A Survey on Fairness Without Demographics

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Abstract

The issue of bias in Machine Learning (ML) models is a significant challenge for the machine learning community. Real-world biases can be embedded in the data used to train models, prior studies have shown that ML models can learn and even amplify these biases. This can result in unfair treatment of individuals based on their inherent characteristics or sensitive attributes such as gender, race, or age. With the increasing use of ML models in high-stakes scenarios, ensuring fairness is crucial and has gained significant attention from researchers in recent years. However, the challenge of ensuring fairness becomes much greater when the assumption of full access to sensitive attributes does not hold. The settings where the hypothesis does not hold include cases where (1) only limited or noisy demographic information is available, or (2) demographic information is entirely unobserved due to privacy restrictions. In this survey, we review recent research efforts aimed at ensuring fairness when sensitive attributes are missing. We propose a taxonomy of existing works, and more importantly, highlight current challenges and future research directions to stimulate research in ML fairness in the setting of missing sensitive attributes.

1 Introduction

The growing success of Machine Learning (ML) and Deep Learning has led to successful applications in several domains such as healthcare (Shailaja et al., 2018; Jafri & Arabnia, 2009), criminal justice (Berk et al., 2019; Rudin, 2019; Berk, 2012; Tollenaar & Van der Heijden, 2013), and finance (Dixon et al., 2020; Heaton et al., 2016; Culkin & Das, 2017). The decisions provided in such domains can have profound social impacts, such as allowing or denying a loan to an individual (Pandey et al., 2017), releasing a defendant from jail (Angwin et al., 2016), admitting an individual to a university (Waters & Miikkulainen, 2014), or hiring an applicant for a certain job position (Van den Broek et al., 2021). In this regard, such high-stakes decision-making supported by ML systems has raised concerns about how these systems operate and the fairness of the decisions. Recent empirical studies have shown that a data-driven approach can unintentionally learn human biases, perpetuate or amplify them, and even introduce new ones (Caliskan et al., 2017; Bolukbasi et al., 2016; Buolamwini & Gebru, 2018; Zafar et al., 2017), leading to discriminatory outcomes against certain groups of individuals (Mehrabi et al., 2021; Barocas et al., 2017). Thus, in recent years, the social impacts of ML systems have led to an increasingly growing interest and efforts to address unfairness in machine learning.

Initial efforts have focused on identifying the source of biases and defining and quantifying unfairness. In this regard, many fairness notions have been proposed, which can be grouped into two main categories: individual fairness (Dwork et al., 2012) and group fairness (Dwork et al., 2012; Hardt et al., 2016; Zafar et al., 2017). *Individual fairness* requires that individuals who are similar with respect to the task at hand should receive similar outcomes. While *group fairness* requires groups of individuals, identified by sensitive attributes such as gender and race, to be treated equally by the model. Group fairness (aka, *statistical parity* Dwork et al. (2012)) and its derived notions such as *equalized odds* and *equal opportunity* (Hardt et al., 2016) require the model to have access to the sensitive attributes with respect to which fairness will be assessed and enforced. Many algorithms have been proposed to achieve these fairness notions. They can be grouped into three main approaches: pre-processing (Madras et al., 2018; Kamiran & Calders, 2012; Kenfack et al., 2021), in-processing (Kamishima et al., 2011; Bechavod & Ligett, 2017; Noriega-Campero et al., 2019), and post-processing (Hardt et al., 2016; Nabi & Shpitser, 2018). Depending on whether the fairness notion

is enforced before the model training, during the model training, or after training the model respectively. However, these algorithms often cannot be applied when the assumption of full access to sensitive attributes is not satisfied. On the other hand, protected attributes could be correlated with other non-protected features that affect models' predictions Kilbertus et al. (2017). For example, a decision-making process could not have access to the race of individuals but use their zip code. As people from the same origins tend to live in the same neighborhood, the zip code will act as a proxy for race. The model could indirectly rely on people's race to make decisions, leading to discrimination in the outcomes. However, without a causal graph (Kilbertus et al., 2017) or domain expert knowledge, non-sensitive proxy features are generally unknown, and describing their relationship precisely is often unfeasible (Zhao et al., 2021).

It has become imperative for the ML fairness community to develop methods that accommodate various constraints on sensitive attributes. Our survey identifies five primary constraints: (i) Missing sensitive attributes, stemming from privacy or legal restrictions (Hashimoto et al., 2018); (ii) Noisy sensitive attributes, arising from flawed data labeling or data corruption (iii) Private sensitive attributes, arising from constraints concerning the privacy-preservation sensitive attributes (Chen et al., 2022a); (iv) Partially available sensitive attributes, due to missing values or availability only in a different dataset (Diana et al., 2022); and (v) Availability of only non-sensitive attributes, especially those correlating with the sensitive ones (Zhao et al., 2021). Effectively addressing these constraints is crucial for advancing fairness in machine learning and ensuring the practical applicability of these methods across real-world scenarios. We review fairness notions that do not (fully) rely on sensitive attributes[1] and recent algorithms to achieve fairness in various settings where there are constraints on the sensitive attributes.

The rest of this paper is organized as follows. We present related surveys in Section 2. In Section 3, we delve into the concept of protected attributes, exploring scenarios where the assumption of their availability does not hold. We examine how the absence of access to these attributes can give rise to unforeseen biases in the ML pipeline. Section4 provides a background of various concepts utilized by methods presented in the survey, such as group fairness notion, fairness enhancing algorithms, and differential privacy. Fairness notions and methods to mitigate unfairness in missing sensitive attribute settings are introduced in section 5 and 6 respectively. Section 7 is dedicated to the conclusion and future perspectives.

2 Related surveys

There are several surveys within the fair machine community. Some of these surveys cover broadly the same topics with some specificity. In this section, we briefly present some of them in position to our work. Mehrabi et al. (2021) proposed a survey on machine learning biases, covering several sources and types of biases along with some mitigation strategies. A similar survey is proposed by Caton & Haas (2020); Wan et al. (2022); Le Quy et al. (2022); Pessach & Shmueli (2020) with an emphasis on bias mitigation techniques for classification tasks and beyond. Le Quy et al. (2022) survey benchmarks for machine learning research. Several datasets are presented, for a variety of domains in machine learning, including natural language processing and computer vision. For each of the datasets, the set of available sensitive features is described, a causal graph between features is presented and different fairness notions are measured. Soremekun et al. (2022); Bansal (2022) survey fairness definitions and bias mitigation technique in natural language processing. While Zehlike et al. (2021), Wang et al. (2022) and Pitoura et al. (2021) focus on fairness in ranking and recommender systems. Table 2 presents an overview of existing surveys along with the position of this work.

To complement existing surveys, this paper focuses on efforts that have been made to mitigate unfairness when there are various constraints over the sensitive attributes, e.g., they are missing, limited, private, or noisy. This context has received less, but growing attention within the past years and we hope this paper will lay the groundwork for much more research effort to address fairness issues under these challenging constraints on demographic information. Most closely in the spirit of our work is the survey by Ashurst & Weller (2023). It provides an overview of the risk in collecting demographic data and approaches to enhance fairness without demographics. In addition, this paper provides a more comprehensible review, a taxonomy of approaches, and current challenges with future future perspectives.

[1]Throughout the paper we use (sensitive/protected/demographic) group/attribute interchangeably

Paper	**Key topic(s) of the survey**	**Cover missing demographics?**	**Enhancements in this paper**
(Ashurst & Weller, 2023)	Benefits and Risks of collecting demographic data; Privacy methods for protecting demographic data; Overview of approaches for addressing missing sensitive attributes.	Yes	Fairness definitions with missing sensitive attributes; A taxonomy of approaches; Systematic review of existing methods; Current challenges and future perspectives;
Mehrabi et al. (2021)	Different sources of bias; type of discrimination and fairness definitions; Fair ML algorithms for classification; Fairness beyond classification; Datasets for ML fairness.	No	Sensitive attributes free fairness definitions and mitigation algorithms; Source of bias when the sensitive attribute is unknown;
Caton & Haas (2020)	Fairness definitions; Fairness algorithms for binary classification; Fairness beyond classification	No	Fairness definitions and mitigation algorithms without sensitive attributes; Bias audition under missing sensitive attributes.
Le Quy et al. (2022)	A comprehensive review of datasets set for ML research; Fairness definitions; Sensitive attributes and statistics of existing fair ML datasets	Fairly	NA
Zehlike et al. (2021)	Fairness definitions in ranking; Techniques to enforce fair ranking;	Fairly	NA
Pessach & Shmueli (2020)	Source of bias; Fairness definitions; Fair ML algorithms; Fairness beyond classification; and Datasets for ML fairness research	Fairly	Fairness-enhancing algorithms without full access to the sensitive attributes.
Wan et al. (2022)	Fairness definitions; In-processing techniques for bias mitigation	Fairly	In processing techniques with unknown or noisy sensitive attributes
Makhlouf et al. (2021)	Causality-based fairness notions; Algorithms to estimate causal quantities	No	NA
Chhabra et al. (2021)	Fairness definitions for clustering; Algorithms to enforce fairness in clustering.	Yes	NA
Garrido-Muñoz et al. (2021)	Type of bias in NLP; Bias mitigation techniques in NLP.	Yes	NA
(Dunkelau & Leuschel, 2019)	Fairness definitions; Bias mitigation techniques; dataset for fair ML and fairness toolkits.	No	NA

Table 1: Existing surveys on machine learning fairness

LAW OR CONVENTION	GOAL
The Human Rights Act Ewing (1999)	Prevents discrimination on a wide range of grounds including 'sex, race, color, language, religion, political or other opinions, national or social origin, association with a national minority, property, birth or any status
US Fair housing Act Yinger (1999)	Protect people against discrimination for different housing services including renting, buying, getting a mortgage, and housing assistance. The act makes unlawful any decision or action that is taken solely on the basis of race, color, religion, or national origin.
CEDAW Women (1979)	The UN Convention on the Elimination of All forms of Discrimination against Women.
Equal Credit Opportunity Act Hsia (1978)	Make unlawful for creditors to discriminate against applicants on the basis of their race, color, religion, national origin, sex, marital status, or age.
UNESCO Convention against Discrimination in Education	Enforces anti-discrimination in education making it available to all in any circumstances.

Table 2: Some examples of conventions and laws against discrimination around the world.

3 Unfairness in Automated Decision Making

In this section, we discuss the notion of protected attributes and their importance for bias assessment and mitigation. We present various settings under which protected attributes are not fully available. We also discuss the origins of bias and the impact they might have on ML model output in particular when demographic groups are unknown.

3.1 Protected attributes

Features are considered protected when they can be grounds for discrimination and their use is impertinent for decision-making. Many conventions and laws prohibit the use of protected attributes as a basis for decision-making. These laws and conventions seek to avoid discrimination against groups of people in various domains. Table 2 provides a non-exhaustive list of anti-discrimination laws and conventions around the world. Some common protected attributes in these laws and conventions include gender, race, ethnicity, sexual orientation, religion, and much more. Regulations and conventions in place also prohibit the collection and use of sensitive information to ensure privacy for individuals. These restrictions pose various challenges when designing algorithms that rely on sensitive attributes to ensure fair outcomes across demographic groups.

3.2 Constraints on the Protected Attributes

This section covers various settings where access to complete and clean sensitive attributes is not possible and their challenges for both unfairness measurement and mitigation. This includes cases where sensitive attributes are entirely missing, partially available, noisy, or accessible only through related features.

3.2.1 Missing Sensitive Attribute

Sensitive attributes can be missing for a number of reasons, some of the most common reasons include constraints in the data collection process and privacy concerns.

- **Data collection**: During data collection, the sensitive attributes of people might not have been recorded. For example, users were not requested to provide their gender.

- **Privacy or legal compliance**: As people become more concerned about the privacy of their sensitive information, data-driven algorithms are increasingly subject to data protection by regulators such as the Electronic Communications Privacy Act (ECPA) and General Data Protection Regulation (GDPR). Legal compliance can restrict direct access to users' sensitive attributes.

Most existing bias assessment and mitigation methods require direct access to sensitive attributes (Dwork et al., 2012; Hardt et al., 2016). In the absence of sensitive attributes, these methods are not directly applicable making bias assessment and mitigation challenging in these scenarios. We present in Section 6.2 and Section 6.5 methods proposed for bias mitigation and assessment without access to sensitive attributes respectively.

3.2.2 Partial Sensitive Attritutes

In some cases, sensitive information is not mandatory during the data collection and reluctant users might prefer to not provide their sensitive information for privacy reasons. For example, credit card companies can collect personal information for creditworthiness assessment. While some information is mandatory for risk assessment, others might be optional such as demographic information. As a result, only a few data points will have a value for the sensitive attributes. In such a scenario, data imputation approaches such as replacing the most frequent value or inferring the missing values from other features could be used (Coston et al., 2019). However, this should be done carefully as incorrect estimation of the demographic information can lead to more harm (see Section section 6.1.2). In other settings, the sensitive attributes are available in a different but related dataset or task (Awasthi et al., 2021). For example, in a loan application task where the feature gender is missing, a related task could be a model that predicts gender based on other information in a separate context. Although the feature gender is not directly utilized in the loan application model, the insights gained from predicting gender in the related task might indirectly inform decision-making processes, contributing to bias mitigation without explicitly using gender on the base task.

3.2.3 Noisy Sensitive Attributes

In some cases, sensitive attributes are available but are noisy. One of the most common reasons why sensitive attributes are noisy is that they have been corrupted during data collection or estimated using a non-optimal classifier. For example, we can be interested in assessing the fairness of a facial recognition system across different demographic groups. However, demographic information is not included in a large number of image datasets. One may rely on a different classifier trained to predict demographic attributes to obtain the group labels, which are likely noisy (Buolamwini & Gebru, 2018). Sensitive attributes are likely to be corrupted when users are required to self-report their sensitive information (Rosenman et al., 2011).

3.2.4 Private sensitive attributes

A common reason for missing demographic information is restrictions from laws or regulations that prohibit the collection and use of sensitive information about individuals in algorithmic decision-making. For instance, the GDPR prevents the use of racial information about customers. At the same time, these laws and restrictions enforce non-discrimination in automated decision-making systems. On the other hand, automated decision-making systems require protected attributes to audit and mitigate discrimination from the system. This raises the new challenge of design methods that comply with these two seemingly contradicting principles, i.e., design methods to build fair models while preserving the privacy of sensitive information. In order to alleviate the privacy restrictions, sensitive attributes can be made available under privacy-preserving mechanisms, i.e., a mechanism operating on the data that can expose or use sensitive data with strong privacy guarantees for individuals involved (Dwork et al., 2014). We further discuss this in Section 6.4.

3.3 Discrimination in machine learning

Unfairness or discrimination in a decision-making process made by humans is quite clear: it occurs when the outcome of a decision systematically depends on an individual's protected attribute and not on characteristics that are useful in assessing that individual's abilities with respect to the task or desired outcome. For example,

an officer assessing a consumer's loan application may be qualified sexist or racist if the decision to refuse the loan is solemnly based on the applicant's sex or race. A decision that does not rely on non-sensitive features such as the customer's financial or production management capabilities to repay the loan can be considered discriminatory. Therefore, a judgment made by a human can be described as racist or sexist (biased) if it discriminates against individuals based on their ethnic origin or gender. However, *can ML systems be described as racist or sexist?*. We argue no to this question because, unlike humans, ML systems are not capable of having feelings, "like" or "dislike" people. In contrast, ML systems are solely designed to maximize the utility of the outcomes without any intent to discriminate, and this can however foster the false belief that only justified discrimination can happen.

Machine learning models are trained using historical data and the goal is to discover patterns (general trends) in order to make predictions on future data. This training process, therefore, does not have any intention to discriminate against individuals based on their group membership (unless the model is trained for that purpose) and it can be misleading to consider ML models as racist or sexist as these models are not capable of *direct* discrimination like humans. However, unfairness in ML systems is more similar to *systemic discrimination* that also exists in some human decision-making processes (Craig, 2007). Systemic discrimination happens when the decision-making process, often unintentionally, is less or more advantageous for some groups of people. For example, a hiring decision process that considers applicants' criminal records may have disparate outcomes for equally qualified applicants (despite a race-neutral hiring rule) because of racial disparities in criminal records caused by discrimination in policing (Bohren et al., 2022). Therefore direct discrimination that occurs in policing leads to systemic discrimination in the hiring process. As such systemic discrimination can be the result of successive past direct discrimination.

Performances of ML systems are generally evaluated using different metrics such as accuracy, correct classification rates, misclassification rates, or error with respect to a loss function. The fairness of these models is often assessed in terms of disparities in performances across different demographic groups. As a result, fairness in machine learning is a very subjective notion that is defined based on three main aspects: the metric used, the type of task, and the learning paradigm. For example:

- **Classification**: The model is considered unfair when the accuracy is higher for one group than another (Barocas et al., 2019). Unfairness is also measured by comparing the correct classification and/or misclassification rates (Zafar et al., 2017; Hardt et al., 2016). More generally, fairness is measured using metrics derived from the confusion matrix of the classifiers. The ratio or difference between considered metrics for each protected subgroup and be used to measure the disparities.
- **Generative models**: For models such as generative adversarial networks (GANs) Goodfellow et al. (2020)–where two competing networks are used to estimate the true distribution of the data–the model is considered unfair when the generator at the test time samples data from one protected subgroup more often than another Tan et al. (2020). (Tan et al., 2020) and Kenfack et al. (2022) measured unfairness in generative models using the Kullback-Leibler (KL)-divergence between the distribution of protected subgroups and the uniform distribution. Hence, a generative model is considered fair when the distribution of subgroups in the generated data is uniform, i.e., all demographic groups are equally represented.
- **Reinforcement learning (RL)**: Chi et al. (2021) defined fairness in RL as parity in the reward returned for different demographic groups. Unfairness occurs when the returned reward of two policies trained of different groups sharing the same states and action spaces is higher for one group than another.
- **Natural language processing**: the model is considered unfair or biased when it encodes racial or gender stereotypes from the data. For example, in machine translation, translation from gender-neutral languages such as the Turkish language to non-gender-neutral languages such as English tends to assign articles such as "she" to professions such as nurses, and housekeepers. while assigning articles "he" to professions such as Doctor, Engineer (Prates et al., 2020).
- **Raking system**: The model is considered unfair when it under-ranks individuals from protected groups (Zehlike et al., 2021). Fairness is measured using a ranking score function that measures the

disparities disparity between demographic groups in the top-k ranking results. A ranking result gets a lower score if the top-ranked results consist of samples from mostly one group.

As can be seen, fairness in various areas of machine learning involves analyzing and quantifying the impact of trained models on different demographic groups. Therefore, addressing unfairness in machine learning systems consists of identifying the source of bias, quantifying the performance disparities in different demography groups, and developing methods to mitigate them.

4 Background

This section provides an overview of the concept used by various methods covered in the paper. The background information provided in this section represents the basic building blocks for existing techniques proposed for bias mitigation when complete and clean sensitive attributes are not available, as presented in Section 6. We present different source biases in the absence of the sensitive attributes, group fairness metrics, fairness enhancing methods, and differential privacy used by some work to build fair models with privacy guarantees on the sensitive attributes. A reader familiar with these concepts can skip this section.

