Can Querying for Bias Leak Protected Attributes? 
Achieving Privacy With Smooth Sensitivity

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ABSTRACT
Existing regulations often prohibit model developers from accessing protected attributes (gender, race, etc.) during training. This leads to scenarios where fairness assessments might need to be done on populations without knowing their memberships in protected groups. In such scenarios, institutions often adopt a separation between the model developers (who train their models with no access to the protected attributes) and a compliance team (who may have access to the entire dataset solely for auditing purposes). However, the model developers might be allowed to test their models for disparity by querying the compliance team for group fairness metrics. In this paper, we first demonstrate that simply querying for fairness metrics, such as, statistical parity and equalized odds can leak the protected attributes of individuals to the model developers. We demonstrate that there always exist strategies by which the model developers can identify the protected attribute of a targeted individual in the test dataset from just a single query. Furthermore, we show that one can reconstruct the protected attributes of all the individuals from \(O(N_{k}\log(n/N_{k}))\) queries when \(N_{k} \ll n\) using techniques from compressed sensing (\(n\) is the size of the test dataset and \(N_{k}\) is the size of smallest group therein). Our results pose an interesting debate in algorithmic fairness: Should querying for fairness metrics be viewed as a neutral-valued solution to ensure compliance with regulations? Or, does it constitute a violation of regulations and privacy if the number of queries answered is enough for the model developers to identify the protected attributes of specific individuals? To address this supposed violation of regulations and privacy, we also propose Attribute-Conceal, a novel technique that achieves differential privacy by calibrating noise to the smooth sensitivity of our bias query function, outperforming naive techniques such as the Laplace mechanism. We also include experimental results on the Adult dataset and synthetic dataset (broad range of parameters).

CSCS CONCEPTS
- Social and professional topics → Governmental regulations; 
  User characteristics; • Computing methodologies → Philosophical/theoretical foundations of artificial intelligence; • General and reference → Evaluation; • Security and privacy → Privacy-preserving protocols.

KEYWORDS
algorithmic fairness, compliance, compressed sensing, differential privacy, machine learning.

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1 INTRODUCTION
The ethical goal of algorithmic fairness [5, 60] is closely tied to the legal frameworks of both anti-discrimination and privacy. For instance, Title VII of the Civil Rights Act of 1964 [5] introduces two different notions of unfairness, namely, disparate impact [58], and disparate treatment [73], which are often at odds with each other [5]. It is widely believed that a machine learning model can avoid violating disparate treatment (and privacy concerns) if the model does not explicitly use the protected attributes [5]. However, it has been demonstrated that even if no protected attributes are explicitly used during training, a model might still be held liable for disparate impact, due to proxies of the protected attributes among other attributes in the dataset [17]. In fact, existing literature on algorithmic fairness demonstrates that leveraging protected attributes during training can essentially prevent disparate impact, e.g., by minimizing a fairness metric as a regularizer with the loss function during training [36, 43]. Thus, mitigating disparate impact often seems to be at odds with disparate treatment [49] (and privacy), depending on whether the protected attribute is being explicitly used or not.

One potential resolution (still debated [45]) is to use the protected attributes only during training to mitigate disparate treatment but not after deployment. Nonetheless, the use of protected attributes during model training remains to be a source of active debate and contention for various applications [49, 51]. On one hand, using protected attributes during training enables one to actively audit and account for biases, as well as understand how specific groups of people are affected. On the other hand, these protected attributes can also be used maliciously, e.g., to exacerbate discrimination [57]. An interesting example arises where the protected attributes can even be used to "mask" discrimination [22, 26, 27, 44], e.g., an expensive housing Ad is shown to only high-income White individuals and low-income Black individuals but not to low-income White individuals and high-income Black individuals (assuming an equal proportion of all these four sub-groups) [27]. The decision is clearly discriminatory against high-income Black individuals for whom
the Ad is relevant and yet they do not get to see it. This discrimination is masked since the decision might still satisfy statistical independence between the two races.

In several applications, e.g., in finance, anti-discrimination and privacy regulations adopt a stance that completely prohibits the use of protected attributes during training. In the finance domain, institutions cannot ask about an individual’s race for credit decisioning, while at the same time having to prove that their decisions are non-discriminatory [15]. The Apple Card credit card was recently accused of discriminatory credit decisioning since women received lower credit limits than equally qualified men, despite not using the gender explicitly during training [67].

Fairness assessment of these models is extremely challenging when the protected attributes are unavailable1. To address this, institutions often adopt a separation between the model developers and the compliance team [15]. The compliance team is responsible for ensuring methods do not violate anti-discrimination and privacy laws. As a result, the compliance team has access to the entire dataset, including the attributes protected by law (i.e., race, gender, etc.) [14, 15]. Only a subset of the data fields is visible to the model developers who train these models. The compliance team determines which attributes the model developers are allowed to see and use to train their models. Clearly, the model developers would not have access to the protected attributes. For fairness assessment, the model developers may however query the compliance team for certain group fairness metrics, e.g., statistical parity, equalized odds, etc. The model developers can then choose which model to deploy or discard based on the query responses.

In this paper, we first demonstrate that simply querying for fairness metrics (bias) can also leak the protected attributes of targeted individuals. Furthermore, we demonstrate that there exist strategies by which the model developers can always identify the protected attributes of all the individuals in the test dataset. We collectively refer to these strategies as Attribute-Reveal. Our finding poses an interesting debate in the policy aspects of fairness and privacy: Should querying for fairness metrics be viewed as a neutral-valued solution to ensure compliance with regulations? Or, does it constitute a violation of regulations and privacy, particularly if the number of queries answered is enough for the model developers to identify the protected attributes of specific individuals? To address this supposed violation of regulations and privacy, we also propose Attribute-Conceal, a novel differentially-private technique to answer queries without leaking the protected attributes.

To summarize, our main contributions are as follows:

1. **Demonstrate that querying for bias can leak protected attributes:** We first demonstrate that querying for fairness metrics, e.g., statistical parity, or equalized odds, can indeed leak the protected attributes of individuals. In Theorem 1, we provide the general criterion for reconstructing the protected attributes of all the individuals in the test dataset by querying for the statistical parity of several models (reduces to a linear system of equations).

