On Fair Classification with Mostly Private Sensitive Attributes

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ABSTRACT

Machine learning models have demonstrated promising performance in many areas. However, the concerns that they can be biased against specific groups hinder their adoption in high-stake applications. Thus it is essential to ensure fairness in machine learning models. Most of the previous efforts require access to sensitive attributes for mitigating bias. Nonetheless, it is often infeasible to obtain large scale of data with sensitive attributes due to people’s increasing awareness of privacy and the legal compliance. Therefore, an important research question is how to make fair predictions under privacy? In this paper, we study a novel problem on fair classification in a semi-private setting, where most of the sensitive attributes are private and only a small amount of clean sensitive attributes are available. To this end, we propose a novel framework FairSP that can first learn to correct the noisy sensitive attributes under privacy guarantee via exploiting the limited clean sensitive attributes. Then, it jointly models the corrected and clean data in an adversarial way for debiasing and prediction. Theoretical analysis shows that the proposed model can ensure fairness when most of the sensitive attributes are private. Experimental results on real-world datasets demonstrate the effectiveness of the proposed model for making fair predictions under privacy and maintaining high accuracy.

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1 INTRODUCTION

Machine learning has demonstrated promising performances in a variety of high-stake applications such as disease identification [39], crime prediction [37], and loan application filtering [21]. However, in these applications, an emerging concern is that the prediction derived from machine learning can often be biased and unfair to individuals from specific (and often marginalized) groups. For example, in medical analysis, racial bias towards minorized groups exists in electronic health record which can lead to disparate treatments [39]. In addition, a recent report from Forbes shows that the machine learning bias has caused 80% of black mortgage applicants to be denied\(^1\). Such bias and discrimination can have detrimental societal effects that weaken the public trust among individuals, groups and the society. Therefore, it is important to ensure fairness in machine learning for social good.

The recent advancements of fairness machine learning—aiming to develop effective algorithms to achieve fairness and maintain good prediction performance—has attracted increasing attention [26, 35]. The majority of existing fair machine learning models require the access to sensitive attributes (e.g., race, gender) to preprocess the training data, regularize the model design or postprocess the prediction results to derive fair predictions [16, 32]. For example, Madras et al. propose to use adversarial learning on sensitive attributes and prediction labels for debiasing classification results [32]. Kamiran et al. propose to assign the weights of each training sample differently via reweighting w.r.t. sensitive attributes to reduce bias within the data distribution [26]. However, sensitive attributes are often hard to collect or properly protected due to people’s increasing awareness of privacy and the legal compliance such as Electronic Communications Privacy Act (ECPA)\(^2\) and General Data Protection Regulation (GDPR)\(^3\) that restrict the direct access to sensitive attributes. Due to such restrictions, analysts may access to mostly private sensitive attributes processed by privacy algorithms such as Differential Privacy (DP) [17] or Local Differential Privacy (LDP) [11]. Such privacy mechanisms are widely deployed in data analytics and can provide strong privacy guarantee to the data by adding noise [19, 33]. In addition, it is often possible to collect a small amount of sensitive attributes due to people’s voluntary and organizations’ desire to build effective models under certain circumstances [7]. It is critical to consider the limited clean sensitive attributes and the privacy-protected sensitive attributes simultaneously for fair machine learning.

However, it is non-trivial to build fair machine learning models with mostly private sensitive attributes. First, private sensitive attributes are noisy and directly applying conventional debiasing techniques on them can lead to sub-optimal performances [30, 41]. For example, Lamy et al. proposes a noisy-tolerant fairness model that can estimate the true sensitive attributes in the presence of class-dependent noise [30]. Wang et al. explore a robust fairness criteria using soft sensitive attributes with distributionally robust optimization (DRO) [41]. However, these initial efforts assume that only noisy sensitive attributes are available and there are specific types of noise model between the true sensitive attributes and noisy ones. Second, incorporating the clean sensitive attributes may be helpful while the amount is limited. Such limited instances with

\(^1\)https://www.forbes.com/sites/korihale/2021/09/02/ai-bias-caused-80-of-black-mortgage-applicants-to-be-denied/?sh=3865fbc136fe
\(^2\)https://bja.aip.gov/program/it/privacy-civil-liberties/authorities/statutes/1285
\(^3\)https://www.consumerfinance.gov/rules-policy/regulations/1002/5/
clean sensitive attributes are inadequate for training a fair classification model directly as they can easily overfit the small amount of data with sensitive attributes [13].

Therefore, we propose to study a novel problem of fair classification with semi-private sensitive attributes. In essence, we investigate the following challenges: (1) how to correct the private sensitive attributes by properly leveraging the limited clean sensitive attributes; and (2) how to perform classification accurately and satisfy fairness criteria under privacy. To tackle these challenges, we propose a novel framework FAIRSP for fair classification with semi-private sensitive attributes. FAIRSP first learn to correct noisy sensitive attributes under privacy guarantee via exploiting the limited clean sensitive attributes. Then, it jointly models the corrected and clean data in an adversarial way for debiasing and prediction.

Our main contributions are summarized as follows:

- We study a novel problem of fair classification with semi-private sensitive attributes.
- We provide a new end-to-end framework FAIRSP which simultaneously derive corrected sensitive attributes from private ones and learn a fair classifier with adversarial learning on both clean and corrected data.
- We conduct theoretic analysis demonstrating the fairness can be achieved with mostly private sensitive attributes.
- We perform extensive experiments on real-world datasets to demonstrate the effectiveness of the proposed method for fair classification in a semi-private setting.

2 RELATED WORK

In this section, we briefly describe the related work on (1) Fairness in machine learning; and (2) Differential privacy in machine learning.