Table 3: Table of Notation

X	Random variable defining data sample.
Y	Random variable defining the class label
A	Random variable defining the protected attribute.
$\hat{Y}$	Random variable defining the predicted class.
$\hat{A}$	Random variable describing corrupted or predicted sensitive attributes.
a_i	Sensitive attribute of the sample i
$\hat{a}_i$	Predicted or corrupted sensitive value of sample i
x_i	data sample sample i, $x_i \in \mathbb{R}^d$, described with d features.
y_i	Label of sample i
$\hat{y}_i$	Predicted label of sample i

4.1 Group Fairness Metrics

In general, group fairness metrics are defined by quantifying the disparities of metrics that can be derived from the confusion matrix of each demographic group; see Makhlouf et al. (2021) for an exhaustive list of group fairness metrics. The most popular group fairness notions include:

- *Statistical parity*: also known as *demographic parity*, this fairness notion requires that the classifier positive outcome must be independent to the protected attributes Dwork et al. (2012), i.e., $A \perp \hat{Y}$. Where A is the binary sensitive attribute and $\hat{Y}$ is the predicted label. A classifier achieves statistical parity if the following expression is satisfied

$$\mathrm{P}(\hat{Y} = 1|A = 0) = \mathrm{P}(\hat{Y} = 1|A = 1) \tag{1}$$

  However, a classifier that satisfies this fairness notion could also lead to discrimination against individuals from the non-protected group. for example, consider a model for hiring and gender as the sensitive attribute. If the goal is to hire the ten most qualified candidates and the hiring process applies statistical parity as fairness notion, the hired candidates should have equal gender representation. Therefore, if the ten most qualified candidates are men, the model will select five less qualified women to achieve statistical parity, hence harming five candidates from the non-protected group (violating *individual fairness*). Moreover, when the sensitive attribute is correlated with the class label, a classifier that achieves statistical parity cannot provide perfect predictions Verma & Rubin (2018).

- *Equalized odds* Zafar et al. (2017); Hardt et al. (2016): This fairness notion promotes the conditional independence between the classifier outcome and the sensitive attribute given class label, i.e., $A \perp \hat{Y}|Y$. Equalized Odds are therefore based on the confusion matrix and promote the true positive rates (TPR) and the false positive rates (FPR) across groups. A model satisfies equalized odds if

$$\begin{aligned} \mathrm{P}(\hat{Y} = 1|Y = y, A = 0) = \mathrm{P}(\hat{Y} = 1|Y = y, A = 1) \\ y \in \{0, 1\} \end{aligned} \tag{2}$$

  In our example, the hiring model will satisfy equalized odds if it gives the same advantages (TPR) and disadvantages (FPR) to all groups. i.e., candidates that are actually qualified and candidates that are actually unqualified should have a similar classification, regardless of their gender.

- *Equal opportunity* Hardt et al. (2016); Zafar et al. (2017): In some applications, one might be more interested in being fair when a positive outcome is made. Equal opportunity is similar to equalized odd, but focuses on equal TPR across groups and thus promotes *equal true positive rate* across groups. Therefore, a model will achieve equal opportunity if

$$\mathrm{P}(\hat{Y} = 1|Y = 1, A = 0) = \mathrm{P}(\hat{Y} = 1|Y = 1, A = 1) \tag{3}$$

  Similarly, one might be concerned about being fair when the model gives a negative outcome while the true one is positive. Therefore, the fairness notion to promote in this scenario will be *equal true positive rates* across groups Zafar et al. (2017). We refer the readers to Verma & Rubin (2018); Mehrabi et al. (2021) for a complete list of group fairness notions.

- *Disparate impact*: This fairness notion measures the ratio between the fractions of disadvantaged and advantaged samples that are assigned to the positive class. It is measured as follows:

$$DI = \frac{\mathrm{P}(\hat{Y} = 1|A = 0)}{\mathrm{P}(\hat{Y} = 1|A = 0)} > 1 - \epsilon \tag{4}$$

  where $A = \{0, 1\}$ represent the advantaged (0) and the disadvantaged groups (1). Typically, one sets $\epsilon \approx 0.2$ which suggests $DI > 0.8$ for a fair classifier, as stated by the four-fifths rule of maximum acceptable disparate impact proposed by the US Equal Employment Opportunity Commission (EEOC) Zafar et al. (2017).

4.2 Fairness Enhancing Methods

This section covers fairness-enhancing techniques —that rely on sensitive attributes— leveraged by some exciting works presented in Section 6.1 for bias mitigation when sensitive attributes are noisy or predicted sensitive attributes.

Post-processing technique. Fairness-enhancing post-processing techniques involve methods that treat the model as a black box and enforce fairness constraints over the model's output. Hardt et al. (2016) an optimization problem over the model's output ($\widehat{Y}$) to derive a classifier ($\widetilde{Y}$) that satisfies fairness constraints (Equalized Odds) while minimizing the classification loss. When the model output is continuous (a score function) the derived classifier is based on a threshold of each demographic group such that it maximizes the classification loss while satisfying fairness constraints, i.e., equal opportunity and equalized odds. Similar methods are proposed in the literature, and they differ mainly in the way the optimization problem is defined.

Adversarial Debiasing Proposed by Zhang et al. (2018) this adversarial-based approach enforces the independence between the classifier outcome and the sensitive attributes. The classifier's output is used as input for the adversary network, which tries to predict the sensitive attribute. In the minimax optimization problem, the goal of the classifier is to prevent the adversary from predicting the sensitive attribute, thus enforcing statistical parity. To enforce Equalized Odds, the adversary takes as input the predicted outcome and ground truth. Thus fooling the adversary enforces the independence between the model's output and the sensitive attributes. To enforce Equal Opportunity, the adversary gets the classifier outputs only for samples with positive outcomes.

Exponentiated gradient The exponential gradient is a reduction approach for fairness that transforms a classification problem with fairness constraints into a sequence of cost-sensitive classification problems. The new problem is solved by the Exponential Gradient method that looks for the saddle point where the classification loss is minimized and fairness is maximized (the disparities are minimal). The method yields randomized classifiers for which classifiers with the lowest prediction error satisfying the fairness constraint are returned (Agarwal et al., 2018). This approach can work for a various range of base models (e.g., Logistic regression and Random Forest) and work with most existing group fairness metrics.

4.3 Differential Privacy (DP)

This section provides an overview of differential privacy (DP). DP is used by some existing works presented in Section 6.4 for addressing fairness concerns under privacy constraints on the sensitive attribute.

Differential privacy Dwork et al. (2006) is a mathematical framework to formally quantify the privacy/utility trade-offs of an algorithm that operates on personal data. It seeks to maintain the privacy of individuals when releasing results derived from a confidential database, by limiting the impact of any single record on the outcome and incorporating noise. Differential privacy finds applications across various domains, but its significance in machine learning is especially notable. In machine learning, differential privacy helps in training models on private data Abadi et al. (2016) while ensuring that the trained model does not memorize or leak specifics about the training data, thus preventing potential attacks such as membership inference Shokri et al. (2017). Differential privacy can be applied in a centralized manner (Global DP) when data subjects trust a data analyst to enforce privacy when realizing the result of an algorithm that requires their data, using different mechanisms such as the Laplace mechanism Dwork et al. (2014) and the Exponential mechanism McSherry & Talwar (2007). It can also be applied in the absence of a trusted centralized party (Local DP), allowing data subjects to directly create noisy versions of their private inputs through protocols like randomized response Warner (1965), initially designed to address evasive answer bias in social science, allowing useful analysis of responses provided for embarrassing or sensitive questions. More formally, DP for the sensitive attribute can defined as follows:

Definition 1 (Differential Privacy w.r.t. Sensitive Attributes) *Given $\epsilon \geq 0$, $\delta \in [0, 1]$. A randomized mechanism $\mathcal{M}$ is $(\epsilon, \delta)-$differentially private w.r.t. protected attributes A if, for any adjacent datasets D and D', i.e, datasets that only differ with a single protected attribute entry, we have*

$$\mathrm{P}(\mathcal{M}(D) \in R) \leq \exp(\epsilon) \cdot \mathrm{P}(\mathcal{M}(D') \in R) + \delta \tag{5}$$

Where $R \in \mathcal{R}$ is a subset of the output response, $\epsilon > 0$ the privacy budget with values close to 0 meaning strong privacy, and δ the probability of the algorithm not being ϵ-DP.

The definition 1 can allow companies to privately use sensitive attributes while complying with legal restrictions or regulations.

Another framework leveraging DP with strong privacy guarantees is PATE (Private Aggregation of Teacher Ensembles) (Papernot et al., 2016). PATE involves two components: the teachers and the student model. Teachers are trained on independent partitions of sensitive or private data, while the student model is trained on public, unlabeled data, utilizing labels derived from aggregating predictions of the teachers. The objective of the teachers is to provide labels for public data while upholding strong privacy guarantees for the private data. For any public, unlabeled data point, the label is determined through a noised majority voting mechanism applied to the teachers' predictions, only the student model is made public. The incorporation of noisy aggregation and knowledge transfer from the teachers to the student model ensures robust safeguards for sensitive private data (Papernot et al., 2016).

5 Fairness Notions without Sensitive Attributes

In most of the existing group fairness notions, individuals are grouped based on their sensitive attributes with the aim of achieving fairness across these groups. Making classical group fairness notions not directly

applicable when the sensitive attributes are unobserved. In this section, we discuss fairness definitions that do not rely on sensitive information for measurement. Figure 1 showcases an overview of existing fairness notions that do not assume access to sensitive attributes.

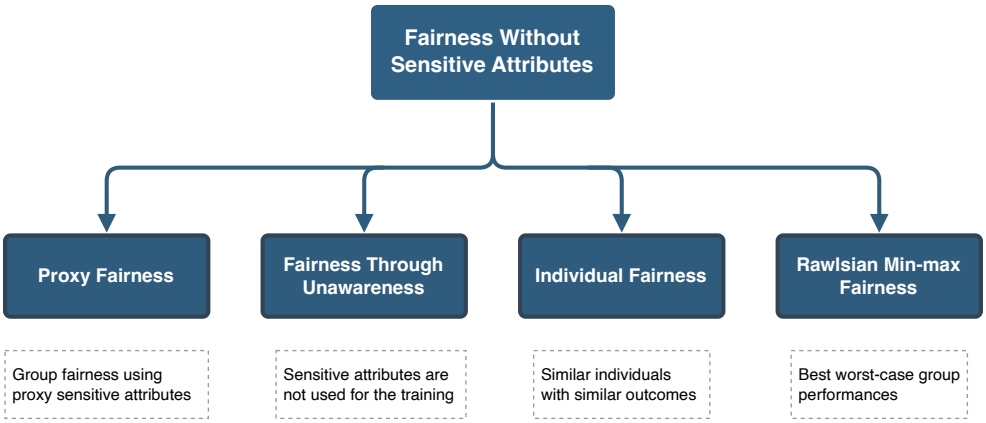

Figure 1: Overview of fairness notions without sensitive attributes.

5.1 Individual Fairness

Proposed by Dwork et al. (2012), this definition requires that similar individuals with respect to a given task should receive similar outcomes. Within this fairness notion, the sensitive attribute used to group individuals is irrelevant as fairness is assessed at the individual level, making individual fairness feasible even when the demographic information is not available (as long as the distance metric between individuals is given).

Definition 2 (Individual Fairness (Dwork et al., 2012)) *Given a distance metric on individuals:* $d : V \times V \rightarrow \mathbb{R}$*, a mapping function from individuals to the outcomes probability:* $M : V \rightarrow \Delta(A)$*, and a distance metric* D *over the distribution of outcomes. Individual fairness is achieved iff:*

$$D(M(x), M(y)) \leq d(x, y). \tag{6}$$

Individual fairness properly captures the (D, d)-Lipschitz property and provides meaningful fairness guarantees. Dwork et al. (2012) showed that when the classifier satisfies the Lipschitz property, it also achieves statistical parity with a certain amount of bias. For example, a model for scoring resumes will achieve individual fairness if applicants with similar resumes get similar predictions. Despite its fairness guarantees, individual fairness suffers from the assumption that task-specific similarity metric between individuals is given, which is hard to measure in practice (Lahoti et al., 2019; Dwork et al., 2012).

Relaxations of individual fairness have been proposed for various purposes such as, to solve the problem related to the task-specific similarity metric, or the generalization of individual fairness from a training set to the underlying population. In this regard, Yona & Rothblum (2018) proposed *approximate metric-fairness*, a relaxation of individual fairness with guarantees of generalization on the underlying population. This fairness notion allows a small fairness error and requires that, for two individuals sampled from the underlying population, with all but a small probability, if they are similar then they should be treated similarly (Yona & Rothblum, 2018). The statistical distance between the classification distributions is used to measure the similarity between two given individuals. Thus, a model h is said to be (α, γ)-*approximately metric-fair* w.r.t. the metric d and the distribution $\mathcal{D}$ if

$$\Pr_{x,x' \sim \mathcal{D}} \left[\left| h(x) - h\left(x'\right) \right| > d\left(x, x'\right) + \gamma \right] \leq \alpha \tag{7}$$

Where d represents the similarity metric, $\mathcal{D}$ the data distribution, γ is the small additive slack in the similarity measure, and α the fraction of pairs of individuals for which the metric-fairness does not hold. However, this

notion also assumes that the task-specific distance metric between individuals is given. Although this fairness notion opens the door to fairness-generalization bounds, there exist settings where the fairness error that it accepts might harm certain individuals in the population.

5.2 Fairness through unawareness

This definition of fairness used in some contexts, such as in law enforcement in certain countries, requires that sensitive attributes should not be explicitly used in the decision system (Kusner et al., 2017). This means that as long as the model does not rely on the sensitive attribute during training or decision-making, the model is considered fair. For example, in the case of resume screening, the model is considered fair as long as the resume of the candidates does not disclose information about their gender, and the model does not explicitly use gender to make its predictions. However, it's important to note that the model being unaware of the sensitive attributes is not a sufficient condition to avoid discrimination in the outputs.

While not using sensitive attributes directly in the decision system is a step toward fairness, it is not a foolproof solution. For instance, certain features can be correlated with sensitive attributes, allowing the model to implicitly rely on them. For example, research has shown that the age at which someone starts programming is correlated with gender (Barocas et al., 2019). Similarly, factors such as salary expectations and working hours per week may tend to be lower for female applicants, or the zip code can be correlated with the origins of some applicants as people from the same demography tend to live in the same neighborhood. While these proxy features can be relevant to the decision on hand, they may also reflect existing biases and lead to unfair decisions. For instance, how long someone has been programming is a factor that gives us valuable information about their suitability for a programming job, but it also reflects the reality of gender stereotyping (Barocas et al., 2019). Thus, while this fairness notion seeks to prevent the explicit use of sensitive attributes, it is important to be aware that information about these attributes can still leak into the model through other means.

5.3 Rawlsian Minimax fairness

One challenge in achieving fairness in machine learning is the unavailability or incompleteness of sensitive attributes. This may be due to legal or privacy reasons or a user's unwillingness to provide such information. As a result, existing fairness notions that rely on sensitive attributes may be difficult to implement or apply in such cases.

The Rawlsian mini-max fairness notion, on the other hand, is a fairness notion that does not rely on sensitive attributes. It is derived from social sciences and is based on the principle of distributive justice proposed by John Rawls (Rawls, 1999). Rawl's principle of justice states (among other things):

> "*Social and economic inequalities are to be arranged [...] to the greatest benefit of the least advantaged members of society, consistent with the just savings principle.*" (Rawls, 1999, p. 226)

In other words, this principle suggests that the right decision is one that maximizes the minimum outcome, i.e., the decision that makes the worst outcome as good as possible (Rawls, 2001). More formally, Rawlsian fairness can be defined in the context of machine learning as follows:

Definition 3 (Rawlsian Max-Min Fairness) *Given a set of hypotheses $\mathcal{H}$ and demographic groups $a \in A$, a hypothesis $h^* \in \mathcal{H}$ achieves Rawlsian Max-Min fairness if it maximizes the accuracy of the worst-off groups, i.e.,*

$$h^* = \arg\max_{h \in \mathcal{H}} \min_{a \in A} U_{\mathcal{D}_a}(h) \tag{8}$$

where $U_{\mathcal{D}_a}$ is the expected utility/accuracy of the hypothesis h over the group a. In the general setting, the group information (a) is unknown. The intuition is that making the worst case as good as possible would have a positive impact on truly disadvantaged groups.

While this notion has gained attention in recent years as a potential solution to the challenge of achieving fairness in the absence of sensitive attributes, it also inherits the critiques of the Rawlsian notion of distributive

justice. Among these criticisms, is the emphasis on the notion of the least advantaged, which may not take into account demographics or individuals within the population (Altham, 1973). The least advantaged is not a single individual, but a group that is difficult to define. Rawls proposed to select least advantaged groups from the least fortunate with respect to (i) family and class, (ii) natural endowments, and (iii) fortune and luck (Rawls, 1999). In the context of algorithmic fairness, in particular, for classification, the least advantaged group can be formed from samples that are mostly misclassified. Therefore, a model that aims to achieve Rawls's principle by focusing on improving misclassified samples, or samples from the worst-off distribution in a set of distributions created from the empirical distribution, might not only fail to improve fairness with respect to the truly disadvantaged group but may also make the model highly sensitive to outliers (Hashimoto et al., 2018; Lahoti et al., 2020). In contrast to other group-based fairness notions, Rawlsian fairness might allow disparate outcomes between demographic groups and its application is particularly pertinent in medical applications (Ricci Lara et al., 2022) or any other domains where decreasing the model performance to achieve parity is not acceptable.

5.4 Proxy Fairness

Proxy fairness notions are derived from group fairness notions. They assume correlated features are known and can be used as *proxy* to measure fairness with respect to the true protected attributes.

Considering scenarios where direct access to sensitive attributes is not possible, *proxy fairness* notions rely on features that exhibit correlation with the sensitive counterparts. These proxy-sensitive attributes can also be predicted through an attribute classifier. The underlying idea is to utilize correlated or predicted features as *proxy* for the actual sensitive attributes. In particular, the sensitive attributes for group fairness metrics presented in Section 4.1 can be replaced by the proxy-sensitive attributes to measure fairness in the model. By evaluating the selected group fairness notion with respect to these proxies, one can measure the fairness of models w.r.t *true* sensitive attributes. However, a drawback of proxy fairness notions lies in their assumption that the features correlating with unobserved sensitive features are known, and determining the degree of correlation proves challenging without input from a domain expert. Furthermore, auditing model fairness based on proxy might lead to an underestimation or overestimation of the actual fairness violation, special care must be taken in the design of proxy-sensitive attributes for optimal bias estimation (see Section 6.5).

6 Fairness Enhancing Techniques Without Demographic.

We presented in the previous section fairness notions that do not (fully) rely on sensitive attributes. In this section, we review works that have been done to enforce fairness notions when the assumption of full access to accurate sensitive attributes is not met, i.e., they are either missing, noisy, or predicted.