2. **Leverage compressed sensing to reconstruct protected attributes with fewer queries:** Building on our initial result (Theorem 1), we then demonstrate how protected attributes of individuals

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1While [35] suggests that proxies may be used to approximate missing protected attributes for bias assessment, others [15, 42] argue that proxies may be problematic since they often underestimate bias.
auditing algorithms to estimate the statistical parity of ML models. Another related work is [59], which focuses on the issue of fair washing, where manipulation techniques are utilized to mask unfairness when presenting the model’s explanations to an auditor.

2 PROBLEM SETUP

2.1 Preliminaries

Let \( S = (X, Y, A) \) represent a test dataset consisting of \( n \) samples, where \( A = (a_1, a_2, ..., a_j, ..., a_m) \) denotes the protected/sensitive attributes (binary), \( X = (x_1, x_2, ..., x_j, ..., x_n) \) denotes the model inputs with each \( x_j \in \mathbb{R}^d \), and \( Y = (y_1, y_2, ..., y_j, ..., y_n) \) being the corresponding true labels used for supervised learning. We let \( a_j = 1 \) denote the advantaged group and \( a_j = 0 \) denote the disadvantaged group. We consider two types of classifiers: binary and logistic classifiers. The binary classifiers are represented by the function \( h(\cdot) : \mathbb{R}^d \rightarrow \{0, 1\} \). For a logistic classifier \( h(\cdot) : \mathbb{R}^d \rightarrow [0, 1] \), the output corresponds to the probability of input \( x \) being accepted. When we have several classifiers, we let \( h_1(x_j) \) represent the \( i \)-th classifier’s output to the input \( x_j \) (input feature vector of the \( j \)-th individual in the dataset) for \( i \in [m] \), where \( [m] = \{1, 2, ..., m\} \) for a positive integer \( m \). Let \( h_1(X) \) represent the \( i \)-th classifier’s outputs to all individuals in the dataset, i.e., \( h_1(X) = (h_1(x_1), ..., h_1(x_j), ..., h_1(x_n)) \). We let \( N_0 \) and \( N_1 \) be the size of the disadvantaged and advantaged group, i.e., \( N_0 = \sum_{j \in [n]} \mathbb{I}\{a_j = 0\} \) and \( N_1 = \sum_{j \in [n]} \mathbb{I}\{a_j = 1\} \). Note that \( N_1 + N_0 = n \), the size of the test dataset.

2.1.1 Review of Relevant Group Fairness Metrics.

**Definition 2.1 (Statistical Parity Gap (SP)).** Statistical parity gap (SP) is defined as the difference in expected outcome between the advantaged and disadvantaged groups, i.e.,

\[
SP_1 = \frac{1}{N_1} \sum_{j=1}^{N_1} h_1(x_j) - \frac{1}{N_0} \sum_{j=0}^{N_0} h_1(x_j).
\]

**Definition 2.2 (Equal Opportunity Gap (EO)).** Equal opportunity gap (EO) is defined as:

\[
EO_1 = \frac{1}{N_1} \sum_{j=1}^{N_1} h_1(x_j) - \frac{1}{N_0} \sum_{j=0}^{N_0} h_1(x_j),
\]

where

\[ N_1 = \sum_{j \in [n]} \mathbb{I}\{y_j=1, a_j=1\}, \quad N_0 = \sum_{j \in [n]} \mathbb{I}\{y_j=1, a_j=0\}. \]

We also denote the absolute values of statistical parity and equal opportunity gap as \(|SP_1|\) and \(|EO_1|\) respectively.

**Remark 1.** We note that although we only define statistical parity and equal opportunity, our techniques can be extended to several other group fairness measures, such as equalized odds, predictive parity, etc. as well as their absolute values. We further discuss this in Remark 5.

2.2 Problem Statement

Institutions often adopt a separation between the model developers and the compliance team to ensure anti-discrimination and privacy laws are met. The model developers do not have access to protected attributes and therefore cannot use them for training. The compliance team, however, has access to the entire dataset, but only for auditing purposes. In our setting, the model developers train \( m \) different classifiers \( h_i(\cdot) \) with \( i \in [m] \) on the training dataset.

For the fairness assessment of these models before deployment, the model developers are allowed to test for algorithmic bias by querying the compliance team for certain fairness metrics on the test dataset \( S = (X, Y, A) \). Note that the classifier \( h_i(\cdot) \) is only a function of the input \( x \) and not the protected attributes \( a \). The fairness metrics that the model developers can query for includes the statistical parity gap, and equal opportunity gap as well as their absolute values (see system model in Figure 1). The main question that we ask in this work is: Is this technique of querying for fairness metrics effective in keeping the protected attributes hidden from the model developers? Or in general, does querying for fairness leak protected attributes? And if so, how can one answer queries without leaking protected attributes?

**Remark 2.** The approach outlined in this paper can be extended to a scenario with an institution (that trains a model without access to protected attributes) and an external fairness auditing team, e.g., in [70]. The auditing team has access to the entire data for the purpose of evaluating the bias of the models and is responsible for informing the model developers on whether their deployed model passes fairness tests based on some fairness metric. In this setting, our concern is whether auditing for fairness compromise and leak the protected attributes to the institution.

3 ATTRIBUTE-REVEAL: QUERYING FOR BIAS LEAKS PROTECTED ATTRIBUTES

3.1 Demonstrating Leakage From Querying

Here, we show that simply querying for fairness metrics such as statistical parity can reveal the protected attribute of any targeted individual to the model developers. In fact, there exist strategies (that we collectively refer to as Attribute-Reveal) that can reveal the protected attributes of all the individuals in the test dataset. We begin with a simple toy example.

**Example 1 (Single Query).** The model developers train only one binary classifier \( h_1(\cdot) \) and query the compliance team for statistical parity gap. Suppose, the model developers want to find the protected attribute of the first individual. They can choose a classifier that accepts only the first individual, i.e., \( h_1(x_1) = 1 \) and \( h_1(x_j) = 0 \) for \( j = 2, 3, ..., n \). Observe that the statistical parity gap of this model will reveal the protected attribute of the first individual as follows:

\[
SP_1 = \frac{1}{N_1} \text{ if } a_1 = 1, \quad SP_1 = -\frac{1}{N_0} \text{ if } a_1 = 0.
\]

Thus, a positive
statistical parity gap $SP_1$ would give away that the individual belongs to the advantaged group, whereas a negative gap indicates that the individual belongs to the disadvantaged group. The query also reveals the sizes of these groups $N_1$ and $N_0$.

