Bias in model development lifecycle

Project Title: Bias in model development lifecycle questionnaire

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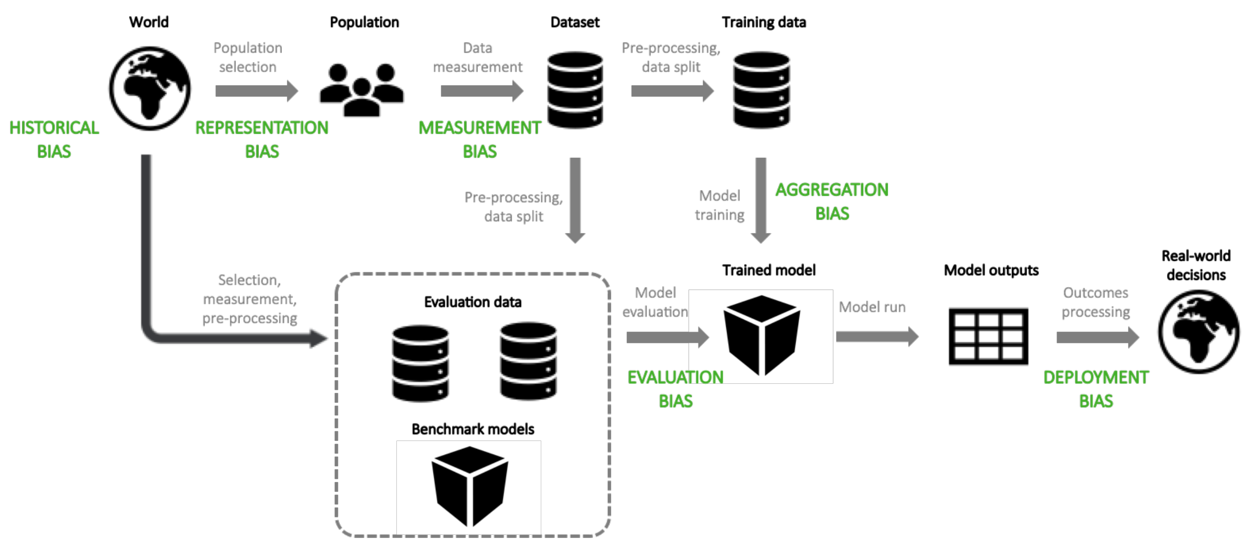
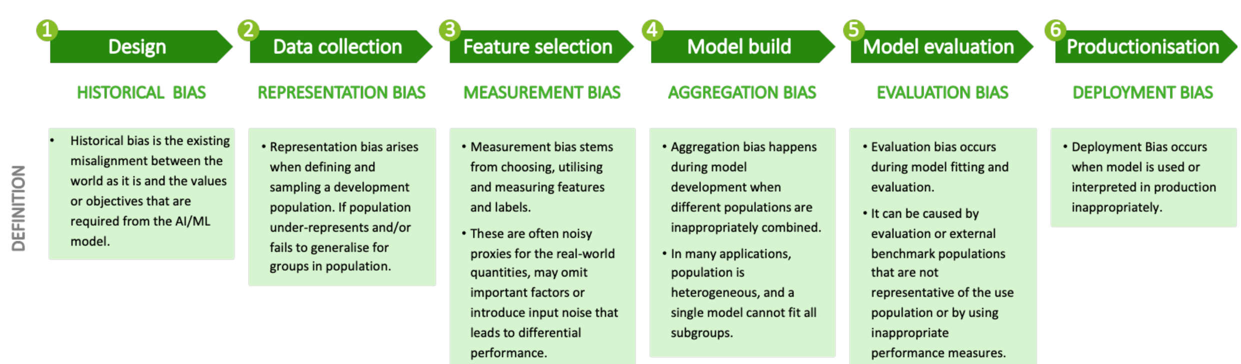
This survey will go through an assessment to identify the potential biases in a model development lifecycle.

Think of a model that you would like to assess for potential unfair bias and discrimination.

Below are the biases and their definitions for your reference.



Source: Harini Suresh and John V Guttag. 2019. A Framework for Understanding Unintended Consequences of Machine Learning. *arXiv preprint arXiv:1901.10002* (2019)



Describe a model you would like to assess for potential unfair and discriminatory bias.

Ex) a supervised machine learning model to predict whether a mortgage loan will default

What positive impact can this model have on the target population?

Ex) predicting default risk can help prevent unaffordable loans being approved

What is the benefit of higher accuracy / precision for the target population?

Ex) better credit risk evaluation model leads to greater financial inclusion, better hiring algorithm leads to overall higher employee performance / reduction in attrition

Can these objectives be measured and quantified? If yes, list how they can be formalised.

