We present a regularization-inspired approach for reducing bias in learned classifiers. In particular, we focus on binary classification tasks over individuals from two populations, where, as our criterion for fairness, we wish to achieve similar false positive rates in both populations, and similar false negative rates in both populations. As a proof of concept, we implement our approach and empirically evaluate its ability to achieve both fairness and accuracy, using the COMPAS scores data for prediction of recidivism.

1 INTRODUCTION
As machine learning-based methods have become increasingly prevalent in decision-making processes that crucially affect people’s lives, accuracy is no longer the sole measure of a learning algorithm’s success. In settings such as loan approvals [19], policing [7], targeted advertisement [20], or criminal risk assessments [12], algorithmic fairness has to be taken into account in order to ensure the absence of discrimination.

Concerns of bias in classification were at the center of a recent media stir regarding the potential hazards of computer algorithms for risk assessment in the criminal justice system [12, 15]. The COMPAS system [9] is a proprietary algorithm developed by Northpointe, widely used in the United States for risk assessment and recidivism prediction. At the center of the controversy was an investigative report by Angwin et al. [12], who observed that although the COMPAS algorithm, when used to label individuals as either high or low risk for recidivism, demonstrated similar accuracy on whites and blacks, the direction of errors made on whites vs. blacks was very different. More specifically, the rate of individuals who were classified as “high risk” but did not re-offend was almost twice as high for black individuals as for whites; among those who were classified as “low risk” and did re-offend, the rate was significantly higher for whites than it was for blacks [10].

This paper proposes a new approach, inspired by the concept of regularization, to mitigating such unfairness in learned classifiers. Our approach is practical and computationally efficient. We demonstrate its promise on the the COMPAS scores dataset [11].

2 RELATED WORK
Approaches to algorithmic fairness generally fall into two categories—situations where no ground truth is known (or perhaps the notion of ground truth is not well-defined), and settings where the algorithm has access to labeled examples on which to learn (perhaps from historical examples). In situations without access to ground truth, typical approaches to fairness include changing the data (e.g., to prevent the learner from having direct/indirect access to attributes that are considered sensitive) [3, 6, 23], or adapting the classifier (e.g., to treat similar people similarly) [5, 13]. When ground truth information is available, we wish to prevent situations where the algorithm errs in favor of one group within the population. In the specific context of criminal risk assessments, Berk et al. [2] give a thorough comparison of various recently introduced fairness notions.

The fairness objective we adopt in this paper, that of matching false positive rates (FPR) across populations and matching false negative rates (FNR) across populations in classification tasks, was recently formalized by Hardt et al. [8]. In particular, they propose two definitions: equal opportunity (equal false negative rates across all groups, when “positive” is the desirable label), and equalized odds (matching the rates of both false negatives and false positives). As Chouldechova [4] points out, when learning a predictor over a dataset which consists of groups with different base rates (in the COMPAS scenario, a different percentage of re-offenders among whites vs. blacks), it is commonly the case that false positive errors (error against) are more likely on the group with the higher base rate, while false negatives (error in favor) are more likely on the group with the lower base rate. Both Kleinberg et al. [14] and Chouldechova show that there are unavoidable trade-offs in the determination of risk scores, and that there are a number of reasonable desiderata that cannot in general be achieved simultaneously [1].

That being said, learning fair classifiers remains a practical problem that must be solved—decisions must be taken, and trade-offs must be made. To this end, there have been a number of recent specific technical proposals for achieving algorithmic fairness. Hardt et al. [8] propose a post-hoc approach, randomly flipping some of the decisions a given (unfair) trained classifier in order to ensure equalized odds or equal opportunity. Although this is an elegant and appealing idea, followup work of Woodworth et al. [21], shows that the Hardt et al. approach may yield a highly sub-optimal classifier in certain cases. As Woodworth et al. [21] conclude, post-processing an unfair classifier may not be sufficient to achieve the best possible combination of fairness and accuracy; perhaps, at least in some settings, fairness considerations must be actively integrated into the learning process, as also suggested by Berk et al. [2].