We note that such a model might seem contrived; it might also have low accuracy. Thus, in Example 2, we demonstrate a more realistic scenario that can occur more commonly in practice: two models of comparable accuracy can be used to reveal the protected attribute of a targeted individual.

**Example 2 (Double Query With Realistic Models).** Consider two models $h_1(\cdot)$ and $h_2(\cdot)$. The model $h_1(\cdot)$ is trained by model developers (to maximize accuracy) and accepts several individuals in the dataset. The model developers also use a second classifier, $h_2(\cdot)$, that provides the same prediction as $h_1(\cdot)$ except for one targeted individual, i.e., $h_1(x_1) = 1 - h_1(x_1)$ and $h_2(x_1) = h_1(x_1)$ for $j = 2, 3, \ldots, n$. Notice that $h_1(\cdot)$ and $h_2(\cdot)$ differ only in the first prediction. Their accuracies are almost similar: If one queries for statistical parity of these two models, they can identify the protected attribute of the first individual as follows: $SP_2 - SP_1 = \frac{1}{N_1}$ if $a_1 = 1$ and $SP_2 - SP_1 = -\frac{1}{N_0}$ if $a_1 = 0$.

A similar approach can be adopted to reveal the protected attributes of all the individuals in the test dataset. Our next result provides the general criterion for reconstructing the protected attribute of all the individuals in the test dataset using the statistical parity queries (see Appendix A for proof).

**Theorem 1 (Reveal From Linear System of Equations).** Let $SP = [SP_1\ SP_2\ \ldots\ SP_m]^T$ be a vector of statistical parity gap queries for $m$ models, $h_i(x_j)$ denote the $i$-th model’s prediction for the $j$-th individual, and $H$ be an $m \times n$ matrix where each row represents the binary or logistic predictions of the $i$-th model. If $\text{rank}(H) = n$, then the protected attributes $A = (a_1, a_2, \ldots, a_j, \ldots, a_n)$ of the entire dataset can be identified by solving a linear system of equations:

$$
\begin{pmatrix}
SP_1 \\
SP_2 \\
\vdots \\
SP_m
\end{pmatrix} =
\begin{pmatrix}
 h_1(x_1) & h_1(x_2) & \ldots & h_1(x_n) \\
h_2(x_1) & h_2(x_2) & \ldots & h_2(x_n) \\
\vdots & \vdots & \ddots & \vdots \\
h_m(x_1) & h_m(x_2) & \ldots & h_m(x_n)
\end{pmatrix}
\begin{pmatrix}
 v_1 \\
v_2 \\
\vdots \\
v_m
\end{pmatrix}
\quad \Rightarrow \quad
\begin{pmatrix}
 v_1 \\
v_2 \\
\vdots \\
v_m
\end{pmatrix} = H^{-1}SP.
$$

This can also be expressed as,

$$
SP = H_{m \times n}v,
$$

where $v$ is the unknown vector with elements taking values:

$$
a_j = \begin{cases} 
\frac{1}{N_1}, & \text{if } a_j = 1 \\
\frac{1}{N_0}, & \text{if } a_j = 0.
\end{cases}
$$

**Remark 3.** Strictly speaking, one needs $m = n - 1$ queries since the last individual can be identified using group sizes $N_1$ and $N_0$. However, one may encounter numerical errors when solving for $N_1$ from $1/N_1$ or, $N_0$ from $1/N_0$. This can happen when $N_1, N_0 >> 1$ and $N_0 \approx N_1$.

Algorithm 1 provides a more realistic strategy by which model developers can choose practical models with comparable accuracy to reveal the protected attributes of all the individuals. Essentially, one base model $h_0(\cdot)$ could be trained, and several similar models $h_i(x_j)$ could be chosen so that the prediction of $h_i(x_j)$ is flipped only when $i = j$. The accuracy of these models would remain comparable to the base model $h_0(\cdot)$ since they differ in only one prediction.

We note that if the size of the test dataset is large, it may not be desirable to have as many models as the size of the dataset. This motivates our next question: *Is it possible to obtain the protected attributes of individuals in the dataset with fewer models and queries?*

### 3.2 Leaking Protected Attributes with Fewer Queries using Compressed Sensing (CS)

In this section, we demonstrate that compressed sensing (CS) techniques can be used to obtain the protected attributes of individuals using a significantly smaller number of queries ($m$). First, we provide a brief background on compressed sensing in Section 3.2.1. Readers already familiar with this topic may skip this subsection.

#### 3.2.1 Brief Background on Compressed Sensing

The goal [24, 53] is to recover a vector $x \in \mathbb{R}^n$ from a set of linear measurements $\eta = \Phi x$, where $\eta$ is an $m \times 1$ measurement vector, $\Phi \in \mathbb{R}^{m \times n}$ is the sensing matrix. CS relies on the sparsity of $x$. A vector $x$ is $k$-sparse if it has only $k$ non-zero entries (typically $k \ll n$). The measurements $m$ are typically much smaller than $n$, making this an under-determined system of equations, having many solutions for $x$. CS focuses on finding the sparsest solution for $x$. This can be expressed as an optimization problem: $\min_x ||x||_0 \text{ s.t. } \eta = \Phi x$. Here, $||x||_0$ is the number of nonzero entries$^2$ of $x$. By minimizing an $l_1$ norm instead, this problem can be relaxed into a convex optimization problem which can be solved using linear programming or other CS algorithms, e.g., Orthogonal Matching Pursuit [54].

$$
\min_x ||x||_1 \text{ s.t. } \eta = \Phi x.
$$

The $l_1$-norm $||x||_1$ is the absolute sum of all entries of $x$. We refer the reader to an excellent survey [13] for more information on CS.

