Privacy for All: Demystify Vulnerability Disparity of Differential Privacy against Membership Inference Attack

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ABSTRACT

Machine learning algorithms, when applied to sensitive data, pose potential threat to privacy. A growing body of prior work has demonstrated that membership inference attack (MIA) can disclose specific private information in the training data to an attacker. Meanwhile, the algorithmic fairness of machine learning has increasingly caught attention from both academia and industry. Algorithmic fairness ensures that the machine learning models do not discriminate a particular demographic group of individuals (e.g., black and female people). Given that MIA is indeed a learning model, it raises a serious concern if MIA “fairly” treats all groups of individuals equally. In other words, whether a particular group is more vulnerable against MIA than the other groups.

This paper examines the algorithmic fairness issue in the context of MIA and its defenses. First, for fairness evaluation, it formalizes the notion of vulnerability disparity (VD) to quantify the difference of MIA treatment on different demographic groups. Second, it evaluates VD on four real-world datasets, and shows that VD indeed exists in these datasets. Third, it examines the impacts of differential privacy, as a defense mechanism of MIA, on VD. The results show that although DP brings significant change on VD, it cannot eliminate VD completely. Therefore, fourth, it designs a new mitigation algorithm named FAIRPick to reduce VD. An extensive set of experimental results demonstrate that FAIRPick can effectively reduce VD for both with and without the DP deployment.

1 INTRODUCTION

Research and advances in the field of machine learning has resulted in algorithms and technologies for improving cybersecurity by helping identifying security threats and system vulnerabilities [50, 51, 60]. However, a line of recent research has shown that machine learning also can enable novel and sophisticated privacy attacks that leak information about the training dataset [23, 47, 54]. Particularly, one such attack called membership inference attack (MIA) can infer whether an individual record is included in the model’s training dataset [53] by using machine learning techniques. It has been shown that MIA can lead to serious privacy concerns when the training data contains sensitive information (e.g., medical records and financial information).

The problem of algorithmic fairness of machine learning has attracted considerable attention from both academic and industry in the recent years. The key of algorithmic fairness is to ensure that a machine learning model does not discriminate against a particular demographic group (e.g., black people). There have been several cases showing that the current ML models are indeed discriminated. For example, as shown by a recent study [13], the current criminal risk assessment tool named COMPAS (standing for Correctional Offender Management Profiling for Alternative Sanctions) predicts the criminals’ recidivism risk (i.e., the criminal will re-offend) within 2 years indeed discriminates black defendants - black defendants who did not recidivate were incorrectly predicted to re-offend is nearly twice as high as their white counterparts. To address the fairness issue, enormous efforts have been spent on defining fairness models and metrics [5, 7, 21] as well as developing fairness-enhancing machine learning algorithms [7, 35, 38, 61]. It has been identified that one of the main reasons of bias in learning is the heavy imbalance of different groups in the training data [17]. For example, the underlying cause of the discrimination by COMPAS is the imbalanced distribution between black and white defendants in the training dataset.

Many real-world datasets that the prior MIA works have explored not only contain demographic information of individuals but also are heavily imbalanced among different demographic groups (as we will show in the empirical study). Therefore, MIA, as a learning model, faces the same concern if it is biased towards some particular demographic groups (e.g., black and female people). Therefore, one of the fundamental questions that has to be investigated is whether some demographic groups are more vulnerable to MIA than other groups, due to the skewed distribution of the input data.

The fairness issue is also related to the defense mechanisms against MIA. In the literature, multiple defense mechanisms against MIA (e.g., [34, 44, 48]) have been explored. However, none of these defense mechanisms can provide a theoretical privacy guarantee against MIA. On the other hand, differential privacy (DP) [15] provides a rigorous privacy guarantee against MIA if the training process is differentially private [53]. However, DP only provides a theoretical bound of such privacy protection. Typically, the application of DP does not specifically consider the demographic features of individuals, whereas these features are important for the fairness measurement. Thus it remains unclear how applying DP on the target model will impact the fairness of MIA.

In summary, in this paper, we address the following important research questions:

- Does MIA treat different demographic groups unfairly such that some demographic groups are more vulnerable than the others? If it does, what is the underlying cause of such unfairness?
- What is the impact of differential privacy, as a defense mechanism against MIA, on MIA’s treatment of different groups? Will it reduce the vulnerability disparity by MIA?
- How to design effective bias mitigation methods to reduce the vulnerability disparity, before and after applying DP as the defense?

Our contributions. Fairness and privacy are two equally important issues of machine learning. Most of the existing studies
have investigated these two issues separately. To our best knowledge, this is the first work that studies algorithmic fairness in the context of membership inference attack and its defenses. We make the following contributions:

- We formalize the notion of vulnerability disparity (VD) to quantify the degree of fairness in MIA’s prediction results. VD is adapted from the state-of-the-art fairness definition named equal opportunity [28]. Intuitively, VD measures the difference in the success probability of MIA for different demographic groups.
- On four real-world datasets, we evaluate VD of MIA for different race and gender groups. Our results prove the existence of VD for both without DP and with DP applied on the target model. The results also show that DP incurs unpredictable, sometimes significant, change of VD.
- We analyze the underlying cause of VD as well as the impacts of DP on VD under different privacy settings, and demonstrate that VD is largely determined by the data distribution of the training data, for both without and with DP deployment.
- We propose a new reweighting method named FairPick to mitigate VD. The key idea of FairPick is to reduce the disparity of data distribution among different groups by a user-specified threshold, where the threshold controls the fairness of MIA output. The experiments result show that FairPick can greatly reduce VD while preserving the utility of the target model.

The paper is organized as following. Section 2 introduces the preliminaries. Section 3 presents the details of implementing DP as the defense mechanism against MIA. Section 4 demonstrates the existence of vulnerability disparity and detailed analysis. Section 5 discusses the details of our mitigation algorithm. Section 6 discusses the related work. Section 7 concludes the paper.

2 PRELIMINARIES

In this section, we elaborate on the preliminaries of membership inference attack (MIA), differential privacy (DP), and algorithmic fairness in the literature.

