Dimensions of Diversity in Human Perceptions of Algorithmic Fairness

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Abstract

Algorithms are increasingly involved in making decisions that affect human lives. Prior work has explored how people believe algorithmic decisions should be made, but there is little understanding of which individual factors relate to variance in these beliefs across people. As an increasing emphasis is put on oversight boards and regulatory bodies. it is important to understand the biases that may affect human judgements about the fairness of algorithms. Building on factors found in moral foundations theory and egocentric fairness literature, we explore how people's perceptions of fairness relate to their (i) demographics (age, race, gender, political view), and (ii) personal experiences with the algorithmic task being evaluated. Specifically, we study human beliefs about the fairness of using different features in an algorithm designed to assist judges in making decisions about granting bail. Our analysis suggests that political views and certain demographic factors, such as age and gender, exhibit a significant relation to people's beliefs about fairness. Additionally, we find that people beliefs about the fairness of using demographic features such as age, gender and race, for making bail decisions about others, vary egocentrically: that is they vary depending on their own age, gender and race respectively.

Author Keywords

Algorithmic Fairness; Diversity; Human Perceptions of Fairness; Human-Centered Machine Learning.

Introduction

Algorithms are increasingly used to assist humans with making decisions, in scenarios ranging from granting bail [2] to assigning social benefits [31]. The impact of algorithmic decision-making on human lives has sparked interest in issues of *algorithmic fairness* [1, 2, 3, 14]. Taking a computational approach, the algorithmic fairness community has since proposed various notions of fairness and mechanisms to achieve them [5, 9, 11, 13, 22, 23, 26, 30, 38, 43, 44]; yet, it has been shown that some of these notions are mutually incompatible [6, 10, 15, 28].

As such, determining whether an algorithm is fair and whether it is ethical to use is not merely a computational problem. As a result, there have been increasing calls for oversight of the ethics and fairness of algorithms implemented by corporations, for example through oversight boards [24, 34, 36]. Yet, the selection of individuals to staff these boards has been controversial, in part because of concerns around biases of those holding positions on the boards [34].

In this work, we extend past work studying human perceptions of algorithmic fairness to understand the factors that may introduce biases into those perceptions. Specifically, prior work suggests that certain demographics as well as personal experience related to the algorithmic scenario may alter perceptions and create biases. Prior work in social psychology on the moral foundations theory [12, 18] finds that demographic features such as gender and age, and political views correlate with people's moral views. Additionally, research on egocentric interpretations

of fairness [40] suggests that people's judgments of fairness are biased in an egocentric direction, especially in individualistic societies [16], such as the US. Accordingly, respondents who have personal experience with the decision-making task may make fairness judgments differently than those who do not have the same personal experience. Similarly, people's perceptions of the fairness of using a specific feature, such as age, may vary based on the respondents' age.

Building on this prior work, we study the variance in people's judgements of the fairness of an algorithm based on (i) demographics (age, race, gender, political view) and (ii) personal experience with the algorithmic task being evaluated. In so doing, we aim to provide insight into the necessary dimensions of diversity for composing a fair algorithmic oversight board.

Related Work. Human perceptions of fairness have been extensively studied in social psychology [4, 7, 8, 19, 27, 42]. Recently, the algorithmic fairness community started exploring human perceptions of algorithmic fairness, in domains such as targeted advertising [35], granting loans [37], allocating donations [29], and making bail decisions [20, 21, 22, 39]. In a series of works, Grgić-Hlača et al. study human perceptions of fairness of using features [21, 22, 20] in algorithmic predictions. They observe that people often do not reach consensus in their moral judgments about the fairness of using features. However, very little prior work studied whether this variance can be explained by people's individual characteristics. To the best of our knowledge, only Pierson [33] pursued this question, exploring the impact of gender on algorithmic fairness, finding women to be less likely than men to favor including gender as a feature in an algorithmic decision-making system. We explore a broader set of respondent features

Demographic	Sam-	Cen-
Attribute	ple	sus
<35 years	54%	46%
35-54 years	33%	26%
55+ years	13%	28%
Male	48%	49%
Asian	8%	6%
Black	10%	13%
Hispanic	4%	18%
White	77%	61%
Other	2%	4%
Liberal	49%	33%†
Moderate	24%	34%†
Conservative	27%	29%†
Bachelor's or	52%	30%
above		

Table 1: Demographics of our survey sample, compared to the 2016 U.S. Census. Attributes marked with a † were compared to Pew data for political leaning.

Experience with Task	Sam-
at Hand	ple
Heard of scenario	5%
Attended bail hearing	13%
(Knows) victim of crime	11%
Legal profession – you	4%
Legal profession –	22%
friends and relatives	

Table 2: Prior personal experiences of our respondents related to the task at hand.

(demographics and prior personal experiences), based on findings from prior work on moral beliefs [18, 12] and egocentric interpretations of fairness [40].

Methodology

Survey Instrument. Using the pre-validated approach of Grgić-Hlača et al. [20], we asked participants to assess the fairness of using different features in an algorithm predicting recidivism risk, which is used by judges to make decisions about bail (the COMPAS scenario) on a 7-point Likert scale from "Strongly Disagree" to "Strongly Agree". The COMPAS scenario was described to participants as: Judges in Broward County, Florida, have started using a computer program to help them decide which defendants can be released on bail before trial. The computer program they are using takes into account information about <feature>.