For accurate recovery of $k$-sparse vector $x$ from measurements $\eta$, the sensing matrix $\Phi$ has to satisfy a necessary and sufficient condition called Restricted Isometry Property (RIP) [9].

---

**Algorithm 1 Attribute-Reveal ($m = n$)**

Train base model $h_0(\cdot)$ (reasonable accuracy)
Choose $m=n$ models $h_1(\cdot), \ldots, h_n(\cdot)$ as:

for $i = 1, 2, \ldots, m$ do

for $j = 1, 2, \ldots, n$ do

$h_i(x_j) = \begin{cases} 
h_0(x_j), & \text{if } i \neq j \\
1 - h_0(x_j), & \text{if } i = j.
\end{cases}$

Query for Statistical Parity Gap for each model and store in $SP$
Create matrix: $H_{m \times n} = [h_1(X)^T, h_2(X)^T, \ldots, h_m(X)^T]^T$
Solve linear system of equations:

$$
SP = Hv
$$

This algorithm is based on Theorem 1

for $j = 1, 2, \ldots, n$ do

Detect $\hat{a}_j = \begin{cases} 
1, & \text{if } \eta_j > 0 \\
0, & \text{otherwise}.
\end{cases}$

---

$^2$Note that $||x||_0$ is not a norm. $||x||_p$ denotes a standard $l_p$-norm for $p \geq 1$, i.e., $||x||_p = (\sum_{i=1}^n |x_i|^p)^{\frac{1}{p}}$ for all $x \in \mathbb{R}^n$. 

**Definition 3.1 (k-Restricted Isometry Property).** A matrix \( \Phi \in \mathbb{R}^{m \times n} \) satisfies the Restricted Isometry Property of order \( k \) if for all \( k \)-sparse vector \( x \in \mathbb{R}^n \), and for some constant \( \delta_k \in (0, 1) \), we have
\[
(1 - \delta_k)||x||_2^2 \leq ||\Phi x||_2^2 \leq (1 + \delta_k)||x||_2^2.
\]

For a matrix \( \Phi \) that satisfies the RIP condition of order \( 2k \) with \( \delta_{2k} < \sqrt{2}-1 \) (see [10]), the vector \( x \) can be reconstructed from \( \eta \) and \( \Phi \) by solving (5). Random matrices satisfy RIP of any order \( k \) with high probability provided that \( m = O(k \log(n/k)) \) [4, 11]. Therefore, provided \( x \) is sufficiently sparse, smaller measurements \( m \) suffice to ensure a high-quality reconstruction of \( x \). It is also known that any CS algorithm will require at least \( m = \Omega(k \log(n/k)) \) for reconstruction [16].

In general, designing or checking whether a sensing matrix satisfies the RIP condition is computationally difficult. RIP only gives a condition on whether a matrix can be used as a sensing matrix but does not necessarily mention how to design one in practice. There are certain random matrices that are known to satisfy the RIP condition with high probability [12, 53]. The most common is the Gaussian matrix, i.e., \( \Phi_{m \times n} \) consists of \( m \) independent samples from a zero-mean Gaussian distribution with a variance of \( 1/m \) [12]. The random binary matrix is another well-studied sensing matrix that is known to satisfy the RIP condition [72].

### 3.2.2 Reveal from Compressed Sensing

**Theorem 2 (Reveal From Compressed Sensing).** Assume that \( N_0 \ll N_1 \), i.e., the size of the disadvantaged group in the dataset is much smaller than the advantaged group, and \( H_{m \times n} \) is a random matrix strongly concentrated around its mean. Then, the protected attribute vector \( A = (a_1, a_2, \ldots, a_j, \ldots, a_n) \) of the entire test dataset can be obtained using \( m = O(N_0 \log(n/N_0)) \) statistical-parity-gap queries.

**Proof.** To prove Theorem 2, we convert (4) into a compressed sensing problem (we refer the reader to Section 3.2.1 for a background on compressed sensing). Recall from the proof of Theorem 1 that the reconstruction of the protected attributes reduces to solving the linear system of equations in (4), i.e., \( \tilde{S}_P = H_{m \times n} \eta \).

Compressed sensing allows the number of queries \( m \) to be much less than \( n \) by exploiting the sparsity of one group in the dataset. Let \( \mathbf{v} = \tilde{r} - \tilde{s} \) where \( \tilde{r} = (1/N_1 \ 1/N_1 \ \cdots \ 1/N_1)^T \) and,
\[
\tilde{s}_j = \begin{cases} 0, & \text{if } a_j = 1 \\ \frac{1}{N_0} + \frac{1}{N_1}, & \text{if } a_j = 0 \end{cases}
\]
We have, \( \tilde{S}_P = H(\tilde{r} - \tilde{s}) \), leading to \( \tilde{S}_P - H \tilde{r} = H \tilde{s} \). Now, let \( \eta = \tilde{S}_P - H \tilde{r} \). Then, we have,
\[
\eta = H_{m \times n} \tilde{s}.
\]
By simple manipulations, we converted (4) into a standard compressed sensing problem (7) where \( \eta \) is the measurement vector, \( H \) is the sensing matrix, and \( \tilde{s} \) is a sparse vector with \( N_0 \) non-zero entries. From Theorem 1.2 in [10], the unknown vector \( \tilde{s} \) can be recovered if \( H \) satisfies RIP (see Definition 3.1) of order \( 2N_0 \) with constant \( \delta_{2N_0} < \sqrt{2} - 1 \). Furthermore, Theorem 9 in Appendix B shows that a random matrix that is strongly concentrated around its expectation satisfies RIP of order \( 2N_0 \) with high probability provided \( N_0 \leq cm/\log(n/N_0) \) (implies \( 2N_0 \leq c' m/\log(n/(2N_0)) \)) for constants \( c, c' > 0 \). Therefore \( m = O(N_0 \log(n/N_0)) \) statistical parity gap queries suffice to successfully reconstruct the protected attribute vector \( A \) of the entire test dataset.

**Remark 4.** For the model developers to use the CS technique, they also might need to know \( N_1 \) and \( N_0 \). This can be found by querying using a model that only accepts one individual and first checking the sign of \( S_P \). If \( S_P \) is positive, then \( N_1 \) is the member of the advantaged group, otherwise, \( N_1 \) is the member of the disadvantaged group. In practice, this motivates us to use small bounded noise so that the output values deviate as little as possible (Algorithm 2).