Bilal-Zafar et al. [22] give one such approach to integrating fairness into learning, with the goal of matching FPR and FNR. Their algorithm relaxes the (non-convex) fairness constraints into proxy information between the prediction and the sensitive attribute.
The present work introduces a new type of regularization-inspired method, designed to enforce the equalized odds criterion. Our approach is easy to use, and quite general (requiring only mild conditions such as differentiabilility of the scoring model). In our empirical section, we compare the performance of our approach with the algorithms of Bilal-Zafar et al. [22] and Hardt et al. [8], on the COMPAS dataset [11].

3 FAIR LEARNING

In classical machine learning theory, the objective is typically to minimize a loss function that reflects the amount of errors the chosen classifier makes on a fresh sample of data. One might naturally adjust the loss function to penalize differently for different sorts of errors (false positive or false negative, in the binary case), however, a priori, the classical approach does not do anything to control the distribution of errors across different subpopulations.

We now introduce notation that will allow us to formalize our fairness objectives. We assume that our data points \((x, y)\) are drawn i.i.d. from a joint distribution \((X, Y)\) with the following interpretation: \(x \in \mathbb{R}^d\) represents the features of an individual, the first feature (which we assume to be binary) represents a protected attribute (e.g., black vs. white) and we write it as \(a \in \{0, 1\}\), and \(y \in \{0, 1\}\) represents the true label (e.g., “re-offended” or “did not re-offend”). We write \(\hat{Y} : \mathbb{R}^d \rightarrow \{0, 1\}\) for a classifier which, given an individual’s features including her protected attribute, predicts her label.

Then, given a labeled data set \(S = (x_i, y_i)_{i=1}^n\) and a classifier \(\hat{Y}\), writing \(\hat{y}_i = \hat{Y}(x_i)\), we can formally define the FPR and FNR as follows:

\[
\text{FPR} = \frac{\{i : \hat{y}_i = 1, y_i = 0\}}{\{i : y_i = 0\}} \\
\text{FNR} = \frac{\{i : \hat{y}_i = 0, y_i = 1\}}{\{i : y_i = 1\}}
\]

The next definitions are adopted from Hardt et al. [8]; here we abuse notation and, when clear, we write \(\hat{Y}\) not just for the classifier, but for the random variable over outputs it induces.

Definition 3.1. (Equalized odds). We say a classifier \(\hat{Y}\) satisfies equalized odds with respect to \(A\) and \(Y\), if \(\hat{Y}\) and \(A\) are independent conditioned on \(Y\).

In the binary case, equalized odds can be written as

\[
\Pr[\hat{Y} = 1 | A = 0, Y = y] = \Pr[\hat{Y} = 1 | A = 1, Y = y], \quad y \in \{0, 1\}.
\]

One can relax the equalized odds notion to focus only on positive outcomes:

Definition 3.2. (Equal opportunity). We say a classifier \(\hat{Y}\) satisfies equal opportunity with respect to \(A\) and \(Y\) if

\[
\Pr[\hat{Y} = 1 | A = 0, Y = 1] = \Pr[\hat{Y} = 1 | A = 1, Y = 1].
\]

4 REGULARIZATION-INSPIRED APPROACH FOR FAIRNESS

Our approach to learning a fair classifier integrates fairness into the learning process. The approach we take is inspired by the concept of \textit{regularization}, a common technique in machine learning for ensuring the learned classifier’s stability and preventing overfitting [16]; the basic idea is that a term (known as a \textit{regularizer}) is added to the loss function to penalize complexity in the selected solution. Traditionally, the penalty term is a function only of the learned hypothesis (as is the case, for example, with L2 regularization). Here, we introduce a penalty which is not only hypothesis-dependent, but is also data-dependent. As our goal is to learn a classifier that (nearly) achieves the equalized odds criterion, we define two regularizers that capture the difference in the FPR and FNR (respectively) between the groups in the population.

