



Social norm bias: residual harms of fairness-aware algorithms

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Abstract

Many modern machine learning algorithms mitigate bias by enforcing fairness constraints across coarsely-defined groups related to a sensitive attribute like gender or race. However, these algorithms seldom account for within-group heterogeneity and biases that may disproportionately affect some members of a group. In this work, we characterize Social Norm Bias (SNoB), a subtle but consequential type of algorithmic discrimination that may be exhibited by machine learning models, even when these systems achieve group fairness objectives. We study this issue through the lens of gender bias in occupation classification. We quantify SNoB by measuring how an algorithm's predictions are associated with conformity to inferred gender norms. When predicting if an individual belongs to a male-dominated occupation, this framework reveals that “fair” classifiers still favor biographies written in ways that align with inferred masculine norms. We compare SNoB across algorithmic fairness techniques and show that it is frequently a residual bias, and post-processing approaches do not mitigate this type of bias at all.

Keywords Algorithmic fairness · Gender bias · Automated hiring · Group fairness · Social norms · Occupation classification · Online recruiting

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1 Introduction

As automated decision-making systems play a growing role in our daily lives, concerns about algorithmic unfairness have come to light. It is well-documented that machine learning (ML) algorithms can perpetuate existing social biases (Buolamwini and Gebru 2018; Noble 2018; Stark et al. 2020). To avoid algorithmic discrimination based on sensitive attributes, various approaches to measure and achieve “algorithmic fairness” have been proposed. These approaches are typically based on *group fairness*, which partitions a population into groups based on a protected attribute (e.g., gender, race, or religion) and then aims to equalize some metric of the system across the groups. Popular group fairness metrics include equality of opportunity and demographic parity, among others (Hardt et al. 2016; Agarwal et al. 2018; Dwork et al. 2012; Pleiss et al. 2017; Kamiran et al. 2012; Lohia et al. 2019).

Group fairness makes the implicit assumption that a group is defined solely by the possession of particular characteristics (Hu and Kohler-Hausmann 2020), ignoring the heterogeneity within groups. For example, most work on gender bias in ML compares groups (and typically assumes there are only two groups); however, different women’s experiences of gender and concept of womanhood vary drastically (Shields 2008; Wood and Eagly 2009). These approaches do not account for the complex, multi-dimensional nature of concepts like gender and race (Hanna et al. 2020; Butler 1989), and how this intersects with discrimination. Consider, for instance, social norms which represent the implicit expectations of how particular groups behave. In many settings, adherence to or deviations from social norms result in harm, but current algorithmic fairness approaches overlook whether and how ML replicates these harms.

Social norms may influence an algorithm’s predictions even after group fairness approaches have been applied. We characterize Social Norm Bias (SNoB)—the associations between an algorithm’s predictions and individuals’ adherence to inferred social norms—as a source of algorithmic unfairness. We propose an approach to measure inferred social norms, and show that the inferred norms, specific to a dataset, reflect real-world norms and stereotypes that arise in certain settings. Thus, penalizing individuals for their adherence or deviation to social norms is an overlooked form of algorithmic bias and a residual harm of many fairness-aware algorithms.

We study SNoB through the task of occupation classification, a prediction problem relevant in various applications ranging from targeted job opportunity advertisements (De-Arteaga et al. 2019) to Google’s “People Cards.” The risk of (group) gender bias in this task has been studied in the literature (De-Arteaga et al. 2019; Ceren and Tekir 2021), and Twitter users have expressed concern over Google search results mislabeling famous women scientists as teachers while labeling their male peers correctly.¹ In this setting, SNoB occurs when an algorithm favors biographies written in ways that adhere to inferred gender norms of the majority, which we show reproduce real-world norms. These associations, which remain even after applying bias-mitigation approaches, may lead to representational and allocational harms for feminine-expressing people in male-dominated occupations (Bartl et al. 2020; Blod-

¹ Twitter thread started by Dr. Timothy Verstynen: <https://twitter.com/tverstynen/status/1501386481415434245>

gett et al. 2020). For example, consider a male-dominated occupation in which men are less likely to present themselves as family-oriented, or more likely to describe themselves using adjectives that denote success (Garg et al. 2018). SNoB occurs when an algorithm is more likely to correctly classify the women in this occupation who adhere to these norms over the women in the same occupation who do not adhere to them. This phenomenon compounds existing patterns of discrimination and gender bias in the workplace.

Our framework quantifies algorithmic bias on a dimension that extends beyond group-level disparities, illuminating a gap between algorithmic harms and current techniques for algorithmic fairness. We find that approaches aiming to improve group fairness, which we refer to as fairness-aware classifiers, may still exhibit SNoB. In particular, post-processing approaches that maintain within-group ordering are especially prone to producing harms on the basis of inferred social norms, while some in-processing approaches mitigate this type of bias. Failing to explicitly account for and assess SNoB may lead to the deployment of “fair” algorithms that not only perpetuate these harms but also obscure them.

2 Related work

It is well-established that ML models can reflect and amplify societal biases. For example, semantic representations such as word embeddings encode gendered and racial biases (Bolukbasi et al. 2016; Caliskan et al. 2017; Rudinger et al. 2017; Swinger et al. 2019). In coreference resolution, systems associate and thus assign gender pronouns to occupations when they co-occur more frequently in the data (Rudinger et al. 2018). In toxicity detection, language related to marginalized groups is disproportionately flagged as toxic (Zhou et al. 2021). Various fairness-aware algorithms aim to mitigate these issues from a group fairness perspective (Park et al. 2018; Kumar et al. 2020; Bordia and Bowman 2019; Gonen and Goldberg 2019).

However, algorithms that satisfy group fairness metrics may still exhibit discriminatory behavior and cause harm to marginalized populations based on *reductive definitions* (Antoniak and Mimno 2021). Our work identifies a concrete type of harm, arising from reductive definitions, that is not captured by group-based metrics of bias and frequently remains in fairness-aware algorithms. We go beyond group fairness to characterize algorithmic predictions’ associations with inferred social norms. Our approach builds upon work such as Lipton et al. (2018), Cryan et al. (2020) and Tang et al. (2017) to assess inferred gender norms. Cryan et al. (2020) develop an ML-based method to detect gender stereotypes and compares the approach to crowd-sourced lexicons. Tang et al. (2017) take a simpler approach, relying on manually-compiled lists of gendered words and using only the frequency of these words as a measure of gender bias.

There is a growing body of work on how algorithms operationalize stereotypes, which are related to social norms (Nadeem et al. 2021; Nangia et al. 2020; Blodgett et al. 2021). We focus on social norms as a broader phenomenon than stereotypes (Russell 2012). Since inferred social norms arise from the structure of the dataset, we capture not only stereotypes but gender-related patterns present in the data. For

example, the mention of a women’s college or fraternity in one’s biography is a proxy for gender; it is a norm rather than a stereotype that women’s colleges are attended by women while members of fraternities are men.

Adherence to social norms is a form of heterogeneity within groups, which is connected to the concept of subgroup fairness. For example, work on multicalibration (Hébert-Johnson et al. 2018) and fairness gerrymandering (Kearns et al. 2018) provide theoretical perspectives on bridging the gap between group and individual fairness by mitigating unfairness for subgroups within groups, even when they are not explicitly labeled. Our approach differs from this work by focusing on a specific type of harm that affects subgroups, drawing its connection to social discrimination and providing an approach to assess it in practice.

