time the regularization loss, $LFc(FPR,1)$, continues to decrease, showing a decoupling between the core fairness measure and the loss function at this point. The reason is that in order to obtain a differentiable loss function it was necessary to interpret the network output as a probabilistic prediction and thus, for example, decreasing the output for one negative item from 0.4 to 0.1 while simultaneously decreasing an output for a positive data item from 0.51 to 0.49 here represent an improvement in loss function value while reducing the corresponding fairness BPS as the second item classification became incorrect.

Sigmoided Loss Function One way to address this decoupling are the proposed sigmoided fairness loss functions. Figure 3 shows the corresponding results using the sigmoided version of the fairness loss $LFS_{(FNR,1)}$, $LFS_{(FPR,1)}$, and $LFS_{(FNR,1)} + LFS_{(FPR,1)}$. Again, BPS values, Accuracy, and loss function values are shown.

While these results, compared to the linear results in Figure 2, as expected show less decoupling between loss and fairness, tend to impose higher levels of fairness earlier, and maintain fairness more reliably, they also show a stronger degradation in accuracy and, when looking at regularization loss for higher weights and corresponding variances also exhibit strong signs of instabilities. This implies that while there are advantages in terms of how well sigmoided loss functions represent fairness, optimizing them is significantly harder, leading to less stable convergence. When choosing

Figure 2: BPS Measures, Accuracy, and Loss function values as a function of regularization weight, $\alpha$, for the continuous, linear case using $LFc(FPR,1)$ (left), $LFc(FNR,1)$ (middle), and $LFc(FPR,1) + LFc(FNR,1)$ (right).
between these two options it is thus important to consider this tradeoff and to have ways to monitor gradient stability.

**Effect of Loss Function Power**  Another way to modify the effect of regularization losses is to increase the loss function power. This reduces the impact of small amounts of bias near a fair solution while increasing importance if fairness losses are high. The goal is to reduce the small scale adjustments near a solution most responsible for decoupling. Figure 4 shows the effect of different powers for continuous loss function $L_{Fc}(FPR,k)$, the case where strong decoupling occurred.

These graphs show that as the power increases, improvement in fairness becomes smoother and decoupling of loss and fairness occurs significantly later. However, a larger weight is needed to optimize, with power 4 not reaching the best fairness. This might be a problem in datasets with larger fairness loss. The best performance seems with power 3.

**Effects in More Balanced Data**  Dataset 1 contains relatively biased data, reflected in the low base fairness scores of 70 - 80 and accuracy of 65%. Thus it offers significant room for improvement in fairness without loss of accuracy. To see if similar benefits can be achieved in less biased datasets, the experiments were repeated on Dataset 2 which has initial fairness near 90 and accuracy of 89%. To see how similar settings work here, Figure 5 shows results for the best continuous and sigmoided settings for FPR-based regularization. In particular, it shows the continuous case with power 3, $L_{Fs}(FPR)$, and the sigmoided case of $L_{Fs}(FPR,1)$.

These results show that even for less biased datasets where fairness gain is more difficult, the proposed method can increase fairness without a dramatic drop in accuracy. However, improved fairness in one metric here yields degra-

**Performance on Adult Income Data**  To show applicability beyond recidivism and to compare performance with other state of the art approaches, we applied our approach on Dataset 3 and compared the results with those in [Krasanakis et al. 2018][Krasanakis et al. 2018; Beutel et al. 2017; Zafar et al. 2017; Kamishima et al. 2012].

**Neural Network Architectures**  To find the best network we experimented with a number of hyperparameters to find the network with the highest baseline accuracy. Starting from Architecture 1 from the recidivism datasets (two ReLU hidden layers, each with 108 neurons), we derived Architecture 2 (two leaky ReLU hidden layers with 108 and 324 neurons, respectively), yielding a
Figure 6: BPS Measures, Accuracy, and Loss function values as a function of regularization weight, $\alpha$, for Architecture 2 on Adult income data for $LFc_{(STP,1)}$ (left), $LFc_{(STP,2)}$ (right), $LFc_{(STP,3)}$ (eft), and $LFc_{(STP,4)}$ (right)

