Gender Discrimination in Data Analysis: a Socio-Technical Approach

Supervisor: Prof. Viola Schiaffonati
Co-supervisor: Prof. Letizia Tanca
Prof. Pierre Senellart
Prof. Karine Gentelet

M.Sc. Thesis by:
Riccardo Corona
927975
07/10/2021

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 a lot of actions of our daily routine are based, can be **unfair**. Unfair, or better to say, **biased** data, may influence, directly or indirectly, our perception of reality, and lead us 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)*

Sociological Perspective

Global Gender Gap Index

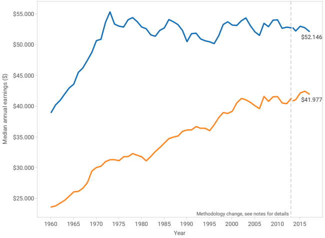
Cumulative measure for ranking countries which benchmarks national gender gaps on economic, education, health, and political criteria.

U.S. ranking: $49/144$, overall score: 0.718 ($1 =$ gender parity)
$\rightarrow$ 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.
- Institutional environment.
- Unequal bargaining power.

Median annual earnings by sex
March 1960-2017



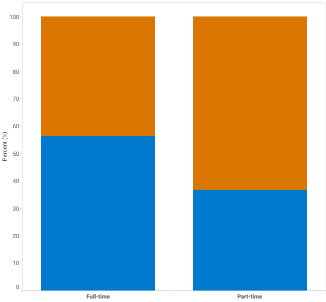
Hover over chart to view data. Click filter and legend items to change data display.

Select Year Range
Tutti i valori

Highlight Population Group
Men
Women

Notes: Earnings are based on median annual earnings of full-time, year-round workers, 15 years old and over beginning in March, 1980, and age 14 years old and over as of March of the following year for previous years. Before 1989 earnings are for civilian workers only.
The comparability of historical data has been affected at various times by methodological and other changes in the Current Population Survey. The 2014 CPS ASEC included redesigned questions for income and health insurance coverage for a subsample of the 98,000 addresses using a probability split panel design. Approximately 68,000 addresses were eligible to receive a set of income questions similar to those used in the 2013 CPS ASEC and the remaining 30,000 addresses were eligible to receive the redesigned income questions, resulting in two estimates for 2013. Estimates based on the portion of the sample that received the redesigned income questions are the most appropriate for comparing estimates from ASEC 2014 with ASEC 2015 and beyond.
Earnings are in 2017 CPI-U-RS adjusted dollars.
Source: 1961-2018 Annual Social and Economic Supplements, Current Population Survey, U.S. Census Bureau.
Graph by the Women's Bureau, U.S. Department of Labor

Percent distribution of workers employed full- and part-time by sex



Select Population Group
- [x] Women
- [x] Men

- [x] Full-time
- [x] Part-time

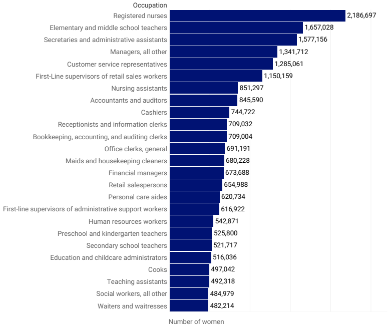
Highlight Population Group
Women
Men

Notes: Based on persons in the civilian noninstitutional population 16 years of age and older. Employed persons are classified as full- or part-time workers based on their usual weekly hours at all jobs regardless of the number of hours they are at work during the reference week. Persons absent from work also are classified according to their usual status. Full time is 35 hours or more per week; part time is less than 35 hours.

Data: U.S. Bureau of Labor Statistics, Current Population Survey 2020
Graphic: U.S. Department of Labor, Women's Bureau

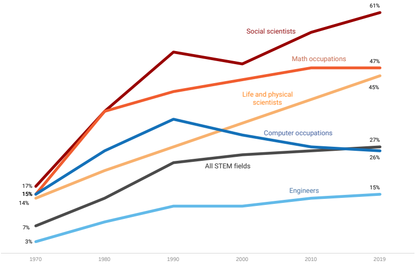
Sociological Perspective – Data & Statistics

Most Common Occupations for Women in the Labor Force



Note: Full-time, year-round civilian employed 16 years and older. Occupations with at least 100 sample observations.
Data: U.S. Census Bureau, American Community Survey 2019
Graphic: U.S. Department of Labor, Women's Bureau

Percentage of science, technology, engineering, and math (STEM) workers who are women



