Gender Discrimination in Data Analysis: a Socio-Technical Approach

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Research Context

Data analysis

Set of processes for inspecting, cleaning, transforming, and modeling data with the aim of discovering useful information, informing conclusions, and supporting decision making.

Gender discrimination

Specific (sub)category of social problems, here expressed in the form of the so-called 'gender gap', definable as:

> *A difference between the way men and women are treated in society, or between what men and women do and achieve. (Cambridge Advanced Learner's Dictionary, 2013)*

Scenarios & Problem Statement

Problem

Data and datasets, on which algorithms that regulate our daily life are based, can be unfair. Unfair, or better to say, biased data, may influence our perception of reality, and lead us (or the algorithms in our place) to make decisions that, although seemingly fair and just, contain in turn bias, and discriminate against individuals or groups of individuals.

Example scenarios

- COMPAS tool used in the U.S. to predict recidivism risk biased against Black people *(Angwin et al., 2016)*
- Amazon software to screen candidates for employment biased against women *(Dastin, 2018)*

Goal

- ~~Solve the huge and multifaceted problem of discrimination in data~~ → practically impossible
- Take a look at the current state of the art
- Observe some tools in action, trying to highlight their strengths and weaknesses and to understand which design choices have the greatest impact on the so-called ‘fairness’ of the results
- Provide a non-technical perspective, since the technical one alone is partial and not sufficient to understand phenomena of a social nature, which are reflected and may be exacerbated by technology but which in fact originate in society

We try to understand to what extent the problem is found in the instrumentation and technical choices and to what extent it is instead rooted in society (specifically, the U.S. one).

Methodology

Dual perspective on the problem: qualitative and conceptual approach typical of sociology combined with technical and pragmatic approach of engineering and computer science.

- Systematic literature review
- Experimental case studies to verify not only whether men and women are paid fairly, but also if there are other collateral issues related to gender discrimination in the data and what tools can possibly catch them
- Technical results discussed in the light of the sociological background

Sociological Perspective

Global Gender Gap Index *(Schwab et al., 2017)*

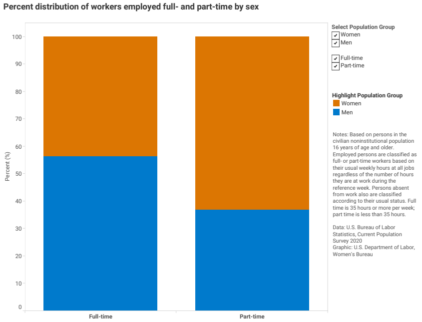
Cumulative measure for ranking countries which benchmarks national gender gaps on economic, education, health, and political criteria.

U.S. ranking: 49/144, overall score: 0.718 (1 = gender parity)
→ men more participatory in labor force; women tend to earn less than men, be employed part-time, or not to be paid for their work, and are underrepresented in managerial and higher-paying jobs

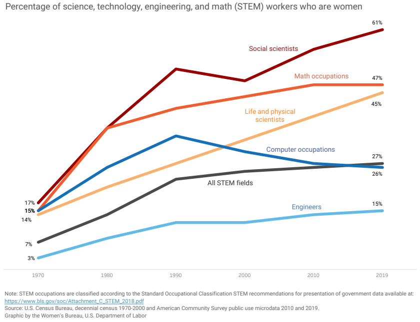
Some possible reasons:

- Statistical discrimination *(Tilcsik, 2021)*
- Institutional environment *(Beggs, 1995)*
- Unequal bargaining power *(Folbre, 2021)*

Sociological Perspective – Data & Statistics



(a) Percent distribution of workers employed full- and part-time by sex (2020).
U.S. Department of Labor. Source:
`https://www.dol.gov/agencies/wb/data`.



(b) Percentage of Science, Technology, Engineering, and Math (STEM) workers who are women (1970-2019).
U.S. Department of Labor. Source:
`https://www.dol.gov/agencies/wb/data`.

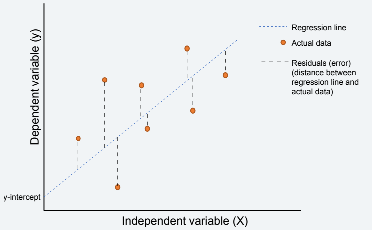
Tools for Assessing Fairness

- The 'Glassdoor Method': a framework for evaluating gender pay gap which relies on linear regression *(Chamberlain, 2017)*

Linear regression

Preprocessing technique used to smooth out noise or to find patterns within a dataset, which attempts to model the relationship between two or more variables by fitting data to a linear equation.

$$y = \beta_0 + \beta_1 x + \epsilon$$



Simple linear regression graph.
Source: `https://www.reneshbedre.com/assets/posts/reg/mlr/residual.svg`.

Tools for Assessing Fairness

- FAIR-DB: an algorithm to detect bias in data based on functional dependencies and the related evaluation metrics *(Azzalini, Criscuolo, and Tanca, 2021)*

Functional Dependencies (FDs)

Constraint involving two (sets of) attributes of the same relation in which the first uniquely determines the second.