2.1 Fairness in Machine Learning

Recent research on fairness in machine learning has drawn significant attention to develop effective algorithms to achieve fairness and maintain good prediction performance. Existing methods generally focus on individual fairness [27] or group fairness [22, 45]. Individual fairness requires the model to give similar predictions to similar individuals [8, 10]. In group fairness, the similar predictions are desired among multiple groups categorized by a specific sensitive attribute (e.g., gender). Other niche notions of fairness includes subgroup fairness [28] and Max-Min fairness [29], which aims to maximize the minimum expected utility across groups. The majority of existing debiasing techniques have been applied at different stages of a machine learning model [35]: (1) Pre-processing approaches [26] apply dedicated transformations on the original dataset to remove intrinsic discrimination and obtain unbiased training data prior modelling; (2) In-processing approaches [2, 6] tackle this issue by incorporating fairness constraints or fairness-related objective functions to the design of machine learning models; and (3) Post-processing approaches [16] revise the biased prediction labels by debiasing mechanisms after the model training. Such machine learning methods generally require the access to sensitive attributes, which is often infeasible in practice. Very few recent work study fairness with limited or private sensitive attributes available. For example, Zhao et al. explore and use the related features as proxies of the sensitive attribute to achieve improve fairness prediction when sensitive attributes are unknown [46]. Dai et al. propose to achieve fairness on graph neural networks when the available sensitive attributes are private [12]. However, these methods may design for a specific type of data (e.g., graphs) or not considering the sensitive attributes being private.

In this paper, we study a novel problem of fairness with semi-private sensitive attributes, and propose a new framework that can jointly learn from a limited amount of clean sensitive attributes and most private ones to achieve fair classification performances.

2.2 Differential Privacy in Machine Learning

Different from traditional anonymization models [18, 31], differential privacy (DP) [15, 17] ensures that for any pair of neighboring inputs, the probability of generating the same output is within a small multiple of each other. DP provides strong privacy guarantee regardless of the adversaries’ prior knowledge [33], which can protect user privacy in various machine learning tasks such as supervised learning and unsupervised learning [24]. Differentially private machine learning models can be generally categorized into two categories based on the mechanism of adding noise: the Laplace/Gaussian/exponential mechanism and the output/objective perturbation mechanism [19]. For example, a ε-differentially private naïve Bayes model mechanism is proposed by adding Laplace noise to the counts of instances [40]. Abadi et al. propose to add noise to training objective of stochastic gradient descent to ensure differential privacy with proper guarantee [1]. Recently, local differential privacy (LDP) has been extensively studied in the distributed setting such that private data can be locally perturbed without a trusted aggregator [11, 42]. Due to the inherent connection of privacy and fairness (e.g., protecting or debiasing on user sensitive attributes), several recent work look into trade-offs and mutual risks between privacy and fairness [3, 9]. Other approaches aim to ensure both DP and fairness while preserving good utility [43], or learn fair models with only private data [30, 36, 41]. For example, Lamy et al. proposes a noisy-tolerant fairness model that can estimate the true sensitive attributes effectively in the presence of class-dependent noise [30]. Wang et al. explore a robust fairness criteria using soft sensitive attributes with distributionally robust optimization (DRO) [41]. However, these initial efforts assume that only noisy sensitive attributes are available and a specific type of noise model between the true sensitive attributes and noisy ones.

In this paper, investigate a new and practical semi-private setting for fair classification where most sensitive attributes are protected with differential privacy and only a limited clean sensitive attributes are available.

3 ASSESSING THE INTERSECTION OF PRIVACY AND FAIRNESS

In this section, we first introduce the definition of local differential privacy. Then we conduct a preliminary pilot study to assess the impact of privacy on fairness performances.

3.1 Local Differential Privacy Guarantee

Local differential privacy (LDP) mechanism provides guarantees by directly injecting noises into data before aggregation. The formal Local differential privacy definition is as follows:
**Definition 3.1.** Given \( \epsilon > 0 \), a randomized mechanism \( M \) satisfies \( \epsilon \)-local differential privacy, if for all possible pairs of users’ private data \( s_i \) and \( s_j \), the following equation is met:

\[
\forall a \in \text{Range}(M) : \frac{P(M(s_i) = a)}{P(M(s_j) = a)} \leq e^\epsilon
\]

where Range(\( M \)) denotes every possible output of \( M \).

The parameter \( \epsilon \) denotes the privacy budget to balance the utility and privacy guarantee of the model. A smaller \( \epsilon \) represents stronger privacy guarantees and weaker utility. In order to ensure the privacy of sensitive attributes, we obtain the following lemma:

**Lemma 3.2.** To achieve \( \epsilon \)-local differential privacy on the binary sensitive attribute, we can randomly flip the sensitive attributes with a probability of

\[
p = \frac{\exp(\epsilon) + 1}{\exp(\epsilon) + 2}
\]

The detailed proof of the lemma refers to the lemma 3 in [30].

Based on the lemma, we can obtain differentially private sensitive attributes by flipping at a certain probability. If the flipping probability satisfies the condition that \( p = \frac{\exp(\epsilon) + 1}{\exp(\epsilon) + 2} \), then the sensitive attributes have \( \epsilon \)-local differential privacy guarantee.