2.1 Membership Inference Attack

Membership inference attack (MIA) is a privacy-leakage attack that predicts whether a given record was used in training a target model [52]. It works under a setting where the target model is opaque but remotely accessible, and it requires the target model to report the prediction probability of different classes.

Technically, MIA follows a workflow as shown in Figure 1. Given a target model $\mathcal{H}$ which can be considered as a black-box to the attacker, the attack starts with synthesizing data that mirrors the training samples of $\mathcal{H}$. The most general means of data synthesis is to initialize a random sample and gradually improve its quality by using the output of $\mathcal{H}$. On basis of the synthesized data, MIA creates a group of shadow models to approximate the target model. Each shadow model is trained with the samples that are randomly picked from the synthesized data as well as the output of these samples by $\mathcal{H}$. Aided by the shadow models, MIA derives the final attack model, which is typically a binary classifier in the format of a neural network. This model is trained by taking as the inputs as the shadow models’ prediction probability on the initially synthesized data and the output as considering whether those samples participated in the training of the shadow models. As demonstrated by Shokri et al. [52], the attack models constructed in such an manner can produce high attacking fidelity. As $\mathcal{H}$ outputs more than 1 label class, MIA indeed consists of multiple attack models, each pertaining to a unique classification label class of $\mathcal{H}$. In summary and formally, MIA can be described as:

$$M : x^* , \mathcal{A}[\mathcal{H}] \rightarrow \{0, 1\}$$

where $\mathcal{A}[\mathcal{H}]$ represents the access to the target model $\mathcal{H}$, $x$ is an arbitrary data point, and 0 means MIA predicts $x^*$ as a non-training sample of $\mathcal{H}$ and 1 otherwise.

2.2 Algorithmic Fairness

The problem of algorithmic fairness in machine learning (ML) algorithms has attracted considerable attention in the recent years. Formally, given a dataset consisting of $n$ i.i.d. samples $\{(A_i, X_i, Y_i)\}_{i=1}^n$ from a joint distribution $p_{A, X, Y}$ with domain $A \times X \times Y$, where $A$ denotes one or more protected (discriminatory) features (e.g., gender and race), $X$ denotes other non-protected features used for decision making, and $Y$ denotes the outcome feature. A fair ML system should ensure that the predicted values $\hat{Y}$ of $Y$ do not have discriminatory effects towards particular groups (defined by the associated $A$ values) or individuals. In this paper, we use $A = 1$ ($A = 0$, resp.) to denote the protected (unprotected, resp.) group. In the fairness community, Gender=$\text{female}$ and Race=$\text{black}$ are typically considered as the protected groups on the sensitive attributes Gender and Race. The ML community has proposed a multitude of formal, mathematical definitions of fairness. Intuitively, these fairness definitions are concerned with the protected groups (such as racial or gender groups) and require some statistic of interest be approximately equalized across different groups. Standard choices for these statistics include positive classification rates [8], false positive or false negative rates [28, 39] and positive predictive value [11].

In this paper, we consider a commonly-used fairness measurement named equal opportunity [28], which requires that protected and unprotected groups should have equal true positive rate. We pick this fairness definition among a number of candidates (e.g., statistical disparity [7] and equalized odds [28]) because we are only interested in the true positive results by MIA (i.e., the member records that are identified by MIA). Formally, equal opportunity is defined based on disparity $DI$, which is measured as below:

$$DI = Pr(\hat{Y} = 1 | A = 1, Y = 1) − Pr(\hat{Y} = 1 | A = 0, Y = 1),$$

(1)
where \( A = 1 \) (\( A = 0 \), resp.) denotes the protected (unprotected) group respectively, and \( \hat{Y} \in \{0, 1\} \) denotes the predicted value of label \( Y \). We only consider the binary classification (i.e., \( \hat{Y} \in \{0, 1\} \)) as the MIA model is a binary classifier. Intuitively, given the target outcomes, \( DI \) quantifies the discrepancy between the true positive rate on the protected group (\( A = 1 \)) and the unprotected group (\( A = 0 \)) based on their protected characteristic. While \( DI = 0 \), \( Y \) satisfies equal opportunity [28], indicating enforcement of equal discrepancies across different groups.

2.3 Differential Privacy

Differential privacy (DP) is the de facto standard in measuring the disclosure of privacy pertaining to individuals in a group [15]. Roughly speaking, a differentially private algorithm ensures that the inclusion or exclusion of an individual record does not significantly affect the result of arbitrary analysis. Formally, given an arbitrary data domain \( X \), and an arbitrary output domain \( T \), a randomized algorithm \( F \) that maps a dataset to output satisfies \( \epsilon \)-DP if for all dataset pairs \( D_1 \) and \( D_2 \) differing on at most one record, and for all subsets \( S \) of the output domain \( T \):

\[
Pr[F(D_1) \in S] \leq e^\epsilon \times Pr[F(D_2) \in S],
\]

where the probability is taken over the randomness of \( F \), and \( \epsilon \) (called privacy budget) specifies the level of guaranteed privacy. Intuitively, larger (smaller, resp.) \( \epsilon \) providers weaker (stronger, resp.) privacy protection.

3 DEFENDING MIA WITH DIFFERENTIAL PRIVACY

To serve the objectives of our study, we first reproduce MIA attacks on several real-world datasets and demonstrate the use of DP as a defense. This section covers the details.

3.1 Reproduction of MIA

In general, the reproduction of MIA follows the workflow as described in Section 2.1. In the following, we explain the important specifics.

Data collection and pre-processing. We use four real-world datasets\(^1\) that were widely used by the fairness and privacy communities. We introduce these four datasets briefly:

\[^1\]Both Adult and Hospital datasets are used in the original evaluation on MIA [52].