6.1 Enforcing Fairness Using Proxy Sensitive Attributes.

Proxy-sensitive attributes can be obtained using related non-sensitive features or using limited demographic information available. Proxy attributes must be designed carefully, as incorrect proxies or predictions of sensitive attributes may result in adverse effects, such as sub-optimal solutions or incorrect disparities estimation in the model (explained in Section 6.5). In this section, we review methods to enforce fairness using proxy-sensitive attributes. Proxy attributes are generally obtained either via related features or limited demographic information. Table 4 showcases an overview of existing methods, the datasets, and fairness metrics used for evaluation. Each method is also grouped based on mechanism type, i.e., at which step of the ML pipeline the fairness mechanism can be applied: at the data level (pre-processing), during the model training (in-processing), or after training the model (post-processing); Existing methods are also grouped based on proxy features obtained via related features or partial demographic information.

6.1.1 Using Related Features.

In some applications, non-sensitive features may be closely associated with sensitive ones. In recent works, related features have been used as "proxies" for the sensitive features that are unobserved (Zhao et al., 2021; Gupta et al., 2018; Diana et al., 2022). The proxy features are any non-sensitive features that correlate with

Papers	Related Features	Partial Demographic	Mechanism Type	Evaluation Metrics	Datasets	General Description
FairRF Zhao et al. (2021)	✓	✗	In	• Accuracy • EOP • DP	• Adult • Compas • LSAC	Assumes the knowledge of non-sensitive features correlating with unknown sensitive ones and adds a regularization term to minimize their influence over the classifier's output.
NOCCO Pelegrina et al. (2023)	✓	✗	Pre	• Accuracy • EOP • PE	• Adult • Compas • LSAC • Taiwanese credit	Proposes a preprocessing method to automatically detect sensitive features in the datasets using the Hilbert–Schmidt independence between class labels and features splitting the data into groups.
KSMOTE Yan et al. (2020)	✓	✗	Pre	• F1-score • EOP • EOD	• Adult • Compas • Violent crime	The proposed method relies on clustering techniques to restore class balance while improving model fairness on downstream tasks, all without the need to observe sensitive attributes.
Proxy-learner (Diana et al., 2022)	✗	✓	In	• Accuracy • EOP • EOD	• FolkTable datasets	The work shows that training a model to predict the sensitive attributes can serve as a good substitute for the ground truth sensitive attributes when the latter is missing.
CGL (Jung et al., 2022)	✗	✓	Pre	• Accuracy • EOP	• Compas • CelebA • UTKFace	The paper proposes a confidence-based attribute classifier, that randomly assigns group labels on samples with low confidence prediction, and shows its benefits on fairness in downstream tasks.
SR-CVAE (Grari et al., 2021)	✓	✗	In	• Accuracy • EOP • EOD	• Adult • Default Data	Assuming a causal graph of the data, the approach uses Bayesian inference to reconstruct the sensitive attribute in the latent space and uses an adversarial approach to enforce fairness.
FairDSR (Kenfack et al., 2023)	✗	✓	Pre	• Accuracy • EOP • EOD • SP	• Adult • LSAC • Compas • CelebA	The paper proposes an uncertainty-aware sensitive attribute classifier to improve fairness-accuracy tradeoffs on downstream tasks with missing sensitive attributes.
MTL-fair (Aguirre & Dredze, 2023)	✗	✓	In	• Accuracy • EOP	• Clinical-Notes • Online-Reviews • Twitter	A multi-task learning setup where the partial demographic is available in one task and the objective is to improve fairness on tasks with missing sensitive attributes.
FairDA (Liang et al., 2023)	✗	✓	In	• Accuracy • F1-score • EOP • SP	• Toxicity • Compas • Adult • CelebA	A domain adaptation setup where partial demographic information is available in one domain. An adversary is used to enforce fairness in the target domain where the demographic information is missing.
Proxy-fairness Gupta et al. (2018)	✓	✗	Post	• Accuracy • EOP	• Adult • Default Data	Study bias mitigation when proxy-sensitive attributes are used. Show that proxy-sensitive attributes can be useful to improve fairness but they can also overestimate or underestimate it.
BiFair (Ozdayi et al., 2021)	✗	✓	In	• Accuracy • EOP • EOD • SP	• Adult • Bank data	Proposes a bilevel optimization where the partial demographic is used to compute sample weights, and the target classifier is trained with a weighted loss to improve fairness on samples with missing sensitive data.
FURL-PS (Zhang et al., 2022)	✗	✓	Pre	• Accuracy • EOD	• CelebA • UTKFace	Uses the partial demographic information to train a contrastive sample generator, which generates images with edited sensitive attributes. A contrastive loss is adapted to improve fairness in the latent representation.
APOD (Wang et al., 2023)	✗	✓	Pre	• Accuracy • EOD • EOP	• Loan default • Adult • German • MEPS	An active learning setup where the goal is to select the optimal data points, with missing sensitive attributes, for which human annotations will improve fairness for the protected groups.

Table 4: Overview of methods to enforce fairness using proxy demographic information.

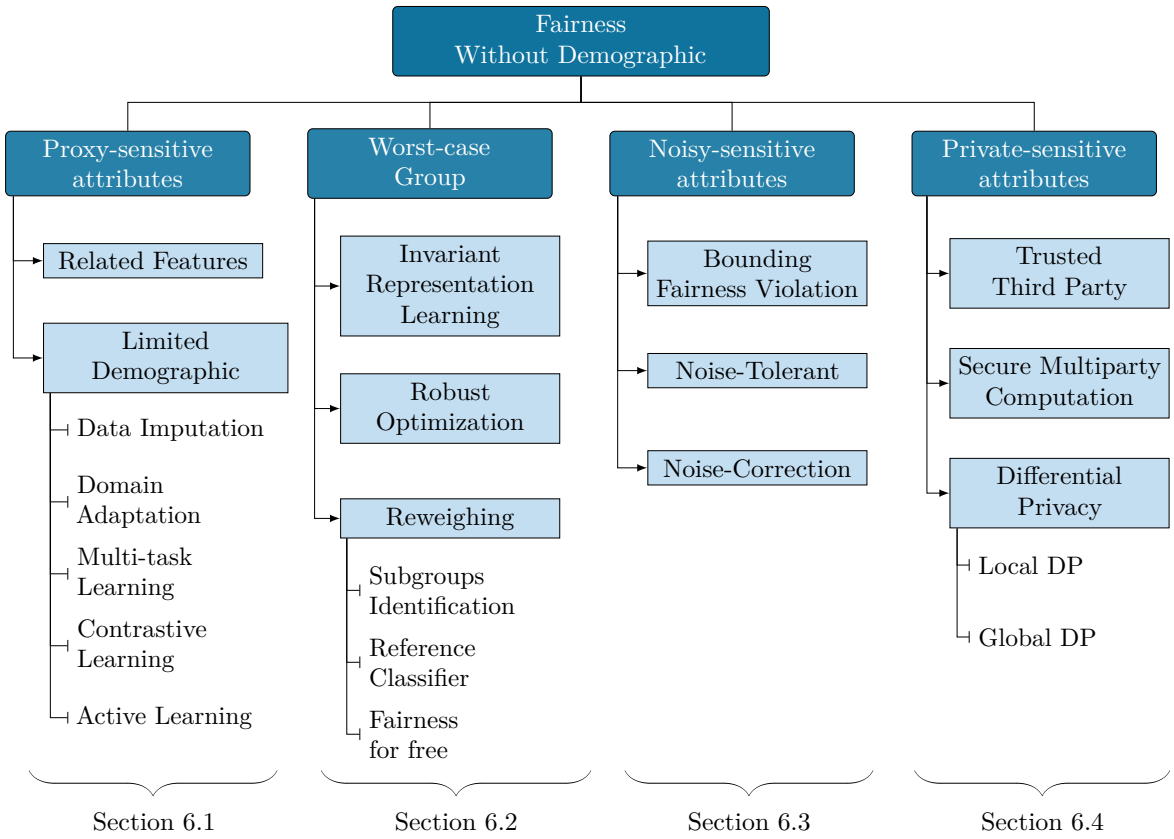

Figure 2: A taxonomy of fairness enhancing techniques without demographic information

the sensitive ones. For example, the origins of customers can be estimated using their last name and address of residence (Elliott et al., 2009). The core idea is that by enforcing fairness with respect to the proxy features, the model will produce fairer results toward samples from the true protected groups. A straightforward approach is to remove these related features from the feature set before training the model, but this can result in a significant decrease in accuracy since the related features are also useful for the task at hand. Gupta et al. (2018) showed that enforcing fairness with respect to proxy attributes also improves fairness with respect to the true unobserved protected attributes. The authors characterize the good proxy as related features that share the same semantics with the true demographic group. Their empirical results suggest that applying the post-processing technique by Hardt et al. (2016) to enforce fairness constraints on the proxy features can improve fairness for the *true* protected groups. However, a poor proxy can have an impact on accuracy and fairness. To learn fairer classifiers while maintaining accuracy, Zhao et al. (2021) proposed a framework that leverages proxy features and adjusts their importance weights. The framework includes a regularization term in the loss function to minimize the correlation, $\mathcal{R}(x_j, \hat{y})$, between the classifier's output ($\hat{y}$) and each related feature (x_j). The optimization problem of the framework is defined as follows:

$$\begin{array}{ll} \min_{\theta,\lambda} & \mathcal{L}_{cls} + \eta \cdot \sum_{j=1}^{K} \lambda_j \cdot \mathcal{R}\left(\mathbf{x}_j, \hat{\mathbf{y}}\right) + \beta \|\lambda\|_2^2 \\ \text{s.t.} & \lambda_j \geq 0, \forall f_j \in \mathcal{F}_S; \quad \sum_{j=1}^{K} \lambda_j = 1 \end{array} \tag{9}$$

where $\mathcal{L}_{cls}$ is the classifier loss (typically a cross-entropy loss), η controls the regularization term, $\{x_j\}_{j=1}^{K}$ is the set of highly correlated features, and $\{\lambda_j\}_{j=1}^{K}$ weights associated to each related feature. As all features are not equally correlated with sensitive features, the authors assumed that the weight of each relationship could be given by a domain expert. To alleviate this assumption, and besides the fact that the given weights

can be noisy, the proposed framework can also learn the weights of related features during the optimization process. To avoid trivial solutions, weights are regularized ($\|\lambda\|_2^2$) to enforce non-zero weights of related features. In many real-life situations, it can be difficult to identify the correlated non-sensitive features in the datasets, let alone the level of correlations. To alleviate this issue, Chang et al. (2023) propose a framework to automatically identify the correlated non-sensitive features and mitigate their influence in the model during the training. The method involves a sensitive attribute reconstruction model that is leveraged by a self-attention mechanism to learn the interactions (weights) between the sensitive and non-sensitive features. The detected biased feature interactions are then mitigated via a regularization term to mitigate their influence. The method however requires demographic information at the training time to uncover the correlated features. In a more principled way, Pelegrina et al. (2023) proposed a statistical method to automatically detect the sensitive features without relying on real sensitive ones. The proposed method is formalized around the hypothesis that a given feature might be considered sensitive if it splits data into two groups of people (e.g., gender male or female) and the Hilbert–Schmidt (Gretton et al., 2005) independence between this feature and the target label is high. Put differently, when a feature divides individuals into groups and exerts significant influence over the target variable, it is highly probable that disparities will emerge. For example, the authors show that by applying the proposed method to the Adult dataset, the features *marital-status* and *relationship* provide a high Hilbert–Schmidt score and are thus returned as sensitive as sensitive features. These features are known to correlate with gender in the Adult dataset, suggesting the efficiency of the method to automatically uncover sensitive features when they are unknown. The method acts as a preprocessing step that produces sensitive features toward which fairness will be enforced or measured on the downstream task.

A common source of unfairness is the under-representation of the protected group within the dataset (Mehrabi et al., 2021). One way to mitigate that is to balance the representation of each group in the dataset Kamiran & Calders (2012). Leveraging this observation, Yan et al. (2020) addressed representation bias by adapting K-Means SMOTE (Last et al., 2017) for *fair class balancing*. K-Means SMOTE works in three steps. In the first step, clusters are created using any clustering algorithm, and in the second step, the samples closest to the cluster boundaries are removed (as these samples are more likely to be misclassified). Finally, in the last steps, for each cluster, the least represented classes are considered minorities, from which new samples are generated (oversampled) based on the nearest neighbors within the minority class. Although this sampling technique does not rely on any sensitive features, the authors showed that it provides an improvement in fairness (w.r.t statistical parity and equal opportunity) in downstream tasks. This line of work shows the effectiveness of clustering methods in identifying groups even when their sensitive features are unknown. Alternatively, Grari et al. (2021) assumes a causal graph underlying the training data and uses the causal dependencies between variables to reconstruct the sensitive attribute (proxy). Within the causal graph, the variables are grouped into two subsets: the subset of variables not caused by the sensitive attribute (x_c) and the subset of variables caused by both the sensitive and non-sensitive features (x_d). The first step of the proposed framework leverages the variables x_c, x_d, and the class label (y) to learn a latent space that contains as much information about the sensitive attribute as possible. The latent space is constructed using the variational autoencoder (Kingma et al., 2019) for modeling exogenous variables in causal graphs. Assuming a Gaussian prior $p(a)$ for the sensitive attribute, the encoder $q_\phi = (a|x_c, x_d, y)$ and the decoder $p_\theta(x_d, y|x_c, a)$ are implemented as neural networks parameterized by ϕ and θ respectively and are optimized to obtain a latent space that reconstructs the sensitive attribute. A fair classifier is then built using an adversarial approach, that enforces the independence of the predictions ($\hat{y}$) and the learned latent representation (proxy sensitive attribute, i.e., a), which is obtained from the learned posterior $q_\phi = (a|x_c, x_d, y)$ for each individual.

6.1.2 Using Limited Demographic Information.

Also referred to as *demographic scarce regime*, this setting occurs when the sensitive attributes are not explicitly collected for the target task dataset (Bharti et al., 2022; Kenfack et al., 2023; Coston et al., 2019) or are they are available in different a dataset. This setup also occurs when a record of the sensitive attributes has not been maintained throughout data collection, resulting in some samples in the dataset with missing sensitive attributes. In the literature, most methods proposed to address fairness concerns in the demographic scarce regime are based on established machine learning algorithms or paradigms used in semi-supervised

learning (Van Engelen & Hoos, 2020). These adaptations include techniques such as data imputation, domain adaptation, multi-task learning, contrastive learning, and active learning.

Data imputation. In the demographic scarce regime, proxy-sensitive attributes can be obtained via imputation, i.e., using the labeled instance to infer missing sensitive attributes. Specifically, we consider two datasets, D_1 and D_2, containing $\{X, Y\}$ and $\{X, A\}$, respectively. D_1 contains the class label and is used to train the target task while D_2 contains the demographic information. It is assumed that every dataset shares the same feature space. In this setting, one is interested in enforcing fairness with respect to D_1 using demographic information in D_2 or estimating bias of a model trained on D_1 using demographic information available in D_2.

In most cases, D_2 is utilized to train a sensitive attributes predictor. The attribute predictor is then used to augment D_1 such that it jointly observes the non-sensitive feature, the class label, and the demographic information (proxy), i.e., $\hat{D}_1 = \{X, Y, \hat{A}\}$, where $\hat{A} = \{\hat{a}_i\}_{i=1}^N$ is the proxy sensitive attribute obtained from the attribute predictor. A highly accurate sensitive attribute predictor can help better quantify or mitigate the unfairness of models built from the augmented dataset $\hat{D}_1$. However, the predictor should be constructed carefully, as incorrect predictions of sensitive attributes may result in adverse effects, such as incorrect disparities estimation in the model or the amplification of disparities. We cover in section 6.5 techniques to assess bias using the proxy-sensitive attributes.

Diana et al. (2022) and Ozdayi et al. (2021) demonstrate that if the dataset with sensitive attributes (D_2) is distributed identically to the data used for training the target task (D_1), the demographic predictor p, known as the proxy model, can accurately estimate the missing sensitive features and fairness enforced on $\hat{A}$ can yield a model with good enough fairness-accuracy tradeoffs with respect to the true sensitive attributes. The results suggest that practitioners having access to limited demographic information can impute the missing ones and still improve fairness with respect to the true sensitive attributes. However, the performances achieved are not as good as what could be attained by using true sensitive attributes. To overcome this limitation, Kenfack et al. (2023) demonstrated that when the uncertainty associated with predicting sensitive attributes is low, the trade-offs between fairness and accuracy closely resemble those for true sensitive attributes. Additionally, the authors illustrate that enforcing fairness constraints primarily on samples with lower predictive uncertainty can lead to enhancements in fairness-accuracy trade-offs. Likewise, Jung et al. (2022) employ a threshold on the output probability of the attribute classifier to discern instances where sensitive attributes are predicted with low confidence. Subsequently, for samples with sensitive attributes predicted low confidence, random attribute values are assigned. These values are drawn from the empirical conditional distribution over the sensitive attributes given the class label. The authors posit that this random labeling serves as a form of regularization. In the same spirit, Diana et al. (2022) show that if the proxy model $\hat{A}$ is multi-accurate over different groups, then a downstream task constrained on fairness with respect to $\hat{A}$ can achieve a similar level of fairness as it would have with the *real* sensitive features.

Domain adaptation. Another line of work formulates fairness in the limited demographic setup as *domain adaptation* problem (Schumann et al., 2019; Madras et al., 2018; Coston et al., 2019; Liang et al., 2023). In domain adaption, the goal is to train a model on a source domain so that it performs well on a target domain, with a constraint that both domains might be drawn from different but related distributions, e.g., robustness to distribution shift. See (Farahani et al., 2021) for a review on domain adaptation.

Formulated as a fairness problem, the objective is to build a fair model in a domain possessing the sensitive attributes and then transfer the fairness properties to another task or domain where the sensitive attribute is missing. For example, Coston et al. (2019) assume the limited demographic information is available either in a source or a target domain. When demographic information is available in the source domain, the authors propose to learn the weights of each sample such that they are as close as possible to the covariate shift weights[2] subject to prevalence constraints for fairness. The covariate shift weights are measured as $q_X(x)/p_X(x)$, where $p_X(x)$ is the density distribution of data from the source domain and $q_X(x)$ the density of the target domain. The prevalence constraint ensures that all pairs of groups are close to each other. When demographic information is available in the target domain, the authors propose to learn sample weights by

[2]Loss function minimizes the L_1 between the predicted weights and the covariate shift weights

minimizing a double loss consisting of the fairness loss (group disparity) and the classification loss. The group disparity loss is then defined as the difference between the classifier score across demographic groups and is measured on the target domain, in which demographic information is available. Liang et al. (2023) propose a dual adversarial approach to build a fair model on a target domain where the sensitive attribute is solely accessible in the source domain. In the source domain, a sensitive attribute is trained with a domain adversary to enforce domain invariance in the latent space. Meanwhile, in the target domain, the label classifier is trained alongside an adversary, preventing the prediction of pseudo-sensitive attributes of samples in the target domain. These pseudo-sensitive attributes are derived from the attribute classifier trained on the source domain. The general objective of these methods is to transfer the knowledge of the sensitive attribute from one domain to improve fairness in the domain with missing sensitive attributes. In the same spirit, Madras et al. (2018) proposes a fair representation learning approach that is transferable. The transferability property of the fair representation can be particularly useful when the sensitive attribute is missing on the downstream task.