Algorithmic fairness definitions that extend beyond group disparities and capture causal dependencies, such as counterfactual fairness (Kusner et al. 2017), are in part motivated by concerns similar to those underlying SNoB. Accounting for causal dependencies between group membership and other features would help account for social norms. However, causal graphs are rarely available. Our work proposes an approach to capture (some) dependencies using a statistical machine learning model, rather than a causal model, which enables the assessment in practice of an important type of residual harms.

3 Background

Considering sensitive group membership alone is not sufficient to establish fairness. While the relevance of SNoB is not exclusive to the task of occupation classification nor to gender, its potential harms stem from tight connections with existing patterns and forms of discrimination in contexts where individuals that belong to a marginalized group but have more similarities to the dominant group, such as adherence to social norms, are treated more favorably. Thus, in this paper we study SNoB through a case study in the occupation classification context. In this section, we provide background on various axes of gender and how they are operationalized in the workplace and in the use of English language. We also describe existing approaches to address gender bias in tasks related to automated hiring.

3.1 The multiplicity of gender

The term “gender” is a proxy for different constructs depending on the context (Keyes et al. 2021). It may mean *gender identity*, which is one’s “felt, desired or intended identity” (Glick et al., 2018, p.2), or *gender expression*, which is how one “publicly expresses or presents their gender... others perceive a person’s gender through these attributes” (Commission, 2021, p.1). These concepts are also related to *gender norms*, i.e. “the standards and expectations to which women and men generally conform,” (Mangheni et al., 2019, p.717) including personality traits, behaviors, occupations, and appearance (Agius and Tobler 2012). These various notions of social gender encompass much more than the categorical gender labels that are used as the basis for

group fairness approaches (Cao and III 2019). Using name or pronouns as a proxy for gender (Sen and Wasow 2016; Bolukbasi et al. 2016) reinforces categorical definitions, which leads to further harms to those who are marginalized by these reductive notions (Keyes et al. 2021; Larson 2017; Mitchell et al. 2020). We focus on discrimination related to the ways that individuals' gender expression adhere to social gender norms.

3.2 Harms related to gender norms in the workplace

Our concerns about the use of gender norms in ML systems are grounded in studies of how gender norms have been operationalized in various occupations, causing harm to gender minorities. It is well-established that “occupations are socially and culturally ‘gendered’” (Stark et al. 2020); many jobs in science, technology, and engineering are traditionally masculine (Ensmenger 2015; Light 1999). In social psychology, *descriptive stereotypes* are attributes believed to characterize women as a group. The perceived lack of fit between feminine stereotypic attributes and male gender-typed jobs result in gender bias and impedes women’s careers (Heilman 2001, 2012). If and when these patterns are replicated by ML algorithms, this results in two types of harms. The associations that we highlight may lead to 1) representational harm, when actual members of the occupation are made invisible, and 2) allocational harm, when certain individuals are allocated fewer career opportunities based on their degree of adherence to gender norms (Bartl et al. 2020; Blodgett et al. 2020).

3.3 Gender norms in language

Different English words have gender-related connotations (Moon 2014). Crawford et al. (2004) provide a corpus of 600 words and human-labeled gender scores, as scored on a 1–5 scale (1 is the most feminine, 5 is the most masculine) by undergraduates at U.S. universities. They find that words referring to explicitly gendered roles such as *wife*, *husband*, *princess*, and *prince* are the most strongly gendered, while words such as *pretty* and *handsome* also skew strongly in the feminine and masculine directions, respectively. Gender also affects the ways that people are perceived and described (Madera et al. 2009). A study on resumes describes gender-based disparities in how people represent themselves, despite having similar experiences (Snyder 2015). In letters of recommendation, women are described as more communal and less agentic than men, which harms the women who are perceived in this way (Madera et al. 2009). Wikipedia articles also contain significant gender differences, such as notable women’s biographies focusing more on their romantic and family lives (Wagner et al. 2015).

3.4 Addressing gender bias in automated hiring

Audit studies reveal that employers tend to discriminate against women (Bertrand and Mullainathan 2004; Johnson et al. 2016). These biases are also replicated in automated hiring, as demonstrated by the gender gap in error rates of an occupation

classification algorithm (De-Arteaga et al. 2019). Many in academia and industry alike have been motivated to mitigate these concerns (Raghavan et al. 2020; Bogen and Rieke 2018; Sánchez-Monedero et al. 2020). For instance, LinkedIn developed a post-processing approach for ranking candidates so that their candidate recommendations are demographically representative of the broader candidate pool; their system is deployed across a service affecting more than 600 million users (Geyik et al. 2019). Other intervention techniques have also been proposed (Dwork et al. 2018; Romanov et al. 2019). These approaches share a reliance on categorical gender labels to measure fairness.

4 Measuring social norm bias

We develop a framework to measure SNoB in a classification model by (1) identifying inferred social norms specific to a dataset and (2) measuring the correspondence between these norms and the outcomes of the model.

4.1 Identifying inferred social norms

We use a supervised learning approach to infer social norms from a dataset. We train a predictive model G on the dataset to distinguish between data labeled with different values of l , where l is the group label (corresponding to a sensitive attribute) that takes on n categorical values.

For a given datum x , let $G_l(x)$ be the predicted probability that $x \in L_l$, where L_l is the subset of the data that has group label l . We refer to G as a norm scorer, as its output is indicative of how much x adheres to a set of norms, i.e. dominant characteristics, of L_l . For example, to study inferred gender norms in a dataset of biographies, the gender label L is obtained from the pronouns that someone uses in their biography. $G_{\text{she}}(x)$ is the predicted probability that x uses “she”, which is a measure of adherence to feminine social norms inferred from the dataset. Due to predictive multiplicity (Marx et al. 2020), there is not a unique norm scorer, thus, SNoB does not constitute a unique metric inherent to a dataset and classifier pair, but rather a diagnostic framework to identify potential residual harms. In our experiments, we show results for two variants of a norm scorer, one of which also integrates task irrelevance constraints.

4.2 Measuring social norm bias

4.2.1 Binary classification setting

Assume that a binary classification algorithm outputs the predicted probability $\hat{Y}(x)$ that the label of the datum x is Y . To evaluate SNoB, we consider the correlation r between $G_l(x)$ and $\hat{Y}(x)$, the predicted probabilities from the two models, across the subset L_l . Specifically, we compute Spearman’s rank correlation coefficient r between $\{\hat{Y}(x)|x \in L_l, Y(x) = 1\}$ and $\{G_l(x)|x \in L_l, Y(x) = 1\}$. We use Spearman’s correlation rather than Pearson’s since the latter measures only the strength of a linear

association, while we aim to capture general monotonic relationships. The magnitude of r is a measure of the degree of SNoB exhibited by the algorithm \hat{Y} with respect to norms G_l . Since r is computed only from the subset L_l , this metric captures associations present *within* the group; that is, it establishes if within-group ordering of predicted probabilities within a class is correlated with adherence to inferred norms.