We denote our dataset by \(S = (x_i, y_i)_{i=1}^n\). For clarity, in what follows, we will denote the two possible protected attributes as \(A\) and \(B\). We will partition our dataset into the following groups:

- \(N_A^{pos} = \{i : a_i = A, y_i = 1\}\)
- \(N_A^{neg} = \{i : a_i = A, y_i = 0\}\)
- \(N_B^{pos} = \{i : a_i = B, y_i = 1\}\)
- \(N_B^{neg} = \{i : a_i = B, y_i = 0\}\)
- \(S^{pos} = N_A^{pos} \cup N_B^{pos}\)
- \(S^{neg} = N_A^{neg} \cup N_B^{neg}\)

Following the notions of fairness from the previous section, we will consider the difference in FPR and the difference in FNR within the groups \(A\) and \(B\):

\[
[FPR(A) - FPR(B)] = \left| \frac{\sum_{i \in N_A^{pos}} \hat{y}_i}{N_A^{pos}} - \frac{\sum_{i \in N_B^{pos}} \hat{y}_i}{N_B^{pos}} \right|
\]

The difference in the FPR of the two groups can be expressed in a similar fashion.

We focus our attention on boundary-based classifiers, which are trained in the form of a decision boundary in the feature space. Such classifiers define the distance of each sample from the boundary, and binary classification is performed using the sign of this distance. We denote a boundary-based classifier by \(\hat{f} = g \circ h : \mathbb{R}^d \rightarrow [0, 1]\), where \(h : \mathbb{R}^d \rightarrow [0, 1]\) maps a sample to its distance from the decision boundary, and \(g : [0, 1] \rightarrow \{0, 1\}\) performs the cut-off according to a cut-off parameter \(c\).

In our context, the 0-1 loss is \(L_{0-1}(\hat{y}, y) = \mathbb{1}_{\hat{y} \neq y} = \mathbb{1}_{(f(x)) \neq y}\). Since the 0-1 loss is non-differentiable, we use the margin \(L(x, y) = y - h(y(x))\) instead as a proxy for achieving equalized odds (with respect to the original 0-1 loss).

We define the FNR penalty term to be

\[
R_{FNR}(\theta; S^{pos}) = \frac{\sum_{i \in N_A^{pos}} h_\theta(x_i)}{N_A^{pos}} + \frac{\sum_{i \in N_B^{pos}} h_\theta(x_i)}{N_B^{pos}}.
\]

The FPR penalty term can be derived in a similar fashion:

\[
R_{FPR}(\theta; S^{neg}) = \frac{\sum_{i \in N_A^{neg}} h_\theta(x_i)}{N_A^{neg}} - \frac{\sum_{i \in N_B^{neg}} h_\theta(x_i)}{N_B^{neg}}.
\]
5 CASE STUDY: FAIR CLASSIFICATION USING LOGISTIC REGRESSION

In this section, we instantiate our method of penalization for achieving fairness in the context of logistic regression. In logistic regression, we fit the parameters \( \theta \in \mathbb{R}^d \) of a model \( h_\theta : \mathbb{R}^d \to [0, 1] \), s.t. \( h_\theta(x) = \frac{1}{1 + e^{\theta^T x}} \). Binary prediction is done using a cut-off parameter.

Given a set of probabilistic assumptions, we can fit the parameters of logistic regression by maximizing the log-likelihood function of \( \theta \) [17]. In what follows, we use \( \text{Pr}[y = 1 \mid x; \theta] = h_\theta(x) \), and \( \text{Pr}[y = 0 \mid x; \theta] = 1 - h_\theta(x) \).