Multi-task learning (MTL). Aguirre & Dredze (2023) formalized the problem in a multi-task learning framework. In MTL, the goal is to optimize simultaneously different but related tasks during the training. The model is generally designed by defining a shared encoder layer and task-specific layers for each task (Zhang & Yang, 2018). The idea is that the knowledge gained from learning one task can benefit the performance of other related tasks. To handle missing sensitive attributes, Aguirre & Dredze (2023) considered two tasks. The first task consists of training a classifier on the dataset with missing sensitive attributes. The other task consists of training the classifier with fairness constraints on the dataset with sensitive attributes. The intuition is that fairness constraints on the second task will improve fairness on the task with missing sensitive attributes. The authors also proposed a generalized approach to intersectional fairness, where the two tasks are trained with fairness w.r.t different sensitive attributes, e.g., the first task has gender and the second task race. The proposed methods show fairness improvement with respect to the missing sensitive attribute across each task.

Contrastive Learning Contrastive learning, as an unsupervised approach, aims to construct a latent space where samples sharing similar features are drawn together while distancing those that differ (Chen et al., 2020). To obtain a representation that exhibits this property, positive examples consist of paired views of the same image, whereas negative examples involve pairs of views from different images. The loss function incorporates a distance metric between examples, with the objective of minimizing the distance between positive pairs and maximizing the distance between negative pairs. Park et al. (2022b) show that contrastive learning can rely on sensitive attributes to better optimize the contrastive loss, i.e., in the latent space the separation between dissimilar samples is more effective for some demographic groups than others. As a result, the learned representation will incur disparate performance on downstream tasks. The authors integrate a group-wise normalization factor to contrastive loss to improve the fairness of the representation. However, the proposed fair contrastive loss fully depends on demographic information.

Zhang et al. (2022) propose a contrastive learning approach to acquire fair representations despite having limited demographic information. The available demographic data is utilized to train an image attributes editor. Upon receiving an input image, the editor produces its contrastive counterpart—an image with a different sensitive attribute while preserving other visual features. For instance, it can generate a realistic photo resembling a man when presented with an image of a woman. The process involves a sensitive attribute classifier, responsible for labeling the generated contrastive examples. Images with confidently labeled attributes are then used to iteratively enhance the attribute editor in a mutually improvement manner. The goal of this first step is to generate an augmented and balanced dataset where each sample has a contrastive example with a different sensitive attribute. In the second step of the method, a fair representation is acquired through contrastive learning applied to the augmented dataset. To obtain a fair representation, the authors propose to consider contrastive samples with different sensitive attributes as positive examples and negative samples as views originating from different images with the same sensitive attributes. Feature weighting is integrated into the contrastive loss, assigning higher importance to specific sensitive-attribute dependent features in the latent space. This method however heavily depends on the attribute editor model and its application is limited to image datasets. Chai & Wang (2022) propose a contrastive learning approach to

learn fair representations and use limited labels to guide the training. The contrastive loss is weighted using a weighting scheme that up-weights samples with higher classification errors on the validation set. With the weighted contrastive loss, the leaned representation is enforced to ensure high separability of samples from minority groups, thus improving fairness on downstream tasks in terms of equalized odds.

Active learning Active learning is a prevalent machine learning method in semi-supervised learning, that addresses scenarios with costly data labeling. The model is initially trained on a small proportion of labeled data and subsequently predicts labels for unlabeled data Settles (2009). Instances predicted with low confidence are then referred to an oracle for annotation, e.g., a human annotator. The newly annotated data points are then used to enhance the current model in the next training round. The objective is to reduce the number of queries for annotators. To learn a fair model, one can request demographic information of certain samples but with compensation. The objective is to train a fair model with a minimum number of *demographic query* (Liu & Lan, 2020).

In this spirit, Wang et al. (2023) propose an active learning approach for developing fair models under limited demographic information. The goal is to find the optimal instance for sensitive attribute annotation that can help improve the model's fairness in the next iteration while minimizing the number of label queries. In each iteration, the model is trained to minimize the classification loss with regularization over the labeled data points. The regularization term serves to penalize the model for any disparities such as equalized odds or equal opportunity. In the subsequent step, a sample from the unlabelled set is selected to promote bias mitigation maximally. The sample selection is done using the demographic group of samples with the highest classification error. Groups of samples are defined using predicted sensitive attributes provided by an attribute classifier. The sample selected for annotation is the one at a maximal distance with annotated samples in the latent space. On the other hand, Liu & Lan (2020) explore the decoupled fair model proposed by Dwork et al. (2012), where a distinct model is trained for each demographic group. The authors introduce two strategies for selecting data points to query demographic information: 1) using samples with the most significant outcome variations across each model, and 2) using samples that, when added to the labeled dataset, amplify the disparity of the current model. While empirical results show the efficacy of these query strategies, the method necessitates retraining the model after each demography query, which can be computationally expensive.

Existing methods, based on demographic predictors, are based on the assumption that non-sensitive characteristics are highly descriptive of sensitive characteristics. However, this assumption may not always hold in practice. On the other, predicting sensitive information poses ethical concerns and in some cases is unlawful. Kenfack et al. (2023) suggest that obtaining datasets with high uncertainty in the inference of the sensitive attribute can yield models (trained without fairness constraints) that inherently exhibit fairness properties. Additionally, Ozdayi et al. (2021) introduce BiFair, an approach structured around a bilevel optimization setup. This optimization process uses the limited demographic information to compute the samples' weights instead of trying to reconstruct the missing sensitive attributes with a demographic predictor. In the bilevel optimization process, the inner optimization focuses on the minimization of the classification loss, while the outer optimization computes the fairness loss for samples with sensitive attributes and leverages these computations to determine sample weights such that they minimize the fairness loss.

6.1.3 Evaluation Protocol in Proxy Demographic Setting.

When fairness constraints are enforced over features correlating with the sensitive features, the evaluation process does not differ greatly from the setting where demographic information is observed. The particularity is that sensitive attributes are not directly used during the training phase, but the correlated features Zhao et al. (2021), the causal graph Grari et al. (2021), or the clusters Yan et al. (2020) are considered. For example, Zhao et al. (2021) use age, relation, and marital status in the Adult dataset as the features correlating with the unknown sensitive feature: considered gender. For the Compas dataset, the unknown sensitive attribute is race, and its correlated features are score, decile text, and sex. The evaluation of the fairness performance follows most existing works where the sensitive attributes are known at test time, and fairness performances are reported using the true sensitive attributes.

In settings where partial demographic information is available, most approaches generally split the dataset into three subsets: A subset where the sensitive attributes are missing, a subset as the dataset where the

partial demographic is available, and a subset for the evaluation as the test set where the sensitive attribute is also available. For example, Kenfack et al. (2023), Diana et al. (2022), and Ozdayi et al. (2021) split the Adult dataset into 60%, 20%, 20% for the training, labeled demographic, and test dataset respectively. For the evaluation metric, in addition to the traditional accuracy metric, fairness metrics commonly used include equalized odds, equal opportunity, and statistical parity.

As an ablation study, some methods (Zhang et al., 2022; Ozdayi et al., 2021; Wang et al., 2023; Jung et al., 2022) generally vary the ratio of the dataset with labeled sensitive attributes in order to see its impact on the proposed method.

6.2 Achieving Rawlsian Max-Min Fairness

The main objective of the Rawlsian Max-Min Fairness notion is to minimize the model error on the least advantaged protected groups. When group information is available during the training, there are methods that are proposed to optimize for the group performing worst (Martinez et al. (2020); Diana et al. (2021); Sagawa et al. (2019)). However, the task of defining the least advantaged groups becomes challenging when the necessary criteria are not provided. Nevertheless, the Rawlsian fairness notion can be particularly useful to address the major challenge of intersectional fairness, where the model performance could be worse across an intersection of sensitive attributes, e.g., gender & race, age & nationality. For example, Buolamwini & Gebru (2018) showed that most commercial face recognition systems are significantly less accurate in identifying darker-skinned females. In fact, the pursuit of Rawlsian fairness or improving model performance for the worst-case group shares a common goal with Out-Of-Distribution (OOD) generalization. OOD aims to enhance the model's performance on an (unknown) test domain that differs from the training domain and is not independent and identically distributed (i.i.d) (Ben-Tal et al., 2009; Shen et al., 2021; Arjovsky et al., 2019; Krueger et al., 2021). To achieve fairness, domains are defined as demographic groups, with the objective of learning a model that generalizes effectively across different groups[3]. The optimization objective, in this case, is to minimize the error of the domain/group with maximum error:

$$\mathcal{R}_{\mathcal{F}}(\theta) = \max_{e \in \mathcal{F}} \mathcal{R}_e(\theta) \tag{10}$$

A model (θ) that does not control the worst-case loss across groups has a low overall loss, i.e., $\mathcal{R}(\theta)$, but a high worst-case loss ($\mathcal{R}_{\mathcal{F}}(\theta)$). We define three main categories of methods to improve model performance on the unknown worst-case groups: robust optimization, reweighting, and invariant representation learning. Table 5 shows an overview of existing methods, the datasets, and fairness metrics used for evaluation.

6.2.1 Robust Optimization

When demographic information is known a priori, Sagawa et al. (2019) proposed Group Distributionally Robust Optimization (DRO) to improve model performance on groups with higher loss. Unlike the classical Empirical Risk Minimization (ERM), DRO does not optimize for the average loss. When demographic information is not observed, Hashimoto et al. (2018) showed that EMR does not control the worst-off groups and the authors adapted DRO (Duchi et al., 2016) to achieve Rawlsian Max-Min Fairnes by minimizing the error of the worst-case distribution of perturbations around the empirical distribution, i.e.,

$$\mathcal{R}_{\text{dro}}(\theta; r) = \sup_{\mathcal{Q}:\, D\left(\mathcal{Q} \| \mathcal{P}\right) \leq r} \mathbb{E}_{\mathcal{Q}} \left[l(\theta; X) \right] \tag{11}$$

Where $D\left(\mathcal{Q} \parallel \mathcal{P}\right)$ is the $\mathcal{X}^2$-divergence between the empirical distribution ($\mathcal{P}$) and probability distributions around $\mathcal{P}$ at a distance r and $l(\theta; X)$ represents the model loss over samples Z. The authors showed that $\mathcal{R}_{\text{dro}}(\theta; r)$ upper bounds the worst-case unknown groups and optimizing it can help to control the model performance over the worst-case group. In practice, the problem 11 can be solved by using the following dual:

[3]In general, the terms "domains", "environments", and "groups/subgroups" can be used interchangeably

Papers	Subgroup Identification	Robust Optimization	Reference Classifier	Mechanism Type	Evaluation Metrics	Datasets	General Description
Yenamandra et al. (2023)	✓	✗	✓	Pre	• Precision	• Waterbirds • CelebA • NICO++	Use a "weak" model to amplify bias then uncover samples from worst-case groups by clustering the latent space.
(Chai et al., 2022)	✗	✗	✓	In	• Accuracy • EOD • DI	• New Adult • Compas • CelebA	Reweighed trained via soft labels obtained from knowledge distillation.
Hashimoto et al. (2018)	✗	✓	✗	In	• Group Acc. • EOP	• Twitter	Distributionally Robust Optimization to control the utility of the worst-case groups.
Chakrabarti (2023)	✓	✗	✓	In	• Group Acc.	• Adult • Compas • LSAC	Upweights samples identified with statistical significance as members of the worst-case group.
Idrissi et al. (2022)	✗	✗	✗	Pre	• Group Acc.	• Waterbirds • CelebA • MultiNLI • Civil-Comments	Data subsampling or reweighing can achieve state-of-art performance on worst-case groups.
CVaR (Duchi et al., 2019)	✗	✓	✗	In	• Group Acc.	• MNIST • ImageNet	Optimizes for worst-case distribution around uncertainty set of the empirical distribution.
JTT (Liu et al., 2021)	✓	✗	✓	In	• Group Acc.	• CelebA • Waterbirds • MultiNLI • Civil-Comments	Use a reference classifier to find misclassified samples that are up-weighted to improve model performance on the worst groups (unknown).
ARL Lahoti et al. (2020)	✓	✗	✗	In	• Group AUC • EOP	• Adult • Compas • LSAC	Weighted empirical risk minimization with adversarial reweighting
BPF Martinez et al. (2021)	✗	✓	✗	In	• Group Err.	• Adult • Compas • LSAC • MIMIC-II	Optimize worst-case groups with minimum harm on best-case groups under Pareto optimality.
Ahn et al. (2022)	✓	✗	✓	In	• Group Err.	• CMNIST • MB-MNIST • CelebA • Civil-Comments	It uses per-sample gradients to improve the performance of the worst-case groups.
LfF Nam et al. (2020)	✓	✗	✓	In	• Group Acc.	• CMNIST • CIFAR-10	It uses a generalized cross entropy to uncover worst-case group samples and then upweight them.
EIIL Creager et al. (2021)	✓	✗	✓	In	• Group Acc.	• CMNIST • Adult • Waterbirds • Civil-Comments	Train a reference model using soft-group assignment to identify worst-case group samples.
Ko et al. (2023)	✗	✗	✗	In	• Group Acc.	• CIFAR100 • Tiny-Imagenet	Show the utility of DNN ensembles for improving worst-case group performance.

Table 5: Overview of methods to enforce Rawlsian Max-Min fairness.

$$\min_{\theta \in \Theta} \mathbb{E}_{\mathcal{Q}} \left[l(\theta; X) - \eta \right]^2 \tag{12}$$

Where η is a hyperparameter controlling the strength of the robust loss. By minimizing the equation 12, the model exhibits improvement across all directions around the data-generating distribution, leading to reasonable performance across sufficiently large subgroups, particularly for the worst-case unknown groups Hashimoto et al. (2018). Hu & Chen (2022) built upon Hashimoto et al. (2018) to improve fairness in Survival Analysis, where the goal is to "*model the amount of time that will elapse before a critical event of interest happens*" such as death or patient recovery. Soma et al. (2022) propose a generalized DRO with faster convergence and tighter bound over the worst-off groups. While Peet-Pare et al. (2022) argued that enforcing fairness on models with static distributions does not capture the dynamic environment in which these models are deployed. Consequently, such an approach may not effectively model most real-world scenarios with fairness concerns. They showed that in repeated risk minimization, while DRO and ERM have similar convergence behavior, ERM converges to a fixed point where the model is biased towards majority groups and DRO converges to a fair fixed point. Peet-Pare et al. (2022) adapt *performative prediction* to distributional robust optimization and studied its properties for fairness. Performative prediction (Perdomo et al., 2020) studies a more dynamic setup, wherein the predictions of the model have an influence on the data distributions on which the model makes subsequent predictions.

It is worth noting that DRO operates as a reweighing approach, wherein, unlike ERM which assigns equal weights to all data points, DRO up-weights samples where the model incurs high loss. While the robust optimization process has demonstrated its benefit to the (unknown) worst-case group, its key drawback is its sensitivity to outliers, i.e., the model could focus on optimizing noisy outliers rather than the real worst-case protected groups. To overcome the limitation of DRO, Martinez et al. (2021) propose Blind Pareto Fairness (BPF) an algorithm that can improve the worst-case performances of all groups of a certain size while ensuring the solution is also Pareto-optimal, i.e., ensures that there is no other solution that provides better group risks uniformly for all groups. With the Pareto optimality, the method optimizes for the worst-case groups with a minimum performance drop on the best-performing groups.

Papadaki et al. (2022) use robust optimization to enforce fairness in a *federated learning* setup when demographic information is unknown. In federated learning, the dataset is not centralized but distantly available on different devices. Each device trains a model using its local dataset and sends its model's weights to the central model that will average all weights from the client. The core advantage of federated learning is to enhance the privacy of individuals involved as their data are stored locally (Li et al., 2019). In their work, Papadaki et al. (2022) use a robust loss in each client to improve the worst-case performance of all groups of a certain size in the centralized model.

6.2.2 Reweighing

Reweighing techniques typically operate by devising a mechanism to identify subgroups where the model exhibits worse performance. The approach involves assigning greater weights to samples from these identified subgroups, thereby enhancing the model's performance on minority groups. An alternative set of methods aims to show the advantageous impact of certain established deep learning techniques on fairness. Among these techniques are knowledge distillation, ensemble learning, and class balancing. We delve into both weighing using *subgroup identification* and implicit weighing with techniques that improve *fairness by design*.

Subgroups identification. To overcome the sensitivity of DRO to noise, Lahoti et al. (2020) propose Adversarially Reweighted Learning (ARL) that leverages the notion of *computationally identifiable groups*. These groups are regions where the model makes more mistakes. The method uses an adversarial approach where an adversary learns samples' weights by maximizing the learner (classifier) error, while the learner minimizes the classification weighted loss function. Intuitively, the adversary will assign higher weights to samples where the classifier makes make most misclassification, and to minimize its error, the learner must focus on improving on these samples. Figure 3 shows an overview of ARL.

Chakrabarti (2023) argues that ARL may encounter challenges in comprehensively identifying all subgroups due to the variability of unfairness patterns across training steps and datasets. To address this challenge, the

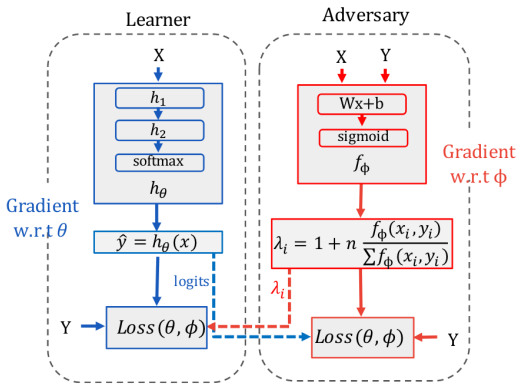

Figure 3: Overview of Adversarially Reweighted Learning (ARL) (Lahoti et al., 2020)

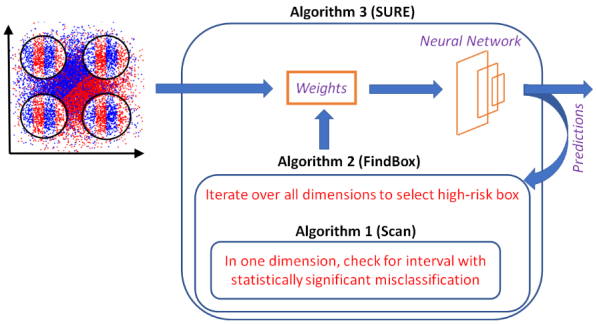

Figure 4: Overview of Significant Unfairness Risk Elimination (SURE) (Chakrabarti, 2023)

author suggests a strategy: selecting the region in the latent space where the model exhibits *statistically significant* errors and upweighting samples within that chosen region even for the correctly classified samples for the next training iteration. The emphasis on the statistical significance of unfairness risk, specifically the higher misclassification rate within the selected region, proves valuable in averting the upweighting of misclassified samples resulting from randomness during training epochs. In cases where no region is identified with a significant risk of unfairness, the training in the next iteration reverts to the classical EMR without sample weights. To identify subgroups, the latent feature vectors for both correctly and incorrectly misclassified samples in the current iteration are segmented into bins (Cf. Figure 4). The number of samples per bin is a hyperparameter. The subgroup identified as having a high unfairness risk comprises samples belonging to the bin with the most significant misclassification error across all latent feature vectors. To ensure that the selected subgroup is large enough and handles the intersectionality of groups, the selected bin is merged with samples from the surrounding bins. Empirical results show evidence that identifying subgroups with statistically significant worst-case error can outperform ARL in various ranges of settings (Chakrabarti, 2023).