4.2.2 Multiclass classification setting

In the multi-class classification problem, where C is the set of classes, the algorithm outputs the predicted probability $\hat{Y}_c(x)$ that the label of the datum x is c , for $c \in C$. Let

$$p_c = \frac{|\{x|x \in L_l, Y_c(x) = 1\}|}{|\{x|Y_c(x) = 1\}|},$$

i.e. the fraction of data in class c that have group label l . Let r_c be the metric r for a specific class c , i.e. the correlation between $\{\hat{Y}(x)|x \in L_l, Y_c(x) = 1\}$ and $\{G_l(x)|x \in L_l, Y_c(x) = 1\}$. To quantify SNoB across all classes, we use $\rho(\mathbf{p}_C, \mathbf{r}_C)$, the Spearman's rank correlation coefficient between \mathbf{p}_C and \mathbf{r}_C , where

$$\begin{aligned}\mathbf{r}_C &= \{r_c|c \in C\} \in [0, 1]^{|C|}, \\ \mathbf{p}_C &= \{p_c|c \in C\} \in [0, 1]^{|C|}.\end{aligned}$$

The quantity $\rho(\mathbf{p}_C, \mathbf{r}_C)$ enables us to compare the extent to which an algorithm relies on inferred social norms across different classes, and whether this is correlated with the group imbalance across classes. For example, in the occupation classification setting, gender imbalance varies by occupation, and $\rho(\mathbf{p}_C, \mathbf{r}_C)$ establishes whether the likelihood of correctly predicting that someone belongs to a male-dominated occupation has higher associations with masculine gender norms as gender imbalance in the occupation increases.

Note moreover that the metric $\rho(\mathbf{p}_C, \mathbf{r}_C)$ only emerges in the multi-class setting, where the pattern across multiple classes reveals information about the behavior of the classifier. In this setting, the correlation between the existing gender imbalances (\mathbf{p}_C , found in the data distribution) and the imbalances of classification scores (\mathbf{r}_C , a product of the model) enables us to measure the degree to which a classifier benefits those who are also more likely to be classified in the majority gender. In the binary classification case, the metric \mathbf{r}_C is enough to assess whether such a pattern exists.

5 Inferred social norms in occupation classification

We present a case study of SNoB in occupation classification, a task relevant to various real-world recruiting and hiring applications, and in which SNoB may compound harms. Several forms of online presence, such as a personal websites, often do not list individuals' occupations in a structured way. Thus, ML methods to automatically

classify occupation can support companies conducting targeted recruiting efforts (De-Arteaga et al. 2019; Peng et al. 2022). We assume that a fair occupation classification algorithm should not exhibit gender bias, including any association with inferred social norms, since career prospects should not depend on gender.

5.1 Occupation classification

5.1.1 Dataset

We use the dataset² and task described by De-Arteaga et al. (2019). The dataset, containing 397,340 biographies spanning twenty-eight occupations, is obtained by using regular expressions to filter the Common Crawl for online biographies. Each biography is labeled with its gender based on the use of “she” or “he” pronouns (in “Appendix B”, we study SNoB on a newly-collected small set of biographies with nonbinary pronouns). Let H_c , S_c be the sets of biographies in occupation c using “he” and “she”, respectively. $|H_c|$, $|S_c|$ are the numbers of biographies in the respective sets. To preserve the ratios between $|H_c|$ and $|S_c|$, we use a stratified split to create the training, validation, and test datasets, containing 65%, 10%, and 25% of the biographies respectively. This split is consistent with other work that uses this dataset (De-Arteaga et al. 2019; Romanov et al. 2019). We use the data to train and evaluate algorithms that predict a biography’s occupation title from the subsequent sentences. For training, we remove names, titles, and explicit gender indicators.³

5.1.2 Semantic representations and learning algorithms

For the occupation classification algorithms, we use three semantic representations with different degrees of complexity: bag-of-words, word embeddings, and BERT. In the bag-of-words (BOW) representation, a biography x is represented as a sparse vector of the frequencies of the words in x . BOW is widely used in settings where interpretability is important. In the word embedding (WE) representation, x is represented by an average of the fastText word embeddings (Bojanowski et al. 2017; Mikolov et al. 2018) for the words in x . Previous work demonstrates that the WE representation captures semantic information effectively (Adi et al. 2017). For the BOW and WE representations, we train a one-versus-all logistic regression model with L_2 regularization on the training set, as done by De-Arteaga et al. (2019). The BERT contextualized word embedding model (Devlin et al. 2019) is state-of-the-art for various natural language processing tasks, and it has been widely adopted for many uses. Unlike the other language representations, a biography’s BERT encoding is context-dependent. The BERT representation of a word depends on its meaning within the sentence, which is determined by an attention mechanism that considers the surrounding words in the word’s sentence. We fine-tune a BERT model (specifically bert-base-uncased) for the occupation classification task (Wolf et al. 2020).

² The dataset is publicly available at <http://aka.ms/biasbios> and licensed under the MIT License.

³ Consistent with previous work (De-Arteaga et al. 2019), we used regular expressions to remove the following words from the data: he, she, her, his, him, hers, himself, herself, mr, mrs, ms, ph, dr.

5.1.3 Group fairness metric

Gap^{RMS} Prior research on group fairness in occupation classification (De-Arteaga et al. 2019; Romanov et al. 2019) focus on reducing Gap^{RMS} , a measure of the difference in the classifier’s true positive rate (TPR) between “she” and “he” data. Let $a, \neg a$ be values of the group label for the sensitive attribute l (gender). For an occupation $c \in C$, we have

$$\begin{aligned}\text{TPR}_{c,a} &= \Pr[\hat{Y}_c = 1 | Y_c = 1, l = a], \\ \text{GAP}_{c,a} &= \text{TPR}_{c,a} - \text{TPR}_{c,\neg a}.\end{aligned}$$

Then, Gap^{RMS} is defined as:

$$\text{Gap}^{\text{RMS}} = \sqrt{\frac{1}{|C|} \sum_{c \in C} \text{GAP}_{c,a}^2}.$$

Root mean square (RMS) penalizes larger values of the gender gap more heavily than a linear average across the occupations. This metric is closely related to equality of opportunity, a measure of fairness introduced by Hardt et al. (2016).

5.2 Inferred gender norms

We apply the method described in Sect. 4.1 to infer gendered social norms specific to the dataset and obtain a score of how each individual adheres to the norms of “s/he” biographies using a logistic regression model. In this setting, the norms arise from the natural language properties of our data. As discussed in Sect. 3, language is deeply gendered. Since some occupations are dominated by biographies of a single gender, we pre-process the data such that the “she” and “he” biographies in each occupation are weighted equally, preventing G from learning to identify gender from occupation alone (Wang et al. 2019). Specifically, we assign weight α_x to a biography x as follows:

$$\alpha_x = \begin{cases} \frac{|H_c|}{\max\{|S_c|, |H_c|\}} & \text{if } x \in S_c, \\ \frac{|S_c|}{\max\{|S_c|, |H_c|\}} & \text{if } x \in H_c. \end{cases}$$

We train G using the WE semantic representation. G achieves 0.68 accuracy. In Sect. 7, we show correspondence between these inferred norms and real-world gender norms.

6 Social norm bias in occupation classification

Algorithmic group fairness approaches fall broadly into three paradigms: pre-, post-, and in-processing techniques (Kamiran and Calders 2012). We describe the algo-

rithmic fairness approaches that we evaluate, and then compare their SNoB in the occupation classification setting.

6.1 Fairness intervention techniques

Pre-processing fairness approaches modify the data before it is used to train the algorithm, such as by reweighting the training distribution to account for representation imbalances or by changing features of the data (Calmon et al. 2017; Kamiran and Calders 2012). Since many of the occupations are gender-imbalanced in our dataset, we adopt the pre-processing approach of re-weighting the data such that half of the total weight belongs to each of S_c and H_c (set of biographies in c using “she” and “he”, respectively), using the weights α_x as described in Sect. 5.2.