### 3.2 The Impact of Privacy on Fairness

![Figure 1: Assessing the impact of fairness performances under private data.](image)

(a) ADULT  
(b) COMPAS

In this subsection, we investigate the impact of local differential privacy on fairness. The original local differential privacy mechanism focuses on the trade-off between privacy and utility. As for the impact of local differential privacy on fairness, we conduct two groups of preliminary experiments. For the first group of experiments, we study the impact of LDP on models like vanilla multi-layer perceptron (MLP) network without debiasing. For the second group of experiments, we study the impact of LDP on debiasing models like adversarial debiasing. We conduct each group of experiments on two datasets ADULT and COMPAS, which are two typical fairness datasets. We set six privacy budgets for each group of experiments as 0.5, 1, 1.5, 2, 2.5, 3. We follow Lemma 3.2 to implement the LDP mechanism. From Figure 1, we have following observations from the experiments:

- For models like MLP without debiasing, stronger privacy guarantees improve the fairness performance. Based on the results on two datasets, we can see that with lower privacy budget, the model without debiasing have better fairness performance on \( \Delta E_O \). With stronger privacy guarantee, the privacy budget decreases, the flipping probability increases, there is more noise injected into the sensitive attributes of the dataset. With more noisy sensitive attributes, the models like MLP network without debiasing cannot learn the explicit bias contained in the sensitive attributes.

- For debiasing models like adversarial debiasing, stronger privacy guarantee leads to worse fairness performance. From Figure 1, we can observe that with lower privacy budget, the debiasing models like adversarial debiasing have worse fairness performance on \( \Delta E_O \) over two datasets. This is because debiasing models like adversarial debiasing need to explicitly leverage sensitive attributes for debiasing. With stronger privacy guarantee, there is lower privacy budget and more noisy sensitive attributes, which causes that the debiasing models like adversarial debiasing cannot mitigating the implicit fairness bias contained in non-sensitive attributes.

Based on the preliminary experiments, if we want to improve the fairness performance of debiasing models like adversarial debiasing under LDP, one method is to reduce the noise in sensitive attributes.

### 4 FAIR CLASSIFICATION WITH SEMI-PRIVATE SENSITIVE ATTRIBUTES

In this section, we first explain the setting and motivation of semi-private sensitive attributes. Then we formulate the problem of fair classification with semi-private sensitive attributes.

#### 4.1 Semi-Private Sensitive Attributes

Training fair classification models with only private sensitive attributes is challenging since they have high capacity to fit and memorize the noise. Recent work shows that if the noisy sensitive attributes are used to learn fair models, the learned model might have severe bias [30, 41]. Hence, it is useful to also incorporate clean sensitive attributes data in the training process. However, as discussed earlier, it is hard to collect the data with ground-truth sensitive attributes scale especially in high-stake areas. To better reflect these constraints in our experimental setup, we keep at most 20% of all the samples to be non-private (see Section 7.1.1 for more details). Such non-private samples provide the clean sensitive attributes and will not have overlap to those private ones.

#### 4.2 Problem Statement

We first introduce the notations of this paper, and then give the formal problem definition. Let \( D = (\mathcal{X}, \mathcal{A}, \mathcal{Y}) \) denote the data, where \( \mathcal{X}, \mathcal{A}, \) and \( \mathcal{Y} \) represent the set of data samples, sensitive attributes, and corresponding labels. For the sensitive attributes \( \mathcal{A} \), it consists of a small number of clean data points \( \mathcal{A}_c \), and a large number of private sensitive attributes \( \mathcal{A}_p \), i.e., \( \mathcal{A} = \mathcal{A}_c \cup \mathcal{A}_p \). Usually, the size of clean sensitive attributes is smaller than the size of private sensitive attributes due to the increasing awareness of privacy of users and service providers. The private sensitive attributes \( \mathcal{A}_p \) are collected from user-obfuscated input and a third-party privacy-preserving algorithm such as DP [17] or LDP [11].

Following existing work of fair classification [5, 34], we evaluate the performance of fairness using metrics such as equal opportunity and demographic parity. Without loss of generality, we consider the binary classification. Equal opportunity requires that the probability of positive instances with arbitrary sensitive attributes \( A \) being
The problem of fair classification with semi-private sensitive attributes is formally defined as follows:

$$E(Y|A=a,Y=1) = E(Y|A=b,Y=1),$$

where $$Y$$ is the predicted label, demographic parity requires the behavior of the prediction model to be fair on different sensitive groups. Concretely, it requires that the positive rate across sensitive attributes be equal: $$E(Y|A=a) = E(Y|A=b), \forall a, b.$$ The problem of fair classification with semi-private sensitive attributes is formally defined as follows:

**Problem Statement:** Given the training data $$\mathcal{D}$$ with a limited number of clean sensitive attributes and a large amount of private sensitive attributes, learn an effective classifier which generalizes well onto unseen instances, while satisfying the fairness criteria such as demographic parity.

5 PROPOSED MODEL - FAIRSP

Having defined the problem setting for fair classification in the presence of a small set of samples with clean sensitive attributes and a large set of private ones, we now propose our approach to leverage them jointly to learn an end-to-end model. Next, we present the details of the proposed framework for fair classification with semi-private sensitive attributes.

5.1 Semi-Private Adversarial Debiasing

In our semi-private scenario, we have two distinct types of sensitive attributes: clean and private. Our objective is to build a framework that leverages the information from both clean and private samples and learn an underlying common representation that can induce fair classification. Recently, adversarial debiasing has been proven to be effective in alleviating the bias of representations. In adversarial debiasing, an adversary is used to predict sensitive attributes from the representations of the classifier; while the classifier is trained to learn representations that make the adversary unable to predict the sensitive attributes while keeping high accuracy in the classification. Directly applying adversarial debiasing is not feasible in our scenario as only limited clean sensitive attributes are available and most of the sensitive attributes are private (noisy). To this end, we propose to use a shared encoder layer to learning the embedding vector, which is fed into separate layers for debiasing. Specifically, we first propose a label predictor to minimize the prediction errors of the labels with the following objective function:

$$\min_{\theta_\mathcal{Y}} \mathcal{L}_Y = \mathbb{E}_{(X,Y) \in \mathcal{D}}(Y, f_\theta_\mathcal{Y}(h(X)))$$