Leveraging a Reference Classifier. Another line of work leverages the information provided by an auxiliary model (reference classifier) to identify samples from disadvantaged groups. Existing methods empirically show that the errors or the gradient of an auxiliary model can be used to identify unknown worst-case groups (Ahn et al., 2022; Zhao et al., 2023). Fairness is then enforced using a reweighting scheme based on subgroups identified by the auxiliary model, with the hope that the new reweight will improve the performances of true protected groups. Nam et al. (2020) empirically demonstrated that a model can easily fit groups satisfying spurious correlations in the data (*bias-aligned* samples), at the early stage of the training, while groups that do not satisfy spurious correlation (bias conflicting samples) are fitted later. For example, in the Waterbird dataset, waterbirds on water and landbirds on land are bias-aligned samples, while landbirds on water are *bias-conflicting* samples. Following this observation, the authors proposed a debiasing scheme that consists of two networks trained simultaneously. The "biased" network is fitted to amplify its early-stage predictions, using generalized cross-entropy loss, while the unbiased model is enforced to focus on the mistakes of the biased model. As the biased model mostly learns the spurious correlations, misclassified samples are mostly bias-conflicting samples, that are upweighted to mitigate the bias. The approach demonstrated its efficacy in improving the performance of the model over the wort-case group. Building upon these results, Liu et al. (2021) introduce "Just Train Twice" (JTT) a two-step framework designed to enhance the model's performance on worst-case groups without relying on group information during the training. In the first step, a non-complex model is trained on the target task for a few steps, intentionally leading the model to better fit bias-aligned samples, thus underfitting bias-conflicting samples. The set of misclassified samples by the reference classifier serves as a proxy for the worst-case groups. In the second step, the misclassified samples, which mostly contain data points from the worst-case group, are up-weighted to enable the model

to improve on this group of samples. The ability of the reference classifier to effectively learn spurious correlation depends on the number of steps used to fit the classifier, which is a hyperparameter. The authors perform upweighting by oversampling misclassified by a factor λ_{up}, which is also a hyperparameter. As a drawback, JTT requires expensive hyperparameter tuning, and most of the time requires sensitive attributes in the validation set, to achieve good results. To address this limitation, Veldanda et al. (2023) proposes a mechanism to generate pseudo-sensitive attributes efficient for tuning hyperparameters over the training set. In the same spirit, Yenamandra et al.'s (2023) approach involves leveraging a *weak model* to uncover bias-conflicting samples in the data. The authors demonstrate that bias can be amplified using a weak model, trained to deliberately underfit the training set, which maximizes the separation between minority and majority groups. In the subsequent step, samples from minority groups (bias-conflicting samples) are derived by clustering the bias-amplified latent space obtained in the initial phase, combined with the embedding of visual concepts of each image to preserve the semantic coherence of the clusters (Radford et al., 2021). These clusters are formed by fitting a Gaussian mixture for each class and arranging them based on cluster accuracy in ascending order. The top k clusters are then returned as samples representing minority groups, which can then be upweighted to mitigate bias in the downstream step.

Another line of work identifies worst-case groups using gradient magnitude during the optimization or confidence of the reference classifier. Especially, Ahn et al. (2022) hypothesized that minority samples get higher gradients when training a model with the generalized cross-entropy loss (Zhang & Sabuncu, 2018). Based on this hypothesis, authors the propose a method that involves two steps to mitigate bias. In the first step, a *biased* model is trained using the generalized cross-entropy loss to amplify the gradient of minority samples. In the second step, the final classifier is trained using data points sampled with probability proportional to their gradient provided by the reference model. Samples are therefore weighted proportionally to their gradient magnitude in the first step. Zhao et al. (2023) follows a similar approach but updates the biased model in the first step only using samples whose predictions are highly confident (mostly samples from the majority group). In the second step, sample weights are derived using the prediction probability of the biased auxiliary model such that samples with low confidence in prediction (mostly from the minority group) will receive higher weights. This weighting scheme enforces the alignment of gradients of the different groups during the training in order to mitigate bias.

Fairness for free. There is a line of work that shows that some existing deep learning techniques inherently have a positive impact on the worst-case group or some fairness metrics such as equal opportunity (Chai et al., 2022; Idrissi et al., 2022; Ko et al., 2023). For instance, Chai et al. (2022) theoretically demonstrated the connection between label smoothing and reweighing, i.e., with smooth labels, the model focuses more on samples that are hard to classify. The authors then empirically demonstrated the utility of label smoothing via knowledge distillation to improve fairness; without relying on demographic information during the training. The framework consists of teacher-student models, where the teacher with a larger capacity is trained to overfit the training data, and its logits are used as smooth labels to train the student model. Remarkably, the authors show that knowledge distillation not only improves the worst-case groups but can also effectively improve fairness in terms of equalized odds. On the other hand, Idrissi et al. (2022) show that applying simple data balancing techniques such as subsampling or reweighting can improve the test accuracy of the worst-case group, and demonstrate that simple class balancing can be used when the group information is not available. While Ko et al. (2023) show that ensemble models have a positive impact on fairness, in particular for minority groups.

6.2.3 Invariant Representation Learning

Invariant representation learning is a group of methods aiming to learn representations that are invariant to different environments or domains. In contrast to robust optimization that optimizes for distributions close to the empirical distribution, invariant representation learning is a more general framework aiming to optimize for distributions that are eventually far from the empirical distribution (Arjovsky et al., 2019). A representation $\Phi(x)$ is environment invariant if, for any given environment e_1 and e_2 from the environment

space $\mathcal{E}^{obs}$, it satisfies:

$$\mathbb{E}\left[y|\Phi(x) = h, e_1\right] = \left[y|\Phi(x) = h, e_2\right] \quad \forall h \in \mathcal{H}, \forall e_1, e_2 \in \mathcal{E}^{obs} \tag{13}$$

In other words, a representation satisfying this relation induces the same conditional class labels across environments. This formulation has different applications for different tasks such as privacy, domain adaptation, and fairness(Zhao et al., 2022). For fairness, the invariant representation formulation (Equation 13) is similar to the equation 1 for statistical parity, where the environments are replaced by demographic groups. When group information is available, the invariant representation can be achieved through Invariant Risk Representation (IRM) (Arjovsky et al., 2019) or fair representation learning (Zemel et al., 2013; Madras et al., 2018; Kenfack et al., 2023).

When group information is not available, Creager et al. (2021) propose a method to infer the environment (or group) from data automatically. The proposed method infers group partition using a fixed classifier trained to maximize the invariance violation using a soft group assignment function ($q(e|x, y)$) optimized over the training data. Once the group assignment is acquired, existing IRM or GroupDro methods can be used to enforce a representation that satisfies Equation 13.

6.2.4 Evaluation Protocol in the Rawlsian Fairness Setting.

In this setting, the model is trained without any access to sensitive attributes. However, the evaluation of the performances of the worst-case groups is performed using partitions of the datasets based on sensitive attributes assumed known for the evaluation. Demographic groups are generally defined using an intersectionality of the sensitive attributes. For instance, Lahoti et al. (2020) and Chai et al. (2022) establish demographic groups in the Adult and Compas datasets based on a combination of Race and Sex. Moreover, they report groups' worst-case performance (accuracy or AUC) using an intersection of sensitive attribute values, such as [White, Male], [White, Female], [Black, Female], and [Black, Male]. Alongside the worst-case performance evaluation, group fairness metrics such as equalized odds and disparate impact are also considered (Lahoti et al., 2020; Chai et al., 2022). The results from these evaluations suggest that improving Rawlsian Min-Max fairness can have a positive impact on group fairness in terms of equalized odds.

6.3 Mitigating Bias Under Noisy Demographic Information

As we discussed in Section 3.2.3, sensitive attributes could be noisy because they have been corrupted during data collection. Noise could also be introduced when the sensitive attributes are estimated or collected with privacy-preserving mechanisms. Recent works have emerged to mitigate bias with respect to the true sensitive attribute when only a noisy version of sensitive attributes is available, i.e., there is a limited number of clean sensitive attributes. A straightforward method involves naïvely enforcing fairness using the noisy protected attributes, with the expectation that it will enhance fairness for the true protected groups. The empirical evidence presented by Gupta et al. (2018) suggests that this objective can be realized when the noise in the protected attribute's space arises from estimation, i.e., pseudo-sensitive attributes are derived through an attribute predictor model. However, the bias of the model could still be higher than that of a model with fairness on the true sensitive attributes (Celis et al., 2021; Gupta et al., 2018; Kallus et al., 2022).

There are several works that attempt to provide theoretical bounds on fairness violation when the sensitive attribute is noisy.

6.3.1 Bounding Fairness Violation.

When fairness constraints are applied using noisy protected attributes, one is interested in finding the conditions or assumptions that guarantee fairness improvement on the true protected groups. In this regard, Awasthi et al. (2020) theoretically analyze the impact of noisy attributes on the post-processing technique proposed by Hardt et al. (2016) (presented in Section 4.2) to improve fairness in terms of equalized odds. The post-processing mechanism takes a trained classifier and adjusts its decision boundary to satisfy fairness constraints while maintaining the accuracy as much as possible (Hardt et al., 2016). The authors show that when a certain conditional assumption is satisfied ($\hat{Y} \perp \hat{A}|(A, Y)$) and the sum of the corruption probabilities of each sensitive

attribute value is upper bounded by one (i.e., $\sum_a P(\hat{A} \neq A|Y = y, A = a) \leq 1,\ \forall a \in \{0, 1\}, y \in \{0, 1\}$), the post-processing fairness mechanism using the noisy protected attribute $\hat{A}$ can be robust to the noise in the attribute space, i.e., mitigate bias w.r.t the true protected groups. This essentially means that constraints imposed on the noisy protected groups do not exacerbate fairness violations in the true protected groups. However, this fairness violation bound by Awasthi et al. (2020) is only validated on a post-processing technique. On the other hand, Wang et al. (2020) provide an upper bound on the fairness violation for in-processing constraint optimization techniques. They demonstrate that if the total variation of conditional probability distributions of the data, given the true and noisy protected groups, is bounded for all groups, then fairness criteria will be satisfied with respect to the true groups within the specified total variation bounds for each group. In practice, the corruption rate of the sensitive attributes can be used as the upper bound of the total variation between the conditional distributions, i.e., $P(A \neq \hat{A}|A = j) \leq \lambda,\ \forall j \in A$. The authors show that this bound on the fairness violation holds for a variety of fairness metrics using performance disparity rates, such as demographic parity and equal opportunities. Pursuing a comparable objective, Bharti et al. (2022) establishes a worst-case upper bound on fairness violation in the context of equalized odds. This upper bound is defined under the assumption that the attribute classifier is sufficiently accurate, and makes fewer misclassifications than the label classifier. However, this assumption may only hold in a limited number of applications.

While evaluating the fairness violation bounds of the naïve approach that employs noisy protected attributes could be valuable for practitioners, these assessments often fall short in providing fairness guarantees for the true protected groups. Another line of research concentrates on developing methods that go beyond the naive utilization of noisy protected attributes. Instead, these methods address the noise to construct fair models that exhibit tolerance to variations in sensitive attributes, ultimately providing guarantees of fairness improvement for the true protected groups. We broadly classify these methods into two categories: Noise Tolerant and Noise Correction methods.

6.3.2 Noise Tolerant Methods.

We have seen in section 6.2.1 that DRO can control worst-case error of groups with certain sizes when demographic information is not available. The optimization process is defined around the distance metric over probability distributions and the maximum distance (radius) of the neighboring distributions that are likely to include all groups Hashimoto et al. (2018). Having access to noisy protected attributes can help to define a more meaningful boundary that improves fairness on true protected groups. In this spirit, Wang et al. (2020) formulate DRO using the corruption rate of the sensitive attributes as the upper bound of the divergence metric in the robust constraints. The corruption rate is assumed to upper bound of the total variation between the conditional probability distributions of the data given the true and noisy protected groups. The authors show this formulation is guaranteed to improve fairness in the true groups. However, it can lead to higher overall classification errors due to the assumption about the corruption rate in the robust loss. Wang et al. (2020) propose an alternative approach that uses *soft group assignment*. Soft group assignment leverages an axillary dataset, where the true sensitive attributes are available, to compute sample weights. Each weight is an estimated probability that the sample belongs to a given demographic group. The proposed method builds upon Kallus et al.'s (2022) definition of robust fairness criteria for efficient bias assessment to design a robust optimization approach that is guaranteed to improve the fairness of the true groups while maintaining better accuracy compared to the DRO base method. In (Lamy et al., 2019), the authors propose a noise-tolerant approach that utilizes noise estimation methods, such as a mutually contaminated distribution, to model noise in the sensitive attribute space. The noise model provides corruption proportions for the sensitive attributes. The study demonstrates that any fairness-enhancing technique, accepting a minimum fairness violation parameter τ, can be made robust to noise. This is achieved by deriving a new fairness violation from the noise model, i.e., $\tau' = (1 - \alpha - \beta) \cdot \tau$, where α and β represent the (estimated) noise rates for each demographic group. in particular, the authors illustrate the ability to maintain fairness in clean sensitive attributes when running the exponentiated gradient fairness mechanism by Agarwal et al., with the noise scaled τ' instead of τ as the fairness violation tolerance.

6.3.3 Noise Correction Methods.

Chen et al. (2022a) propose an approach that involves correcting noisy sensitive attributes that have been collected with privacy preservation techniques, such as differential privacy. This method assumes the availability of both clean and private sensitive attributes, which are used to train a model to "correct" the noisy sensitive attributes. To perform the correction, the authors use the Corruption Matrix proposed by Hendrycks et al. (2018). This is a $K \times K$ matrix that models the corruption process of sensitive attributes and contains probabilities that a label i is corrupted to class j. The matrix is obtained by training a model on the noisy part of the sensitive attribute. Using the corrected sensitive attributes, Chen et al. (2022a) adapted the *adversarial debaising* (presented in Section 4.2) algorithm to enforce fairness with respect to statistical parity (equation 1).

6.4 Enforcing Fairness Under Privacy-Preserving Demographics

One way to alleviate privacy restrictions on sensitive attributes is the design of fairness-enhancing methods employing mechanism to preserve the privacy of the sensitive attribute. These mechanisms, offering strong privacy guarantees, typically involve the addition of statistical noise to the data, effectively addressing privacy concerns on access to demographic information. The most popular mechanisms include *trusted third party*, *secure multiparty computation, and differential privacy* .

6.4.1 Trusted Third Party

A trusted third party can be used to provide access to private demographic information. A third party can hold private sensitive information and allow data centers or models to access it while providing a privacy guarantee to the users. The trusted third party can preserve the privacy of the sensitive attributes using a global differential privacy mechanism (Dwork et al., 2012). In contrast to Local DP, noise in Global DP is added after the data are aggregated. Although Global DP requires the user to *trust* the data aggregator (server), it ensures that any adversary observes the same output if only one dataset entry is removed or replaced. The third parties providing differentially private demographic information can alleviate regulatory constraints on privacy. Still, a model using the differential private sensitive attribute should account for the noise introduced for a better improvement or assessment. In some cases, the third party might not provide access to the sensitive attributes but can only perform fairness analysis, e.g., given the classifier outcomes, the third returns its group fairness score. Hu et al. (2019) assumed a trusted third party holding the sensitive attributes to adapt different fairness algorithms to enforce fairness via the trusted third party. The trusted party is used to assess fairness violations by providing a signal used to select the best model in terms of fairness. Hu et al. (2021) assume the sensitive attributes are held by different trusted agents and aim at training a fair model on non-private data without directly exchanging demographic information with the trusted agents. However, such approaches are vulnerable to inferential attacks Hu et al. (2021); Ferry et al. (2023), i.e., attacks to reconstruct sensitive information. In addition, it is difficult in practice to find a trusted party that will collect or possess useful demographic information for a variety of tasks and datasets.

6.4.2 Secure Multiparty Computation (SMC).

Originating in the 1980s, protocols for Secure Multiparty Computation aim to compute a function based on inputs from multiple parties in a distributed manner, while ensuring that only the computation result is disclosed, and the inputs of each party remain confidential. In an ideal scenario, a reliable third party would handle the entire computation process, later delivering the result to all participants before erasing any memory of the transaction. SMC, however, aims to facilitate this process without requiring such a third party. Yao first formulated what is now known as Yao's Millionaires problem, providing a provably secure solution for two-party comparison problem Yao (1986). Since Yao's groundbreaking work, the SMC field has seen numerous innovations. One such advancement is `Blind Justice`, a framework introduced by Kilbertus et al. (2018). This framework enables the creation of fair machine learning models without requiring access to sensitive attributes. Specifically, `Blind Justice` first employs additive secret sharing Shamir (1979) to randomly distribute parts of the sensitive attribute's value between two non-colluding entities: the model creator and the regulator. These two parties then engage in a two-server secure protocol Mohassel & Zhang

(2017) to develop a fair machine learning model. Although SMC helps to maintain the confidentiality of the sensitive attribute during the training phase, it is still possible to deduce this attribute from the fair model Jagielski et al. (2019); Ferry et al. (2023).