- Adult\(^2\) dataset that includes 48842 instances and 14 attributes describing information about individuals from the 1994 U.S. census. The prediction task is to determine whether a person makes over 50K a year.
- COMPAS\(^3\) dataset contains criminal history, jail and prison time, demographics and COMPAS (which stands for Correctional Offender Management Profiling for Alternative Sanctions) risk scores for defendants from Broward County, Florida. The prediction task is to infer a criminal defendant’s likelihood of becoming a recidivist (i.e., a criminal who re-offend).
- Broward\(^4\) dataset is a refined and cleaned version of COMPAS dataset. It can achieve better MIA accuracy than COMPAS dataset.
- Hospital\(^5\) dataset stores the hospital discharge data of the in-patients stays in several health facilities and released by the Texas Department of State Health Services from 2006 to 2009. The dataset includes the demographic information such as the gender, age, race of the patients, their treatments, and length of stay. The prediction task is to infer the patient’s main procedure based on the attributes other than secondary procedures.

More details of these four datasets are summarized in Table 1. We consider two attributes, namely gender (G) and race (R), as they are law-regulated protected attributes [1] in the fairness community. We also further pre-process the four datasets prior to training and testing; the records with missing values are removed and all the features are converted into numeric values. We keep the categorical features and do not encode them into binary values.

Table 1: Details of data-sets used in our study

| Data-set | # of Record | # of Attr | # of Class | Prof Attr\(^1\) |
|----------|-------------|-----------|------------|----------------|
| Adult    | 4.5K        | 14        | 2          | G & R          |
| COMPAS   | 24.5K       | 10        | 2          | G & R          |
| Broward  | 17.2K       | 8         | 2          | G & R          |
| Hospital | 110K        | 20        | 4          | G & R          |

\[^1\]Prot Attr indicates the protected attributes, with G and R meaning Gender and Race.

\[^2\]Adult dataset: https://archive.ics.uci.edu/ml/datasets/Adult

\[^3\]COMPAS dataset: https://github.com/propublica/COMPAS-analysis/

\[^4\]Broward dataset: https://farid.berkeley.edu/downloads/publications/scienceadvances17/

\[^5\]Hospital dataset: https://www.dhs.state.texas.us/THCIC/Hospitals/Download.shtm

\[^6\]For the COMPASs dataset, more than 15% of original samples are used due to the small size of the entire dataset.
3.2 Defending MIA with DP

Design of defense. As MIA runs solely on the outputs of the target model, making the target model differentially private, by design, can defend against the MIA attack. There are two approaches to enforce DP on the target model: (1) introduce noise to the input data [10, 18] and (2) add perturbation to the target model [24, 31]. The first approach, however, often perturbs the data points, and thus possibly ruins the mapping between the original samples and the differentially private ones. This, as we will explain later, prevents our measurement of vulnerability disparity. Hence, we decide to enforce the ID3 target model with DP by following the design and implementation in [19, 24]. The algorithm is summarized in Algorithm 1 and we name it DP-ID3. Briefly speaking, DP-ID3 adds Laplace noise to the count that is used to compute information gain (line 15–16) and the voting on the leaf node (line 7). DP-ID3 has been proven to satisfy DP [6].

The performance of DP-ID3 depends on the setup of privacy budget $\epsilon$. We base the selection of privacy budget on performance of MIA. To be specific, we pick a range of privacy budgets where the performance of MIA persists and finally approach the level of random guess. We analyze why DP can defend against MIA. In essence, the defense of DP derives from its effects on reducing the over-fitting property of the target model. More specifically, DP introduces Laplace noise to the training process of the target model,
which, on one hand, fuzzifies the choice of attribute for tree splitting (line 15–16 of Algorithm 1) and, on the other hand, dilutes the purity of the leaf nodes (line 7 of Algorithm 1). Therefore, DP generalizes the decision boundary of the target model, making it less fit the training data.

We also notice that on COMPAS dataset, the recall of MIA surprisingly increases quickly while DP gets stronger. We investigated the underlying cause of this phenomenon. It turned out that MIA labels more samples in the testing data as positive when DP gets stronger. Therefore, the recall increases sharply while the precision drops to approximately 0.5 (i.e., random guess).

4 UNDERSTANDING OF VULNERABILITY DISPARITY

In principle, DP only constrains the upperbound of privacy that each individual can lose. However, DP does not ensure that different population groups experience the same amount of actual privacy leakage. In particular, the imbalanced data distribution of different demographic groups (e.g., white vs black people) may lead to inequitable privacy protection. In this section, we unveil this type of inequity in using DP as a defense against MIA.

4.1 Definition of Vulnerability Disparity

To measure the vulnerability a particular group is against MIA attack, We define the concept of vulnerability disparity. Vulnerability disparity (VD) is adapted from the standard fairness definition of equal opportunity (Equation 1). Formally, given a dataset $D$ and a protected attribute $A$, where $A = a$ and $A = \bar{a}$ define the protected and unprotected groups respectively.

We define the vulnerability disparity $VD$ of MIA on $D$ as:

$$VD = P(\hat{Y} = 1|Y = 1, A = a) - P(\hat{Y} = 1|Y = 1, A = \bar{a}),$$

(2)

where $\hat{Y}$ denotes the binary output label of MIA. In particular, $Y = 1$ denotes that the data point is a member of $D$. Intuitively, $VD$ describes the difference of the success probability of MIA for the protected group ($A = a$) versus the unprotected group ($A = \bar{a}$). When $VD > 0$ ($VD < 0$, resp.), the protected group ($A = a$) is more vulnerable (less vulnerable, resp.) than the unprotected group ($A = \bar{a}$) against MIA.

The definition of VD can be applied to measure the protection of DP against MIA too. Formally, the vulnerability disparity $VD_{DP}$ of a differentially private mechanism $DP$ can be measured by simply adapting Formula 2 as following:

$$VD_{DP} = P(\hat{Y}_{DP} = 1|Y = 1, A = a) - P(\hat{Y}_{DP} = 1|Y = 1, A = \bar{a}),$$

(3)

where $\hat{Y}_{DP}$ denotes the prediction of MIA by using the output of the differentially private target model as input. In the ideal case, if a differentially private ML algorithm provides fair group protection, then $VD_{DP} = 0$.