### Table 1: Adult Income Accuracy and pRule Comparison.

| Fairness Technique | Adult Income pRule acc |
|--------------------|------------------------|
| (Krasanakis et al. 2018) (no fairness) | 27% 85% |
| (Krasanakis et al. 2018) | 100% 82% |
| (Zafar et al. 2017) | 94% 82% |
| (Kamishima et al. 2012) | 85% 83% |
| Baseline (current work) | 34% 85% |
| Architecture 1 (current work) | 99% 82% |
| Architecture 2 (current work) | 100% 83% |

### Table 2: Adult Income FPR and FNR Equality Comparison.

| Arch 1: FPR-FNR-Sigmoid-LF,k=4, $\alpha_1=0.05$, $\alpha_2=0.05$ | Arch 2: FPR-FNR-Sigmoid-LF,k=3, $\alpha_1=0.1$, $\alpha_2=0.125$ |
|-------------------|-------------------|
| Beutel et al. 2017 | 0.1875 0.0308 | 0.1200 0.1778 |
| Zhang et al. 2018 | 0.0651 0.0822 | 0.1828 0.1520 |
| Zhang et al. 2018 | 0.4492 0.4458 | 0.3666 0.4339 |
| Arch 1 | 0.0248 0.0647 | 0.0917 0.0701 |
| Arch 2 | 0.4098 0.4431 | 0.3739 0.5105 |
| Arch 2 | 0.4098 0.4785 | 0.3739 0.4862 |

Small baseline accuracy increase from 84.5% to 84.75%.

### Results and Comparison

**Effect of Loss Function Parameters**  Varying loss function parameters again yielded very similar observations as shown in Figure 6 for Architecture 2 and various powers.

The graphs show results for positivity rate ($P(C=1|X)$) as the underlying measure which, as a BPS score corresponds to Statistical Parity. As previously, increasing the power reduced decoupling. Studies with sigmoided loss further demonstrated the same behavior as for the recidivism data, demonstrating the framework’s generality. Here, power 4 on continuous loss achieved the best results.

**Comparison with State of The Art Results**  To compare the approach to recent previous work, we compared it to (Krasanakis et al. 2018) that optimized p-rule (i.e., statistical parity), and to (Zhang, Lemoine, and Mitchell 2018) that used adversarial training to achieve results with closely matching FPR and FNR across genders.

To compare to p-rule, we utilized BPS on prediction rate as our fairness measure. As seen in the previous experiments, applying BPS-based fairness again changed the overall accuracy only to a small degree, yielding a drop from 84.5% to 82.3% using Architecture 1 while p-rule improved from 33.9% to 99.128%. Using Architecture 2 with a power 4 continuous loss and $\alpha = 0.84$, p-rule and accuracy further improved to 99.9% and 83%, as shown in Table 1. As shown, we achieved higher accuracy than (Krasanakis et al. 2018) while maintaining a pRule of approximately 100%.

To compare to the work in (Zhang, Lemoine, and Mitchell 2018) who aim to achieve similar FNR and FPR values for both genders, we utilized a combined $BPS_{FNR}$ and $BPS_{FPR}$ fairness loss. The FPR and FNR using our technique as shown in Table 2 were approximately equal across genders at 0.0589 versus 0.0628 and at 0.4431 versus 0.5105, respectively with Architecture 1 while Architecture 2 further improved $BPS_{FPR}$ and $BPS_{FNR}$ while maintaining low absolute values of FPR and FNR of the two gender-based cohorts and thus outperformed the $BPS_{FPR}$ and $BPS_{FNR}$ in (Zhang, Lemoine, and Mitchell 2018).

### Conclusions

In this work we proposed Bias Parity Score-based fairness metrics and an approach to translate them into corresponding loss functions to be used as regularization terms during training of deep Neural Networks to actively achieve improved fairness between subpopulations. For this, we introduced a family of fairness loss functions and conducted experiments on recidivism prediction to investigate the applicability and behavior of the approach for different hyper-parameters. We demonstrated the generality of the approach and discussed considerations for loss function choices. This work does not depend on changing input or output labels to make fair recommendations while not forsaking accuracy.

Additional experiments performed on a common Adult Income dataset to compare the approach to more specialized state-of-the-art approaches showed that the proposed regularization framework is highly flexible and, when provided...
with an appropriate BPS-based fairness measure can compete with and even outperform these methods.

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