6.4.3 Differential Privacy

Several approaches have been proposed to train fair models with differential privacy (presented in Section 4.3) guarantees w.r.t to the sensitive attributes (Mozannar et al., 2020; Jagielski et al., 2019; Tran et al., 2022; Lowy et al., 2023; Tran et al., 2021b;a). These methods generally involve transforming existing non-DP fair algorithms into fair DP algorithms by leveraging the randomized response mechanism. In particular, Lamy et al. (2019) show that one can release $(\epsilon, 0)-$differentially private sensitive attributes by randomly flipping the sensitive attribute with a probability $p = \frac{1}{\exp(\epsilon)+1}$ (Local DP). As we previously discussed, simply imposing fairness constraints on noisy attributes does not guarantee fairness improvement for the true groups. To overcome this, Mozannar et al. (2020) propose a two-step method using existing fairness algorithms to train fair models with fairness and privacy guarantees on the true protected group. The proposed method initiates by applying the exponentiated gradient (Agarwal et al., 2018) to enforce fairness constraints on private (noisy) attributes. To ensure fairness guarantees on the true groups, Mozannar et al. adopt the post-processing technique introduced by Hardt et al. in the second step. This adaptation aids in deriving a predictor that ensures fairness improvement on true attributes. Given the utilization of randomized response in collecting protected attributes, the fairness constraints in the optimization process are defined using the conditional probability of the true protected attribute given the private one, to account for the noise and ensure no fairness violations on true groups. Jagielski et al. (2019) integrate DP in the postprocessing of Hardt et al. by adding Laplace noise in the computed conditional probabilities before solving the resulting linear problem to drive the fair classifier. However, this postprocessing technique generally incurs a higher drop in accuracy and requires sensitive attributes at test time. To overcome this, Jagielski et al. (2019) incorporate DP in the in-processing fairness algorithm by Agarwal et al. (2018) (exponentiated gradient). The training is made DP by adding a Laplace noise to the gradient of the Auditor model during the two-player zero-sum game employed in the original algorithm to optimize the fairness constraints (Agarwal et al., 2018). On the other hand, Lowy et al. (2023) argue that previous methods do not provide fairness and privacy convergence guarantees when the training is done using mini-batch stochastic gradient descent as in most large-scale deep learning models. Lowy et al. use regularization technique by Lowy et al. (2021) to enforce fairness constraints in ERMa . This regularized loss is optimized using a DP variant of the stochastic gradient descent-ascent of Lin et al. (2020). In their method, Gaussian noise is added to the gradient of the weights to ensure differential privacy during training. Similarly, the work of Tran et al. (2021a) proposes a training inspired from *DP-Stochastic Gradient Descent* (DP-SGD) (Abadi et al., 2016) for training deep learning models with privacy guarantees. In DP-SGD, the gradient of each sample is clipped and noise is added before the updating model's weights. Tran et al. use a Lagrangian formulation of ERM with fairness constraints. In addition to the Gaussian noise added to the model's weights, Gaussian noise is added to the updates of the Lagrangian multipliers to ensure differential privacy w.r.t sensitive attributes.

On the other hand, Tran et al. (2022) leverage the PATE framework (presented in Section 4.3) to propose two methods to build fair models with strong privacy guarantees for demographic information. In the first approach, the teachers are trained to predict demographic information and the student is trained with fairness constraints on the noisy aggregated demographic information from teachers. In the second approach, each teacher is trained to predict the target labels but with fairness constraints w.r.t to true (private) protected attributes. The goal is to transfer the fairness of the teachers to the student model. The authors demonstrate that both approaches effectively bound and enhance fairness on true protected groups while simultaneously providing privacy guarantees for sensitive attributes.

Ensuring the privacy of the sensitive attribute in fair learning however introduces a tradeoff between fairness and privacy, i.e., smaller privacy budgets yield might models with higher bias (Lowy et al., 2021; Tran et al., 2021a). This leads to the triple accuracy-fairness-privacy tradeoff dilemma. Moreover, differentially private methods such as PATE and DP-SDG have shown disparate impacts on the model accuracy, i.e., the drop in accuracy is higher for minority groups (Uniyal et al., 2021). This suggests that training fair models under

these frameworks might lead to a violation of the Rawslian Max-Min fairness metric, i.e., worse accuracy performance on the minority groups.

6.4.4 Evaluation Protocol in Noisy Demographic Setting.

When evaluating methods in noisy sensitive attribute setups, a noise model is considered for corrupting sensitive attributes. For example, Lamy et al. (2019); Awasthi et al. (2020); Wang et al. (2020); Celis et al. (2021) consider a stochastic matrix $H \in [0,1]^{p\times p}$, i.e., $\sum_{j\in[p]} H_{ij} = 1$, where H_{ij} is the probability corruption probability. This noise model is applied to the training data. The testing dataset is assumed clean for evaluation. In other settings, the noise model is defined based on a randomized response of sensitive attributes, i.e., a local differential private mechanism was applied to the sensitive attribute to perverse its privacy. The evaluation protocol in privacy in privacy-preserving settings does not differ greatly from settings where demographic information is available. Specifically, the sensitive attributes are privately used during the training and testing phase (Tran et al., 2021b; Hu et al., 2019; Mozannar et al., 2020). The primary goal is to construct a fair model with strong privacy guarantees concerning the demographic data used in training. In ablation studies, existing methods introduce variations in the corruption probability of sensitive attributes or the privacy budget to assess their impact on the proposed methods. For instance, Chen et al. (2022b) demonstrate that, in the context of local differential privacy, reducing the privacy budget — resulting in a higher corruption rate in the sensitive attribute space — leads to a degradation in fairness performance.

6.5 Auditing Bias Under Missing Protected Attributes

While auditing bias in AI systems generally requires access to protected attributes, regulations and laws prohibiting their use raise the need for designing alternative methods for efficient bias assessment. We Existing methods attempt to provide efficient bias estimation of the true attributes when proxy attributes are available (Baines & Courchane, 2014; Chen et al., 2019; Kallus et al., 2022; Awasthi et al., 2021; Kallus et al., 2022), bias assessment under privacy-preserving of the sensitive attribute (Park et al., 2022a; Toreini et al., 2023), and bias assessment using group-free metrics (Liu et al., 2023).

Auditing Bias Using Proxy Attributes. When estimating biases with respect to true demographic groups using proxy demographic information, the proxy model can exhibit biases/errors in predicting the true sensitive features and lead to adverse effects in disparities assessment on downstream tasks. For example, Baines & Courchane (2014) show that bias assessment using an approximation of racial information tends to overestimate the true disparity in a mortgage dataset. In general, for probabilistic models, the estimation of the sensitive attribute is *thresholded*, meaning that group membership is assigned when the output probability of the classifier is greater than a defined threshold $q \in [0.5, 1)$:

$$\hat{a}_i = \begin{cases} 0, \mathbb{P}\left(a_i = 0 \mid x_i\right) < q, \\ 1, \mathbb{P}\left(a_i = 1 \mid x_i\right) > q, \\ \text{NA, otherwise} \end{cases} \tag{14}$$

With this estimation, some samples (NA) are not used to compute the disparity when the proxy model outcome is lower than the threshold. Considering the equation 1, the demography disparity ($\hat{\Delta}$) of a model that uses a *thresholded estimator* of the sensitive attribute can be measured as follows:

$$\begin{aligned} &\hat{\Delta} = \hat{\mu}(0) - \hat{\mu}(1) \\ &\text{with } \hat{\mu}(\alpha) = \frac{\sum_N^{i=1} \mathbb{I}(\hat{a}_i = \alpha \mid x_i)\hat{y}_i}{\sum_N^{i=1} \mathbb{I}(\hat{a}_i = \alpha \mid x_i)}, \ \alpha \in \{0,1\} \end{aligned} \tag{15}$$

where $\mathbb{I}$ represents the indicator function and $\hat{y}_i = f(x_i)$ the predicted label using the classifier f. The overestimation or the underestimation of the true disparity is defined by comparing the computed disparity based on the thresholded estimator ($\hat{\Delta}$) with disparities obtained from the true sensitive feature (Δ), i.e, $\hat{\Delta} - \Delta$. The positive and negative values of this difference represent the overestimation and underestimation

of the true disparity, respectively. As protected attribute classifiers always provide noisy labels when used for estimating unknown protected features, algorithms for auditing unfairness should account for the noise in sensitive attributes for better bias estimation or mitigation. In particular, Chen et al. (2019) perform an analysis of *thresholded* proxy models and show that bias assessment with the derived proxies can result in an overestimation or underestimation of the true disparities, e.g., the disparity in terms of positive prediction rate computed using the proxy-protected attribute is relatively lower or greater than the positive prediction rate w.r.t the true protected groups. The authors suggest that instead of computing the disparities based on thresholded estimation of the sensitive features, it is more efficient to use a soft group assignment within a Weighted Estimator (WE). i.e., by replacing $\hat{\mu}$ in the equation 15 with the following $\hat{\mu}_w$:

$$\hat{\mu}_w(\alpha) = \frac{\sum_N^{i=1} \mathbb{P}(a_i = \alpha \mid x_i)\hat{y}_i}{\sum_N^{i=1} \mathbb{P}(a_i = \alpha \mid x_i)},\ \alpha \in \{0, 1\} \tag{16}$$

With the weighted estimator, the uncertainty of the probabilistic proxy model is propagated into the final estimation of the demographic parity, which may be more useful for the outcome disparity evaluations when proxy models are used (Chen et al., 2019). Contrastingly, Kallus et al. (2022) demonstrate that without observing the joint distribution $P(A, Y, X)$, it is challenging to precisely identify the true disparity measure when relying on proxy attributes derived from marginals, specifically $P(X, Y)$ and $P(A, X)$. This limitation arises due to the insufficient information provided by the corresponding marginal distributions, preventing the unique determination of the joint distribution. Consequently, there are numerous valid full joint distributions that can provide various potential disparities, leading to ambiguity in the true disparity measure. This ambiguity can be alleviated only if an independence assumption is satisfied (i.e., $Y, \hat{Y} \perp A|X$) or there are few samples drawn from the joint distribution $P(A, Y)$ available. To reduce the set of possible disparity measures emerging from the marginal distributions, the Kallus et al. assume one has access to two datasets drawn from the marginals $P(A, X)$ and $P(\hat{Y}, Y, X)$. This assumption aligns with the scenario we outlined in Section 6.1.2, where the sensitive attribute is solely available in an auxiliary dataset. With the two datasets, the authors show that it is possible to limit the number of disparity values and to derive the closed-form of the disparity estimation for various fairness metrics such as equalized odds and equal opportunity.

Perhaps counterintuitively, Awasthi et al. (2021) demonstrate that the accuracy of the protected attribute classifier does not necessarily correlate with the accuracy of the bias estimation, i.e., the gap between the disparity measured using the true sensitive attributes and the predicted ones. Furthermore, the authors show that accounting for the uncertainty of the sensitive attribute predictor using an *active sampling* technique can yield a better estimation of the model disparity. In essence, estimation is done using samples for which the sensitive attribute predictor is most certain. A limitation of the use of the probabilistic proxy models is the assumption that the features that correlate with the unknown sensitive features are known and available.

On the other hand, Fabris et al. (2023) formulate bias estimation without sensitive attributes as a *quantification* problem. The goal of quantification methods is to derive an estimation that can provide for a given sample the prevalence of a given class label in that sample, i.e., the proportion of the class in the given sample. A naive quantification method is the *classify and count* (CC) approach. It consists of training a classifier and counting the frequency of each class in the unlabelled dataset. Fabris et al. (2023) show that group fairness metrics can be formulated using prevalence scores. For example, the equal opportunity metric (Equation 3) can be expressed using the prevalence score of the sensitive attribute as follows:

$$\begin{aligned} \mathrm{P}(\hat{Y} = 1 \mid A = a, Y = 1) &= \frac{\mathrm{P}(Y = 1, \hat{Y} = 1, A = a)}{\mathrm{P}(Y = 1, A = a)} \\ &= \underbrace{\frac{\mathrm{P}(A = a \mid Y = 1, \hat{Y} = 1)}{\mathrm{P}(A = a \mid Y = 1)}}_{\text{obtained from prevalence estimator}} \cdot \frac{\mathrm{P}(Y = 1, \hat{Y} = 1)}{\mathrm{P}(Y = 1)} \\ &\forall a \in \{0, 1\} \end{aligned} \tag{17}$$

This suggests that an efficient prevalence estimator can serve as a better estimator of the true bias in a model. In particular, when applied to bias estimation using a proxy attribute classifier, the naive prevalence

estimator with hard labels corresponds to the thresholded proxy model (Equation 15), and the estimator with soft labels corresponds to the weighted estimator presented above (Equation 16). However, the naive quantification approach is not robust to distribution shifts in the feature or the label space. Fabris et al. (2023) leverage more principled existing quantification methods that are robust to distribution shift. For example, Bella et al. (2010) propose *adjusted classify and count* (ACC), a better prevalence estimator that accounts for true positive rate and false positive rate. On the unlabelled data, the true positive rates and false positive rates are estimated from the training data using K-fold cross-validation. (Fabris et al., 2023) provide empirical evidence that quantification-based approaches can be more effective in estimating the true bias in the dataset with missing sensitive attributes, compared to other methods such as thresholded proxy and weighted estimation,

Cornacchia et al. (2023) introduce CFlips (Counterfactual Flips), a new metric for auditing bias based on counterfactual reasoning. Given a trained model to be audited, a sample x and its protected attribute x_a, when the model predicts a negative outcome for x (i.e., denied a loan) a *counterfactual generator* is used to generate a set of samples that are closer to x but for which the model predicts a positive prediction. The sensitive attribute classifier is then used to predict the sensitive attributes of samples in the counterfactual set of x. The bias score (CFlips score) is then calculated as the proportion of samples in the counterfactual set having a predicted sensitive attribute different from x_a. The intuition is that a model that does not encode any dependency to the sensitive attribute should have the same predicted sensitive attribute for all the counterfactual samples, i.e., a CFlips score equals one. Empirical results show that a model trained with fairness constraints tends to provide a CFlips score closer to one. In contrast, models without fairness constraints get a score closer to 0, meaning there is a majority sample in the counterfactual set with positive predictions that were assigned to a different demographic group. While these results show the efficiency of CFlips score for bias assessment, its effectiveness highly depends on the quality of the counterfactual generator.

While the bias estimation methods presented above can be effective in assessing the true fairness violation, they pose ethical or privacy risks due to the use of proxies or inference of sensitive information about individuals using non-sensitive information.

Auditing Bias Under Privacy Preservation. Bias assessment under secured and privacy-preserving frameworks represents an alternative approach to the use of proxy-sensitive attributes. This group of methods generally considers a black box access to the model to be audited. For example, Park et al. (2022a) propose a trusted execution environment (TEE) for secure and privacy-preserving bias assessment. This method leverages confidential computing technology, utilizing specialized hardware to store sensitive data in encrypted form and ensuring verifiability guarantees for computation integrity. Within the TEE, the proposed approach not only offers fairness certification and verification protocol for regulatory bodies but also extends public verifiability of fairness certificates to end-users. However, this protocol is sensitive to attacks such as data poisoning for fairness (Solans et al., 2020). In such attacks, poisoning points can be crafted and introduced in the test set used by the regulator to mislead and enforce the issuing of a fairness certificate to a biased model. Toreini et al. (2023) propose a different protocol that incorporates three key components: the black-box model under scrutiny, a group of individuals serving as auditors, and a dedicated *fairness computation module*. Auditors interact with the model through secured and encrypted communications, receiving predictions in encrypted form. Subsequently, each auditor encrypts essential information for bias assessment—namely, the predicted outcome, ground truth label, and locally observed and privately held demographic information. The encrypted information is then independently transmitted to the fairness computation module, which conducts fairness assessments based on a specified fairness notion. This evaluation protocol prioritizes the security and privacy of data by employing computation over encrypted data and integrating *zero knowledge proof* (Goldreich & Oren, 1994) for verifying the integrity of the computations. In addition, the proposed bias assessment protocol provides public access to users interested in verifying the bias auditing process.

Auditing Bias Without Group Labels. Liu et al. (2023) introduce *Group-Free Group Fairness* a bias assessment process that does not rely on demographic group labels. This group fairness measure is based on *homophily*, a property in social networks where people sharing the same attributes (both sensitive and non-sensitive) are more likely to be connected to each other compared to people who are dissimilar. In social science and social networks analysis of homophily, there is strong empirical evidence of homophily in

demographic dimensions, i.e., in community networks, there is high connectivity between individuals sharing attributes such as race, gender, religion, and age (Verbrugge, 1977). In contrast to bias estimation methods using proxy group labels, *group-free group fairness* measures group disparities using pairwise similarities between individuals (Liu et al., 2023). The authors evaluate the effectiveness of this approach in quantifying the disparities of a model on several tasks such as node classification, recommender systems, and information access maximization in a graph. The main drawback of group-free bias estimation comes from the assumption that there is a social network that exhibits the homophily property for all the demographic attributes of interest.

7 Conclusion and Future Directions

In this paper, we explored the issue of bias estimation and mitigation when the assumption of full access to demographic information does not hold. We presented various real-world scenarios where the large body of work on fairness using demographic information is not directly applicable. In particular, we presented the settings where the sensitive attributes are entirely missing, partially available, noisy, or available only under privacy guarantees. We presented existing works aiming at addressing fairness issues in each of these settings and provided a taxonomy. In particular, when demographic information is not available: 1) fairness can be enforced by focusing on improving the performance of the worst-case group. This goal can be achieved using methods from robust optimization, invariant representation learning, or reweighting using various methods of identifying protected subgroups; 2) related features or attribute classifiers can be used as a proxy to true demographic groups; 3) sensitive attributes can be noisy due data corruption (e.g., for privacy concerns), existing works focus on bounding fairness violation on the true protected groups, and designing methods that correct or are tolerant to noise in the attributes space; 4) fair and privacy-preserving models can be used to alleviate the privacy restrictions from regulators or laws. Despite this large and growing body of work, there are challenges to be addressed, given room for the following future perspectives:

Bridging Fairness and Generalization. In the survey, we highlighted the similarities between generalization and fairness, in particular for the Rawslsian Max-Min fairness. We observed that improving the performance of the model over the worst-case group can be formulated as a generalization problem, where different domains are considered as the unknown demographic groups. However, the fields of fairness and generalization are mostly studied independently. The work by Creager et al. (2021) makes initial steps in studying them jointly, by leveraging techniques from fairness without demographics to design a domain generalization method without domain knowledge. More broadly, some existing works aim to improve generalization by mitigating dataset bias, framed as spurious correlation (Nam et al., 2020; Zhao et al., 2023; Ahn et al., 2022). The main objective in mitigating spurious correlation in the data is to identify the *bias-conflicting* and *bias-aligned* samples (Nam et al., 2020), which are samples from the minority and the majority groups respectively. Besides their similarities, methods for generalization problems are often evaluated only on generalization benchmarks with known spurious correlations such as Waterbird, CMNIST, and CIFAR100 datasets. It will be interesting if different proposed methods are also evaluated on fairness benchmarks to assess their effectiveness in improving the performance of worst-case demographic groups.

Robustness to distribution shifts. Most existing work presented in the survey assumes the data-generating process is fixed over time and does not consider dynamic settings where the model is deployed in changing environments (distribution shift). There are various reasons for the change in the environment such as changes in the covariate, label, or protected attribute distribution (Barrainkua et al., 2023; Prost et al., 2021). There are many practical scenarios in which distribution shifts occur, reflecting the constant evolution of our society, such as in healthcare (Chen et al., 2021; Finlayson et al., 2021). It is therefore essential to design robust fair models without demographic information while preserving fairness guarantees when data-generating processes change in the deployed environment.