To measure the impact of DP on VD, we measure the change of $VD$ before and after the deployment of DP. Formally, let $VD$ and $VD_{DP}$ be the $VD$ before and after DP deployment on the target model. The change $c$ of vulnerability disparity is measured as:

$$c = \frac{VD_{DP} - VD}{VD}.$$  

(4)

Intuitively, $c < 0$ ($c > 0$, resp.) means that the DP mechanism decreases (increases, resp.) $VD$. 

![Figure 2: Performance of target model and MIA under different privacy budgets.](image)

![Figure 2: Performance of target model and MIA under different privacy budgets.](image)

![Table 3: Skewness of group distribution](image)
4.2 Measurement of Vulnerability Disparity

In this section, we present the results and analysis of vulnerability disparity. To eliminate the impact of randomness by DP, we ran the experiments 25 times on all four datasets and took the average. 

Protected attributes and groups. By following the literature on algorithmic fairness research, we pick race and gender as the protected attributes. We must note that in all the four datasets that we use, the classification labels do not have strong correlation with race and gender. In other words, the classification results do not strongly depend on these two protected attributes. Two groups exist on the gender attribute: male and female. The data on the race attribute consists of four groups. However, for simplicity, we categorize the data into two race groups only: black and non-black. The non-black group consists of all members that are not black (e.g., White, Asian, and Hispanic).

Skewness of group distribution. The distribution of different population groups on the protected attributes of the four datasets are shown in Table 3. Obviously, the group distribution of all the four datasets is heavily imbalanced. Furthermore, the same race group does not always have the same distribution in different datasets. For example, the white group dominates in Adult dataset, while the black group dominates in Broward dataset. On gender attribute, the male group always dominates the female group in all the four datasets. Although it seemly has no direct connection between the vulnerability disparity and race/gender, we will explore if there is any hidden disparity due to the imbalanced data distribution of these two protected attributes.

Main results. The results of VD before and after applying DP on the target model are illustrated in Figure 3. The results of VD reduction for various privacy budgets is shown in Figure 4. We briefly summarize the main observations below:

1. Different datasets show different amounts of VD, for both before and after DP deployment (as shown in Figure 3).
   - Adult dataset: insignificant VD ($< 0.04$) on both race and gender groups before and after DP enforcement.
   - Broward and COMPAS datasets: significant VD ($\geq 0.1$) on the gender groups before and after DP deployment. Insignificant VD ($< 0.04$) on the race groups before and after DP enforcement.
   - Hospital dataset: insignificant VD ($< -0.01$) on both gender and race groups before DP. Significant VD ($\geq 0.1$) after DP on gender groups but insignificant VD on race groups after DP enforcement.

2. DP cannot eliminate VD completely on both gender and race attributes. There is no consistent pattern of how VD changes by DP deployment (as shown in Figure 4).
   - Adult dataset: On both gender and race attributes, VD decreases until the privacy budget decreases to 1. Then VD switches to opposite direction and increases.

![Figure 3: Vulnerability disparity before and after DP enforcement ("No DP" means before DP is deployed).](image)

![Figure 4: Change of Vulnerability disparity by DP.](image)
• **Broward** dataset: VD increases after DP deployment on both gender and race groups. The increment is small and stable on race groups, but significant and unstable on gender groups.
• **COMPAS** dataset: VD increases after DP deployment, except when privacy budget is 1 and 0.5. The pattern is opposite to **Broward** dataset - VD increment is small and stable on gender groups, but significant and volatile on race groups.
• **Hospital** dataset: On gender attributes VD increases to be significant (> 0.1) after DP deployment. On race attribute, VD keeps stable.

Next, we explain more details of our observations. We will provide detailed analysis of the underlying reasoning behind these observations in Section 4.3.

**VD measurement before DP deployment.** We make one interesting observation from Figure 3 (for the case of “No DP”). In all datasets, the smaller group is not always more vulnerable against MIA than the larger group. For example, as shown in Figure 3 (b), the male group is always more vulnerable than the female group in Broward & Adult datasets, while the female group is more vulnerable than the male group in COMPAS and Hospital datasets. This shows that VD is not directly related to the group distribution of the protected attributes alone.

**VD measurement after DP.** As shown in Figure 3, our results support the conclusion that DP cannot eliminate VD. Furthermore, the strength of DP (controlled by using various privacy budgets) has some clear impacts on VD. However, the change of VD does not change linearly with the privacy budget.

**Change of VD by DP.** The results (Figure 4) do not show a consistent pattern of VD reduction when the privacy budget increases. Furthermore, DP does not always reduce the amounts of VD. On Hospital dataset DP even increases VD (as shown in Figure 3 (d)) from close to 0 to as large as 0.2.

### 4.3 Analysis of Vulnerability Disparity

In this section, we explain the reasons behind our main observations in Section 4.2.

In a MIA attack, both target and attack models together create a mapping from the input domain to MIA predictions. Remind that the input of MIA, which is also the output of the target model, consists of a vector of prediction probabilities, each probability measuring if an input data point belongs to a specific class $i$. In essence, MIA maps each prediction probability to a binary label. Certain ranges of prediction probabilities are projected to the positive label by MIA (i.e., predicted as members). Intuitively, VD is directly related to how the training samples from different groups are mapped to the binary label. Recall that VD indeed measures the difference of recall of different groups. Following the above reasoning, we performed a set of experiments to measure the recall of different groups before and after DP is enforced on the target model. To better illustrate our results, we evenly split the probability domain $[0, 1]$ into 10 ranges, each of size $0.1$. For each range $r$, we count the number of records (denoted as $c^A_a$) in group $A = a$ that are labeled with the positive label by MIA and their prediction probability falls into $r$. Then we calculate the recall of a group $A = a$ in the range $r$, denoted as $Rec^A_a$, as

$$Rec^A_a = \frac{c^A_a}{c^A}.$$  \hspace{1cm} (5)

where $c^A_a$ is the number of records in group $A = a$ that are labeled with the positive label by MIA. Apparently, the difference $(Rec^A_a - Rec^\bar{A}_a)$ between the recall of the two groups in the range $r$ equals the amount of VD in $r$. Also it must be true that:

$$VD = \sum_{i=1}^{10} (Rec^A_{r_i} - Rec^{\bar{A}}_{r_i}).$$

In other words, the sum of the recall difference in each range should equal to VD of the whole dataset. We illustrate the results of recall by probability range in Figure 5.