**Theorem 3.** Let \( \Phi \in \mathbb{R}^{m \times n} \) be a random sensing matrix whose entries are drawn from an i.i.d Uniform\([-\sqrt{3}/m, \sqrt{3}/m]\) distribution, then the matrix \( \Phi \) satisfies the Restricted Isometry Property (RIP) of order \( k \leq c_1 m/\log(n/k) \) with at least probability \( 1 - 2e^{c_2 m} \), for some constant \( c_1, c_2 > 0 \).

See proof in Appendix B.

This motivates Algorithm 2, a novel and realistic strategy by which model developers can choose practical models with comparable accuracy to reveal the protected attributes of all the individuals. Essentially, one base model \( h_0(\cdot) \) could be trained. For the other \( m \) models, small noise sampled from a uniform distribution is added to each output of the base model. If an output value goes outside \([0, 1]\), clip the value to lie between \([0, 1]\).

### 3.3 Extension to Absolute Statistical Parity Gap

With absolute statistical parity, it is still possible to partition individuals into two groups but no longer possible to determine which group represents the advantaged or disadvantaged populations with certainty. Being able to partition individuals in the test dataset based on their protected attributes is still a privacy infringement.
which. In many cases, the disadvantaged group is often known to be significantly smaller than the advantaged group. This is mostly due to the ease with which the advantaged and disadvantaged groups can be identified. If somehow the model team could only tell the protected attribute of one individual in a group, e.g., from the other attributes, the partitioning would allow them to learn the protected attribute of the entire test dataset. The partitioned sizes can also be used to determine which group is which. In many cases, the disadvantaged group is often known to be significantly smaller than the advantaged group.

**Theorem 4.** Given $m = n$ absolute-statistical-parity-gap queries, there exists a strategy that partitions individuals in the test dataset into two different groups based on their protected attributes.

Proof. We discuss such a strategy in the proof. Let us use $\alpha$ and $\beta$ to represent the two partitions of the dataset, i.e., $A \in \{\alpha, \beta\}^n$. Let $N_\alpha$ and $N_\beta$ denote the size of $\alpha$ and $\beta$ partitions respectively. Note that $N_\alpha + N_\beta = n$.

First, obtain $N_\alpha$ and $N_\beta$. This can be done by querying a model that accepts only one individual. The query will return $|SP_1| = 1/N_\alpha$ or $1/N_\beta$, revealing the size of the partitions. Now, consider the two cases.

Case 1: $N_\alpha \neq N_\beta$. If the size of the two groups is not equal, query a model $h_1(X)$ that accepts only the first individual in the dataset $x_1$. Assume that the individual belongs to the $\alpha$ partition, i.e., $a_1 = \alpha$. $|SP_1|$ would therefore be $1/N_\alpha$. Then, query a second model, $h_2(X)$, that accepts only the second individual $x_2$. If $|SP_2| = 1/N_\alpha$, then $a_2 = \alpha$. If $|SP_2| = 1/N_\beta$, then $|SP_2|$ must equal $1/N_\beta$, implying that $a_2 = \beta$. Continue this procedure for every individual until everyone is classified into $a_j = \alpha$ or $\beta$.

Case 2: $N_\alpha = N_\beta$. If the size of the two groups is the same, it would not be possible to differentiate between $1/N_\alpha$ and $1/N_\beta$. Hence, a slightly different approach is taken. First, query a model $h_1(X)$ that only accepts $x_1$ and assume $a_1 = \alpha$, resulting in $|SP_1| = 1/N_\alpha$. Next, query a second model $h_2(X)$ that accepts only $x_1$ and $x_2$. The protected attribute of $x_2$ can be obtained using the query $|SP_2|$, i.e.,

$$|SP_2| = \begin{cases} \frac{1}{N_\alpha}, & \text{if } a_2 = \alpha \\ \frac{1}{N_\alpha} - \frac{1}{N_\beta}, & \text{if } a_2 = \beta \end{cases}$$

In general, to obtain the group of the $j$-th individual $a_j$, select a model that accepts only $x_1$ and $x_j$. To partition the whole dataset using this technique, the model developers would need at most $m = n$ models and queries.

**Remark 5.** Our results extend to other fairness metrics, such as equalized odds, equal opportunity, and predictive rate parity. However, when querying for measures like equal opportunity, the model developers can only identify the protected attributes of individuals with true label $Y = 1$. Since equal opportunity conditions on $Y = 1$, one does not get any information about individuals with $Y = 0$.

## 4 DIFFERENTIALLY-PRIVATE APPROACHES TO BIAS ASSESSMENTS

In this section, we discuss approaches to prevent the problem of leaking protected attributes. The main goal is to answer fairness queries as accurately as possible but without leaking the protected attributes of any individual in the test dataset. This motivates us to leverage differential privacy [29, 31].

The notion of $\epsilon$-differential privacy was introduced in [29, 31]. The definition of differential privacy used in this work focuses on keeping the protected attributes private. Because the model developers already have access to a portion of the test dataset $(X, Y)$, we define neighboring datasets as datasets that differ only on one individual’s protected attribute $A$. For $A, A' \in \{0, 1\}^n$, $S = (X, Y, A)$ and $S' = (X, Y, A')$ are neighboring if $\|A - A'\|_1 = 1$. Let $D$ denote a universe of all possible datasets.

**Definition 4.1 (($\epsilon, \delta$)-Differential Privacy).** Consider any two test datasets $S = (X, Y, A)$ and $S' = (X, Y, A')$, where $A$ and $A'$ differ on the protected attribute $A$ of one individual. We say that a randomized mechanism $M$ is ($\epsilon, \delta$)-differentially private if, for all neighbouring $S, S', \text{ and all } \tau \subseteq \text{Range}(M)$, we have:

$$\Pr[M(S) \in \tau] \leq e^\epsilon \Pr[M(S') \in \tau] + \delta \quad \forall S, S' \in D,$$

where the randomness is over the choices made by $M$ and $\epsilon > 0$ is the privacy budget parameter.