Consistent Evaluation Protocols with Provable Fairness Guarantees. When demographic information is missing, most existing approaches assume sensitive information is observed during the evaluation phase. The reasons for the unavailability of the sensitive attributes during the training phase might also apply to the testing phase or during internal bias screening. This makes the application of the proposed

methods less realistic in real-world scenarios, where the sensitive attributes are also not available for bias assessment. Therefore, it is important to design bias estimation methods that make the same assumptions about the sensitive attributes across the training, validation, and testing stages. For example, when the sensitive attribute is noisy, the bias assessment on the testing set should also be performed on a noisy attribute set. This assessment should be done using bias assessment methods with provable fairness guarantees on true fairness violations, that also account for the noisy sensitive attributes. The same observation applies to fairness-enhancing methods that use proxy sensitive attributes where the test is made on true sensitive attributes instead of using bias assessment methods — over the proxy attributes — with provable fairness guarantees on the true sensitive attributes (Diana et al., 2022; Jung et al., 2022; Kenfack et al., 2023). We have covered some of these methods in section 6.5, however, they are yet to be employed for evaluation on different benchmarks.

Establishsing the Limits of Fairness with Missing Protected Attributes. We observed throughout the survey that alternative solutions in enforcing fairness in missing protected attribute settings generally come with new dilemmas that are yet to be addressed. For example:

- Using proxy models to infer sensitive attributes poses privacy risks (Andrus et al., 2021). In fact, the prediction of sensitive information could also violate the privacy constraints from regulations that prohibit their collection and the restriction could also be applied to predicted sensitive information. Furthermore, predicting sensitive attributes can be unlawful and raises ethical concerns, e.g., inferring gender using a photo or inferring racial/ethnicity using last names. Besides, there is no way to evaluate the accuracy of the proxy-sensitive information when real values are not observed. This leads to a risk of incorrect bias estimation and discrimination exacerbation.
- Training fair models under privacy preservation of sensitive attributes raises the fairness-privacy tradeoffs dilemma (Tran et al., 2021a; Jagielski et al., 2019). We observed that privacy-preserving mechanisms such as differential privacy can provide strong privacy guarantees and alleviate the restrictions from regulators or laws. However, existing works show that the stronger the privacy of sensitive attributes the higher the fairness violation. While regulators or laws enforce both discrimination-free and privacy-preserving decision-making processes, it remains unclear which value between fairness and privacy should be prioritized when there is no tradeoff satisfying the different expectations. Moreover, privacy-preserving mechanisms exhibit disparate impact on minority groups (Bagdasaryan et al., 2019; Uniyal et al., 2021), their use in fair learning can worsen the performance in terms of worst-case groups.
- Enforcing worst-case group fairness does not necessarily mitigate the disparities between demographic groups (Chai et al., 2022; Ozdayi et al., 2021; Lahoti et al., 2020). We observed that while achieving the Rawlsian principle of distributed justice can be an effective fairness metric in different scenarios, it also inherits the critiques of the Rawlsian principles. In particular, the difficulty in defining and targeting the *right* disadvantaged groups (Franke, 2021). On the other hand, while empirical evidence shows that aiming to improve the worst-case group can positively impact equalized odds, it generally fell short in improving group fairness compared to sensitive-attribute aware fair learning. These shortcomings therefore limit the practical application of Rawlsian Max-Min fairness in contexts where group fairness notions are required, particularly group notions in trade-offs with accuracy.

These dilemmas raise the need to clarify the limits of what can be achieved when the sensitive attributes —that are the most important information for bias mitigation and assessment — are missing. This would provide regulators and practicians with tools and information to take appropriate actions for bias-free automated decision-making. Furthermore, addressing these dilemmas might require rethinking the formulation of unfairness in machine learning.

Benchmarking Existing Methods. A research direction that is worth exploring is to perform an empirical comparison of the existing methods in order to establish state-of-the-art performances on different fairness benchmarks. This will be particularly useful in providing the research community with methods that should be used for comparison, the evaluation process (choice of the worst-case group), and the evaluation metrics.

In particular, we observed that some newly proposed methods aimed at improving group fairness metrics such as demographic parity are compared with methods designed to improve worst-case performance. The benchmark will guide the community toward comparing methods on fairness metrics that they are designed to improve.

References

Martin Abadi, Andy Chu, Ian Goodfellow, H Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. Deep learning with differential privacy. In *Proceedings of the 2016 ACM SIGSAC conference on computer and communications security*, pp. 308–318, 2016.

Alekh Agarwal, Alina Beygelzimer, Miroslav Dudík, John Langford, and Hanna Wallach. A reductions approach to fair classification. In *International conference on machine learning*, pp. 60–69. PMLR, 2018.

Carlos Aguirre and Mark Dredze. Generalizing fairness using multi-task learning without demographic information. *arXiv preprint arXiv:2305.12671*, 2023.

Sumyeong Ahn, Seongyoon Kim, and Se-young Yun. Mitigating dataset bias by using per-sample gradient. *arXiv preprint arXiv:2205.15704*, 2022.

JEJ Altham. Rawls's difference principle. *Philosophy*, 48(183):75–78, 1973.

McKane Andrus, Elena Spitzer, Jeffrey Brown, and Alice Xiang. What we can't measure, we can't understand: Challenges to demographic data procurement in the pursuit of fairness. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*, pp. 249–260, 2021.

Julia Angwin, Jeff Larson, Surya Mattu, and Lauren Kirchner. Machine bias: There's software used across the country to predict future criminals. and it's biased against blacks. propublica, 23 may. `https://www.propublica.org/datastore/dataset/compas-recidivism-risk-score-data\/--and-analysis`, 2016.

Martin Arjovsky, Léon Bottou, Ishaan Gulrajani, and David Lopez-Paz. Invariant risk minimization. *arXiv preprint arXiv:1907.02893*, 2019.

Carolyn Ashurst and Adrian Weller. Fairness without demographic data: A survey of approaches. In *Equity and Access in Algorithms, Mechanisms, and Optimization*, pp. 1–12. 2023.

Pranjal Awasthi, Matthäus Kleindessner, and Jamie Morgenstern. Equalized odds postprocessing under imperfect group information. In *International conference on artificial intelligence and statistics*, pp. 1770–1780. PMLR, 2020.

Pranjal Awasthi, Alex Beutel, Matthäus Kleindessner, Jamie Morgenstern, and Xuezhi Wang. Evaluating fairness of machine learning models under uncertain and incomplete information. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, pp. 206–214, 2021.

Eugene Bagdasaryan, Omid Poursaeed, and Vitaly Shmatikov. Differential privacy has disparate impact on model accuracy. *Advances in neural information processing systems*, 32, 2019.

Arthur P Baines and Marsha J Courchane. Fair lending: Implications for the indirect auto finance market. *Study Prepared for the American Financial Services Association*, 2014.

Rajas Bansal. A survey on bias and fairness in natural language processing. *arXiv preprint arXiv:2204.09591*, 2022.

Solon Barocas, Moritz Hardt, and Arvind Narayanan. Fairness in machine learning. *Nips tutorial*, 1:2017, 2017.

Solon Barocas, Moritz Hardt, and Arvind Narayanan. *Fairness and Machine Learning*. fairmlbook.org, 2019. `http://www.fairmlbook.org`.

Ainhize Barrainkua, Paula Gordaliza, Jose A Lozano, and Novi Quadrianto. Preserving the fairness guarantees of classifiers in changing environments: a survey. *ACM Computing Surveys*, 2023.

Yahav Bechavod and Katrina Ligett. Learning fair classifiers: A regularization-inspired approach. *arXiv preprint arXiv:1707.00044*, pp. 1733–1782, 2017.

Antonio Bella, Cesar Ferri, José Hernández-Orallo, and Maria Jose Ramirez-Quintana. Quantification via probability estimators. In *2010 IEEE International Conference on Data Mining*, pp. 737–742. IEEE, 2010.

Aharon Ben-Tal, Laurent El Ghaoui, and Arkadi Nemirovski. *Robust optimization*, volume 28. Princeton university press, 2009.

Richard Berk. *Criminal justice forecasts of risk: A machine learning approach*. Springer Science & Business Media, 2012.

Richard Berk, Drougas Berk, and Drougas. *Machine learning risk assessments in criminal justice settings*. Springer, 2019.

Beepul Bharti, Paul Yi, and Jeremias Sulam. Estimating and controlling for fairness via sensitive attribute predictors. *arXiv preprint arXiv:2207.12497*, 2022.

J Aislinn Bohren, Peter Hull, and Alex Imas. Systemic discrimination: Theory and measurement. Technical report, National Bureau of Economic Research, 2022.

Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. *Advances in neural information processing systems*, 29, 2016.

Joy Buolamwini and Timnit Gebru. Gender shades: Intersectional accuracy disparities in commercial gender classification. In *Conference on fairness, accountability and transparency*, pp. 77–91. PMLR, 2018.

Aylin Caliskan, Joanna J Bryson, and Arvind Narayanan. Semantics derived automatically from language corpora contain human-like biases. *Science*, 356(6334):183–186, 2017.

Simon Caton and Christian Haas. Fairness in machine learning: A survey. *arXiv preprint arXiv:2010.04053*, 2020.

L Elisa Celis, Lingxiao Huang, Vijay Keswani, and Nisheeth K Vishnoi. Fair classification with noisy protected attributes: A framework with provable guarantees. In *International Conference on Machine Learning*, pp. 1349–1361. PMLR, 2021.

Junyi Chai and Xiaoqian Wang. Self-supervised fair representation learning without demographics. *Advances in Neural Information Processing Systems*, 35:27100–27113, 2022.

Junyi Chai, Taeuk Jang, and Xiaoqian Wang. Fairness without demographics through knowledge distillation. *Advances in Neural Information Processing Systems*, 35:19152–19164, 2022.

Deepayan Chakrabarti. Sure: Robust, explainable, and fair classification without sensitive attributes. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 179–189, 2023.

Chia-Yuan Chang, Yu-Neng Chuang, Kwei-Herng Lai, Xiaotian Han, Xia Hu, and Na Zou. Towards assumption-free bias mitigation. *arXiv preprint arXiv:2307.04105*, 2023.

Canyu Chen, Yueqing Liang, Xiongxiao Xu, Shangyu Xie, Yuan Hong, and Kai Shu. On fair classification with mostly private sensitive attributes. *arXiv preprint arXiv:2207.08336*, 2022a.

Canyu Chen, Yueqing Liang, Xiongxiao Xu, Shangyu Xie, Yuan Hong, and Kai Shu. When fairness meets privacy: Fair classification with semi-private sensitive attributes. In *Workshop on Trustworthy and Socially Responsible Machine Learning, NeurIPS 2022*, 2022b.

Irene Y Chen, Shalmali Joshi, Marzyeh Ghassemi, and Rajesh Ranganath. Probabilistic machine learning for healthcare. *Annual review of biomedical data science*, 4:393–415, 2021.

Jiahao Chen, Nathan Kallus, Xiaojie Mao, Geoffry Svacha, and Madeleine Udell. Fairness under unawareness: Assessing disparity when protected class is unobserved. In *Proceedings of the conference on fairness, accountability, and transparency*, pp. 339–348, 2019.

Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In *International conference on machine learning*, pp. 1597–1607. PMLR, 2020.

Anshuman Chhabra, Karina Masalkovaitė, and Prasant Mohapatra. An overview of fairness in clustering. *IEEE Access*, 2021.

Jianfeng Chi, Jian Shen, Xinyi Dai, Weinan Zhang, Yuan Tian, and Han Zhao. Towards return parity in markov decision processes. *arXiv preprint arXiv:2111.10476*, 2021.

Giandomenico Cornacchia, Vito Walter Anelli, Giovanni Maria Biancofiore, Fedelucio Narducci, Claudio Pomo, Azzurra Ragone, and Eugenio Di Sciascio. Auditing fairness under unawareness through counterfactual reasoning. *Information Processing & Management*, 60(2):103224, 2023.

Amanda Coston, Karthikeyan Natesan Ramamurthy, Dennis Wei, Kush R Varshney, Skyler Speakman, Zairah Mustahsan, and Supriyo Chakraborty. Fair transfer learning with missing protected attributes. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 91–98, 2019.

Ronald L Craig. *Systemic discrimination in employment and the promotion of ethnic equality*, volume 91. Martinus Nijhoff Publishers, 2007.

Elliot Creager, Jörn-Henrik Jacobsen, and Richard Zemel. Environment inference for invariant learning. In *International Conference on Machine Learning*, pp. 2189–2200. PMLR, 2021.

Robert Culkin and Sanjiv R Das. Machine learning in finance: the case of deep learning for option pricing. *Journal of Investment Management*, 15(4):92–100, 2017.

Emily Diana, Wesley Gill, Michael Kearns, Krishnaram Kenthapadi, and Aaron Roth. Minimax group fairness: Algorithms and experiments. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 66–76, 2021.

Emily Diana, Wesley Gill, Michael Kearns, Krishnaram Kenthapadi, Aaron Roth, and Saeed Sharifi-Malvajerdi. Multiaccurate proxies for downstream fairness. In *2022 ACM Conference on Fairness, Accountability, and Transparency*, pp. 1207–1239, 2022.

Matthew F Dixon, Igor Halperin, and Paul Bilokon. *Machine Learning in Finance*. Springer, 2020.

John Duchi, Peter Glynn, and Hongseok Namkoong. Statistics of robust optimization: A generalized empirical likelihood approach. *arXiv preprint arXiv:1610.03425*, 2016.

John C Duchi, Tatsunori Hashimoto, and Hongseok Namkoong. Distributionally robust losses against mixture covariate shifts. *Under review*, 2(1), 2019.

Jannik Dunkelau and Michael Leuschel. Fairness-aware machine learning. *An Extensive Overview*, 2019.

Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam Smith. Calibrating noise to sensitivity in private data analysis. In *Theory of Cryptography: Third Theory of Cryptography Conference, TCC 2006, New York, NY, USA, March 4-7, 2006. Proceedings 3*, pp. 265–284. Springer, 2006.

Cynthia Dwork, Moritz Hardt, Toniann Pitassi, Omer Reingold, and Richard Zemel. Fairness through awareness. In *Proceedings of the 3rd innovations in theoretical computer science conference*, pp. 214–226, 2012.

Cynthia Dwork, Aaron Roth, et al. The algorithmic foundations of differential privacy. *Foundations and Trends® in Theoretical Computer Science*, 9(3–4):211–407, 2014.

Marc N Elliott, Peter A Morrison, Allen Fremont, Daniel F McCaffrey, Philip Pantoja, and Nicole Lurie. Using the census bureau's surname list to improve estimates of race/ethnicity and associated disparities. *Health Services and Outcomes Research Methodology*, 9(2):69–83, 2009.

Keith D Ewing. The human rights act and parliamentary democracy, 1999.

Alessandro Fabris, Andrea Esuli, Alejandro Moreo, and Fabrizio Sebastiani. Measuring fairness under unawareness of sensitive attributes: A quantification-based approach. *Journal of Artificial Intelligence Research*, 76:1117–1180, 2023.

Abolfazl Farahani, Sahar Voghoei, Khaled Rasheed, and Hamid R Arabnia. A brief review of domain adaptation. *Advances in data science and information engineering: proceedings from ICDATA 2020 and IKE 2020*, pp. 877–894, 2021.

Julien Ferry, Ulrich Aïvodji, Sébastien Gambs, Marie-José Huguet, and Mohamed Siala. Exploiting fairness to enhance sensitive attributes reconstruction. In *First IEEE Conference on Secure and Trustworthy Machine Learning*, 2023.

Samuel G Finlayson, Adarsh Subbaswamy, Karandeep Singh, John Bowers, Annabel Kupke, Jonathan Zittrain, Isaac S Kohane, and Suchi Saria. The clinician and dataset shift in artificial intelligence. *New England Journal of Medicine*, 385(3):283–286, 2021.

Ulrik Franke. Rawls's original position and algorithmic fairness. *Philosophy & Technology*, 34(4):1803–1817, 2021.

Ismael Garrido-Muñoz, Arturo Montejo-Ráez, Fernando Martínez-Santiago, and L Alfonso Ureña-López. A survey on bias in deep nlp. *Applied Sciences*, 11(7):3184, 2021.

Oded Goldreich and Yair Oren. Definitions and properties of zero-knowledge proof systems. *Journal of Cryptology*, 7(1):1–32, 1994.

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks. *Communications of the ACM*, 63(11): 139–144, 2020.

Vincent Grari, Sylvain Lamprier, and Marcin Detyniecki. Fairness without the sensitive attribute via causal variational autoencoder. *arXiv preprint arXiv:2109.04999*, 2021.

Arthur Gretton, Olivier Bousquet, Alex Smola, and Bernhard Schölkopf. Measuring statistical dependence with hilbert-schmidt norms. In *International conference on algorithmic learning theory*, pp. 63–77. Springer, 2005.

Maya Gupta, Andrew Cotter, Mahdi Milani Fard, and Serena Wang. Proxy fairness. *arXiv preprint arXiv:1806.11212*, 2018.

Moritz Hardt, Eric Price, and Nati Srebro. Equality of opportunity in supervised learning. *Advances in neural information processing systems*, 29:3315–3323, 2016.

Tatsunori Hashimoto, Megha Srivastava, Hongseok Namkoong, and Percy Liang. Fairness without demographics in repeated loss minimization. In *International Conference on Machine Learning*, pp. 1929–1938. PMLR, 2018.

JB Heaton, Nicholas G Polson, and Jan Hendrik Witte. Deep learning in finance. *arXiv preprint arXiv:1602.06561*, 2016.

Dan Hendrycks, Mantas Mazeika, Duncan Wilson, and Kevin Gimpel. Using trusted data to train deep networks on labels corrupted by severe noise. *Advances in neural information processing systems*, 31, 2018.

David C Hsia. Credit scoring and the equal credit opportunity act. *Hastings LJ*, 30:371, 1978.

Hui Hu, Yijun Liu, Zhen Wang, and Chao Lan. A distributed fair machine learning framework with private demographic data protection. In *2019 IEEE International Conference on Data Mining (ICDM)*, pp. 1102–1107. IEEE, 2019.

Hui Hu, Mike Borowczak, and Zhengzhang Chen. Privacy-preserving fair machine learning without collecting sensitive demographic data. In *2021 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–9. IEEE, 2021.

Shu Hu and George H Chen. Distributionally robust survival analysis: A novel fairness loss without demographics. In *Machine Learning for Health*, pp. 62–87. PMLR, 2022.

Badr Youbi Idrissi, Martin Arjovsky, Mohammad Pezeshki, and David Lopez-Paz. Simple data balancing achieves competitive worst-group-accuracy. In *Conference on Causal Learning and Reasoning*, pp. 336–351. PMLR, 2022.

Rabia Jafri and Hamid R Arabnia. A survey of face recognition techniques. *journal of information processing systems*, 5(2):41–68, 2009.

Matthew Jagielski, Michael Kearns, Jieming Mao, Alina Oprea, Aaron Roth, Saeed Sharifi-Malvajerdi, and Jonathan Ullman. Differentially private fair learning. In *International Conference on Machine Learning*, pp. 3000–3008. PMLR, 2019.

Sangwon Jung, Sanghyuk Chun, and Taesup Moon. Learning fair classifiers with partially annotated group labels. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 10348–10357, 2022.

Nathan Kallus, Xiaojie Mao, and Angela Zhou. Assessing algorithmic fairness with unobserved protected class using data combination. *Management Science*, 68(3):1959–1981, 2022.

