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EC 601 Project 3
Something about data bias

Here are some classifications of data bias
1. Report bias

Reporting bias (also known as selective reporting bias) occurs in partial results or results captured by the data, often covering only a small fraction of the entire actual data. This is because people tend to report less than all the information available.

There are several types of reporting bias:

1) Citation bias: when your analysis is based on other people's research citations.
2) Language bias: Non-native language reports are ignored.
3) Duplicate publication bias: Some studies are given more weight because they were published in more than one place.
4) Location bias: Some studies are harder to locate than others.
5) Publication bias: Studies with positive results are more likely to be published than studies with negative results/no significant findings.
6) Outcome reporting bias: Selective reporting of certain outcomes. For example, you only report positive earnings in your company's quarterly reports.
7) Time lag bias: Some studies take years to be published.
2. Automated Bias
Automation bias is the human tendency to favor results or recommendations produced by automated systems while ignoring contradictory information produced by non-automated systems even though the latter is true.

3. Participation bias: The data are not representative due to the different levels of participation in the data collection process.
Let's say Apple launches a new iPhone and Samsung launches a new Galaxy Note on the same day. You send a tune to 1000 people and collect their comments. Now, instead of randomly selecting reviews for analysis, you decide to select the first 100 customers who responded to your survey. This leads to a sampling bias, since the first 100 customers are likely to expect too much from the product and give it a positive review.
Next, if you decide to collect data by surveying only Apple customers, leaving out Samsung customers, then you will have convergence bias in your dataset.
Finally, if you send the survey to 500 Apple and 500 Samsung customers. 400 Apple customers responded, but only 100 Samsung customers responded. Then, the dataset would not be representative of Samsung customers, which would be participatory bias.

4. Overgeneralization bias
Overgeneralization bias, which occurs when you assume that what you see in one data

set will be the same as what you see in other data sets that evaluate the same information. As shown above, when you see only white swans in a data set, you think there are only white swans in other data.

5. Group attribution bias

Group Attribution Bias

People tend to stereotype the entire group because of the behavior of a few members of the group. This tendency to generalize an individual's circumstances to the entire group to which he belongs is known as group attribution bias.

There are several types of group attribution bias:

1) In-group bias (In-group bias): that is, bias toward members of a group that you belong to or share interests with. For example, a manager who sets up a job description for a data scientist position thinks that suitable applicants must have a master's degree because the manager also has a master's degree (regardless of their work experience).
2) Out-group bias: This is when you stereotype individual members of groups that you do not belong to. For example, a manager (with a master's degree) who set up a job description for a data scientist position felt that an applicant without a master's degree would not have sufficient expertise for the position.

Issues of fairness come up in any discussion of data ethics. We’ve seen analytics on products like COMPASS, maps showing Amazon offering same-day delivery for the first time, and how job listings shown to women are skewed towards lower-paying jobs.

We also know that "fairness" is a difficult concept for a number of reasons, not the least of which is the data used to train machine learning models. Kate Crawford's recent NIPS keynote, The Trouble with Bias, is an excellent introduction to the problem. Fairness is almost always future-proof and aspirational: we want fairness, and we want to build fair algorithms. But, by definition, the data we train on looks backwards, reflecting our history, which is often unfair. Real estate data reflect the impact of racial discrimination in housing that continues to occur years after it became illegal. Employment figures reflect assumptions about what men and women should do (and have historically done): women get jobs as nurses, men get jobs as engineers. Not only is our model based on this historical data, but it has been shown to be very good at inferring characteristics such as race, gender, and age, even though they should be independent of race, age, and gender.

