Gender differences in beliefs about algorithmic fairness

Emma Pierson*

December 10, 2017

1 Introduction

The rapidly growing field of algorithmic fairness has produced many ethical dilemmas and little consensus about how to resolve them. For example, it has been repeatedly shown [3, 4, 8, 13] that different fairness constraints cannot all be satisfied simultaneously, both in theory and in real data. Illuminating these conflicts is invaluable, but thus far there is little agreement about what to do about them.

This disagreement likely occurs in part because the core debates in algorithmic fairness are philosophical, not just technical. Building a classifier that can predict criminal recidivism with high accuracy is a relatively straightforward technical problem with a clearly defined success metric. But determining how to weigh maximizing accuracy against minimizing disparities requires value judgments about which people may disagree. A recent review of the ethical considerations in data science argues, with respect to algorithmic fairness, that “Favoring certain fairness properties over others could just as well have reflected a difference in values” [1].

Previous work has shown that people’s moral judgments correlate with their demographic traits [5, 6], as do beliefs about the ethics of self-driving cars [2] and beliefs about fairness and discrimination [10, 12]. These findings raise the question of whether judgments about algorithmic fairness also correlate with demographic traits. This is a question of particular interest because computer science is extremely demographically skewed [9]. If beliefs about algorithmic fairness correlate with demographics, and computer scientists are demographically skewed, decisions made about algorithmic fairness may not reflect what the population as a whole would want.

Here we present the results of two surveys showing that demographics do predict beliefs about algorithmic fairness. In an initial survey disseminated through social media and

*This is a writeup of a talk for AlterConf 2017, in response to requests to see the results. Thanks to Shengwu Li, Sam Corbett-Davies, and Chris Olah for thoughtful comments. Feedback is welcome at emmapi1@cs.stanford.edu. Replication data and code are available at https://github.com/epierson9/algorithmic_fairness_survey
academic listservs, we examine the effects of gender and academic background on people’s beliefs about algorithmic fairness. We find that gender predicts people’s beliefs on several questions, though we find no statistically significant association between beliefs and academic background. In a follow-up survey conducted using Google Consumer Surveys, we replicate the gender effect.

2 Results

We disseminated an initial survey with four algorithmic fairness questions through social media channels. We asked respondents for their gender, academic background (computer science, other science or math, or humanities), and race / ethnicity. Our sample was not sufficiently racially representative to give us statistical power to assess racial discrepancies in responses: only 6% of respondents identified as black or Hispanic, a caveat which ought to be kept in mind in interpreting our results. A second caveat is that, although we had to present the questions as one-dimensional scales to allow for comparable numerical responses, the questions had nuances which could not always be captured along a single dimension, a fact some respondents commented on. In total 163 respondents filled out our survey completely and identified as male or female: 72 women and 91 men; 49 from computer science, 37 from other science / math, and 77 from humanities.

We found significant associations (p < .05, two-tailed t-test) between gender and responses to two of the four algorithmic fairness questions, with a third question close to significant (Table 1; Figure 1). Male respondents were more likely than female respondents to weight maximizing accuracy over minimizing racial disparities in criminal risk prediction. Male respondents were also more likely than female respondents to favor including gender in an education company’s algorithm that recommended classes to students if it increased accuracy of class recommendations, even if that would make it less likely that women were recommended science classes. We found no significant associations between a respondent’s academic background and their responses to algorithmic fairness questions. (While gender was somewhat associated with academic background – 29% of computer scientists were female, as opposed to 52% of humanities respondents and 49% of other science / math respondents – we verified that gender was still significantly associated with algorithmic fairness beliefs when we controlled for profession).

Surveys conducted through social media study a selected sample (though, of course, many survey populations have biases) and our initial sample size was somewhat small. We therefore assessed whether we could replicate the significant gender associations in a larger, more representative sample using Google Consumer Surveys. In total our data included 573 respondents identified as male or female: 282 females and 291 males. We sought to replicate the “gender in course recommendations” significant association because the “racial disparities versus accuracy” question required too much space to explain on the

\[\text{Survey is available at } \text{https://github.com/epierson9/algorithmic_fairness_survey/}\]
Use gender in course recommendations even if it reduces women in science classes? 1.72 2.87 3.3e-05
Reduce racial disparities in criminal risk prediction at expense of accuracy? 5.01 3.95 4.2e-04
Use computer algorithms (as opposed to human judges) in criminal justice at all? 3.67 4.22 5.6e-02
Allow companies to keep details of criminal justice algorithms secret? 2.38 2.37 1.0

Table 1: Results for social media survey. Answers are on a 7-point scale from 1 to 7, with higher numbers indicating greater agreement.

Figure 1: Results of initial survey; higher numbers indicate greater agreement with the question in the title. Left: male respondents were more likely than female respondents to weight maximizing accuracy over minimizing racial disparities in criminal risk prediction. Right: male respondents were more likely than female respondents to favor including gender in an algorithm that recommended classes to students, even if that would make it less likely that women were recommended science classes.

Figure 2: Replication of gender-in-course-recommendations effect using Google Consumer Surveys. Effect size is smaller than in the social media sample, possibly due to noise introduced by people taking the survey quickly or not understanding the question.
survey platform, and we were not confident respondents would understand the question.

As in the social media sample, we found that male respondents were statistically significantly more likely than female respondents to favor including gender even if it would lead to fewer women in science classes (Figure 2). The mean gap between genders was somewhat smaller — 0.5 points as opposed to 1.1 points — possibly because respondents were more likely to be in a hurry or to not understand the question, introducing noise. Nonetheless, a meaningful gap emerged: male respondents were, for example, 41% likely to give an answer of 4 or above, as opposed to only 29% for female respondents, an odds ratio of 1.7.

3 Discussion

We identify statistically significant and practically meaningful gender discrepancies in beliefs about algorithmic fairness in two separate samples. A caveat to our results is that one of our surveys is disseminated through social media, which will create a biased sample; we mitigate this concern by showing that gender differences in beliefs persist in a more representative sample, collected using Google Consumer Surveys. Our finding is also consistent with the results in [7], which identifies evidence of gender differences in beliefs about which features are acceptable to use in criminal risk prediction, although they do not assess statistical significance because their sample is small. Future work should assess whether the differences we observe persist in other samples; if they do not, that discrepancy is itself of interest. Future work should also seek to measure racial discrepancies in beliefs about algorithmic fairness, a topic of pressing importance given the racial disparities in algorithmic decisions.

One natural question in response to our results is whether these demographic differences would still emerge if participants were given a chance to debate and reflect on the fairness dilemmas. It is possible that, under such circumstances, respondents would converge in their beliefs, an intriguing possibility for future work. Claims of such convergence, however, require evidence, given that participants initially start far apart and that academic disagreements in algorithmic fairness (and moral philosophy more broadly) clearly persist even after careful reflection.

To the extent that they exist, demographic differences in beliefs about algorithmic fairness have two implications. First, disagreements about algorithmic fairness may stem from fundamental aspects of background or life experience, and as such have more subjective answers than purely technical questions. Second, diversity in discussions of algorithmic fairness is particularly pressing. It is worrisome that the race and gender groups least likely to be involved in algorithmic discussions are also the groups most often harmed by algorithmic disparities. If our demographics predict how we believe algorithms should behave, we need our algorithm designers to be more demographically representative if algorithms are to serve the will of the whole population.
References