**Explanations.** Next, we will answer the following three questions raised from our observations in Section 4.2 by analyzing how the recall of different groups vary, and how the recall per group shifts with regards to different degrees of privacy protection (controlled by privacy budget $\epsilon$). We vary $\epsilon$ from 0.1 to 5 (i.e., from strong to weak privacy protection).

**Why does VD exist?** As shown in Figure 5 (a), (f), (k) and (p), before the deployment of DP, various groups have different recall in each probability range. For instance, consider Broward dataset (Figure 5 (a)), the true positive records mostly cover the prediction probabilities in the range of $[0, 0.1)$, which the recall of male and female groups differ around 10%. This leads to the VD (around 0.1) of the two groups (Figure 4 (b)). The same observation also holds on the other three datasets. We have to note that on ADULT dataset, the positive records mainly cover two ranges of prediction probabilities, $[0, 0.1)$ and $[0.9, 1]$. These two ranges show the opposite recall results: the recall of the male group is higher than the female group in the range $[0, 0.1)$ while opposite in the range $[0.9, 1]$. Also the recall difference in these two ranges is of similar amounts. Therefore, the VD on ADULT dataset is relatively small (as shown in Figure 3 (a)).

**What determines the amount of VD?** Since the target model determines such recall difference, we next investigate if the gender feature is the main factor. We identify the important features of Broward dataset, which are those features that directly effect the output probability vector of the target model. It turns out that the top-3 important features of Broward dataset is **Decile**, **Priors**, and **Age**. We studied two data distributions: (1) data distribution $D_1$ on the combination of the four features (i.e., the top-3 important features plus gender); and (2) data distribution $D_2$ on the top-3 important features. We compared $D_1$ and $D_2$, and found out that the difference between $D_1$ and $D_2$ is closely (not completely) consistent with the recall distribution shown in Figure 5 (a). The same observation also holds on other datasets. For example, on ADULT dataset, whose top-3 important features are **Education**, **Marital Status**, and **Cap_Gain**, shows almost identical distributions on the combination of top-3 important features alone and the top-3 features plus gender. This leads to the small VD on Adult dataset (Figure 3 (a)). In summary, the amount of VD is not determined by the data distribution on the protected attribute alone. Instead, it is determined by the data distribution on the combination of the protected attribute with other attributes (sometimes the top-3 important features are sufficient).
Therefore, the amount of VD is unpredictable and changes inco-
herently (i.e., the number of prediction probabilities that are mapped
to the positive label by MIA), due to the randomness of perturba-
tions. To fundamentally solve this problem, generally speaking, t-
here are two approaches. First, we can “optimize” the target model su-
ch that, given the training samples from different groups as inputs, it
pick similarly-distributed data from different groups to train the
models. However, our analysis shows that there is no linear cor-
relation between the privacy budget and the size of unsafe ar-
areas (i.e., the number of prediction probabilities that are mapped
to the positive label by MIA), due to the randomness of perturba-
tion on the target model added by DP. In other words, the mapping
from the input domain to MIA predictions becomes probabilistic.
Therefore, the amount of VD is unpredictable and change in-
consistently with the increment of the privacy budget. This has been

5 MITIGATION ALGORITHMS FOR VULNERABILITY DISPARITY

As is illustrated in Section 4.3, the vulnerability disparity is caused
by inconsistent distribution of training samples from different groups.
To fundamentally solve this problem, generally speaking, there are
two approaches. First, we can “optimize” the target model such that,
given the training samples from different groups as inputs, it produces
equally-distributed outputs. Second, we can elaborately pick similarly-distributed data from different groups to train the
target model. The first approach, however, has several major lim-
itations. First, there lacks theoretical support of designing such a

Figure 5: Recall of different groups by prediction probability range
model. It remains an open question whether we can achieve our goal while preserving the properties of the original model. Second, it needs separate solutions for different types of target models. This brings high complexities to generalize the approach. Finally, it needs several solutions for different types of target models.

### 5.1 Design of Vulnerability Correction

Past research has proposed several data pre-processing approaches for addressing unfairness issues [36]. In particular, reweighing [7] and its variants [36] are widely used to facilitate classification without discrimination. Technically speaking, reweighing picks training samples from each group such that they share identical distribution as the entire data-set in the dimension of label. That is to say, reweighing makes all groups have consistent distribution when we consider the label as the index. By intuition, we can extend reweighing to achieve our goal by considering the feature combination as the label. This approach, however, can have two problems because of reweighing’s strict requirement of distribution. First, reweighing frequently needs to over-weigh (or duplicate) samples from a group to meet the needs of distribution. However, from a practical perspective, the over-picked samples do not truly affect the distribution of real samples. Therefore, reweighing may not provide realistic protection. Second, the feature combinations are often sparsely distributed, in particular when the features are many while the data-set is small. As a consequence, plenty of feature combinations only appear in a specific group and to ensure consistent distributions, reweighing has to delete samples with those feature combinations. This frequently leads to over-deletion and makes the resulted data-set unusable.