Ex) unaffordable loan approval can be measured based on false negative rate (i.e. loans predicted to be repaid but defaulted), and greater financial inclusion can be measured as the total amount of loans given out

What are any potential allocative harms (withholding of opportunities / resources)?

Ex) model may be more likely to give loans to certain groups, e.g. race and gender, which would replicate and widen the societal inequalities

Is there any representational harm (diminished identity)?

Ex) for an image search algorithm for “CEO”, returning more men than women reinforces the bias in identity

Are there any fundamental rights at stake?

Ex) right to self-determination, liberty, due process of law, freedom of movement, privacy, freedom of thought, freedom of religion, freedom of expression, right of peaceful assembly, right to freedom of association

Can these potential harms be measured and quantified? If yes, list how they can be formalised.

Ex) we can measure the loan denial rates for previously disadvantaged groups (e.g. minority race)

End of Block: 0. Ethical risk assessment: design KPIs/KRIs

Start of Block: 1. Design: historical/external bias

Is there documented historical discrimination in the domain area against a protected class, as defined in the UK Equality Act?

Ex) academic studies demonstrate lower mortgage approval rates for racial minorities in the US, especially black and Hispanic applicants

- ☐ age
- ☐ disability
- ☐ gender reassignment
- ☐ marriage or civil partnership (in employment only)
- ☐ pregnancy and maternity
- ☐ race
- ☐ religion or belief
- ☐ sex
- ☐ sexual orientation

Describe which groups are at a disadvantage

For that group, select which of the following layers of inequality is a justifiable source of differences in outcome. The justification may include 1) well-founded causal relationship to an outcome of interest (e.g. income to risk of default) and/or 2) a feature that is within the individual's control and transparently disclosed (e.g. history of paying bills on time)

- [ ] Disability
- [ ] Race
- [ ] National origin
- [ ] Socioeconomic status
- [ ] Talent/ education
- [ ] Personality traits
- [ ] Preferences
- [ ] Culture
- [ ] Discrimination in related markets

Which of the features in your data may be associated with the unjustifiable sources of differences in outcome, e.g. postcode with race?

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Is there any misalignment between the ground truth (world as-is) and the organisation's values? For example, there may be more male senior executives, but the organisation's objective is to have stronger female representation in leadership.

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End of Block: 1. Design: historical/external bias

Start of Block: 2. Data collection: Representation bias

Is the marketing / targeting / data collection strategy returning a representative sample of the population?

Ex) is the mortgage company advertised in majority-white neighborhoods?

- ○ Yes ____
- ○ No ____

Are any of the recorded features affected by human judgment?

Ex) the data set may include the interviewer's scores on the candidates' performance.

- ○ Yes ____
- ○ No ____

Are any of the recorded features produced by a third party data set or model?

Ex) the credit scores may be provided by a specialist agency

◯ Yes ____

◯ No ____

Is the ground truth of actual outcomes known?

Ex) whether denied loans would have defaulted is unknown

◯ Yes ____

◯ No ____

Is there sufficient sample in each subgroup of interest for this analysis?

Ex) only 5% of applicants are Native Americans

◯ Yes ____

◯ No ____

End of Block: 2. Data collection: Representation bias

Start of Block: 3. Feature engineering: measurement bias

Are there differences in the measurement process between groups for either input features or the target outcome?

Ex) high-minority neighborhoods are more frequently patrolled, leading to higher arrest rates

◯ Yes ____

◯ No ____

Are there differences in the data quality between groups?

Ex) schools in poor districts have lower quality recorded data on student performance

- ◯ Yes ____
- ◯ No ____

Are there any features added by the model developer that could it be affected by his/her judgment?

Ex) the data scientist added flags of what he/she considers an important feature from a job applicant's CV, e.g. "participated in university extracurricular activities" or "held a leadership position"

- ◯ Yes ____
- ◯ No ____

Are there proxies of outcome that may be also proxies of a protected group membership, especially those with a history of discrimination in this domain area?

Ex) In US mortgage lending, employees were more likely to recommend loan types that are expensive to finance to black and Hispanic applicants, which would affect their recorded loan type.

- ◯ Yes ____
- ◯ No ____

Does the measurement closely match what the model intends to track?

Ex) arrest ≠ crime rate, GPA ≠ student success

○ Yes ____

○ No ____

End of Block: 3. Feature engineering: measurement bias

Start of Block: 4. Model build and training: aggregation bias

Are the populations heterogeneous in a way that a single model cannot account for all subgroups? (See: Simpson's paradox)

Ex) Medical diagnosis algorithm should be different for men and women given their different body compositions

○ Yes ____

○ No ____

Are there other heterogeneous mechanisms in play that are being inaccurately aggregated that may be associated with protected features?