Post-processing fairness approaches apply an intervention after training the algorithm to balance some metric across groups (Pleiss et al. 2017; Kamiran et al. 2012; Lohia et al. 2019; Hardt et al. 2016). One common approach (PO) is to change the decision threshold for particular groups to equalize relevant fairness-related metrics, such as false positive rates or acceptance rates (Hardt et al. 2016). These approaches are relatively cost-effective to implement since they do not require re-training and have been deployed in large-scale systems such as on LinkedIn (Geyik et al. 2019).

In-processing group fairness approaches modify the algorithm at training time. We evaluate a range of state-of-the-art in-processing approaches, including decoupled classifiers, reductions, Covariance Constrained Loss (CoCL), and adversarial learning. The decoupled approach is relatively simple, with a separate classifier trained for each gender group (Dwork et al. 2018).

The reductions method is the primary in-processing mitigation method in the Fairlearn Python package (Bird et al. 2020). It reduces a classification task to a sequence of cost-sensitive classification problems (Agarwal et al. 2018). We consider it only for the WE representation since it is too computationally expensive to use with BERT and unable to reduce either Gap^{RMS} or $\rho(\mathbf{p}_C, \mathbf{r}_C)$ with BOW.

We evaluate CoCL, which differs from most other in-processing techniques in that it does not require access to gender labels. The method adds a penalty to the loss function that minimizes the covariance between the probability that an individual’s occupation is correctly predicted and the word embedding of their name (Romanov et al. 2019). Romanov et al. (2019) validate CoCL’s effectiveness in reducing Gap^{RMS} on the same biographies dataset using the BOW representation, which we also use.

Finally, the adversarial learning method optimizes directly for independence between sensitive group membership and predictions, while accounting for dependencies between features. It learns to make predictions that maximize accuracy while reducing an adversary’s ability to determine the protected attribute from the predictions (Zhang et al. 2018). We use the implementation in the AI Fairness 360 Python package (Bellamy et al. 2019).

Table 1 Notation used throughout the paper

Term	Definition
c	Occupation
C	Set of all occupations
$H_c \in [0, 1]$	Set of biographies in c using “he”
$S_c \in [0, 1]$	Set of biographies in c using “she”
$p_c \in [0, 1]$	Fraction of “she” biographies in c , measure of gender imbalance in c
$r_c \in [0, 1]$	Correlation between target and gender norm scores across S_c
$\mathbf{p}_C \in [0, 1]^{ C }$	$\{p_c c \in C\}$
$\mathbf{r}_C \in [0, 1]^{ C }$	$\{r_c c \in C\}$
$\rho(\mathbf{p}_C, \mathbf{r}_C) \in [0, 1]$	Correlation between \mathbf{p}_C and \mathbf{r}_C , SNoB metric for a classifier
Gap^{RMS}	Gender Gap in TPR across C , group fairness metric for a classifier
$r_c^{\text{irrev}} \in [0, 1]$	Correlation between target and occupation-irrelevant gender norm scores across S_c
$\mathbf{r}_c^{\text{irrev}} \in [0, 1]^{ C }$	$\{r_c^{\text{irrev}} c \in C\}$
$\rho(\mathbf{p}_C, \mathbf{r}_C^{\text{irrev}}) \in [0, 1]$	Correlation between \mathbf{p}_C and $\mathbf{r}_c^{\text{irrev}}$, robustness check for $\rho(\mathbf{p}_C, \mathbf{r}_C)$

$\rho(\mathbf{p}_C, \mathbf{r}_C)$, Gap^{RMS} , and $\rho(\mathbf{p}_C, \mathbf{r}_C^{\text{irrev}})$ are detailed in Sects. 4.2, 5.1, and 7.1, respectively

6.2 Measuring SNoB

To measure SNoB in the occupation classification setting, we use the metrics r_c and $\rho(\mathbf{p}_C, \mathbf{r}_C)$ introduced in Sect. 4.2. We consider the subset with group label “she”, i.e. we use S_c as L_l . For each occupation c , we compute the correlation r_c between $\{\hat{Y}_c(x) | x \in S_c\}$ and $\{G(x) | x \in S_c\}$, i.e. across the “she” biographies in the occupation. A positive/negative value indicates that adherence to more feminine/masculine norms are rewarded by \hat{Y}_c .

The fraction of biographies in occupation c that use “she” is

$$p_c = \frac{|S_c|}{|S_c| + |H_c|}.$$

If $p_c < 0.5$, c is male-dominated, and vice versa. If r_c is more negative in more male-dominated occupations, this implies that individuals whose biographies are more aligned to masculine gender norms are also more likely to have their occupation correctly predicted by the occupation classification algorithm.

$\rho(\mathbf{p}_C, \mathbf{r}_C)$ quantifies the relationship between gender imbalance and r_c across the set of all occupations C . A high value of $\rho(\mathbf{p}_C, \mathbf{r}_C)$ implies that in more gender-imbalanced occupations, r_c is larger in magnitude. Furthermore, a positive $\rho(\mathbf{p}_C, \mathbf{r}_C)$ indicates that the more gender-imbalanced an occupation is, the more it favors adherence to gender norms of the over-represented gender. This notation is summarized in Table 1.

Table 2 Comparison of group fairness and SNoB metrics across fairness approaches

Approach	\hat{Y}_c Accuracy	Gap ^{RMS}	$\rho(\mathbf{p}_C, \mathbf{r}_C)$	$\rho(\mathbf{p}_C, \mathbf{r}_C^{\text{irrev}})$
BOW, pre-processing	0.92	0.078	0.79**	0.44*
BOW, post-processing	0.95	0	0.80**	0.52**
BOW, decoupled	0.96	0.10	0.78**	0.26
BOW, CoCL	0.95	0.074	0.74**	0.46
BOW, adversarial	0.98	0.14	0.41*	0.044
WE, pre-processing	0.94	0.061	0.77**	0.32
WE, post-processing	0.97	0	0.85**	0.60**
WE, decoupled	0.94	0.060	0.82**	0.43*
WE, reductions	0.88	0.035	0.59**	0.06
WE, adversarial	0.97	0.15	0.55**	0.13
BERT, pre-processing	0.84	0.11	0.46*	0.08
BERT, post-processing	0.85	0	0.46*	-0.04
BERT, decoupled	0.85	0.22	0.48*	-0.05

Refer to Table 1 for definitions of $\rho(\mathbf{p}_C, \mathbf{r}_C)$, Gap^{RMS}, and $\rho(\mathbf{p}_C, \mathbf{r}_C^{\text{irrev}})$, which are introduced in Sects. 4.2, 5.1, and 7.1, respectively. For BOW and WE, the one-versus-all \hat{Y}_c accuracy is averaged across all occupations. For BERT, the model is a multi-class classifier. Although post-processing fairness intervention techniques mitigate Gap^{RMS} the most, they have the highest values of $\rho(\mathbf{p}_C, \mathbf{r}_C)$. This suggests that they are the least effective at reducing SNoB.

6.3 SNoB versus group fairness metrics for different approaches

We use $\rho(\mathbf{p}_C, \mathbf{r}_C)$ to compare the cross-occupation associations of different fairness approaches. Table 2 lists the accuracy, group fairness metric Gap^{RMS}, and $\rho(\mathbf{p}_C, \mathbf{r}_C)$ for each approach. Figure 1 plots the gender proportion in each occupation \mathbf{p}_C versus the corresponding values of \mathbf{r}_C when using the post-processing approach with a WE representation, and Fig. 2 visualizes this trend for various fairness-aware classifiers.