**Algorithm 2 Algorithm for FAIRPick**

1. **Input** $D_{train}$: Private training data-set; $S$: Protected attribute domain; $T$: reduction rate;
2. **Let** $D'_{train} = \emptyset$ to be the training data-set after FAIRPick
3. **Split** $D_{train}$ by the class label and get a set of data-sets $C_{train}$

   **for each** $d \in C_{train}$ **do**
   5. $d_{kmeans} = Kmeans(d)$
   6. **In each cluster**, calculate its center to construct a new feature combination.
7. **Let** $f$ to be all the feature combination of $d_{kmeans}$
8. **Let** $func = \emptyset$

   **for** $i = 1 : |S|$ **do**
   10. create Equation 7 of $del(G_i, C_j)(1 \leq j \leq t)$ for $G_i$
   11. Append the equations to $func$
   **end for**
13. $ans = quadratic.progaming(func)$
14. $d_{reweigh} = pick.samples(ans, d_{kmeans})$
15. $d' = Map$ records in $d_{reweigh}$ to original records
16. Append $d'$ to $D'_{train}$
 **end for**
18. **return** $D'_{train}$

After applying FAIRPick, we require that:

$$\forall i \in [1, n], \forall j \in [1, t], \; dvar(G_i, C_j) = dvar(G_i, C_j, {pre}) \ast T$$  \hspace{1cm} (7)

where $dvar(G_i, C_j, {pre})$ and $dvar(G_i, C_j, {post})$ respectively represent $dvar(G_i, C_j)$ before and after FAIRPick, and $T (0 \leq T \leq 1)$ is a user-specified threshold. To better understand the effects of Equation 7 on VD, let’s assume that the unsafe areas contain $\{C_{u1}, C_{u2}, ..., C_{uk}\}$ (which will be determined as training samples by MIA). For simplicity, we also assume the unsafe areas do not shift after FAIRPick. Under such contexts, VD pertaining to group $G_i$ before and after we apply FAIRPick, respectively equals to $\Sigma_{u=1}^{k} dvar(G_i, C_j, {pre})$ and $\Sigma_{u=1}^{k} dvar(G_i, C_j, {post})$. According to Equation 7, it is not hard to observe that VD will be reduced by $(1 - T)$.

To solve Equation 7, we consider deleting $del(G_i, C_j)(0 \leq j \leq t, 0 \leq i \leq n)$ samples that have feature combinations $C_j$ from group $G_i$. This creates $t \ast n$ variables. Including $del(G_i, C_j)$ to Equation 6, we will have $dvar(G_i, C_j, {post})$ equal to:

$$\frac{sum(G_i, C_j) - \Delta\{del(G_i, C_j)\}}{sum(G_i) - \Sigma_{n=1}^{t} \Delta\{del(G_i, C_n)\}} = \frac{\eta_{pre} \Sigma_{i=1}^{k} \Delta\{sum(G_i, C_j)\} - \Sigma_{i=1}^{k} \eta_{post} \Delta\{sum(G_i, C_n)\}}{\eta_{pre} \Sigma_{i=1}^{k} \Delta\{sum(G_i)\} - \Sigma_{i=1}^{k} \eta_{post} \Delta\{sum(G_i, C_n)\}}$$  \hspace{1cm} (8)

By correlating Equation 8 with Equation 7, we can establish $t \ast n$ equations with $del(G_i, C_j)(0 \leq j \leq t, 0 \leq i \leq n)$ as variables. While it is hard to derive general solutions, these equations are typically solvable with quadratic programming [22].

### Challenges in practice

Under practice settings, FAIRPick, however, can encounter several challenges. We elaborate on these challenges and how we handle them in the following.

- **As aforementioned**, the distribution of feature combination is often sparse. Many feature combinations can only have 1 or 2 instances in a single group. For such feature combinations, FAIRPick often gives small decimal values as the number of instances to delete. By intuition, we can simply round the decimal values up/down to integers. However, rounding these values up can result in data over-deletion while rounding them down will eliminate the reduction effects. To systematically address this problem, we propose **feature aggregation**. Specifically, we run
K-means to classify the training samples into K clusters and consider each cluster center as a new unique feature combination. When applying FairPick, we replace each sample with its K-means center. If data deletion is needed for a K-means center, we randomly pick samples from the corresponding cluster. After the process of FairPick, we then map the remaining samples back.
to their original values. The rationale behind our feature aggregation is that samples in the same cluster are in principle close and therefore, have similar probability of being attacked. To determine $K$ for feature aggregation, we pick the largest $K$ that ensures every group has at least a certain amount of samples in each cluster.

- In certain cases, FairPick can require to delete a negative number of samples (i.e., $\text{del}(G_i, C_j) < 0$). This indicates the needs of duplicating samples. However, as is previously explained, sample duplication provides no real protection. To address this issue, we restrict the number of negative deletions. Specifically, we enumerate $T$ to find the values that preserves the utilities of the target model but requires less than an expected amount of negative deletions. With the above condition holds, we then simply ignore all the negative deletions requested by FairPick.

- In our explanation with the effects of FairPick on VD, we assume the unsafe areas do not shift. This is, however, not the case in practice. As FairPick alters the distribution of training samples, it will bring changes to the target model and hence, affect the unsafe areas. We argue that the shifting of unsafe areas should be insignificant because, as unveiled by the literature [41], MIA essentially attacks outliers which usually span a specific range. Further, our evaluation in Section 5.2 illustrates FairPick works as exacted in practical settings where the unsafe areas may indeed shift.

To sum up, FairPick follows Algorithm 2 to reduce distribution difference among different groups.

### 5.2 Evaluation of Unfairness Correction

To understand the utility of FairPick for VD reduction, we perform a group of evaluation. In the following, we cover the details.

**Experiment setup.** In the evaluation, we first apply FairPick to the training data and then follow Section 3 for the reproduction of MIA and the use of DP against MIA. As introduced in Section 2.1, MIA trains label-class-specific attack models. Therefore, we group the training samples based on their labels and separately apply FairPick to each of the sub-groups. Following Section 4.2, we consider gender and race as the protected groups (gender defines male and female; race defines black and non-black). Recall that FairPick performs $k$-means for feature aggregation. In this evaluation, we pick $K$ to ensure each cluster has more than 10 samples. Further, we follow the approach described in Section 5.1 to determine the threshold for VD reduction. For the simplicity of presentation, we pick three thresholds that work for all the four data-sets (including 0.4, 0.6, and 0.8). Finally, to reduce randomness, we repeat each test 25 times and report the average results.