A smaller $\epsilon$ introduces greater noise, resulting in enhanced privacy but reduced output accuracy. On the other hand, a larger $\epsilon$ incorporates less noise, leading to weaker privacy guarantees but increased output accuracy. Here, $\delta$ is the probability of information being accidentally leaked. If $\delta = 0$, $M$ is $\epsilon$-differentially private.

A popular mechanism that achieves $\epsilon$-differential privacy is the Laplace mechanism [32]. The Gaussian mechanism achieves $(\epsilon, \delta)$-DP for numeric queries (details in [32, Theorem A.1]).

### 4.1 Laplace Mechanism for Answering Bias Queries Using Global Sensitivity

We first introduce the definition of global sensitivity for a set of bias queries, e.g., SP queries for a set of $m$ models.

**Definition 4.2 ($l_1$-Global Sensitivity [32]).** The $l_1$-sensitivity of a query function $f$ for all neighboring $S, S' \in D$ is:

$$\Delta_f = \max_{S, S'} \|f(S) - f(S')\|_1.$$

A classifier satisfies equalized odds if the individuals in the advantaged and disadvantaged groups have equal expected outcomes given their true labels. A classifier satisfies predictive rate parity if both groups have an equal probability of a subject with positive predictive value truly belonging to the positive class [66].
A naive differentially private technique the compliance team could employ is the Laplace mechanism.

**Laplace Mechanism**: Given a query function \( f : \mathcal{D} \rightarrow \mathbb{R}^m \), the Laplace mechanism releases queries as follows:

\[
M(S, f(\cdot), \epsilon) = f(S) + (\Delta f_1(\epsilon), \Delta f_2(\epsilon), \ldots, \Delta f_m(\epsilon))
\]

where \( \epsilon \) is determined by privacy constraints.

**Theorem 5.** Given statistical parity gap queries \( (SP) \) for \( m \) models, the Laplace mechanism that adds noise from Laplace \( \Delta SP \) to each query is \( \epsilon \)-differentially private, where \( \Delta SP = \frac{m}{\epsilon} + \frac{m}{\epsilon^2} \).

**Theorem 6.** Given absolute statistical parity gap queries \( (SP) \) for \( m \) models, the Laplace mechanism that adds noise from Laplace \( \Delta SP \) to each query is \( \epsilon \)-differentially private, where \( \Delta SP = \frac{m}{\epsilon} + \frac{m}{\epsilon^2} \).

Similarly, for equal opportunity gap \( EO \) and absolute equal opportunity gap \( |EO| \) the Laplace mechanism adds noise with sensitivity \( \Delta EO = \frac{m}{\epsilon} + \frac{m}{\epsilon^2} \) and \( \Delta |EO| = \frac{m}{\epsilon} \). See Appendix C for proofs.

**Remark 6.** Because the Laplace and Gaussian mechanisms have infinite support \((-\infty, \infty)\), query results can sit outside the range of our fairness metrics \([-1, 1]\), or \([0, 1]\) for absolute value metrics. In general, these mechanisms do not automatically deal with bounding constraints. Some choose to ignore them and release the raw outputs of the mechanisms since it still satisfies DP's privacy and accuracy guarantees. In our case, probabilities of out-of-bounds values are often small unless \( \epsilon \) is chosen to be very small. If one insists on having bounded outputs, there are recent approaches [52], such as the truncated and boundary-inflated truncation approaches. Other approaches map out-of-bounds outputs to the boundaries of the metric.

### 4.2 Attribute-Conceal: Our Proposed Technique

Using Smooth Sensitivity

We have focused on adding noise to the query calibrated to its global sensitivity. However, this might be excessive in many cases, that is, the frameworks would add so much noise that the output would be meaningless. Since we are interested in a particular test dataset \( S \), we define the local sensitivity of a query function \( f \) and test dataset \( S \) in \( l_1 \) as:

\[
\Delta f^\text{local}(S) = \max_{S' : d(S, S') = 1} \| f(S) - f(S') \|_1.
\]

The challenge of calibrating noise to the local sensitivity \( \Delta f^\text{local}(S) \) is that it might leak information about the test dataset and therefore not sufficient to guarantee DP [56]. To address this, we investigate the idea of smooth sensitivity introduced in [56]. This is an intermediate notion between local and global sensitivity that allows dataset-specific additive noise to be added to achieve DP.

**Definition 4.3 (Smooth sensitivity [56]).** For \( \beta > 0 \), the \( \beta \)-smooth sensitivity of \( f \) is

\[
\Delta f^\text{smooth}(S, \beta) = \max_{S' \in \mathcal{D}} \left( \Delta f(S) \cdot e^{-\beta d(S, S')} \right).
\]

where \( d(S, S') \) denotes the number of entries in which protected attribute vectors \( A \) and \( A' \) disagree.

**Algorithm 3** Attribute-Conceal for Compliance Team

**Input**: Model predictions \( \hat{h}_1(\cdot), \hat{h}_2(\cdot), \ldots, \hat{h}_m(\cdot), N_1, N_0, \epsilon \)

Compute statistical parity gap for each model and store in \( SP \)

Compute Smooth Sensitivity:

\[
\Delta f^\text{smooth}(S, \beta) = \max_{S' \in \mathcal{D}} \left( \Delta f(S) \cdot e^{-\beta d(S, S')} \right)
\]

for \( i = 1, 2, \ldots, m \) do

Sample \( Z_i \) from a standard Cauchy distribution

\[
SP_i \leftarrow SP_i + \frac{\Delta f^\text{smooth}(S, \beta)}{\epsilon} \cdot Z_i
\]

Return: \( SP \)

**Theorem 7** (Dataset Specific \( e \)-DP Statistical Parity Query).

Let \( Z \) be an \( m \)-dimensional random vector with entries independently sampled from a Cauchy distribution \( \mathcal{C}(\cdot)? = \prod_{i=1}^m \frac{1}{1 + Z_i^2}. \) For statistical parity gap query \( SP \), the mechanism \( M(S) = SP(S) + \frac{\Delta SP^\text{smooth}(S)}{\epsilon} \cdot Z \) is \( \epsilon \)-differentially private, where the smooth sensitivity is given by:

\[
\Delta SP^\text{smooth}(S) = \max_{S' : d(S, S') = 1} \left( \Delta LS_{SP}(S') \cdot e^{-\beta d(S, S')} \right)
\]

Here, \( N_0 \) and \( N_1 \) are sizes of disadvantaged and advantaged groups in dataset \( S \), such that \( N_0 \leq N_1 \), \( N_0 + N_1 = n \), and \( \beta = \frac{\epsilon}{6m} \).

