Mitigation of Bias in Data to Achieve Fairness-Aware Classification

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Abstract. Machine learning has seen a rapid growth in recent years in a variety of sectors and services. Automated decision making uses machine learning techniques to remove human interference . It predicts the decision based on past experience of similar situation but makes it challenging because the predictions need to match with accuracy. However, one its major concerns is misclassification errors caused due to bias in the training data. These errors put certain sensitive groups at an unfair advantage creating different types of unfairness: disparate impact, disparate treatment and disparate mistreatment. Therefore fairness concerns have become increasingly important. In this paper, we discuss some of the current methodologies developed recently to mitigate bias and achieve fairness like massaging of the labels, group thresholding, covariance and adaptive sensitive reweighting. We learn that it is unsufficient to remove the sensitive information for eliminating biases because it has an indirect correlation. We analyse and compare the performance of these methods based on different fairness metrics for three datasets. We observe that adaptive sensitive reweighting model achieves better or similar trade-offs between accuracy and unfairness mitigation when compared to other fairness-aware approaches.

Keywords: Machine Learning · Classifier · Unfairness

1 Introduction

Machine learning is a brach of artificial intelligence in which systems can learn from data or experience to make decisions with minimal human intervention. It is growing across many fields because it can analyze large amount of data to identify patterns in a short interval of time. Some of the major appplications are: speech recognition, email spam and malware filtering, search engine result refininng and automated decisition making process and so on.
With the increase in shift towards automated decision making process of machine learning in various services that affects people's lives, there is an immense need for fairness concerns. The decisions should be unbiased and nondiscriminatory in relation to the sensitive features such as gender, sex, religion, race and so on. These sensitive features should be carefully treated, and if not constrained well, it leads to bias in the decision making process which gives an unfair treatment to certain people based on sensitive attributes. For example, training a logistic

regression classifier on the ProPublica COMPAS dataset of crime recidivism [4] yields differences between black and white defendants that amount to 17% for false positives and 25% for false negative rates [9].
Researchers have previously recognized that classification is often caused by data rather than classifier [2] [8]. Elimination of sensitive features from data is insufficient for avoiding misclassification, due to the indirect influencec of the sensitive information. For example, when determining credit scoring, let us remove the sensitive feature race. People of a specific race live in a specific area and address is used as a feature for training the prediction model, then we can expect unfair determinations even though race is not considered. This is called a red-lining effect [1] or indirect discrimination [10]. This happens due to inherent inability to treat datasets and we discuss some of the reasons in the section 5.
In this paper, we discuss the following methods to mitigate bias in the training data:

- Group Thresholding: The goal of this method is to predict a true outcome Y from features X based on labeled training data, while ensuring the prediction is "non-discriminatory" with respect to a specified protected attribute A [3].
- Regularizer: Adjusting regularizers to reduce indirect prejudice (statistical dependence between sensitive information) to restrict learner's beahviour [6].
- Covariance : Convex concave programming is used to reduce the different unfairness measures discussed in the next section [11] [12].
- Adaptive-Sensitive Reweighting : Assumes that there exists an underlying set of class labels corresponding to training samples, that if, predicted would yield unbiased classfification with respect to a fairness objective. Weights are obtained using the CULEP model that stands for Convex Underlying Label Error Pertubation [9].

The structure of the paper is as follows: Section 2 discusses the background and related work. Section 3 constitutes the different methodolgies explained in detail. Section 4 provides information about dataset editing deficiencies. Section 5 provides information on the experiments conducted along with the results depicting the performance analysis of each of the methods. Section 6 concludes the paper summarizing the results and the future work.

2 Background and Related Work

In this section we first elaborate on the different types of unfairness and their corresponding metrics used to measure them in automated decision making process. Throughout this paper, we consider binary classifiers that produce label estimations $\tilde{y}_i \in \{0, 1\}$ for samples i of features x_i and labels $y_i \in \{0, 1\}$. If a certain group of sample is associated with the sensitive attributes then they are considered as sensitive samples S and the non-sensitive complement S'.

2.1 Types of Unfairness

Classification unfairness is often expressed through the notions of disparate treatment, disparate impact and disparate mistreatment [12]. Let us take an example of [11] to illustrate the three types of unfairness. The classifier needs to decide whether or not to stop a person on suspicion of having an illegal weapon based on set of features like bulge in clothing and proximity to a crime scene. The ground truth tells whether a person actually possesses an illegal weapon or not.

User Attributes			Ground Truth (Has Weapon)	Classifier's Decision to Stop		
Sensitive	Non-Sensitive					
Gender	Clothing Bulge	Prox Crime		C_1	C_2	C_3
Male1	1	0	y	1	1	1
Male2	1	0	y	1	1	0
Male3	0	1	n	1	0	1
Female1	1	1	y	1	0	1
Female2	1	0	n	1	1	1
Female3	0	0	y	0	1	0

Table 1. Decision of three classifiers (C_1, C_2 and C_3) on whether (1) or not (0) to stop a pedestrian on the suspicion of possessing an illegal weapon

1. Disparate treatment elimination: ability of a trained classifier to yield the same output $\hat{y}_i$ for features x_i irrespective of the sample belonging to the sensitive group S or the non-sensitive group S' [9].

$$P(\hat{y}_i|x_i, i \in S) = P(\hat{y}_i|x_i) \tag{1}$$

As seen in 1, C_2 and C_3 are unfair due to disparate treatment since C_2's and C_3's decisions for Male1 and Female1 are different even though they have the same values of non-sensitive attributes [11].