We ask respondents to rate the fairness of features¹ from the COMPAS ProPublica dataset², which are a defendant's: (i) current arrest charge description (e.g., grand theft), (ii) current arrest charge degree (e.g., felony), (iii) number of juvenile felonies, (iv) number of juvenile misdemeanors, (v) age, (vi) gender, and (vii) race [2]. All surveys conclude with questions assessing respondents' (i) demographics: age, gender, race, and political leaning (on a 5-point scale from Very Conservative to Very Liberal; and (ii) personal experiences: whether they've heard about the real-life application of COMPAS, attended their own or a close friend or relative's bail hearing, have been or known a victim of a

crime, or are in a law or crime related profession (or are closely attached to a someone who is in such a profession).

Data Gathering. We deployed this survey to 203 Amazon Mechanical Turk (AMT) master workers. Table 1 shows the demographics of our sample, compared with the 2016 U.S. Census [41] and Pew data [32]. Table 2 details the respondents' personal experiences related to the decision-making task.

Results

Patterns persistent across features. We first examine differences in fairness beliefs across all seven features that respondents' evaluated. To do so, we train a linear regression model with the dependent variable being people's fairness ratings on a 7-point Likert scale, of the 7 ProPublica features, and the independent variables being respondents' demographics and personal experiences. We include a respondent random effects term, to account for multiple measurements per-respondent. The regression results are shown in the first column of Table 3.

Consistent with prior findings in the Moral Foundations Theory [18, 12], the respondent's age, gender and political leaning were found to be significantly correlated with their fairness judgments, across all features. Figure 1 illustrates the pattern for people's political leanings. The more right leaning an individual is, the more fairly they perceived all of the features. This trend of conservatives to view information about the individual as fair to use in making decisions about them also aligns with the framework of individualist vs. structuralist beliefs, which have primarily been explored in studies of racism, poverty, and crime in the U.S. [25, 45], showing that conservatives tend to believe in "individualist" explanations for outcomes – which emphasize individual responsibility – as compared to liberals, who tend to make

¹While we assessed all 8 ProPublica features which are typically studied in the algorithmic fairness literature, there was a data collection issue for "number of prior offenses" and thus the results presented here address the other 7 ProPublica features.

² The dataset was gathered by ProPublica [2], and it contains information about more than 7000 criminal defendants who were arrested and subsequently subjected to COMPAS screening in Broward County, Florida in 2013 and 2014.

	Coeff.
Age	0.179**
Male	0.423***
White	-0.146
Political leaning	0.237***
Scenario	-0.111
Bail hearing	-0.423*
(Knows) victim	0.063
Profession – you	0.145
Profession – f&r	-0.057
Constant	2.624***

Table 3: Linear regression model. Dependent variable: fairness ratings, on a 7-point Likert scale. Independent variables (rows): respondents' demographics and experiences. Respondent random effects term included. *** p < .001, * p < .01, * p < .05.

structuralist attributions, which emphasize how social structures create outcomes.

When prior experiences have an impact, this is an example of the influence of an egocentric factor on perceptions of fairness. Since only the most directly related of the 4 prior experiences (having attended a bail hearing, for the bail decision making task) is significant, this hints that it's possible that only closely related experiences raise egocentric effects.

Feature-specific patterns. We proceed to study feature-specific patterns. Building up on literature on egocentric interpretations of fairness [40], we examine how respondents' demographics influence the perceived fairness of using those same demographics – age, gender and race – in the decision scenario. For each of the three ProPublica features, we find that the perceived fairness of using that feature was significantly (MWU tests, each with p < 0.001; Holm-Bonferroni multiple testing correction applied) related to the corresponding respondent feature. In combination with the significance of experience with bail hearings on overall fairness perceptions, these results suggest support for the relevance of egocentric factors – narrowly defined – in perceptions of algorithmic fairness.

Discussion

Implications. The judgment of which features are fair to use in a given decision-making task is a moral decision, requiring human background knowledge and societal context that may often not be present in data provided. In any particular algorithmic setting, the appropriate person(s) to make this judgment may vary: policy makers, domain experts, algorithm designers, oversight boards, or even by the opinions of the general population (a descriptive ethics approach [17]).

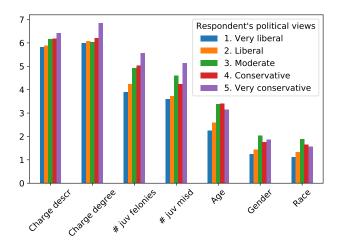


Figure 1: Mean fairness ratings of features by respondents of different political views, on a 7-point Likert scale, from "Strongly disagree" to "Strongly agree".

Our results indicate that people's judgments may vary significantly along demographic and political dimensions. Hence, to obtain a valid estimate of opinions across the relevant group of decision makers, it is important to enforce diversity along various dimensions: not just demographic and ideological, but also *egocentric*.

Limitations and Future Work. In our study, we examine the perceptions of fairness of a small sample of U.S. based respondents, for the task of making bail decisions. As a promising direction for future research, we encourage the development of a cohesive theory on human reasoning about algorithmic fairness, including the study of additional decision-making scenarios and non-U.S. populations.

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