**Impact on target model and MIA.** By intuition, FairPick works by deleting training samples, which can hurt the target model and further affect the attack models. To verify this intuition, we compare the performance of the target model and the attack models before and after we apply FairPick. In Figure 6, we present the comparison results. Note that to better visualize the comparison, we only show FairPick with $T = 0.8$. FairPick with $T = 0.4$ and $T = 0.6$ has similar results.

Overall, FairPick can largely preserve the accuracy of the target model. In the case of Broward, the target model has nearly consistent accuracy after we apply FairPick. On the data-sets of Adult and Hospital, FairPick barely affects the target model’s testing accuracy. It, however, slightly increases the training accuracy of the target model. This is most likely because, to reduce distribution difference, FairPick deletes outlier samples that only appear in certain groups and thus, makes the target model more centralized to better fit the training samples. In the case of Compas, FairPick has no obvious impacts on the testing accuracy but increases the training accuracy by 15% when we consider gender as the protected group. We believe this again is because FairPick deletes irregularly-distributed samples such that the target model becomes less scattered. As we can also observe in Figure 6, FairPick has similar effects on the target model with or without DP. This further proves that FairPick is not impeding the target model and more importantly, FairPick is compatible with using DP as a defense.

With regards to the impacts on MIA, FairPick shows similar patterns to its effects on the target model. This is understandable since MIA is largely determined by the target model. To be specific, on the Adult, Broward, and Hospital data-sets, MIA all has highly similar recall and precision with or without FairPick. The only significant difference incurred by FairPick is MIA’s recall on the Compas data-set. When we consider gender as the protected attribute for Compas, FairPick increases MIA’s recall by around 10%. This, as explained above, is because the data deletion by FairPick makes the target model over-fit the training samples and therefore, leads MIA to have higher effectiveness. If we consider race as the protected attribute for Compas, FairPick increases MIA’s recall by down-graded by around 10%. We believe this is likely due to randomness as the recall consistently increases when DP is augmented. To sum up, FairPick only incurs slight (near zero in many cases) changes to the performance of MIA. This is critical for our study because this helps confirm that VD reduction (if observed) is indeed attributable to FairPick instead of variance in MIA’s performance.

**Effectiveness of VD reduction.** In Figure 7, we present the reduction of VD after we apply FairPick. In general, FairPick demonstrates expected effects on VD reduction. Particularly, when the original VD is significant ($VD > 0.1$, Broward and Compas in Figure 3), we observe stable and effective reduction. With the two data-sets, the average reduction rate consistently exceeds 30% (under different $T$). Also observable in Figure 7 is that the reduction by FairPick is independent with DP. This, again, proves that FairPick is compatible with DP and can complement DP to provide fair protection.

From Figure 7, we can also see a pattern (despite somewhat unstable) that the reduction of VD increases while we decrease $T$ (namely increase the expected reduction rate). Such patterns are especially significant in the case of Compas (with race), Adult (with gender), Broward (with race), and Hospital (with gender). This shows that our set-up of $T$ works as expected, providing user the flexibility of choosing fairness level on demands.

We also note cases where FairPick does not reduce VD but instead increases its value. We reason each of the cases as follows. In the case of Adult (with gender as the protected attribute) and Hospital (with race as the protected attributed), the original VD
is very insignificant. A slight change or randomness will lead to major VD changes. As such, the effectiveness of FAIRPick can be masked and not observable. In the case of Broward with gender as the protected attribute, FAIRPick increases VD when $T = 0.4$. In this case, among all the deletion requests by FAIRPick, over half of them are negative deletions (namely duplication). Recall that FAIRPick ignores such requests. Therefore, it has no reduction effects. On the contrary, its half-done reduction accidentally increases the variances in data distribution.

To sum up, our evaluation shows FAIRPick can provide reliable and effective VD reduction under practical settings.

6 RELATED WORK

In this section, we review the related work on MIA attacks and defenses, DP and its evaluation, and fairness in ML.

Membership inference attacks and defenses MIA was initially proposed by Shokri et al. [53]. Under a black-box setting where the target model is unknown, MIA predicts whether a given record was used in training the target model. Afterwards, several follow-up works provide more detailed study. [57] characterized the attack vulnerability with respect to types of learning models, data distribution, and transferability. [49] proposed new membership inference attacks by relaxing the assumptions of the original attack in [53] in both model types and data. [41] generalized MIA by identifying vulnerable records and indirect inference. Recently, [45] proposed new MIA attack against white-box ML models. Also MIA attack has been used to attack Federated learning [45], collaborative learning [43], generative adversarial networks (GANs) [29], and adversarially robust deep learning models [55].

Several defense mechanisms have been designed to defend against MIA, including dropout and model stacking [49], adversarial regularization [44], $L_2$-regularizer [53], and adversarial examples [34].

None of these techniques can provide a provable privacy guarantee against MIA. In this paper, we mainly consider differential privacy [19] as the defense mechanism against MIA, as it can provide a theoretical privacy guarantee.

Differential privacy and Machine Learning Differential privacy (DP) [19] has become the de facto standard in measuring the disclosure of privacy pertaining to individuals. To accommodate different types of machine learning models, there have developed various mechanisms to enforce DP [14, 42, 59]. The mechanisms can be categorized into two types: (1) pre-processing: the training data is perturbed by generating synthetic data with differential privacy [10, 12]; and (2) in-processing: add noise to the objective function of the learning model (e.g., [9, 30, 31, 62]) or to the gradient in each iteration of gradient descent or stochastic gradient descent that is used to minimize the objective function [4, 56]. We refer the authors to some good surveys [20, 32, 33] for more readings. Going beyond classical machine learning models, Shokri et al. extend DP to deep neural networks [52]. Following that, Abadi et al. propose an alternative approach that performs randomized perturbation during the stochastic gradient descent process [2]. Unlike these works that focus on exploring DP mechanisms on machine learning models and strive for the balance between utility and privacy guarantees, our research considers the fairness issues behind DP and endeavors to providing mitigation.