Note: STEM occupations are classified according to the Standard Occupational Classification STEM recommendations for presentation of government data available at: https://www.bls.gov/soc/Attachment_C_STEM_2018.pdf
Source: U.S. Census Bureau, decennial census 1970-2000 and American Community Survey public use microdata 2010 and 2019.
Graphic by the Women's Bureau, U.S. Department of Labor

Tools for Assessing Fairness

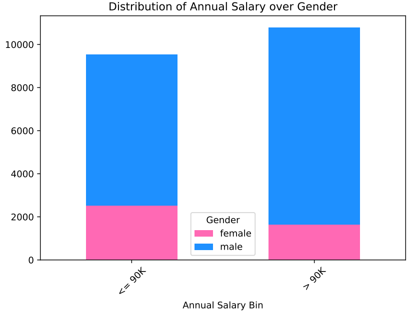
- *The 'Glassdoor Method'*: a framework for evaluating gender pay gap which relies on **linear regression**. *(Chamberlain, 2017)*
- *FAIR-DB*: an algorithm to detect bias in data based on **functional dependencies** and the related evaluation metrics. *(Azzalini, Criscuolo, and Tanca, 2021)*
- *Ranking Facts*: an application built on the idea of **ranking** which makes use of three statistical measures to evaluate fairness. *(Yang et al., 2018)*

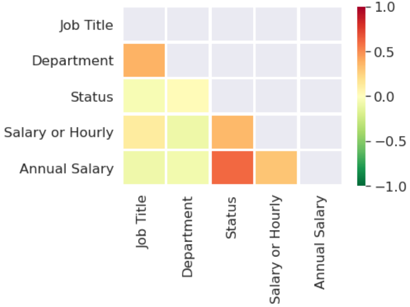
Case Study 1: Chicago

- **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 1: Chicago



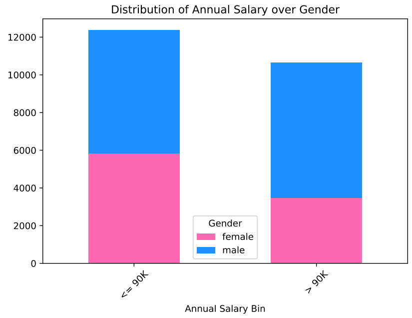


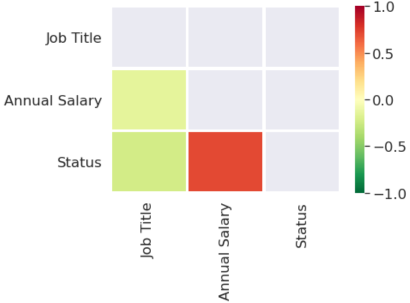
Case Study 2: San Francisco

- **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 → no evidence of a systematic gender pay gap.
- **FAIR-DB**: 10 final functional dependencies; 24.3% of the dataset 'problematic' → 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 → proportion of women in the top-k ranking effectively very low.

Case Study 2: San Francisco





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*.
- **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 (Chouldechova's impossibility theorem).
- 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.

Limitations

- Non-specific literature.
- No direct insights from U.S. workers.
- Original datasets already partial or possibly grouped.
- `gender-guesser` (package to infer employees' gender).
- Removal of job titles with less than 100 occurrences.
- Representation and other facets of equity not taken into account.
- FAIR-DB: parameter values; manual selection of rules; number of bins.
- Ranking Facts: lack of documentation; notebook version.
- Manual grouping of job titles performed using a non-U.S.-specific document.
- Synthetic dataset generated through voluntary introduction of bias not reflecting the real world.

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 these 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).

References

Julia Angwin et al. "Machine Bias". In: *ProPublica* (2016). https://www.propublica.org.

Fabio Azzalini, Chiara Criscuolo, and Letizia Tanca. "FAIR-DB: FunctionAl DependencIes to discoveR Data Bias". In: *EDBT/ICDT Workshops*. http://ceur-ws.org/Vol-2841. 2021.

Cambridge Advanced Learner's Dictionary. ""Gender gap"". In: *Cambridge University Press* (2013). https://dictionary.cambridge.org. Accessed 28 June 2021.

Andrew Chamberlain. "How to Analyze Your Gender Pay Gap: An Employer's Guide". In: *Glassdoor Economic Research* (2017). https://www.glassdoor.com.

Jeffrey Dastin. "Amazon scraps secret AI recruiting tool that showed bias against women". In: *Reuters* (2018). https://www.reuters.com.

References

Ke Yang et al. "A Nutritional Label for Rankings". In: *Proceedings of the 2018 International Conference on Management of Data*. Association for Computing Machinery, 2018, pp. 1773–1776. DOI: 10.1145/3183713.3193568.