**Proof.** We first find the \( \beta \)-smooth sensitivity of statistical parity gap \( \Delta SP^\text{smooth}(S) \).

\[
\Delta SP^\text{smooth}(S) = \max_{S' : d(S, S') = 1} \left( \Delta LS_{SP}(S') \cdot e^{-\beta d(S, S')} \right)
\]

Here, (a) is from the definition of smooth sensitivity in (4.3). Next, (b) is the expression of the smooth sensitivity when looking at datasets at distance \( k \) (for details see [56, Def 3.1]). To obtain (c) we find the maximum local sensitivity over datasets that are at distance \( k \) (see Lemma 5 in Appendix D.3). Finally, (d) holds since the function is convex and hence its maximum occurs at the boundaries \( k \in \{0, N_0 - 2\} \) (see Lemma 6 in Appendix D.3). The rest of the proof follows directly from Lemma 2 and Lemma 3 in Appendix D with \( \gamma = 2 \) and \( \beta = \frac{\epsilon}{6m} \).

To achieve pure differential privacy, noise is introduced following a Cauchy distribution. This motivates Algorithm 3 (Attribute-Conceal), a differentially private technique to answer statistical parity gap queries based on Theorem 7.

We also note that the behavior of the Cauchy distribution can sometimes be unusual, as it does not have an expected value and has heavy tails that decay polynomially, compared to the exponential decay observed in Laplace and Gaussian distributions. In Theorem
8, we therefore also provide a relaxed \((\epsilon, \delta)\)-differentially private mechanism that introduces noise from a Laplace distribution.

**THEOREM 8.** Let \(Z\) be random noise samples from a \(m\)-dimensional Laplace distribution \(P(z) = \frac{1}{m} e^{-\frac{|z|}{\epsilon}}\). For statistical parity gap query \((SP)\), and \(\epsilon, \delta \in (0, 1)\), the mechanism \(M(S) = SP(S) + \frac{2\Delta_{SP,\beta}(S)}{\epsilon} Z\) is \((\epsilon, \delta)\)-differentially private, where the smooth sensitivity is given by:

\[
\Delta_{SP,\beta}^{smooth}(S) = \max \left(\frac{m}{N_1 + 1} + \frac{m}{N_0}, \ e^{-\frac{(N_0 - 1)\epsilon}{4(m\ln(2/\delta))}} \left(\frac{m}{n - 1} + \frac{m}{2}\right)\right).
\]

Here, \(N_0\) and \(N_1\) are sizes of disadvantaged and advantaged groups in dataset \(S\), such that \(N_0 \leq N_1\), \(N_0 + N_1 = n\), and \(\beta = \frac{\epsilon}{4(m\ln(2/\delta))}\).

**Proof.** The proof follows from Lemma 2 and 4 in Appendix D. Sensitivity analysis follow from proof of Theorem 7 with \(\beta = \frac{1}{4(m\ln(2/\delta))}\).

These results can be extended to the absolute statistical parity gap with \(\beta\)-smooth sensitivity (see Appendix D.4), i.e.,

\[
\Delta_{SP,\beta}^{smooth}(S) = \max \left(\frac{m}{N_0}, \ e^{-\frac{(N_0 - 1)\beta}{2}} \right).
\]

### 5 EXPERIMENTS

We include experimental results on the Adult dataset (see Table 1 and Figure 2) and simulations on synthetic dataset (see Figure 3, Table 2 and Table 3). For the Adult dataset, the protected attribute is race (assumed binary). We restrict ourselves to only White and Black with the latter being relatively sparse (10.4%). We first demonstrate how querying using Attribute-Reveal can leak the protected attributes. Then, we show that Attribute-Conceal effectively prevents this leakage (also outperforming the naive Laplace mechanism).

Our performance metrics of interest are (1) Average error in answering the Statistical Parity query \((Avg.\ SP\ Err)\); and (2) Accuracy of correctly recovering (essentially leaking) the protected attribute balanced across both races (Leakage, formally defined in Definition 5.1). To observe the tradeoff between \(Avg.\ SP\ Err\) (query error) and Leakage over a broader range of parameters (privacy parameter \(\epsilon\), sparsity \(N_0\), and test size \(n\)), we also perform simulations on a synthetic dataset. We provide additional experimental results on the German Credit dataset [25] in Appendix E.

**DEFINITION 5.1 (LEAKAGE(%)).** Let \(N_A\) be number of individuals in the advantaged group whose protected attribute was correctly predicted and \(N_D\) be number of individuals in the disadvantaged group whose protected attribute was correctly predicted.
Can Querying for Bias Leak Protected Attributes?
Achieving Privacy With Smooth Sensitivity

Figure 3: Experimental Results on Synthetic data for test size $n = 100, 1000, \text{ and } 10000$: Avg. SP err and Leakage trade-off with Attribute-Conceal. Each point represents an $\epsilon \in [10, 500]$ averaged over 50 runs. Results for varying sparsity $N_0$ and $m = O(N_0 \log n/N_0)$.