(2)

where $$f_\theta_\mathcal{Y}$$ is to predict the labels, $$h(\cdot)$$ is an embedding layer to encode the features into latent representation space, and $$f$$ is a cross entropy loss. In addition, to learn fair representations and make fair predictions, we incorporate two adversaries $$f_\theta_c$$ and $$f_\theta_p$$ to predict the clean and private sensitive attributes, respectively; while $$h(\cdot)$$ trying to learn the representation that can fool $$f_\theta_\mathcal{Y}$$. The adversaries $$f_\theta_c$$ and $$f_\theta_p$$ are jointly optimized with the following objective function:

$$\min_{\theta_c, \theta_p} \mathcal{L}_c = \mathcal{L}_c + \alpha L_p$$

(3)

where $$\alpha$$ hyper-parameter that controls the relative importance of the loss functions computed over the data of clean and private sensitive attributes, and $$\mathcal{L}_c$$ and $$\mathcal{L}_p$$ are defined as follows:

$$\min_{\theta_c} \mathcal{L}_c = \mathbb{E}_{X \sim \mathcal{D}_{X|a=1}}[\log(f_\theta_c(h(X)))] + \mathbb{E}_{X \sim \mathcal{D}_{X|a=0}}[\log(1 - f_\theta_c(h(X)))]$$

(4)

$$\min_{\theta_p} \mathcal{L}_p = \mathbb{E}_{X \sim \mathcal{D}_{X|a=1}}[\log(f_\theta_p(h(X)))] + \mathbb{E}_{X \sim \mathcal{D}_{X|a=0}}[\log(1 - f_\theta_p(h(X)))]$$

(5)

where $$\theta_c$$ and $$\theta_p$$ are the parameters for the adversaries for predicting the clean and private sensitive attributes. Finally, the overall objective function of adversarial debiasing for fair classification is a minimax function:

$$\min_{\theta_c, \theta_p} \mathcal{L}_c = \mathcal{L}_Y - \beta(\mathcal{L}_c + \alpha L_p)$$

(6)

where $$\beta$$ control the importance of the sensitive attributes predictor.

5.2 Private Sensitive Attribute Correction

Private sensitive attributes are noisy and directly applying adversarial debiasing on them may lead to sub-optimal results. An intuitive approach is to consider correcting these noisy sensitive attributes before feeding them into the above model (i.e., $$\mathcal{L}_{\text{adv}}$$). Learning to correct noisy dependent variables (e.g., labels) has been previously studied in weakly-supervised learning [23, 38]. Since we have a small amount of clean sensitive attributes available, we propose to correct private sensitive attributes, with a joint learning paradigm without assuming the underlying distribution between private and sensitive attributes. We explore the idea of learning a Corruption Matrix [23] to estimate true sensitive attributes from the private ones. Specifically, given the dataset $$\mathcal{D}_c = \{X, A_c, Y\}$$ with instances containing clean sensitive attributes of $$l$$ categories, and $$\mathcal{D}_p = \{X, A_p, Y\}$$ with instances’ sensitive attributes being private, we aim to estimate a sensitive attribute corruption matrix $$\mathcal{C} \in \mathbb{R}^{K \times l}$$ to model the sensitive attributes corruption process. We first train a sensitive attribute classifier $$g$$ on the private data $$\mathcal{D}_p$$ as follows:

$$g(X) = \hat{p}(A_p|X)$$

Figure 2: An illustration of the proposed framework FAIRSP. It consists of two major modules: (1) an semi-private adversarial debiasing module for learning fair classification; and (2) a private sensitive attribute correction module for correcting noisy sensitive attributes.
Let $X_m$ be the subset of $X$ with sensitive attributes $A_c = m$. Assuming the conditional independence of $A_p$ and $A_c$ given $X$, i.e., $p(A_p|A_c, X) = p(A_p|X)$, we can estimate the corruption matrix $C$, where each element $C_{mr}$ (the transition probability from $A_c = m$ to $A_p = r$) is calculated as follows,

$$
C_{mr} = \frac{1}{|X_m|} \sum_{X \in X_m} \hat{p}(A_p = r|X) = \frac{1}{|X_m|} \sum_{X \in X_m} \hat{p}(A_p = r|A_c = m, X) \approx p(A_p = n|A_c = m) \tag{7}
$$

With the estimated $C$, then we can train a new prediction model $g'(X) = \hat{p}(A_c|X)$ solving the following optimization problem:

$$
\min_{\theta_p, \theta_p'} \mathcal{L}_c = \mathbb{E}_{(X,A_c) \in \mathcal{D}_c} \mathcal{l}(A_c, g'(x)) + \mathbb{E}_{(X,A_p) \in \mathcal{D}_p} \mathcal{l}(A_p, C^T g'(X)) \tag{8}
$$

where $\ell$ is a differentiable loss function to measure the prediction error, such as the cross-entropy loss.