Algorithmic fairness in ML Several competing notions of fairness have been recently proposed in the machine learning literature. The definition of fairness can be categorized into three types [46]: i) it is not based on protected attributes such as gender or race (fair treatment), ii) it does not disproportionately benefit or hurt individuals (fair impact), and iii) given the target outcomes, it enforces equal discrepancies between decisions and target outcomes across groups of individuals based on their protected characteristic (fair supervised performance).

An example of fair treatment is fairness through unawareness [27] that ignores the protected attributes.

Examples of fair impact constraints include 80% rule [21] and demographic parity [7, 37]. Examples of fair supervised performance constraints include equal opportunity and equal odds [28] and de-correlation [61]. Most of these definitions focus on fairness of groups (i.e., individuals who share the same value on the protected attributes). Individual fairness [16, 40, 58] is defined as a non-preferential treatment towards an individual. Counterfactual fairness [25, 40] evaluates fairness in terms of causal inference and counterfactual examples.

Techniques to design bias mitigation algorithms typically identify a fairness notion of interest first, and modify a particular point of ML pipeline to satisfy it. Methodologically, they fall broadly into three categories: (1) pre-processing: the bias in the training data is mitigated [7, 21, 35]; (2) in-processing: the machine learning model is modified by adding fairness as additional constraint [8, 26, 61]; and (3) post-processing: the results of a previously trained classifier are modified to achieve the desired results on different groups [28].

7 CONCLUSION AND FUTURE WORK

Fairness and privacy are two equally important issues for machine learning. Most of the recent studies have investigated these two issues separately. No attention has been paid to fair privacy, i.e., privacy models and their enforcement mechanisms should not disproportionately benefit or hurt individuals. We are the first to examine fair privacy in the context of membership inference attack and differential privacy as the defense mechanism. We provide extensive empirical evidence that vulnerability disparity against MIA exists, without and with DP applied. We performed detailed analysis to identify the source of such vulnerability disparity. Based on our findings, we designed a new mitigation method named FAIRPick that adjusts the distribution of the training data. Our results show that FAIRPick can effectively reduce VD for both without and with DP deployment.

Future Work. There are quite a few interesting research directions to explore. First, we will investigate if vulnerability disparity exists for different target models with DP (e.g., differentially private DNN [3]) and different defense mechanisms (e.g., [44, 49, 53]) against MIA. Second, we will consider different fairness metrics to evaluate vulnerability disparity. In this paper, we mainly focus on vulnerability disparity of different groups. Recently, individual fairness has attracted much attention in the machine learning community. Briefly speaking, individual fairness requires that similar objects should receive similar treatment. Consider DP defends against MIA. If a record $R_1$ is exposed by MIA but its similar records are not, apparently it does not ensure the individual fairness. We will examine if such individual vulnerability disparity
against MIA exists before and after DP. As pointed out by [41], an outlier is more likely to be a vulnerable target record. This can be the starting point of the analysis of individual vulnerability disparity.
defenses on machine learning models. *arXiv preprint arXiv:1806.01246* (2018).

[50] Eunbi Seo, Hyun Min Song, and Huy Kang Kim. 2018. GIDS: GAN based Intrusion Detection System for In-Vehicle Network. In 2018 16th Annual Conference on Privacy, Security and Trust (PST). IEEE, 1–6.

[51] Dongdong She, Kexin Pei, Dave Epstein, Junfeng Yang, Baishakhi Ray, and Sunan Jana. 2019. Neuzz: Efficient fuzzing with neural program smoothing. In 2019 IEEE Symposium on Security and Privacy (SP). IEEE, 803–817.

[52] Reza Shokri and Vitaly Shmatikov. 2015. Privacy-preserving deep learning. In *Proceedings of the 22nd ACM SIGSAC conference on computer and communications security*. ACM, 1310–1321.

[53] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. 2017. Membership inference attacks against machine learning models. In *2017 IEEE Symposium on Security and Privacy (SP)*. IEEE, 3–18.

[54] Congzheng Song and Vitaly Shmatikov. 2018. The natural auditor: How to tell if someone used your words to train their model. *arXiv preprint arXiv:1811.00513* (2018).

[55] Liwei Song, Reza Shokri, and Prateek Mittal. 2019. Membership inference attacks against adversarially robust deep learning models. In 2019 IEEE Security and Privacy Workshops (SPW). IEEE, 50–56.

[56] Shuang Song, Kamalika Chaudhuri, and Anand D Sarwate. 2013. Stochastic gradient descent with differentially private updates. In *2013 IEEE Global Conference on Signal and Information Processing*. IEEE, 245–248.

[57] Stacey Truex, Ling Liu, Mehmet Emre Gursoy, Lei Yu, and Wench Wei. 2019. Demystifying Membership Inference Attacks in Machine Learning as a Service. *IEEE Transactions on Services Computing* (2019).

[58] Vladimir Vapnik and Akshay Vashist. 2009. A new learning paradigm: Learning using privileged information. *Neural networks* 22, 5–6 (2009), 544–557.

[59] Stanley L Warner. 1965. Randomized response: A survey technique for eliminating evasive answer bias. *J. Amer. Statist. Assoc.* 60, 309 (1965), 63–69.

[60] Fabian Yamaguchi, Felix Lindner, and Konrad Rieck. 2011. Vulnerability extrapolation: assisted discovery of vulnerabilities using machine learning. In *Proceedings of the 5th USENIX conference on Offensive technologies*. USENIX Association, 13–13.

[61] Muhammad Bilal Zafar, Isabel Valera, Manuel Gomez Rodriguez, and Krishna P Gummadi. 2017. Fairness beyond disparate treatment & disparate impact: Learning classification without disparate mistreatment. In *Proceedings of the 26th International Conference on World Wide Web*. 1171–1180.

[62] Jun Zhang, Zhenjie Zhang, Xiaokui Xiao, Yin Yang, and Marianne Winslett. 2012. Functional mechanism: regression analysis under differential privacy. *Proceedings of the VLDB Endowment* 5, 11 (2012), 1364–1375.