The log-likelihood of \( \theta \) in this case is

\[
ll(\theta; S) = \sum_{i=1}^{n} y_i \log(h_\theta(x_i)) + (1 - y_i) \log(1 - h_\theta(x_i)).
\]

We wish to solve the following optimization problem:

\[
\min_{\theta} \quad -ll(\theta; S) + C_1 |FPR(A) - FPR(B)| + C_2 |FN(R(A) - FN(R)(B))| + \frac{1}{2} C_3 ||\theta||_2^2.
\]

\( C_1 > 0, C_2 > 0, C_3 > 0 \) are constants to be tuned according to the desired trade-off between the components (likelihood, penalization for unfairness, standard regularization). Relaxing the 0-1 loss in the FPR, FNR differences into the margin between \( h_\theta(x) \) and \( y \), we get the following optimization problem:

\[
\min_{\theta} \quad -ll(\theta; S) + \frac{1}{2} C_3 ||\theta||_2^2 + C_1 R_{FPR}(\theta; S^{-y}) + C_2 R_{FN(R)}(\theta; S^{\text{pos}}) + C_2 R_{FN(R)}(\theta; S^{\text{neg}}) + C_1 R_{FPR}(\theta; S^{\text{neg}}).
\]

While \( ll(\theta; S) \) is convex in \( \theta, |FPR(A) - FPR(B)|, |FN(R(A) - FN(R)(B))| \) are not. Using the described proxy terms, we are likely to converge to a (local) minimum in terms of the original problem. Effectively, our (relaxed) penalizers are set under the assumption that the distance between the prediction and the true label serves as a reliable proxy for the 0-1 loss, i.e., when predictions are done with high confidence, close to 0 or 1, far from the decision boundary. The terms are minimized when the average distance is the same for both groups in \( S^{\text{pos}} \) and for both groups in \( S^{\text{neg}} \).

In order to maximize \( ll(\theta; S) \), and at the same time seek fair solutions, we use the following gradient update rule:

\[
\theta^{i+1} = \theta^i - \eta_t (\nabla \theta(-ll) + C_1 \nabla \theta(R_{FPR}) + C_2 \nabla \theta(R_{FN(R)}) + C_3 \theta)
\]

Where \( \eta_t \) is the learning rate (gradient step size).

6 EXPERIMENTS

We put our approach to the test by training (and penalizing for unfairness) a logistic regressor on real life-data—the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) records from Broward County, Florida 2013-2014, made available online by ProPublica [11]. Tables 1 and 2, from [22], describe statistics of the dataset, and the features that were used, along with their possible values.

Table 1: Statistics of the ProPublica COMPAS data.

| Feature          | Description                   | Reoffended (y = 1) | No re-offense (y = 0) | Total |
|------------------|-------------------------------|-------------------|----------------------|-------|
| Black            |                               | 1661              | 1514                 | 3175  |
| White            |                               | 822               | 1281                 | 2103  |
| Total            |                               | 2483              | 2795                 | 5278  |

Table 2: Description of features used from ProPublica COMPAS data.

| Feature          | Description                          |
|------------------|--------------------------------------|
| Age Category     | < 25, between 25 and 45, > 45       |
| Gender           | Male or Female                       |
| Race             | White or Black                       |
| Priors Count     | 0–37                                 |
| Charge Degree    | Misconduct or Felony                 |
| 2-year-rec.      | Whether or not the (target feature)  |
|                  | defendant recidivated within two years|

In Table 3, we compare the performance of our approach with that of three other techniques from the literature. For comparison, we also present the performance of vanilla logistic regression, with no fairness constraints. All of the listed methods were trained based on logistic regression. Results are reported as the averages of 5 different runs, each time splitting data evenly and randomly into a training set and a testing (hold-out) set. Results for Bilal-Zafar et al., Bilal-Zafar et al. baseline, and Hardt et al. appear here as reported in [22]. In the table, we report not only the difference across groups of the FPR and FNR, but the direction: \( D_{\text{FPR}} = FPR(\text{Blacks}) - FPR(\text{Whites}) \), \( D_{\text{FNR}} = FNR(\text{Blacks}) - FNR(\text{Whites}) \).