### 5.3 FairSP: Integrating Corrected Sensitive Attributes into Adversarial Debiasing

We aim to leverage the corrected sensitive attributes and integrate them to the adversarial debiasing algorithm for fair classification. Specifically, using the sensitive attribute correction network in Eqn. 8, we learn a sensitive attribute correction function $g'(X)$ that rectifies the private sensitive attributes for each instance $X \in \mathcal{D}_p$. We now obtain a set of instances with corrected sensitive attributes $\mathcal{D}_p' = \{X, A_p', Y\}, \forall X \in \mathcal{D}_p$ and $A_p' = g'(X)$. Note that the sensitive attribute correction network reduces the noise but the rectified sensitive attributes could still be erroneous. Essentially, we first feed the instances with private sensitive attributes $\mathcal{D}_p$ into the sensitive attributes correction network to obtain the rectified instances $\mathcal{D}_p'$. These rectified instances are used as input to the adversarial debiasing of private sensitive attributes (i.e., Eqn. 5). Formally, the objective function of the adversary $f_{\theta_p}$ is as defined as follows:

$$
\min_{\theta_p} \max_{\theta_p'} \mathcal{L}_{p'} = \mathbb{E}_{X \sim p(X|A_c')} [\log(f_{\theta_p'}(h(X)))] + \mathbb{E}_{X \sim p(X|A_c')} [\log(1 - f_{\theta_p'}(h(X)))] \tag{9}
$$

The overall objective function of our final model FairSP is:

$$
\min_{\theta_p, \theta_p'} \max_{\theta_p, \theta_p'} \mathcal{L}_c = \mathcal{L}_Y - \beta (\mathcal{L}_c + \alpha \mathcal{L}_p) \tag{10}
$$

### 5.4 The Optimization of FairSP

We adopt the mini-batch gradient descent with Adadelta [44] optimizer to learn the parameters. Adadelta is an adaptive method which divides the learning rate by an exponentially decaying average, and is less sensitive to the initial learning rate. For ease of understanding, all the notations we use are summarized in Table 1.

As shown in Algorithm 1, we first train the sensitive attribute correction network to obtain the set of corrected sensitive attributes $\mathcal{D}_p'$. To this end, we train a predictor $g$ on data with private sensitive attributes $\mathcal{D}_p$ and estimate the sensitive attribute corruption matrix $C$. Thereafter, we train a new predictor $g'$ with the corruption matrix on the private data, and obtain the data with corrected sensitive attributes $\mathcal{D}_p'$. Next we train the adversarial debiasing model for classification on both of $\mathcal{D}_p'$ and $\mathcal{D}_c$.

### 6 A THEORETIC ANALYSIS ON FAIRNESS GUARANTEE

In this section, we perform a theoretic analysis of the fairness guarantee under the proposed framework FairSP with key assumptions. The model essentially integrates two major modules: (1) the private sensitive attributes correction ($\mathcal{L}_c$ in Eqn. 8); and (2) the semi-private adversarial debiasing with the corrected sensitive attributes ($\mathcal{L}_c + \alpha \mathcal{L}_p$ in Eqn. 6).

To understand the theoretic guarantee for the semi-private adversarial debiasing, we need to consider the induced noise in the large amount of private sensitive attributes as they are nonnegligible. Next we theoretically show that under mild conditions, we can satisfying fairness metrics such as demographic parity.

First, we can prove that the global optimum of the adversaries in $\mathcal{L}$ ($\theta_p$ and $\theta_p'$) can be achieved if and only if $p(X|A_c = 1) = p(X|A_c = 0)$ and $p(X|A_p = 1) = p(X|A_p = 0)$.

Proceed. This is because according to the Proposition 1 in [20], the adversaries can reach to the optimal $\theta_p^* = \frac{p(X|A_c=1)}{p(X|A_c=1) + p(X|A_c=0)}$ and $\theta_{p'}^* = \frac{p(X|A_p=1)}{p(X|A_p=1) + p(X|A_p=0)}$. Then the optimal of the min-max
The corrected sensitive attributes are not random, i.e., for all \( p \) have adversarial learning to learn an effective estimator \( \hat{X} \) between which they do not share any parameters; it generally holds that the objective function in \( L \) reaches the global optimum, the label prediction \( \hat{Y} \) will achieve demographic parity, i.e., \( p(\hat{Y} | \hat{A}_p = 0) = p(\hat{Y} | \hat{A}_p = 1) \) and \( p(\hat{Y} | A_c = 0) = p(\hat{Y} | A_c = 1) \).

Proof. We first explain the two assumptions: (1) since we use the objective function in \( L_c \) to derive the corrected sensitive attributes \( \hat{A}_p \), and learn the latent presentation through \( h(\cdot) \), between which they do not share any parameters; it generally holds that \( \hat{A}_p \) is independent with the representation of \( X \), i.e., \( p(\hat{A}_p = 1|\hat{A}_p = 0) \neq p(\hat{A}_p = 0|\hat{A}_p = 0) \); (2) Since we are using adversarial learning to learn an effective estimator \( f_{\hat{g}} \) for sensitive attributes, it is reasonable to assume that it does not produce random prediction results. We then prove Theorem 6.1 as follows: since \( p(\hat{A}_p = 1|\hat{A}_p = 0) \neq p(\hat{A}_p = 0|\hat{A}_p = 0) \), we have \( p(X|A_p, \hat{A}_p) = p(X|A_p) \). When the algorithm converges, we have \( p(X|\hat{A}_p = 0) = p(X|\hat{A}_p = 0) \), which is equivalent with \( \sum_{\hat{A}_p} p(X|\hat{A}_p = 0) = \sum_{\hat{A}_p} p(X|\hat{A}_p = 0) \).

\[
R = \mathbb{E}_{X} p(X|A_c = 1) \left[ \log \frac{p(X|A_c = 1)}{p(X|A_c = 0)} \right] + \mathbb{E}_{X} p(X|A_c = 0) \left[ \log \frac{p(X|A_c = 0)}{p(X|A_c = 1)} \right]
\]

Since \( \alpha \) is a nonnegative hyper-parameter and the Jensen–Shannon divergence (JSD) between two distributions is always non-negative and zero only when they are equal, so if and only if \( p(X|A'_p = 1) = p(X|A'_p = 0) \) and \( p(X|A_c = 1) = p(X|A_c = 0) \), the above equation will reach to the minimum. \( \square \)

Next, we introduce the following theorem under two reasonable assumptions:

**Theorem 6.1.** Let \( \hat{Y} \) denotes the predicted labels, if

1. For all \( X \in D_p \), the corrected sensitive attributes \( \hat{A}_p \) and \( X \) are independent conditioned on their ground-truth sensitive attributes \( A_p \), i.e., \( p(A_p, X|\hat{A}_p = p(A_p|\hat{A}_p)p(X|\hat{A}_p) \); \n2. The corrected sensitive attributes are not random, i.e., \( p(A'_p = 1|\hat{A}_p = 0) \neq p(A'_p = 0|\hat{A}_p = 0) \).