There are several AI fairness tools meant to help engineers and data scientists examine, report, and mitigate discrimination and bias in ML models. For example: • IBM’s AI Fairness 360 Toolkit: a Python toolkit focusing on technical solutions through fairness metrics and algorithms to help users examine, report, and mitigate discrimination and bias in ML models. • Google's What-If Tool: a tool to explore a models' performance on a dataset, including examining several preset definitions of fairness constraints (e.g., equality of opportunity).12 This tool is interesting as it allows users to explore different definitions of fairness. • Microsoft's fairlean.py: a Python package that implements a variety of algorithms that seek to mitigate "unfairness" in supervised machine learning. • Facebook is developing a "Fairness Flow" internal tool to identify bias in ML models. Regardless of a focus on data or the broader AI system lifecycle, these tools tend to use a technical lens and focus on technical solutions. Technical solutions are important, but miss important fairness considerations. A tool employing purely technical solutions would not have captured the nuances behind the COMPAS algorithm's discrimination. A purely technical approach is insufficient to understand and mitigate biases. It perpetuates the misleading notion that ML systems can achieve "fairness" or be "un-biased".

There are various ways to improve the systematicness of the selection process. In the current study, we will provide some participants with tools related to job analysis as a way to improve systemicity. Job analysis is a broad term for procedures that examine, document, and infer work activities, worker attributes, and the work environment in order to identify relevant criteria and characteristics of a particular job. The job analysis tools in this study focus on the tasks, skills, and characteristics required to manage a specific job. It helps recruiters specify relevant tasks and responsibilities, as well as the characteristics required to fulfill them. This should be useful as it helps recruiters identify relevant skills, knowledge, and abilities possessed by candidates and reduces the risk of relying on heterogeneous beliefs about job requirements or recruiters' own character traits and attitudes .

In conclusion, job analysis is a method to reduce the reliance of recruiters on pre-existing fixed categories when processing information about applicants, automating the processing known to increase the risk of stereotyping and discrimination . In contrast, information processing is more controlled and therefore potentially less biased. In the current study, participants in the systemic condition would actively process job content and CV reading, which should increase the usability and accessibility of job-related criteria. own personality traits and attitudes . In conclusion, job analysis is a method to reduce the reliance of recruiters on pre-existing fixed categories when processing information about applicants, automating the processing known to increase the risk of stereotyping and discrimination In contrast, information processing is more controlled and therefore potentially less biased. In the current study, participants in the systemic condition would actively process job content and CV reading, which should increase the usability and accessibility of job-related criteria. own personality traits and attitudes In conclusion, job analysis is a method to reduce the reliance of recruiters on pre-existing fixed categories when processing information about applicants, automating the processing known to increase the risk of stereotyping and discrimination.

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References

1. Huffcutt AJ, Arthur W. Jr. Hunter and Hunter (1984) revisited: Interview validity for entry-level jobs. J App Psych. 1994; 79: 184-190. doi: 10.1037/0021-9010.79.2.184

2. Huffcutt AI, Woehr DJ. Further analysis of interview validity: A quantitative evaluation of additional methods for structuring the employment interview. J Org Beh. 1999; 20: 549-560. doi: 3.0.CO;2-Q"
xlink:type="simple">10.1002/(SICI)1099-1379(199907)20:43.0.CO;2-Q

3. Kuncel NR, Klieger DM, Connelly BS, Ones DS. Mechanical versus clinical data combination in selection and admissions decisions: A meta-analysis. J Appl Psych. 2013; 98: 1060-72. http://dx.doi.org.ezproxy.bu.edu/10.1037/a0034156.

4. McDaniel MA, Whetzel DL, Schmidt FL, Maurer SD. The validity of employment interviews: A comprehensive review and meta-analysis. J Appl Psych. 1994; 79: 599-616. doi: 10.1037/0021-9010.79.4.599

5. Highhouse S. Stubborn reliance on intuition and subjectivity in employee selection. Ind Org Psych. 2008; 1: 333-342. doi: 10.1111/j.1754-9434.2008.00058.x

6. Klehe UC. Choosing how to select: Institutional pressures affecting the adoption of personnel selection procedures. Int J Sel Ass. 2004; 12: 327-342. doi: 10.1111/j.0965-075X.2004.00288.x

7. Lievens F, De Paepe A. An empirical investigation of interviewer-related factors that discourage the use of high structure interviews. J Org Beh. 2004; 25: 29-46. doi: 10.1002/job.246

8. Simola SK, Taggar S, Smith GW. The employment selection interview: Disparity among research-based recommendations, current practices and what matters to human rights tribunals. Can J Admin Sci. 2007; 24: 30-44. doi: 10.1002/CJAS.4