Approximate Conditional Functional Dependencies (ACFDs)

FDs holding on a subset of tuples (Approximate) which use conditions on attribute values to specify the subset on which they hold (Conditional).

$$\mathit{Status} = \text{` F '}, \mathit{Gender} = \text{` female '} \rightarrow \mathit{AnnualSalaryBin} = \text{`} \leq 90\text{K '}$$

Tools for Assessing Fairness

- Ranking Facts: an application built on the idea of ranking which makes use of three statistical measures to evaluate fairness *(Yang et al., 2018)*
  - FA*IR: compares the number of protected elements in every prefix of the ranking (i.e., the top-i positions, with $i \in [1, k]$) with the expected number of protected elements if they were picked at random using Bernoulli trials with success probability p
  - Proportion: statistical measure based on the concept of (two-sample) z-test – particular type of hypothesis test which allows to compare two proportions to check whether they are the same
  - Pairwise: compares options in pairs and determines which is the preferred choice or has the highest level of importance based on defined criteria, ultimately ranking the options

Case Study 1: Chicago

- Data preprocessing: 20,309 tuples, of which 16,146 males and 4,163 females, and with 35 distinct *Job Title* values and 20 distinct *Department* values

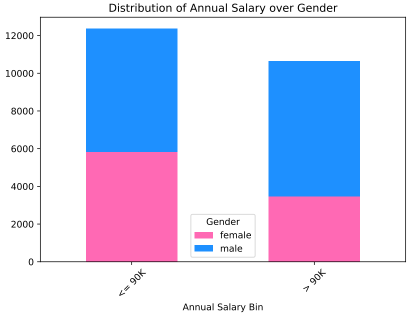
- The 'Glassdoor Method': 24.2% 'unadjusted' pay gap; 0.4% 'adjusted' pay gap → no evidence of a systematic gender pay gap
- FAIR-DB: 6 final functional dependencies; 11.4% of the dataset 'problematic' → dataset quite fair
- Ranking Facts: dataset fair for both males and females, for each statistical measure

Case Study 2: San Francisco

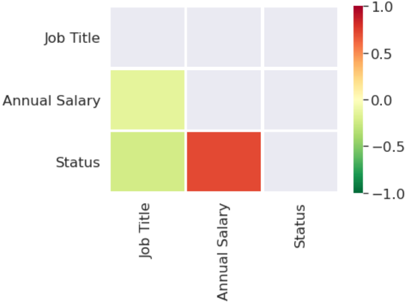
- Data preprocessing: 22,996 tuples, of which 13,688 males and 9,308 females, and with 81 distinct *Job Title* values

- The 'Glassdoor Method': 30.4% 'unadjusted' pay gap; -5% 'adjusted' pay gap $\rightarrow$ no evidence of a systematic gender pay gap
- FAIR-DB: 10 final functional dependencies; 24.3% of the dataset 'problematic' $\rightarrow$ dataset quite fair because of the low values of difference ('unfairness level') and support (number of tuples involved), but for higher-paying jobs men seem to have an economic advantage over women
- Ranking Facts: dataset fair for males and unfair for females, for each statistical measure $\rightarrow$ proportion of women in the top-k ranking effectively very low

Case Study 2: San Francisco



(a) Distribution of the *Annual Salary* values for the San Francisco dataset (2 bins).



(b) Heatmap showing attribute correlations for the San Francisco dataset.

Other Design Choices

- Part-time employees removal: most of the tuples removed related to women (Chicago); excessive amount of tuples removed (San Francisco)
- FAIR-DB: discretization using more bins: less and different final dependencies detected (Chicago and San Francisco)
- FAIR-DB: choice of different dependencies: 85.6% (Chicago) and 92.5% (San Francisco) of the dataset ‘problematic’
- Grouping of job titles: overturning of the outcomes for Ranking Facts (Chicago dataset unfair for males and fair for females, for each statistical measure)
- Voluntary introduction of bias: results from each tool oriented toward unfair Chicago dataset, in which women are discriminated against (retaining 50%, 75%, and 90% of the *Annual Salary* value of female employees)

Outcomes

- Strengths and weaknesses of the tools highlight their non-exhaustiveness and complementarity
- Tools practically fail in capturing the several facets of equity

Equity

The idea that people should have access to resources (possibly of a different nature and to a different extent) in order to be able to reach the same condition.

- Representation problem: disproportion in the percentage of women employed in different sectors
- Part-time problem: higher number of women employed in part-time jobs, typically less paid than full-time ones

Contributions

- Fairness is a multifaceted concept which cannot be exhausted by providing a single definition and pursuing that specific definition experimentally
- Tools are susceptible to decisional choices, and therefore users must be properly trained on the specific area of analysis
- Double perspective on the gender pay gap issue emphasized the importance of multidisciplinarity, especially when dealing with problems of an ethical and sociological nature

Future Work

- Combine all the tools in a unique, more complete instrument, possibly trying to encompass even more facets of equity, or more definitions of fairness
- Support analyses of this kind by sociological research
- Enrich sociological research by conducting an interview with workers and HR practitioners of the cities under study
- Retrieve further information in support of the mere data and create effective documentation, possibly pointing at context-awareness (provide the tools with knowledge on the context of use)

Thank you!

Any question?

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