If \( L \) reaches the global optimum, the label prediction \( \hat{f}_{\hat{g}} \) will achieve demographic parity, i.e., \( p(\hat{Y} | \hat{A}_p = 0) = p(\hat{Y} | \hat{A}_p = 1) \) and \( p(\hat{Y} | A_c = 0) = p(\hat{Y} | A_c = 1) \).

7 EXPERIMENTS

In this section, we present the experiments to evaluate the effectiveness of FairSP.

7.1 Experimental Settings

In this section, we conduct experiments to evaluate the performance of our method. In these experiments, we try to answer the following research questions:

- **RQ1**: Can FairSP obtain fair predictions with mostly private sensitive attributes?
- **RQ2**: How private sensitive attribute correction affect the performance of prediction and fairness?
- **RQ3**: What is the impact of the amount of data with clean sensitive attributes?
- **RQ4**: How does the degree of privacy budget impact the fair classification performance?

7.1.1 Datasets. We conduct experiments on two publicly available benchmark datasets for fair classification: COMPAS [25] and ADULT [4].

- **COMPAS**\(^4\): This dataset describes the task of predicting the recidivism of individuals in the U.S.
- **ADULT**\(^5\): This dataset contains records of personal yearly income, and the label is whether the income of specific individual exceed 50k or not.

We report results on the test set with the model parameters that achieves with the best validation accuracy on the dev set (Table 2 shows the data splits). All experiments are repeated for 5 times and the average is reported. We compare different methods and

\[\begin{array}{llll}
\text{Data} & \text{SA} & \text{Train} & \text{Test} \\
\hline
\text{ADULT} & \text{Gender} & 4,884 & 19,536 & 24,421 \\
\text{COMPAS} & \text{Race} & 611 & 2,446 & 3,058 \\
\end{array}\]

Based on the above equation, we can get,

\[
\frac{p(X|A_c = 1) = p(\hat{A}_p = 0|\hat{A}_p = 1) - p(\hat{A}_p = 0|\hat{A}_p = 0)}{p(X|A_p = 0) = p(\hat{A}_p = 1|\hat{A}_p = 0) - p(\hat{A}_p = 1|\hat{A}_p = 1)} = 1
\]

\[
\Rightarrow p(X|\hat{A}_p = 1) = p(X|\hat{A}_p = 0)
\]

Since we already proof that \( p(X|A_c = 1) = p(X|A_c = 0) \), and \( \hat{Y} = f_{\hat{g}}(X) \), we can get \( p(\hat{Y}|A_c = 1) = p(\hat{Y}|A_c = 0) \) and \( p(\hat{Y}|A_c = 1) = p(\hat{Y}|A_c = 0) \), which is the demographic parity. \( \square \)

\(^4\) https://github.com/propublica/compas-analysis
\(^5\) https://archive.ics.uci.edu/ml/machine-learning-databases/adult/
techniques at different values of the clean ratio defined as:

\[
clean\ ratio = \frac{\#\ samples\ with\ clean\ SA}{\#\ samples\ with\ clean\ SA + \#\ samples\ with\ private\ SA}
\]  

(14)

7.1.2 Baselines. We compare the proposed FairSP with four types of baselines. The first type of baseline is a vanilla multi-layer perceptron (MLP) network without debiasing. The second type of baseline is a state-of-the-art debiasing model that explicitly utilizes the sensitive information. The third type of baseline is a debiasing model that do not need the sensitive information. For the fourth type of baselines, we implement an adversarial debiasing model with three kinds of training strategies including “Clean”, “Private” and “Clean+Private”, which are utilized to illustrate the benefit of our proposed private sensitive attribute correction method:

- Vanilla: It directly uses a classifier without any debiasing method. Since there is a trade-off between fairness and performance, it is used to show the lower bound of any debiasing method.
- RNF [14]: It is a recently proposed state-of-the-art debiasing method, which explicitly leverage the sensitive attributes for mitigating bias.
- FairRF [46]: It is a debiasing method that do not need any sensitive attributes, which can also be applied in our proposed semi-private scenario.
- Clean: We implement MLP-based adversarial debiasing model on only the instances with clean sensitive attributes. 
- Private: We implement MLP-based adversarial debiasing model on only the instances with private sensitive attributes. Private sensitive attributes are treated as regular ones.
- Clean+Private: In this setting, we simply merge both the sets (essentially treating the private sensitive attributes as the clean ones) and use them together for training a MLP-based adversarial debiasing model.

7.1.3 Evaluation Metrics. Following existing work on fair classification, we measure the classification performance with Accuracy (ACC) and F1, and the fairness performance based on Demographic Parity and Equal Opportunity [34]. Next, we introduce fairness measures in the scenario of binary sensitive attributes and labels, which can be naturally extended to more general cases.