Ex) differences in behavior across products, different time periods, different data sets, etc.

○ Yes ____

○ No ____

Have you tested on the fairness metric of choice on all protected subgroup combinations?

Ex) the model has similar error rates for men and women and for black and white applicants, but it has high error rates for black women

◯ Yes ____

◯ No ____

End of Block: 4. Model build and training: aggregation bias

Start of Block: 5. Model evaluation: evaluation bias

Are all trade-offs on objectives identified for all available models? All objectives should be quantified into metrics where possible to enable model comparison

Ex) mapped the trade-off between financial inclusion and minority race denial rates for mortgage lending for 10 versions of predictive models

◯ Yes ____

◯ No ____

Do the metrics cover all measurable objectives related to positive and negative impacts on the target population?

Ex) The assessment of mortgage default prediction algorithm covers unaffordable loans (false positive), financial inclusion, minority race denial rate. It also includes qualitative assessment of explainability.

◯ Yes ____

◯ No ____

Do your metrics align with the relative importance of False Positives vs. False Negatives?

Ex) those predicted to repay but defaulted represent unaffordable loans / cost to the company, and those predicted to default but would have repaid represent missed opportunity / allocative harm

- ◯ Yes ____
- ◯ No ____

Is there a metric the model may be over-fitting to?

Ex) the main credit risk evaluation accuracy metric

- ◯ Yes ____
- ◯ No ____

Are there any disparities in sub-group performance?

Ex) Does the model have more errors among women than men?

- ◯ Yes ____
- ◯ No ____

Are confidence intervals acceptable and understood?

Ex) Especially if a sub-group population is under-represented, they may have a larger confidence interval around their predictions

- ◯ Yes ____
- ◯ No ____

End of Block: 5. Model evaluation: evaluation bias

Start of Block: 6. Model productionisation and monitoring: deployment bias

Is the model a part of a complex sociotechnical system, e.g. inter-connected models or embedded in human processes?

Ex) A CV-scoring algorithm may feed into a candidate's evaluation system

- ◯ Yes ____
- ◯ No ____

Is there an appropriate human feedback mechanism for any errors?

Ex) A human reviewer reads a sample of machine transcriptions to identify any errors and retrains the algorithm with the corrections

- ◯ Yes ____
- ◯ No ____

Is the model robust to any external changes, e.g. shifts in policy, dramatic changes in input data, etc.?

Ex) There is a monitoring mechanism in place to alert the team if there is a significant change in the distribution in the input data beyond a pre-defined threshold

- ◯ Yes ____
- ◯ No ____

Can the feedback loop be reinforcing any existing biases?

Ex) if loans predicted to default are denied. Is there any user interaction with the output?
Ex) user clicking on links recommended by the algorithm

- ○ Yes ____
- ○ No ____

End of Block: 6. Model productionisation and monitoring: deployment bias

Start of Block: Evaluate assessment

Was this survey useful in identifying potential biases in your model development lifecycle?

- ◯ Extremely useful
- ◯ Moderately useful
- ◯ Slightly useful
- ◯ Neither useful nor useless
- ◯ Slightly useless
- ◯ Moderately useless
- ◯ Extremely useless

User-friendliness (system usability scale)

1. I think that I would like to use this system frequently:

- ◯ Strongly agree
- ◯ Agree
- ◯ Neutral
- ◯ Disagree
- ◯ Strongly disagree

2. I found the system unnecessarily complex:

○ Strongly agree

○ Agree

○ Neutral

○ Disagree

○ Strongly disagree

3. I thought the system was easy to use:

○ Strongly agree

○ Agree

○ Neutral

○ Disagree

○ Strongly disagree

4. I think that I would need the support of a technical person to be able to use this system:

○ Strongly agree

○ Agree

○ Neutral

○ Disagree

○ Strongly disagree

5. I found the various functions in this system were well integrated:

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

6. I thought there was too much inconsistency in this system:

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

7. I would imagine that most people would learn to use this system very quickly

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

8. I found the system very cumbersome to use:

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

9. I felt very confident using the system

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

10. I needed to learn a lot of things before I could get going with this system

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Which sections did you find the most informative?
_______ Design: historical bias
_______ Data collection: representation bias
_______ Feature selection: measurement bias
_______ Model build: aggregation bias
_______ Model evaluation: evaluation bias
_______ Productionisation: deployment bias

Please comment on what you learned from the assessment

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Thank you for your time!

End of Block: Evaluate assessment