We find that while the post-processing approaches uphold equality of opportunity, with 0 Gap^{RMS}, they have the largest value of $\rho(\mathbf{p}_C, \mathbf{r}_C)$, i.e. the strongest associations with gender norms. Thus, the notion of SNoB is distinct from, and does not necessarily have correlations with, existing fairness metrics like equality of opportunity or demographic parity.

Since post-processing does not change the ordering within a group, r_c and $\rho(\mathbf{p}_C, \mathbf{r}_C)$ remain identical to that of the approach without any fairness intervention (Fig. 1). Thus, post-processing continues to privilege individuals who align with the occupation's gender norms. Even when the desired group fairness metric is perfectly met, i.e. Gap^{RMS}= 0, the SNoB correlations remain untouched. For post-processing, the group fairness and SNoB metrics are unrelated; the mitigation of one does not affect the presence of the other, which can be explained by the within-group order-preserving nature of post-processing approaches.

The pre- and in-processing approaches mitigate this observed association, as indicated by their lower $\rho(\mathbf{p}_C, \mathbf{r}_C)$ compared to that of post-processing. Table 2

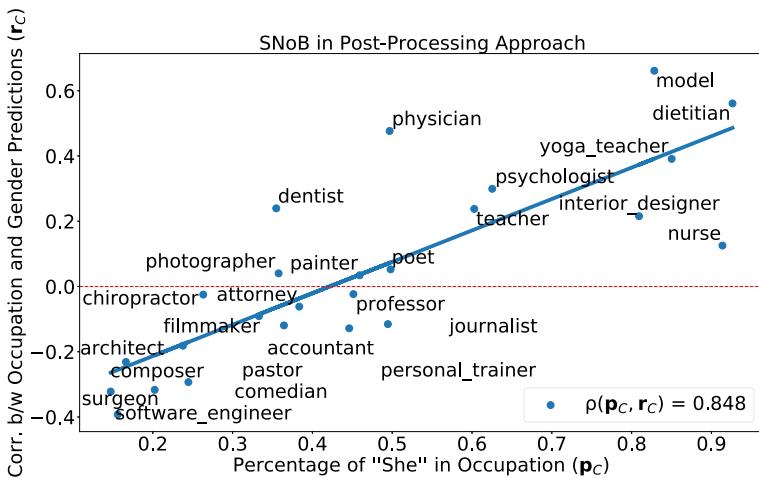


Fig. 1 SNoB across occupations using a post-processing approach. The extent to which an algorithm's predictions align with gender norms (y-axis) is correlated with the gender imbalance in the occupation (x-axis). Ideally, without any SNoB, the correlation $r_c = 0$, so every point would lie on the dotted red line. The WE representation is depicted here, and other representations (BOW, BERT) have similar trends. Note that these values are the same for the fairness-unaware approach as the post-processing approach, since the latter does not change the within-group ordering of individuals

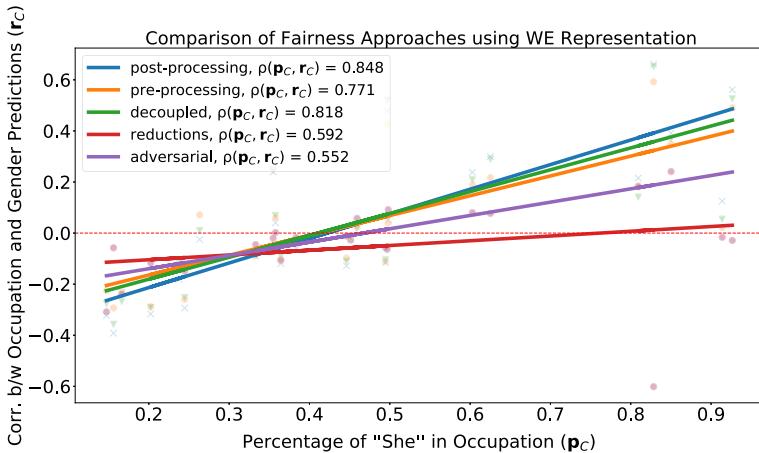


Fig. 2 Comparing fairness interventions. While SNoB persists across group fairness interventions, it is somewhat mitigated by the in-processing approaches. It is minimized by the adversarial technique

reveals that unlike for post-processing, there are more complex relationships between Gap^{RMS} and $\rho(\mathbf{p}_C, \mathbf{r}_C)$ for pre- and in-processing approaches. They generally improve both Gap^{RMS} and $\rho(\mathbf{p}_C, \mathbf{r}_C)$. However, the improvements are not monotonic; for BOW, Gap^{RMS} is smaller for pre-processing while $\rho(\mathbf{p}_C, \mathbf{r}_C)$ is larger compared to the decoupled approach in Table 2. The adversarial learning approach achieves the smallest value of $\rho(\mathbf{p}_C, \mathbf{r}_C)$, although its Gap^{RMS} is the highest. This is an intuitive result, as it directly optimizes to reduce association between the target predictions

and gender group membership. In-processing approaches are most effective at minimizing SNoB, as shown in Table 2 and Fig. 2. Notably, the in-processing techniques have access to features other than sensitive group membership and the target variable, and aim to penalize reliance on spurious correlations. “Appendix A” provides further insight into the mechanisms behind why the classifiers may rely on gender norms. Since in-processing approaches are typically more expensive to implement, this highlights trade-offs between ease of implementation, classifier accuracy, and association with gender norms.^{4,5}

7 Significance of inferred social norms

The potential harms of relying on inferred social norms for classification depend on what is captured by these inferred norms. To measure correspondence between inferred gender norms in the dataset and real-world gender norms, we use a human-labeled corpus of 600 words with gender scores labeled via crowdsourcing (Crawford et al. 2004). For words in the corpus, we compare the human-labeled gender scores with their weights in the gender norm scorer G . The weight of a word w in G is

$$\frac{e_w \cdot W_G}{|e_w| |W_G|},$$

i.e. the cosine similarity between its embedding e_w and the coefficient weight vector W_G learned by G . The magnitude quantifies the word’s importance to G , while the sign indicates the direction of the association. We find a strong correlation (Spearman’s r -value 0.68) between these values (Fig. 4). In Sect. 7.1, we perform a robustness test using a gender norm scorer that omits occupation-relevant words and find the same result. Thus, the inferred norms relate to existing social norms and can lead to compounding harms for individuals who do not adhere to these norms.

7.1 Robustness of associations: occupation-irrelevant gender norm scorers

For some occupations, certain “gendered words” may be acceptable for the occupation classifier to use and thus should not be considered as evidence of SNoB. For example, the word “computer” is learned to be weakly associated with masculine gender norms by G (“computer” has weight 0.124 in the WE approach), but it does not seem discriminatory if the occupation classifier relies on “computer” to determine whether an individual is a software engineer. The word “computer” is relevant to the task of determining this occupation. We define a word w as task-relevant to occupation c if it occurs significantly more frequently in the biographies of c when conditioned on

⁴ We compute p values for the two-sided test of zero correlation between p_c and r_c using SciPy’s `spearmanr` function (Virtanen et al. 2020). Values marked with * and ** indicate that the p value is < 0.05 and < 0.01 respectively.

⁵ CoCL (Romanov et al. 2019) is modulated by a hyperparameter λ that determines the strength of the fairness constraint. We use $\lambda = 2$, which Romanov et al. (2019) finds to have the smallest Gap^{RMS} on the occupation classification task.