2. Disparate impact elimination: ability of a classifier to achieve statistical parity —citekamiran2012data [5] [6] i.e, assigns the same portion of the users to a class for sensitive and non/sensitive groups [9].

$$P(\hat{y}_i = 1|i \in S) = P(\hat{y}_i = 1|i \notin S) \tag{2}$$

As depicted in Fig. 1, C_1 is unfair due to disparate impact because the fraction of males and females that were stopped are different (1.0 and 0.66 respectively) [11].

3. Disparate mistreatment elimination: ability of a classifier to achieve equal misclassification rates across sound ground truth tables(i.e. not suffering from dataset construction problems, such as historical biases) [12] [11] [9]. For example, if the race is a sensitive attribute for prediction of criminal behaviour [4], disparate mistreatment elimination would ensure the same error rate between white and non-white defendants [9]. The most common mistreatment constraint is equal number of false positive rates(FPR) and

false negative rates (FNR).

$$\begin{aligned} P(\hat{y_i} \neq y_i | y_i = 1, i \in S) = P(\hat{y_i} = 1 | i \neq y_i | y_i = 1, i \notin S) \\ P(\hat{y_i} \neq y_i | y_i = 0, i \in S) = P(\hat{y_i} = 1 | i \neq y_i | y_i = 0, i \notin S) \end{aligned} \tag{3}$$

Fig. 1 shows that C_1 and C_2 are unfair due to disparate mistreatment because their rate of erroneous decisions for males and females are different: C_1 has different false negatives for males and females (0.0 and 0.5 respectively) [11].

2.2 A Subsection Sample

Please note that the first paragraph of a section or subsection is not indented. The first paragraph that follows a table, figure, equation etc. does not need an indent, either [7].

Subsequent paragraphs, however, are indented.

Sample Heading (Third Level) Only two levels of headings should be numbered. Lower level headings remain unnumbered; they are formatted as run-in headings.

Sample Heading (Fourth Level) The contribution should contain no more than four levels of headings. Table 2 gives a summary of all heading levels.

Table 2. Table captions should be placed above the tables.

Heading level	Example	Font size and style
Title (centered)	**Lecture Notes**	14 point, bold
1st-level heading	**1 Introduction**	12 point, bold
2nd-level heading	**2.1 Printing Area**	10 point, bold
3rd-level heading	**Run-in Heading in Bold.** Text follows	10 point, bold
4th-level heading	*Lowest Level Heading.* Text follows	10 point, italic

Displayed equations are centered and set on a separate line.

$$x + y = z \tag{4}$$

Please try to avoid rasterized images for line-art diagrams and schemas. Whenever possible, use vector graphics instead (see Fig. 1).

Theorem 1. *This is a sample theorem. The run-in heading is set in bold, while the following text appears in italics. Definitions, lemmas, propositions, and corollaries are styled the same way.*

Proof. Proofs, examples, and remarks have the initial word in italics, while the following text appears in normal font.

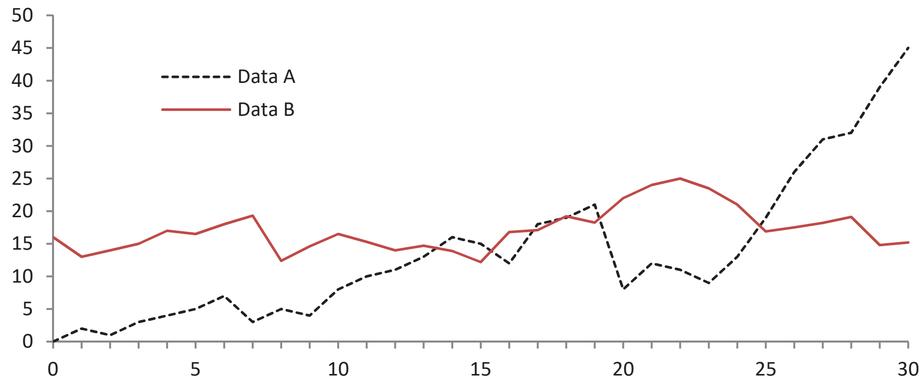

Fig. 1. A figure caption is always placed below the illustration. Please note that short captions are centered, while long ones are justified by the macro package automatically.

For citations of references, we prefer the use of square brackets and consecutive numbers. Citations using labels or the author/year convention are also acceptable. The following bibliography provides a sample reference list with entries for journal articles [**?**], an LNCS chapter [**?**], a book [**?**], proceedings without editors [**?**], and a homepage [**?**]. Multiple citations are grouped [**?**,**?**,**?**], [**?**,**?**,**?**,**?**].

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