We briefly describe the other algorithmic approaches:

**Bilal-Zafar et al.** [22] performs optimization by considering a proxy for the bias: the covariance between the samples’ sensitive attributes and the signed distance between the feature vectors of misclassified users and the classifier decision boundary.

**Bilal-Zafar et al. Baseline** [22] tries to enforce equal FP/FN rates on the different groups by introducing different penalties for misclassified data points with different sensitive attribute values during the training phase.

**Hardt et al.** [8] performs post-processing on a standard trained (unfair) logistic regressor, picking different decision thresholds for different groups, and possibly adding randomization.

We find that the baseline (unfair) logistic regressor results in significant unfairness, with \( D_{\text{FPR}} = 0.187 \) and \( D_{\text{FNR}} = -0.326 \). The overall accuracy of this classifier measured on the hold-out data was 0.665.

Our method (using cut-off \( c = 0.5 \)) succeeds in eliminating bias almost completely on the given dataset. We achieve very low difference rates when regularizing for achieving each of the FPR and FNR criteria individually, and also for both. The Hardt et al. [8] approach as reported removes a smaller portion of the bias in the different scenarios, however for FP/FN constraints alone, it provides higher accuracy rates. The Bilal-Zafar et al. [22] approach as
reported retains significant bias (in most cases), but in some cases achieves slightly superior accuracy rates to the methods above.

These performance comparisons are incomplete in the sense that each of the compared techniques has the potential to trade off between accuracy and fairness, using some degree of parameter tuning: what we report here is only one point on the achievable trade-off frontier for each algorithm. The "correct" trade-off, and, in particular, the best manner in which to weigh unfairness in the FPR against unfairness in the FNR, are matters of opinion. We have chosen to report our method’s performance under parameters designed to very aggressively mitigate unfairness, at some cost to the accuracy.

It would certainly be desirable to evaluate these and other approaches to fair learning on other datasets and on different tasks, particularly on larger datasets, which might afford both greater accuracy and better bias-reduction. The present empirical evaluations, however, suggest that our regularization-based approach provides a new tool worthy of consideration—we succeed in almost entirely eliminating bias on the hold-out set, at a modest price in terms of accuracy.

Due to the fact that our true objective includes the original non-convex penalization terms, our approach does not carry any formal guarantees. However, the ease of implementation, generality, and empirical results are encouraging. Figure 1 illustrates the rate of convergence to a fair, accurate classifier on this dataset. In terms of computation costs, given that at each iteration we must calculate the gradient according to the FPR and FNR regularizers, we are required to predict the labels for the entire training set at each step. However, this does not pose a computational burden, as it is already required by the (classic) gradient descent algorithm in our logistic regressor fitting scheme. Furthermore, when given a sufficiently large dataset (one or two orders of magnitude larger than the one currently available for the COMPAS scores data), this could be relaxed to sampling only a mini-batch of samples from the training data set at each iteration (much as is done in stochastic gradient descent).

| FPR constraints | FNR constraints | Both constraints |
|-----------------|-----------------|-----------------|
| **Our Method**  | 0.646 0.0006 −0.0084 | 0.650 −0.010 −0.0008 | 0.646 0.0006 −0.0084 |
| Bilal-Zafar et al. [22] | 0.660 0.06 −0.14 | 0.662 0.03 −0.10 | 0.661 0.03 −0.11 |
| Bilal-Zafar et al. Baseline [22] | 0.643 0.03 −0.11 | 0.660 0.00 −0.07 | 0.660 0.01 −0.09 |
| Hardt et al. [8] | 0.659 0.02 −0.08 | 0.653 −0.06 −0.01 | 0.645 −0.01 −0.01 |
| Logistic Regression (No fairness Constraints) | 0.665 0.187 −0.326 | 0.665 0.187 −0.326 | 0.665 0.187 −0.326 |

Table 3: Performance comparison. Accuracy, FPR difference and FNR difference as evaluated on the hold-out set.

![Figure 1](image-url)
8 ACKNOWLEDGEMENTS

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