Faisal Kamiran and Toon Calders. Data preprocessing techniques for classification without discrimination. *Knowledge and Information Systems*, 33(1):1–33, 2012.

Toshihiro Kamishima, Shotaro Akaho, and Jun Sakuma. Fairness-aware learning through regularization approach. In *2011 IEEE 11th International Conference on Data Mining Workshops*, pp. 643–650. IEEE, 2011.

Patrik Joslin Kenfack, Adil Mehmood Khan, Rasheed Hussain, and SM Kazmi. Adversarial stacked auto-encoders for fair representation learning. *arXiv preprint arXiv:2107.12826*, 2021.

Patrik Joslin Kenfack, Kamil Sabbagh, Adín Ramírez Rivera, and Adil Khan. Repfair-gan: Mitigating representation bias in gans using gradient clipping. *arXiv preprint arXiv:2207.10653*, 2022.

Patrik Joslin Kenfack, Samira Ebrahimi Kahou, and Ulrich Aïvodji. Fairness under demographic scarce regime. *arXiv preprint arXiv:2307.13081*, 2023.

Niki Kilbertus, Mateo Rojas Carulla, Giambattista Parascandolo, Moritz Hardt, Dominik Janzing, and Bernhard Schölkopf. Avoiding discrimination through causal reasoning. *Advances in neural information processing systems*, 30, 2017.

Niki Kilbertus, Adrià Gascón, Matt Kusner, Michael Veale, Krishna Gummadi, and Adrian Weller. Blind justice: Fairness with encrypted sensitive attributes. In *International Conference on Machine Learning*, pp. 2630–2639. PMLR, 2018.

Diederik P Kingma, Max Welling, et al. An introduction to variational autoencoders. *Foundations and Trends® in Machine Learning*, 12(4):307–392, 2019.

Wei-Yin Ko, Daniel D'souza, Karina Nguyen, Randall Balestriero, and Sara Hooker. Fair-ensemble: When fairness naturally emerges from deep ensembling. *arXiv preprint arXiv:2303.00586*, 2023.

David Krueger, Ethan Caballero, Joern-Henrik Jacobsen, Amy Zhang, Jonathan Binas, Dinghuai Zhang, Remi Le Priol, and Aaron Courville. Out-of-distribution generalization via risk extrapolation (rex). In *International Conference on Machine Learning*, pp. 5815–5826. PMLR, 2021.

Matt J Kusner, Joshua R Loftus, Chris Russell, and Ricardo Silva. Counterfactual fairness. *arXiv preprint arXiv:1703.06856*, 2017.

Preethi Lahoti, Krishna P Gummadi, and Gerhard Weikum. Operationalizing individual fairness with pairwise fair representations. *arXiv preprint arXiv:1907.01439*, 2019.

Preethi Lahoti, Alex Beutel, Jilin Chen, Kang Lee, Flavien Prost, Nithum Thain, Xuezhi Wang, and Ed Chi. Fairness without demographics through adversarially reweighted learning. *Advances in neural information processing systems*, 33:728–740, 2020.

Alex Lamy, Ziyuan Zhong, Aditya K Menon, and Nakul Verma. Noise-tolerant fair classification. *Advances in Neural Information Processing Systems*, 32, 2019.

Felix Last, Georgios Douzas, and Fernando Bacao. Oversampling for imbalanced learning based on k-means and smote. *arXiv preprint arXiv:1711.00837*, 2017.

Tai Le Quy, Arjun Roy, Vasileios Iosifidis, Wenbin Zhang, and Eirini Ntoutsi. A survey on datasets for fairness-aware machine learning. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, pp. e1452, 2022.

Xiang Li, Kaixuan Huang, Wenhao Yang, Shusen Wang, and Zhihua Zhang. On the convergence of fedavg on non-iid data. *arXiv preprint arXiv:1907.02189*, 2019.

Yueqing Liang, Canyu Chen, Tian Tian, and Kai Shu. Fair classification via domain adaptation: A dual adversarial learning approach. *Frontiers in Big Data*, 5:129, 2023.

Tianyi Lin, Chi Jin, and Michael Jordan. On gradient descent ascent for nonconvex-concave minimax problems. In *International Conference on Machine Learning*, pp. 6083–6093. PMLR, 2020.

David Liu, Virginie Do, Nicolas Usunier, and Maximilian Nickel. Group fairness without demographics using social networks. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*, pp. 1432–1449, 2023.

Evan Z Liu, Behzad Haghgoo, Annie S Chen, Aditi Raghunathan, Pang Wei Koh, Shiori Sagawa, Percy Liang, and Chelsea Finn. Just train twice: Improving group robustness without training group information. In *International Conference on Machine Learning*, pp. 6781–6792. PMLR, 2021.

Yijun Liu and Chao Lan. Active query of private demographic data for learning fair models. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, pp. 2129–2132, 2020.

Andrew Lowy, Sina Baharlouei, Rakesh Pavan, Meisam Razaviyayn, and Ahmad Beirami. A stochastic optimization framework for fair risk minimization. *arXiv preprint arXiv:2102.12586*, 2021.

Andrew Lowy, Devansh Gupta, and Meisam Razaviyayn. Stochastic differentially private and fair learning. In *Workshop on Algorithmic Fairness through the Lens of Causality and Privacy*, pp. 86–119. PMLR, 2023.

David Madras, Elliot Creager, Toniann Pitassi, and Richard Zemel. Learning adversarially fair and transferable representations. In *International Conference on Machine Learning*, pp. 3384–3393. PMLR, 2018.

Karima Makhlouf, Sami Zhioua, and Catuscia Palamidessi. On the applicability of machine learning fairness notions. *ACM SIGKDD Explorations Newsletter*, 23(1):14–23, 2021.

Natalia Martinez, Martin Bertran, and Guillermo Sapiro. Minimax pareto fairness: A multi objective perspective. In *International Conference on Machine Learning*, pp. 6755–6764. PMLR, 2020.

Natalia L Martinez, Martin A Bertran, Afroditi Papadaki, Miguel Rodrigues, and Guillermo Sapiro. Blind pareto fairness and subgroup robustness. In *International Conference on Machine Learning*, pp. 7492–7501. PMLR, 2021.

Frank McSherry and Kunal Talwar. Mechanism design via differential privacy. In *48th Annual IEEE Symposium on Foundations of Computer Science (FOCS'07)*, pp. 94–103. IEEE, 2007.

Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. A survey on bias and fairness in machine learning. *ACM Computing Surveys (CSUR)*, 54(6):1–35, 2021.

Payman Mohassel and Yupeng Zhang. Secureml: A system for scalable privacy-preserving machine learning. In *2017 IEEE symposium on security and privacy (SP)*, pp. 19–38. IEEE, 2017.

Hussein Mozannar, Mesrob Ohannessian, and Nathan Srebro. Fair learning with private demographic data. In *International Conference on Machine Learning*, pp. 7066–7075. PMLR, 2020.

Razieh Nabi and Ilya Shpitser. Fair inference on outcomes. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018.

Junhyun Nam, Hyuntak Cha, Sungsoo Ahn, Jaeho Lee, and Jinwoo Shin. Learning from failure: De-biasing classifier from biased classifier. *Advances in Neural Information Processing Systems*, 33:20673–20684, 2020.

Alejandro Noriega-Campero, Michiel A Bakker, Bernardo Garcia-Bulle, and Alex'Sandy' Pentland. Active fairness in algorithmic decision making. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 77–83, 2019.

Mustafa Safa Ozdayi, Murat Kantarcioglu, and Rishabh Iyer. Fair machine learning under limited demographically labeled data. *arXiv preprint arXiv:2106.04757*, 2021.

Trilok Nath Pandey, Alok Kumar Jagadev, Suman Kumar Mohapatra, and Satchidananda Dehuri. Credit risk analysis using machine learning classifiers. In *2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS)*, pp. 1850–1854. IEEE, 2017.

Afroditi Papadaki, Natalia Martinez, Martin Andres Bertran, Guillermo Sapiro, and Miguel RD Rodrigues. Federated fairness without access to demographics. In *Workshop on Federated Learning: Recent Advances and New Challenges (in Conjunction with NeurIPS 2022)*, 2022.

Nicolas Papernot, Martín Abadi, Úlfar Erlingsson, Ian Goodfellow, and Kunal Talwar. Semi-supervised knowledge transfer for deep learning from private training data. In *International Conference on Learning Representations*, 2016.

Saerom Park, Seongmin Kim, and Yeon-sup Lim. Fairness audit of machine learning models with confidential computing. In *Proceedings of the ACM Web Conference 2022*, pp. 3488–3499, 2022a.

Sungho Park, Jewook Lee, Pilhyeon Lee, Sunhee Hwang, Dohyung Kim, and Hyeran Byun. Fair contrastive learning for facial attribute classification. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 10389–10398, 2022b.

Liam Peet-Pare, Nidhi Hegde, and Alona Fyshe. Long term fairness for minority groups via performative distributionally robust optimization. *arXiv preprint arXiv:2207.05777*, 2022.

Guilherme Dean Pelegrina, Miguel Couceiro, and Leonardo Tomazeli Duarte. A statistical approach to detect sensitive features in a group fairness setting. *arXiv preprint arXiv:2305.06994*, 2023.

Juan Perdomo, Tijana Zrnic, Celestine Mendler-Dünner, and Moritz Hardt. Performative prediction. In *International Conference on Machine Learning*, pp. 7599–7609. PMLR, 2020.

Dana Pessach and Erez Shmueli. Algorithmic fairness. *arXiv preprint arXiv:2001.09784*, 2020.

Evaggelia Pitoura, Kostas Stefanidis, and Georgia Koutrika. Fairness in rankings and recommendations: an overview. *The VLDB Journal*, pp. 1–28, 2021.

Marcelo OR Prates, Pedro H Avelar, and Luís C Lamb. Assessing gender bias in machine translation: a case study with google translate. *Neural Computing and Applications*, 32(10):6363–6381, 2020.

Flavien Prost, Pranjal Awasthi, Nick Blumm, Aditee Kumthekar, Trevor Potter, Li Wei, Xuezhi Wang, Ed H Chi, Jilin Chen, and Alex Beutel. Measuring model fairness under noisy covariates: A theoretical perspective. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 873–883, 2021.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pp. 8748–8763. PMLR, 2021.

John Rawls. A theory of justice. revised edition. university press. 1999.

John Rawls. *Justice as fairness: A restatement*. Harvard University Press, 2001.

María Agustina Ricci Lara, Rodrigo Echeveste, and Enzo Ferrante. Addressing fairness in artificial intelligence for medical imaging. *nature communications*, 13(1):4581, 2022.

Robert Rosenman, Vidhura Tennekoon, and Laura G Hill. Measuring bias in self-reported data. *International Journal of Behavioural and Healthcare Research*, 2(4):320–332, 2011.

Cynthia Rudin. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1(5):206–215, 2019.

Shiori Sagawa, Pang Wei Koh, Tatsunori B Hashimoto, and Percy Liang. Distributionally robust neural networks. In *International Conference on Learning Representations*, 2019.

Candice Schumann, Xuezhi Wang, Alex Beutel, Jilin Chen, Hai Qian, and Ed H Chi. Transfer of machine learning fairness across domains. *arXiv preprint arXiv:1906.09688*, 2019.

Burr Settles. Active learning literature survey. 2009.

K Shailaja, B Seetharamulu, and MA Jabbar. Machine learning in healthcare: A review. In *2018 Second international conference on electronics, communication and aerospace technology (ICECA)*, pp. 910–914. IEEE, 2018.

Adi Shamir. How to share a secret. *Communications of the ACM*, 22(11):612–613, 1979.

Zheyan Shen, Jiashuo Liu, Yue He, Xingxuan Zhang, Renzhe Xu, Han Yu, and Peng Cui. Towards out-of-distribution generalization: A survey. *arXiv preprint arXiv:2108.13624*, 2021.

Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. In *2017 IEEE symposium on security and privacy (SP)*, pp. 3–18. IEEE, 2017.

David Solans, Battista Biggio, and Carlos Castillo. Poisoning attacks on algorithmic fairness. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pp. 162–177. Springer, 2020.

Tasuku Soma, Khashayar Gatmiry, and Stefanie Jegelka. Optimal algorithms for group distributionally robust optimization and beyond. *arXiv preprint arXiv:2212.13669*, 2022.

Ezekiel Soremekun, Mike Papadakis, Maxime Cordy, and Yves Le Traon. Software fairness: An analysis and survey. *arXiv preprint arXiv:2205.08809*, 2022.

Shuhan Tan, Yujun Shen, and Bolei Zhou. Improving the fairness of deep generative models without retraining. *arXiv preprint arXiv:2012.04842*, 2020.

Nikolaj Tollenaar and PGM Van der Heijden. Which method predicts recidivism best?: a comparison of statistical, machine learning and data mining predictive models. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 176(2):565–584, 2013.

Ehsan Toreini, Maryam Mehrnezhad, and Aad van Moorsel. Fairness as a service (faas): verifiable and privacy-preserving fairness auditing of machine learning systems. *International Journal of Information Security*, pp. 1–17, 2023.

Cuong Tran, My Dinh, and Ferdinando Fioretto. Differentially private empirical risk minimization under the fairness lens. *Advances in Neural Information Processing Systems*, 34:27555–27565, 2021a.

Cuong Tran, Ferdinando Fioretto, and Pascal Van Hentenryck. Differentially private and fair deep learning: A lagrangian dual approach. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pp. 9932–9939, 2021b.

Cuong Tran, Keyu Zhu, Ferdinando Fioretto, and Pascal Van Hentenryck. Sf-pate: scalable, fair, and private aggregation of teacher ensembles. *arXiv preprint arXiv:2204.05157*, 2022.

Archit Uniyal, Rakshit Naidu, Sasikanth Kotti, Sahib Singh, Patrik Joslin Kenfack, Fatemehsadat Mireshghallah, and Andrew Trask. Dp-sgd vs pate: Which has less disparate impact on model accuracy? *arXiv preprint arXiv:2106.12576*, 2021.

Elmira Van den Broek, Anastasia Sergeeva, and Marleen Huysman. When the machine meets the expert: An ethnography of developing ai for hiring. *MIS quarterly*, 45(3), 2021.

Jesper E Van Engelen and Holger H Hoos. A survey on semi-supervised learning. *Machine learning*, 109(2): 373–440, 2020.

Akshaj Kumar Veldanda, Ivan Brugere, Sanghamitra Dutta, Alan Mishler, and Siddharth Garg. Hyperparameter tuning for fair classification without sensitive attribute access. *arXiv preprint arXiv:2302.01385*, 2023.

Lois M Verbrugge. The structure of adult friendship choices. *Social forces*, 56(2):576–597, 1977.

Sahil Verma and Julia Rubin. Fairness definitions explained. In *2018 ieee/acm international workshop on software fairness (fairware)*, pp. 1–7. IEEE, 2018.

Mingyang Wan, Daochen Zha, Ninghao Liu, and Na Zou. In-processing modeling techniques for machine learning fairness: A survey. *ACM Transactions on Knowledge Discovery from Data (TKDD)*, 2022.

Guanchu Wang, Mengnan Du, Ninghao Liu, Na Zou, and Xia Hu. Mitigating algorithmic bias with limited annotations. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pp. 241–258. Springer, 2023.

Serena Wang, Wenshuo Guo, Harikrishna Narasimhan, Andrew Cotter, Maya Gupta, and Michael Jordan. Robust optimization for fairness with noisy protected groups. *Advances in Neural Information Processing Systems*, 33:5190–5203, 2020.

Yifan Wang, Weizhi Ma, Min Zhang*, Yiqun Liu, and Shaoping Ma. A survey on the fairness of recommender systems. *ACM Journal of the ACM (JACM)*, 2022.

Stanley L Warner. Randomized response: A survey technique for eliminating evasive answer bias. *Journal of the American Statistical Association*, 60(309):63–69, 1965.

Austin Waters and Risto Miikkulainen. Grade: Machine learning support for graduate admissions. *Ai Magazine*, 35(1):64–64, 2014.

UN Women. Convention on the elimination of all forms of discrimination against women (cedaw). *UN Women*, 1979.

Shen Yan, Hsien-te Kao, and Emilio Ferrara. Fair class balancing: Enhancing model fairness without observing sensitive attributes. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, pp. 1715–1724, 2020.

Andrew Chi-Chih Yao. How to generate and exchange secrets. In *27th annual symposium on foundations of computer science (Sfcs 1986)*, pp. 162–167. IEEE, 1986.

Sriram Yenamandra, Pratik Ramesh, Viraj Prabhu, and Judy Hoffman. Facts: First amplify correlations and then slice to discover bias. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 4794–4804, 2023.

John Yinger. Sustaining the fair housing act. *Cityscape*, pp. 93–106, 1999.

Gal Yona and Guy Rothblum. Probably approximately metric-fair learning. In *International Conference on Machine Learning*, pp. 5680–5688. PMLR, 2018.

Muhammad Bilal Zafar, Isabel Valera, Manuel Gomez Rodriguez, and Krishna P Gummadi. Fairness beyond disparate treatment & disparate impact: Learning classification without disparate mistreatment. In *Proceedings of the 26th international conference on world wide web*, pp. 1171–1180, 2017.

Meike Zehlike, Ke Yang, and Julia Stoyanovich. Fairness in ranking: A survey. *arXiv preprint arXiv:2103.14000*, 2021.

Rich Zemel, Yu Wu, Kevin Swersky, Toni Pitassi, and Cynthia Dwork. Learning fair representations. In *International conference on machine learning*, pp. 325–333. PMLR, 2013.

Brian Hu Zhang, Blake Lemoine, and Margaret Mitchell. Mitigating unwanted biases with adversarial learning. In *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 335–340, 2018.

Fengda Zhang, Kun Kuang, Long Chen, Yuxuan Liu, Chao Wu, and Jun Xiao. Fairness-aware contrastive learning with partially annotated sensitive attributes. In *The Eleventh International Conference on Learning Representations*, 2022.

Yu Zhang and Qiang Yang. An overview of multi-task learning. *National Science Review*, 5(1):30–43, 2018.

Zhilu Zhang and Mert Sabuncu. Generalized cross entropy loss for training deep neural networks with noisy labels. *Advances in neural information processing systems*, 31, 2018.

Bowen Zhao, Chen Chen, Qian-Wei Wang, Anfeng He, and Shu-Tao Xia. Combating unknown bias with effective bias-conflicting scoring and gradient alignment. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 37, pp. 3561–3569, 2023.

Han Zhao, Chen Dan, Bryon Aragam, Tommi S Jaakkola, Geoffrey J Gordon, and Pradeep Ravikumar. Fundamental limits and tradeoffs in invariant representation learning. *The Journal of Machine Learning Research*, 23(1):15356–15404, 2022.

Tianxiang Zhao, Enyan Dai, Kai Shu, and Suhang Wang. You can still achieve fairness without sensitive attributes: Exploring biases in non-sensitive features. *arXiv preprint arXiv:2104.14537*, 2021.