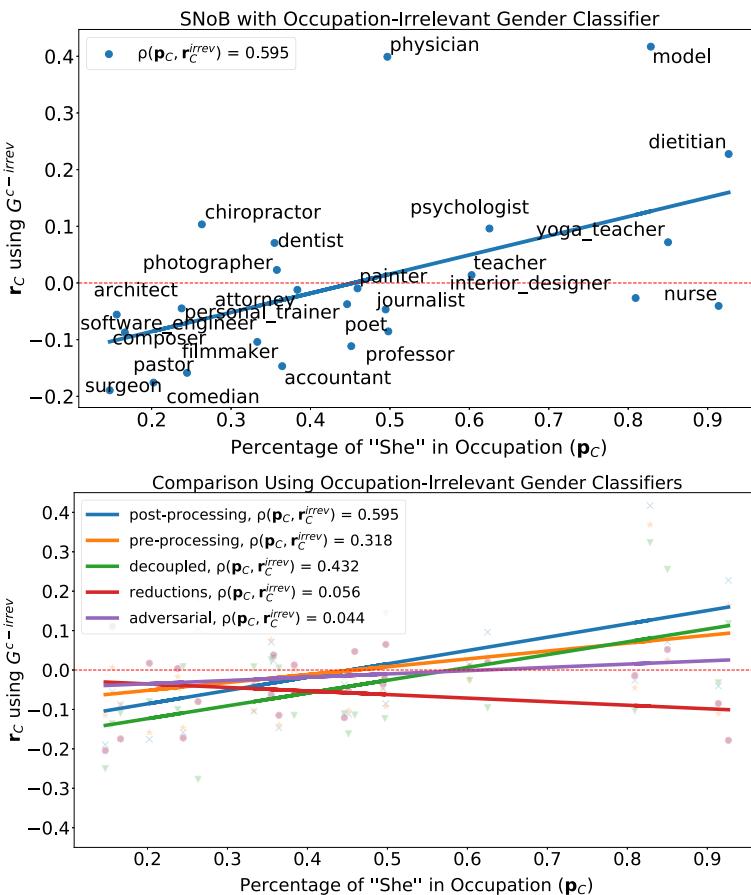


Fig. 3 SNoB using G_c -irrev. These plots measure the same associations as Figs. 1 and 2, using G_c -irrev instead of G to obtain gender scores. The trends are similar, which suggests that our method effectively captures masculine and feminine SNoB

gender, i.e. w occurs more in S_c compared to all other “she” biographies in the dataset, and w occurs more in H_c compared to all other “he” biographies in the dataset. Thus, it is reasonable that a statistical machine learning model uses w as a predictor of c .

More broadly, one could worry that the SNoB identified using $\rho(p_c, r_c)$ in Sect. 6.3 could be attributed to the gender norm scorer using occupation, and task-relevant words, as a proxy. While we have addressed this concern by pre-processing the data to balance gender within each occupation, this section presents an additional robustness check. We train gender norm scorers G_c -irrev using only the words that are *task-irrelevant* for occupation c .

To determine which words are task-irrelevant, we measure the differences between

1. $\text{FREQ}_w(S_{c'})$ versus $\text{FREQ}_w(\{S_c\} | c \in C)$,
2. $\text{FREQ}_w(H_{c'})$ versus $\text{FREQ}_w(\{H_c\} | c \in C)$,

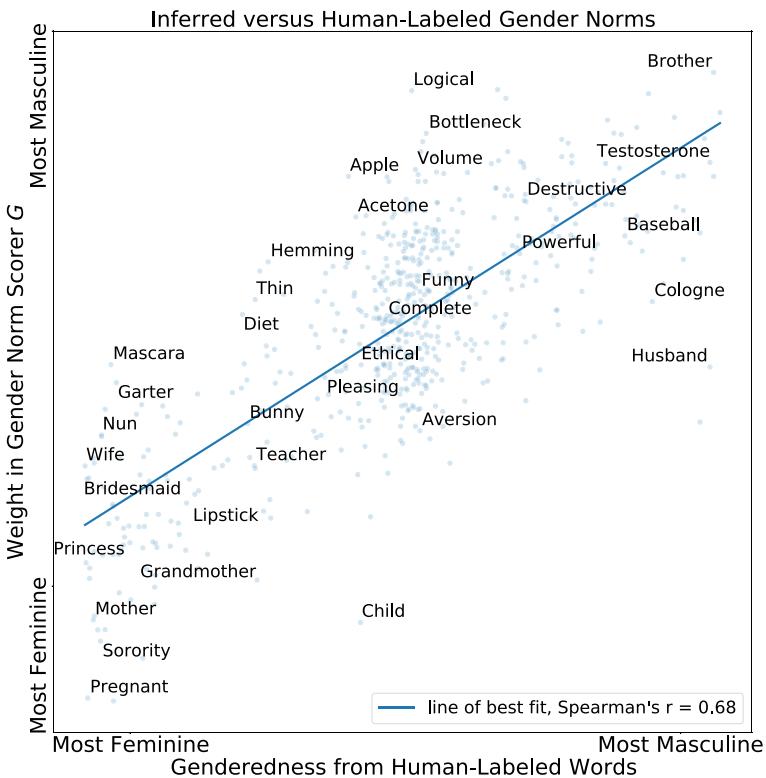


Fig. 4 We use a human-labeled corpus to validate that the scorer G infers gender norms that reflect a notion of real-world gender norms. Comparing the words’ human-labeled gender scores (x -axis) to their weights in G (y -axis), we find a strong correlation between the norms learned by G and the human-labeled gender scores

where $\text{FREQ}_w(S_{c'})$ denotes the number of times w appears in $S_{c'}$, the “she” biographies of occupation c' . $\text{FREQ}_w(H_c)$ is defined analogously.

We determine task-relevance conditioned on gender using a chi-squared test for each occupation and word. To account for multiple testing, we apply the Benjamini-Hochberg procedure (Benjamini and Hochberg 1995) to control the false discovery rate at the level 0.05.⁶

The false discovery rate reflects a trade-off between false positives and false negatives. If too many words are erroneously labeled as task-relevant, then the data will lack words for $G^{c-\text{irrev}}$ to provide insight into adherence to gender norms. To verify that the scores from $G^{c-\text{irrev}}$ relate to real-world social norms, we compared the vocabulary’s weights to the human-labeled gender scores as in Sect. 5.2. Across the classifiers, they have average Spearman’s correlation 0.58 with standard deviation 0.04.

On the other hand, if we erroneously label task-relevant words as task-irrelevant, then $G^{c-\text{irrev}}$ may continue to reflect occupation-relevant words rather than a notion of

⁶ We computed the p values using the `fdrCorrection` method from the `statsmodels` Python package (Seabold and Perktold 2010).