- Demographic Parity: A classifier is considered to be fair if the prediction \( \hat{Y} \) is independent from the sensitive attribute \( A \). In other words, demographic parity requires each demographic group has the same chance for a positive outcome: 

\[
\Pr(\hat{Y} = 1 \mid A = 0) = \Pr(\hat{Y} = 1 \mid A = 1)
\]

We will report the difference of each sensitive group’s demographic parity (\( \Delta_{DP} \)):

\[
\Delta_{DP} = \Pr(\hat{Y} = 1 \mid A = 1) - \Pr(\hat{Y} = 1 \mid A = 0)
\]  

(15)

- Equal Opportunity: It considers one more condition than demographic parity. A classifier is fair if the prediction \( \hat{Y} \) of positive instances is independent from the sensitive attributes. Specifically, it requires the true positive rate of different sensitive groups are equal: 

\[
\Pr(\hat{Y} = 1 \mid A = 1, Y = 1) = \Pr(\hat{Y} = 1 \mid A = 0, Y = 1)
\]

We report the difference of each sensitive group’s equal opportunity (\( \Delta_{EO} \)):

\[
\Delta_{EO} = \Pr(\hat{Y} = 1 \mid A = 1, Y = 1) - \Pr(\hat{Y} = 1 \mid A = 0, Y = 1)
\]  

(16)

Note that demographic parity and equal opportunity measure the fairness performance in different ways, and the smaller the values are, the better the performance of fairness.

7.2 Performance of Fair Classification

To answer RQ1, we compare FairSP with various baselines over two benchmark datasets for fair classification. For each experiment, we select five random seeds to partition the original dataset into training set and test set. We select 80% of the training set as the private training set and the others as the non-private part (i.e., clean ratio = 20%). For the private training set, we set the privacy budget \( \epsilon = 0.5 \), which means the flipping probability on sensitive attributes is around 38% according to the privacy guarantee analysis. The average performance and standard deviation over five times are reported in Table 3. From the table, we can make following observations:

- In general, we observe that FairSP can better improve fairness performance of \( \Delta_{DP} \) and \( \Delta_{EO} \) without causing significant prediction performance drop on both datasets, comparing with other baselines. For example, compared with recently proposed state-of-the-art debiasing model RNF, FairSP has achieved 42.5% improvement in terms of \( \Delta_{EO} \) and 6.0% on \( \Delta_{DP} \) on ADULT.
- We observe that conventional debiasing methods that directly leverage sensitive attributes are generally ineffective under the semi-private scenario. For example, comparing RNF with Vanilla model, we can observe that their fairness performances are similar w.r.t. \( \Delta_{DP} \) and \( \Delta_{EO} \).
- The proposed private sensitive attribute correction can help better utilize the limited clean sensitive attribute for improving fairness. For example, FairSP has 32.3% and 3.7% improvement over “Clean+Private” on ADULT by \( \Delta_{DP} \) and \( \Delta_{EO} \). The reason is that “Clean+Private” directly utilizes the private sensitive attributes;
Table 3, and show the results on ADULT dataset as we have similar five rounds are reported in Table 4. From the table, we can make accordingly. The average performance and standard deviation over corresponding noisy ratio on sensitive attributes are 38% and 27% for the training set to derive private sensitive attributes, and the training set and test set division the same as the main results in RQ2 private sensitive attribute, to answer.

### 7.3 Assessing the Impact of Private Sensitive Attribute Correction

In this subsection, we investigate the impact of the component of private sensitive attribute, to answer RQ2. We keep the setting of the training set and test set division the same as the main results in Table 3, and show the results on ADULT dataset as we have similar observations on COMPAS. We set the privacy budget $\epsilon$ as 0.5 and 1 for the training set to derive private sensitive attributes, and the corresponding noisy ratio on sensitive attributes are 38% and 27% accordingly. The average performance and standard deviation over five rounds are reported in Table 4. From the table, we can make following observations:

- The proposed correction strategy on private sensitive attributes is effective for improving the debiasing performances consistently while the corrected sensitive attributes contain less severe noise and can better guide the debiasing process.
- We can see that it is important to leverage sensitive attributes for ensuring fairness and maintain prediction performance in the semi-private scenario. For example, FAIRSP has significant improvement in w.r.t. Accuracy, F1, $\Delta_{DP}$ and $\Delta_{EO}$ than FairRF consistently, which does not leverage the sensitive attributes directly for debiasing.
- Exploiting both the limited clean sensitive attributes and private ones jointly is important for debiasing. We can generally observe that FAIRSP > Clean+Private > Clean ≈ Private ≈ Vanilla for debiasing performances. First, FAIRSP and “Clean+Private” perform better than the other three baselines shows that leveraging both clean and private sensitive attributes is necessary. Second, the observation that “Clean”, “Private” and Vanilla perform similar indicates that only relying on the clean data or noisy data is less effective for debiasing.

### Table 4: The impact of private sensitive attribute correction.

| Privacy Budget | Metric       | FAIRSP w/o Corr | FAIRSP   |
|---------------|--------------|-----------------|----------|
| $\epsilon = 0.5$ | Accuracy     | 0.848±0.002     | 0.847±0.004 |
|               | F1           | 0.647±0.012     | 0.645±0.007 |
|               | $\Delta_{DP}$| 0.083±0.008     | 0.078±0.003  |
|               | $\Delta_{EO}$| 0.030±0.012     | 0.023±0.012  |
| $\epsilon = 1$ | Accuracy     | 0.847±0.004     | 0.846±0.004 |
|               | F1           | 0.644±0.005     | 0.641±0.007 |
|               | $\Delta_{DP}$| 0.079±0.004     | 0.075±0.001 |
|               | $\Delta_{EO}$| 0.021±0.020     | 0.013±0.014 |

regardless of the privacy budget. For example, when privacy budget $\epsilon$ is 0.5, FAIRSP has achieved 23.3% and 6.0% improvement in terms of $\Delta_{EO}$ and $\Delta_{DP}$, comparing to FAIRSP without private attributes correction.