Table 2: Experimental Results on Synthetic data: Avg. SP err and Leakage for test dataset size $n = 1000$ and $n = 10000$ for Attribute-Conceal varying test dataset sparsity and model number $m$ with $\epsilon = 100$.

| $N_0$ | $n = 1000$ $\epsilon = 100$ | $N_0$ | $n = 10000$ $\epsilon = 100$ |
|-------|-----------------------------|-------|-------------------------------|
|       | Avg. SP err ($\times 10^{-3}$) | Leakage (%) | Avg. SP err ($\times 10^{-3}$) | Leakage (%) |
|       | $m = 500$ | $m = 900$ | $m = 500$ | $m = 900$ | $m = 1000$ | $m = 1000$ |
| 10    | 128.8 | 191.4 | 65 | 64 | 50 | 96.9 | 64 |
| 50    | 90.8  | 156.3 | 67 | 61 | 100 | 76.9 | 61 |
| 100   | 87.4  | 102.9 | 62 | 55 | 500 | 38.3 | 59 |
| 200   | 51.9  | 96.7  | 62 | 47 | 1000 | 26.9 | 59 |
| 300   | 38.9  | 59.9  | 48 | 47 | 3000 | 12.8 | 55 |
| 400   | 41.6  | 54.5  | 47 | 45 | 5000 | 9.9  | 48 |

Table 3: Experimental Results on Synthetic data: Avg. SP err and Leakage for test size $n = 1000$ and $n = 10000$ for Attribute-Conceal varying $N_0$ and privacy parameter $\epsilon$.

| $\epsilon$ | $n = 1000$ | $n = 10000$ |
|------------|------------|--------------|
|            | Avg. SP err ($\times 10^{-3}$) | Leakage (%) | Avg. SP err ($\times 10^{-3}$) | Leakage (%) |
|            | $N_0 = 10$ | $N_0 = 100$ | $N_0 = 10$ | $N_0 = 100$ | $N_0 = 10^2$ | $N_0 = 100$ | $N_0 = 10^3$ |
| 10         | 929        | 838         | 49 | 51 | 832.3 | 678.4 | 51 | 50 |
| 50         | 149.3      | 44.8        | 65 | 55 | 46.5  | 85.3  | 55 | 52 |
| 100        | 83         | 30.5        | 71 | 56 | 33.1  | 47.4  | 55 | 53 |
| 500        | 26.6       | 9.7         | 75 | 53 | 31    | 13.6  | 57 | 56 |

The leakage is defined as:

$$\text{Leakage} = \frac{1}{2} \left( \frac{N_A}{N_1} + \frac{N_B}{N_0} \right) \times 100.$$ 

The leakage is the balanced accuracy of recovery. This is used to deal with imbalanced data, i.e., when one target class appears a lot more than the other.

5.1 Experiments with Adult Dataset

The Adult dataset has 14 attributes for 48842 loan applicants. The classification task is to predict whether an individual’s income is more or less that 50K [25]. The feature “race” is chosen as the protected attribute. This feature is excluded from training and only used for statistical parity evaluation. We restrict ourselves to only White and Black (binary) with the latter being relatively sparse (10.4%). We compare Attribute-Conceal with a naive differential privacy technique, Laplace mechanism. We experiment with different test sizes and show our results in Figure 2 and Table 1.

Given an input, our base model $h_0(\cdot)$ outputs a probability value between 0 and 1. For the other $m$ models, we add a small noise sampled from Uniform(−0.1, 0.1) distribution to each output of the base model.

We observe that the accuracy of the other models is quite close to the original. We created 40 models from the base model: they had a mean accuracy of 86.23% and a standard deviation of 0.2583.

Interestingly, our experiments demonstrate that with the uniform noise, we can still recover the protected attributes with far fewer models than the full-rank case. As shown in Figure 2, we are able to recover all the protected attributes using $m = 40$ models. Notice that, this is roughly $O(N_0 \log(n/N_0))$.

Our recovery of protected attributes is based on the values of the $s$ vector in Algorithm 2. Ideally, it should be 0 if $a_j = 1$ and $1/N_1 + 1/N_0$ if $a_j = 0$. In our practical implementation, the compressed sensing solution is not always exact but still good enough to infer the protected attribute. Due to this, we use a threshold between 0 and $1/N_1 + 1/N_0$ to identify the protected attribute.
We perform simulations on synthetic data to observe the trade-off between Avg. SP Err and Leakage over a broader range of parameters (privacy parameter $\epsilon$, sparsity $N_0$, and test size $n$). In Figure 3, we show this trade-off with Attribute-Conceal for test size $n = 100, 1000$, and $10000$. Each point represents an $\epsilon \in \{10, 500\}$ averaged over 50 runs. We show results for varying sparsity $N_0$ and $m = O(N_0 \log n/N_0)$. Table 2 and Table 3 provide additional experimental results highlighting the Avg. SP err and Leakage for test size $n = 1000$ and $n = 10000$ for different sparsity $N_0$, the model number $m$, and the privacy parameter $\epsilon$. A clear trend observed is that Attribute-Conceal results in a significantly lower Avg. SP err compared to the Laplace mechanism, for a similar level of protected attribute leakage.

6 CONCLUSION AND FUTURE WORK

This work highlights a major concern with fairness assessments in scenarios where protected attributes such as gender or race cannot be accessed during model training. Showing that simply querying for fairness metrics can leak sensitive information to model developers raises important questions about the ethical implications of these assessments. As a remedy, we also propose a novel technique, Attribute-Conceal, which achieves differential privacy by calibration noise to the smooth sensitivity of our bias query.

The results of this study have important implications for regulations and privacy in the field of algorithmic fairness and provide a new approach to protect the sensitive information of individuals in fairness assessments. This also provides a potential resolution to the continuing debate about whether protected attributes should be used in training. Future research could look into expanding the framework to include other fairness metrics or incorporating these techniques into training or post-processing to directly reduce bias without leaking protected attributes.

Our current approach assumes that both model developers and the compliance (or auditing) team work with the same test set. However, this might not hold true in every context. The compliance/auditing team may choose to use a different test set. However, note that a different test set may not adequately represent the true training distribution, which could potentially affect generalization.

We note that while our focus is on leakage from bias queries, future work could also look into inferring the protected attributes from the other available features using alternate techniques [7, 8]. For example, if one has prior knowledge that a feature such as hours-worked-per-week is strongly correlated with gender, one might just be able to infer gender with reasonable accuracy from that feature. However, it remains debatable if such indirect inferring of protected attribute from correlated features would legally constitute a violation of disparate treatment (or privacy). On the other hand, asking the compliance team for bias assessments actually accesses the protected attributes using queries. We do make a distinction between leaking and inferring protected attributes here. An interesting scenario would arise if one exploits a synergy of both bias queries as well as inference mechanisms to obtain even more accurate predictions of protected attributes than using either of them individually, and if such techniques would constitute a violation of anti-discrimination and privacy.

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