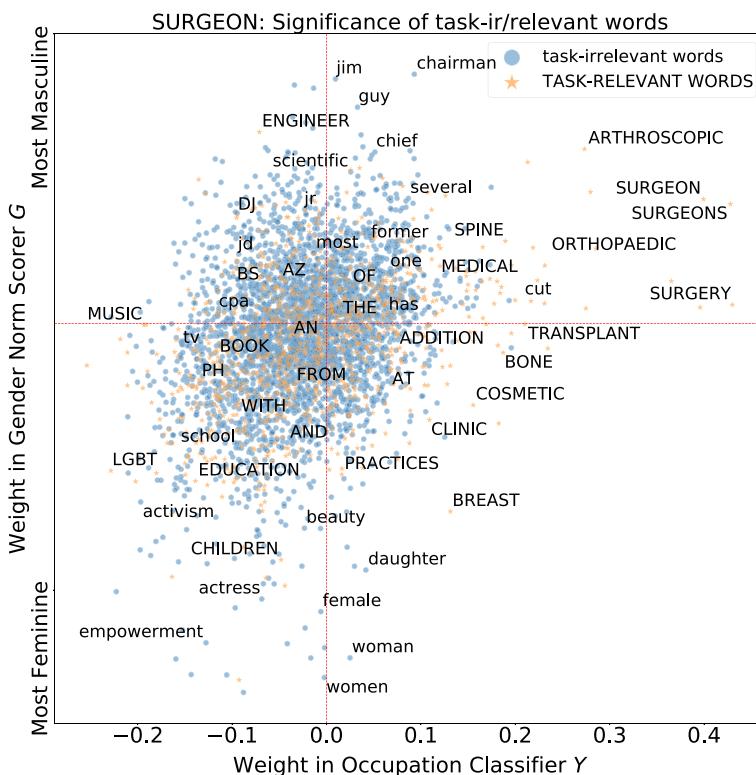


Fig. 5 Identifying task-irrelevant words. Each word is plotted based on its weight in the occupation classifier (x -axis) and gender norm scorer (y -axis). Task-relevant and task-irrelevant words are labeled as uppercase and lowercase respectively. $G^{c-\text{irrev}}$ uses only the task-irrelevant words to infer gender norms. Words highly predictive of the occupation (large x -value) are determined as task-relevant and thus not used in $G^{c-\text{irrev}}$

gender norms. We choose an FDR that prioritizes mitigating this error and eliminating the use of task-relevant words by the gender norm scorer. Our method is cautious in determining “task-irrelevant” words: it may incorrectly label some words as task-relevant and exclude them from the norm scorer $G^{c-\text{irrev}}$.

Figure 5 illustrates the weights in the occupation classifier and gender norm scorer for task-irrelevant versus task-relevant words. We observe that the words with high weights in the occupation classifier are more likely to be labeled as task-relevant. Around 40% of the words are labeled as task-irrelevant for each occupation. The resulting gender norm scorers, $G^{c-\text{irrev}}$, have average accuracy 0.61 with standard deviation 0.04.

We compute r_c^{irrev} and $\rho(\mathbf{p}_C, \mathbf{r}_C^{\text{irrev}})$, which are analogs of r_c and $\rho(\mathbf{p}_C, \mathbf{r}_C)$ respectively, using the outputs obtained from $G^{c-\text{irrev}}$ in place of G . $\rho(\mathbf{p}_C, \mathbf{r}_C^{\text{irrev}})$ is listed in the last column of Table 2. Figure 3 shows the trends of r_c^{irrev} and $\rho(\mathbf{p}_C, \mathbf{r}_C^{\text{irrev}})$ across occupations for different approaches. While the magnitude of $\rho(\mathbf{p}_C, \mathbf{r}_C^{\text{irrev}})$ is smaller than $\rho(\mathbf{p}_C, \mathbf{r}_C)$, we find the same trends. r_c for male-dominated occupations are

more negative, and vice versa for female-dominated occupations. Post-processing approaches have the highest values of $\rho(\mathbf{p}_C, \mathbf{r}_C^{\text{irrev}})$, while in-processing approaches most strongly mitigate this effect. These results suggest that our proposed metrics capture meaningful notions of inferred gender norms beyond occupation-relevant words, thus effectively quantifying SNoB.

8 Conclusion and future work

Our work introduces the risk of social norm bias, a type of harm that is not considered by group fairness techniques, and proposes a framework to quantify it. We measure associations between algorithmic predictions and inferred gender norms in occupation classification, a task that is directly relevant to automated recruiting (De-Arteaga et al. 2019; Peng et al. 2019), and show that the norms inferred from the dataset correspond to real-world gender norms. We reveal that SNoB is the strongest in post-processing approaches. The differences found across pre-, post-, and in-processing approaches should be considered when choosing between these approaches. In particular, our results introduce considerations that may justify the costs of re-training an algorithm rather than relying on post-processing approaches.

More broadly, we characterize how algorithms discriminate based on SNoB, a non-categorical aspect of a sensitive attribute. Our approach can be generalized to capture SNoB in other types of data that reflect social norms, such as images, behavioral data, and other forms of structured data. By illuminating a new axis along which algorithmic discrimination occurs, our work shows a type of harm that stems from the reliance of “group fairness” approaches on reductive definitions. Furthermore, while our work has centered the harm of *deviating* from norms associated with a majority, there may also be a risk of harm from *adhering* to norms associated with a previously marginalized group, which future work should explore. For example, if an algorithm systematically overestimates risk for members of a group (e.g. risk of loan default), it is possible that fairness-aware algorithms that equalize a group fairness metric still penalize those who adhere to certain norms of the group.

SNoB may be exhibited on multiple axes of sensitive attributes, such as social norms related to race, class, and gender. Based on real-world concerns of how intersectional identities can compound bias (Crenshaw 1990), the concept of SNoB serves a starting point to characterize how the intersections among these different dimensions may affect an algorithm. In future work we intend to explore algorithmic approaches to reducing these associations.

8.1 Limitations

As Wojcik and Remy (2020) note, an algorithm’s notion of gender is based only on observable characteristics. There are many other elements of social norms that our methods do not capture. The broader notions of gender expression and gender identity

are ever-changing cultural phenomena (Scheuerman et al. 2019). Also, eliminating SNoB does not necessarily remove other sources of bias.

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Availability of data and material Publicly available at <http://aka.ms/biasbios>.

Code Availability Publicly available at <http://bit.ly/snobcode>.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Appendix A: Gendered words used in classifiers

We provide insight into some of the differences across the classifiers that may be driving the SNoB described in preceding sections. We define β_w as the weight of a word w based on the value of the classifiers' coefficients. We focus on the logistic regression classifiers using the BOW and WE representations since the BERT representations are contextualized, so each word does not have a fixed weight to the model that is easily interpretable.

For the BOW representation of a biography x , each feature in the input vector v_x corresponds to a word w in the vocabulary. We define β_w as the value of the corresponding coefficient in the logistic regression classifier. The magnitude of β_w is a measure of the importance of w to the occupation classification, while the sign (positive or negative) of β indicates whether w is correlated or anti-correlated with the positive class of the classifier.

For the WE representation, we compute the weight of each word as

$$\beta_w = \frac{e_w \cdot W_c}{|e_w| |W_c|},$$

i.e. the cosine similarity between each word's fastText word embedding e_w and the coefficient weight vector W_c of the WE-representation classifier. Like in the BOW representation, the magnitude of β_w quantifies the word's importance, while the sign indicates the direction of the association.

If a word w has positive/negative weight for classifier Y_c , then adding w to a biography x increases/decreases the predicted probability $Y_c(x)$ respectively.

Let $\beta_w(Y_c)$ be the weights for approach Y_c . We examine the words whose weights β_w satisfy

1. $|\beta_w(Y_c)| > T$,
2. $|\beta_w(G)| > T$,
3. $|\beta_w(Y_c)| > T' \cdot |\beta_w(Y'_c)|$,

where T, T' are significance thresholds and Y_c, Y'_c are two different occupation classification approaches.