- The proposed private sensitive attribute correction method does not cause significant prediction performance drop. For example, when privacy budget $\epsilon$ is 1, FAIRSP has achieved comparable performance with FAIRSP without correction in terms of both Accuracy and F1 metrics.

### 7.4 Impact of Private Data Ratio

In this subsection, we investigate the impact of different private data ratio, to answer RQ3. We show the experimental results on ADULT dataset and we observe similar trends on COMPAS. We conduct four groups experiments with different clean data ratio (defined as in Eqn. 14) as in the range $[0.02\%, 0.2\%, 2\%, 20\%]$. Each group of experiments have the same privacy budget $\epsilon$ as 0.5. For each clean data ratio, we compare our proposed model FAIRSP with “Clean+Private” and demonstrate the prediction metrics Accuracy,
F1 as well as fairness metric $\Delta_{DP}$ and $\Delta_{EO}$. For each experiment we run five times and report the average result in Figure 3. From the figure, we can make following observations:

- In general, we can observe from Figure 3 (c) (d) that our proposed FairSP has consistent improvement on fairness performance by a large margin compared with the baseline “Clean+Private” consistently with different clean data ratios.
- It is worth noting that our model FairSP performs even better on fairness when the clean data ratios are smaller. The performance of the baseline “Clean+Private” on fairness slightly drops with smaller clean data ratio, which is expected because smaller clean data ratio means the dataset contains less useful information about sensitive attributes. However, our proposed model FairSP has better fairness performance on both $\Delta_{DP}$ and $\Delta_{EO}$ with smaller clean data ratio. Even with extreme small clean data ratio such as 0.02%, FairSP maintains relatively stable fairness performances. This indicates that the sensitive attributes correction is effective even with only a small amount of clean data and can still be useful under strong privacy requirements.
- From Figure 3 (a) (b), we observe that the proposed FairSP demonstrates comparable prediction performances with the baseline “Clean+Private” regardless of different clean data ratios. The prediction performance of both models slightly drops with smaller clean data ratio. This is because with smaller clean data ratio, there is a larger portion of data with private sensitive attributes.

### 7.5 Impact of Privacy Budget

To answer RQ4, in this subsection, we investigate the impact of different privacy budgets on the fair classification performances. We conduct six groups of experiments with different Privacy Budget $\epsilon$ as 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, which means the flipping probability on sensitive attributes is around 38%, 27%, 18%, 12%, 7%, 4% accordingly. The clean data ratio for each group of experiment is 20%. For each Privacy Budget $\epsilon$, we compare our proposed model FairSP and baseline “Clean+Private” with performance metrics Accuracy, F1 and fairness metrics $\Delta_{DP}$ and $\Delta_{EO}$. For each experiment we run five times and report the average result in Figure 4. From the figure, we have the following observations:

- In general, we can observe from Figure 4 (c) (d) that our proposed model FairSP performs consistently better compared to the baseline model “Clean+Private”. With a larger privacy budget $\epsilon$, the fairness performances of both models are improved. This is because the dataset has fewer noisy sensitive attributes under larger privacy budget $\epsilon$.
- With a larger privacy budget $\epsilon$, we can observe that the gap between FairSP and “Clean+Private” is more narrow. This may due to the estimation accuracy of the private sensitive attributes in FairSP becomes less effective when the flipping probability on sensitive attributes is small enough, which also indicates that FairSP is more effective when the privacy guarantee is strong.
- From Figure 4 (a) and (b), we see that FairSP has comparable classification performance on Accuracy and F1 with the baseline “Clean+Private” regardless of privacy budget $\epsilon$. With a larger privacy budget $\epsilon$, the performances of the both models improve because a larger privacy budget $\epsilon$ indicates that fewer noisy sensitive attributes in the training data.

### 7.6 Parameter Sensitivity Analysis

We now explore the parameter sensitivity of the two important hyperparameters of our model: $\alpha$ controls the impact of the adversary to the sensitive attribute predictor, while $\beta$ controls the influence of the adversary to the debiasing. We vary $\alpha$ in [0.6, 0.7, 0.8, 0.9, 1.0] and $\beta$ from [0.6, 0.7, 0.8, 0.9, 1.0]. The results are shown in Fig. 5. From the figure, we can observe that: (1) The performances of Accuracy and F1 are relative consistent in the range, and the performance of $\Delta_{DP}$ and $\Delta_{EO}$ are also similar. (2) When $\alpha$ and $\beta$ are larger, the performance and fairness are both improved, which suggests the effectiveness of the adversarial debiasing method. (3) Based on the experiments, we can achieve optimal performance on fairness and accuracy when selecting both $\alpha$ and $\beta$ as 1.0.

### 8 CONCLUSION AND FUTURE WORK

In this paper, we study a novel problem of fair classification with semi-private sensitive attributes. We develop an end-to-end adversarial debiasing model FairSP to jointly learn from a small amount of instances with clean sensitive attributes and a large amount of instances with private ones. We provide a theoretic analysis to demonstrate that we can learn a fair model prediction under mild assumptions on privacy. Extensive experimental results on real-world datasets demonstrate the effectiveness of the proposed framework to achieve better fair classification performance compared to existing approaches. For future work, first, we can study a more general semi-private fairness setting in a variety of data types such as text and graphs, and analyze the fairness and privacy guarantee on these data. Second, we will investigate the fairness under privacy in distributed machine learning algorithms such as federated learning and split learning.
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