Words that satisfy these conditions are not only associated with either masculinity or femininity but also weighted more highly in approach Y_c compared to Y'_c . Thus, including these gendered words in a biography influences Y_c 's classification more strongly than that of Y'_c . This suggests that they may contribute more strongly to the $\rho(\mathbf{p}_C, \mathbf{r}_C)$ in one approach than the other. For example, we examined these words for the occupations of SURGEON, SOFTWARE ENGINEER, COMPOSER, NURSE, DIETITIAN, and YOGA TEACHER, which are the six most gender-imbalanced occupations, with $Y_c = \{\text{BOW, post-processing}\}$, $Y'_c = \{\text{BOW, decoupled}\}$, $T = 0.5$ and $T' = 0.7$. The words that satisfy these conditions are “miss”, “mom”, “wife”, “mother”, and “husband.” Conversely, with $Y_c = \{\text{BOW, DE}\}$ and $Y'_c = \{\text{BOW, PO}\}$, the words are “girls”, “women”, “gender”, “loves”, “mother”, “romance”, “daughter”, “sister”, and “female.”

These gendered words illustrate the multiplicity of gender present in the biographies beyond categorical labels, which standard group fairness interventions do not consider.

Our analysis is limited by the fact that we only consider the individual influence of each word conditioned on the remaining words, while the joint influence of two or more words may also be of relevance.

Appendix B: Analysis on nonbinary dataset

We aim to consider how algorithmic fairness approaches affect nonbinary individuals, who are overlooked by group fairness approaches (Keyes et al. 2021). Using the same regular expression as De-Arteaga et al. (2019) to identify biography-format strings, we collected a dataset of biographies that use nonbinary pronouns such as “they”, “xe”, and “hir.” Since “they” frequently refers to plural people, we manually inspected a sample of 2000 biographies using “they” to identify those biographies that refer to individuals. PROFESSOR is the only occupation title with more than 20 such biographies; the other occupations have too few biographies to perform meaningful statistical analysis. We computed $r_{\text{PROFESSOR}}^{\text{NB}}$, which is analogous to $r_{\text{PROFESSOR}}$, the measure of SNoB for an individual occupation classifier introduced in Sect. 4. While $r_{\text{PROFESSOR}}$ is Spearman’s correlation computed across the biographies in S_c , $r_{\text{PROFESSOR}}^{\text{NB}}$ is the correlation across the nonbinary biographies in the profession. The results are reported in Table 3. We

Table 3 Correlation $r_{\text{PROFESSOR}}^{\text{NB}}$ (first three columns) and $r_{\text{PROFESSOR}}$ (latter three columns) across pre-processing (pre-proc), post-processing (post-proc), and decoupled approaches

Correlation Approach	$r_{\text{PROFESSOR}}^{\text{NB}}$			$r_{\text{PROFESSOR}}$		
	Pre-proc	Post-proc	Decoupled	Pre-proc	Post-proc	Decoupled
BOW	0.36	0.34	0.35, 0.32	0.09**	0.10**	0.11**
WE	0.29	0.29	0.31, 0.31	-0.01**	-0.02**	-0.01**

For DE on the nonbinary dataset, we consider both classifiers, trained on the “she” and “he” data respectively. The p value corresponding to $r_{\text{PROFESSOR}}^{\text{NB}}$ is for the hypothesis test whose null hypothesis is that the rankings from G and Y are uncorrelated. Values marked with a * indicate that the p value is < 0.05 . Values marked with ** denotes that the p value is < 0.01 .

find that $r_{\text{PROFESSOR}}^{\text{NB}}$ is positive across different approaches. However, the associated p values are quite large (> 0.1), so it is challenging to analyze these associations. This is likely due to the small sample size; while $r_{\text{PROFESSOR}}$ is computed across the 10677 professor biographies that use “she” pronouns, $r_{\text{PROFESSOR}}^{\text{NB}}$ is across only 21 biographies.

Appendix C: Word weights

In Fig. 6, we plot the weight of each word in the BOW vocabulary in the occupation classifiers and gender classifiers. These weights illuminate some of the mechanisms behind the predictions. Ideally, without SNoB, every point would have small magnitude in either the occupation or gender classifier, i.e. lie on either the x - or y -axis of Fig. 6. We observe that in the DE approach, words are closer to the y -axis compared to the post-processing approach. This corresponds to the smaller value of $\rho(\mathbf{p}_C, \mathbf{r}_C)$ exhibited by the decoupled approach compared to the post-processing one in Table 2. Note that the post-processed classifier is trained on all of the biographies, while the decoupled classifier is trained on only biographies that use the same pronoun.

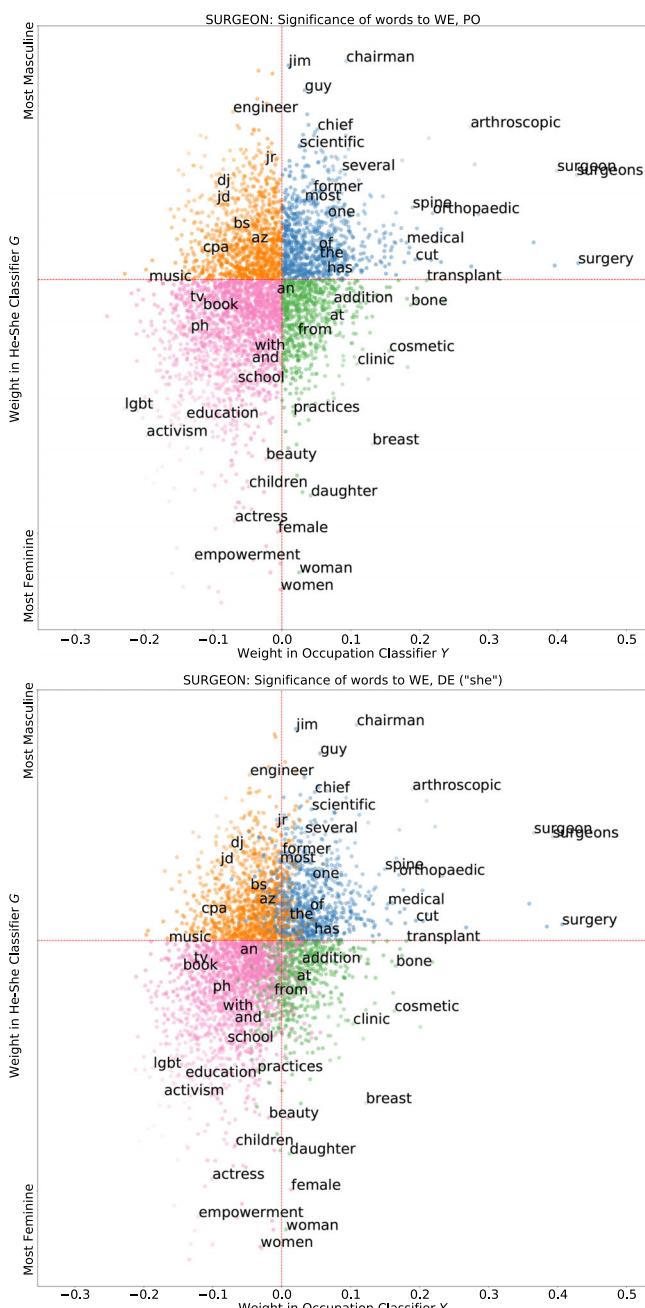


Fig. 6 Words' weights in the occupation and gender classifiers for different approaches in the SURGEON occupation. Each point represents a word; its x -position and y -position represents its weight in \hat{Y}_c and G respectively. Each point is colored based on its quadrant in the post-processing approach. Many points are closer to the y -axis in the decoupled approach

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