Ethics in Data Science

Quantititive Methods

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Bias in Data and Mathematical Models

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Basic Definitions

What is a Model?

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Use of a model in banking is fact-based (data is used to fit the model):

$$\begin{tikzcd} & \textit{data} \arrow[d, Rightarrow, "\textit{fit}"] & \\ \textit{input} \arrow[r] & \boxed{\text{MODEL}} \arrow[r] & \textit{output} \end{tikzcd}$$

What is Bias in Models?

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Definition (Bias in Mathematical Models)

Model Bias (also Algorithmic Bias) refers to the systematic and repeatable error in a Model that creates outcomes that are statistically at odds with the reality of the population whose behaviour it is supposed to reflect.

Bias in Data and Mathematical Models

Algorithmic Fairness

Fairness Assumptions

Assume S the protected feature with an under-privileged group S_u and a privileged group S_p, and predicted outcomes $\hat{Y}$.

1. **Independence**: the probability of being in S_p or S_u has nothing to do with $\hat{Y}$ – $\hat{Y}$ is independent of S.
2. **Separation**: The predicted probability of having a favourable outcome has nothing to do with membership of the protected feature – $\hat{Y}$ is independent of S, given Y.
3. **Sufficiency**: the prediction should not depend on the protected group – Y is independent of S, given $\hat{Y}$.

Bias in Data and Mathematical Models

The Confusion Matrix and Related Measures

Useful Concepts for the Confusion Matrix

The following are useful measures for how good a classification model fits its data:

- *Accuracy:* The proportion of predictions that were correctly identified.
- *Precision* (or positive predictive value): The proportion of positive cases that correct.
- *Negative predictive value:* The proportion of negative cases that were correctly identified.
- *Sensitivity* or Recall: The proportion of actual positive cases which are correctly identified.
- *Specificity:* The proportion of actual negative cases which are correctly identified.

Some Acronyms for the Confusion Matrix

Let us use the following definitions:

- Objective concepts (depends only on the data):
  - *P:* The number of positive observations ($y = 1$)
  - *N:* The number of negative observations ($y = 0$)
- Model dependent definitions:
  - True positive (TP) the positive observations ($y = 1$) that are by the model correctly classified as positive;
  - False positive (FP) the negative observations ($y = 0$) that are by the model incorrectly classified as positive – this is a false alarm (Type I error);
  - True negative (TN) the negative observations ($y = 0$) that are by the model correctly classified as negative;
  - False negative (FN) the positive observations ($y = 1$) that are by the model incorrectly classified as negative – miss (Type II error).

The Definition of the Confusion Matrix

	Observed pos.	**Observed neg.**	
Pred. pos.	TP	FP	$\text{Pos.pred.val} = \frac{TP}{TP+FP}$
Pred. neg.	FN	TN	$\text{Neg.pred.val} = \frac{TN}{FN+TN}$
	Sensitivity $= \frac{TP}{TP+FN}$ $= \frac{TP}{TP+FN}$	Specificity $= \frac{TN}{FP+TN}$ $= \frac{TN}{FP+TN}$	Accuracy $= \frac{TP+TN}{TP+FN+FP+TN}$ $= \frac{TP+TN}{TP+FN+FP+TN}$

Table 1: The confusion matrix, where "pred." refers to the predictions made by the model, "pred." stands for "predicted," and the words "positive" and "negative" are shortened to three letters.

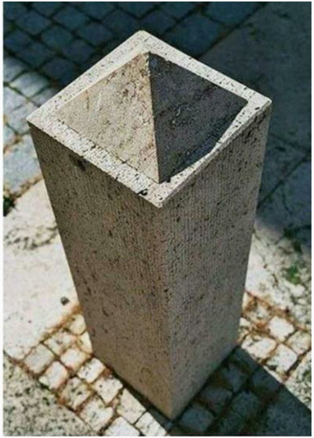
Bias in Data and Mathematical Models

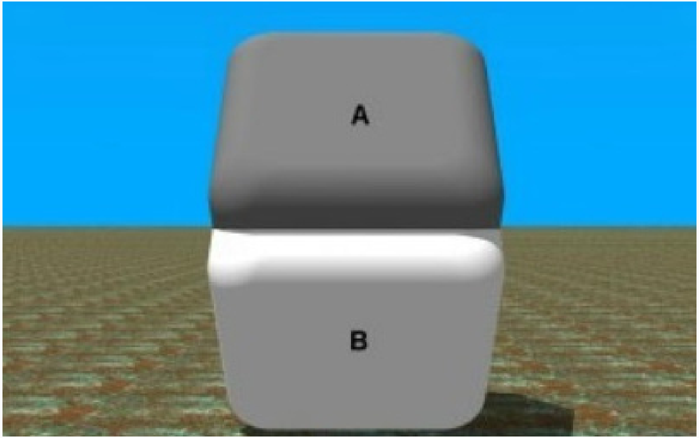
Measures for Algorithmic Fairness

Fairness Metrics

1. **Equal Opportunity**: $FNR_p = FNR_u$ (equivalent with $TPR_p = TPR_u$)
2. **Predictive Equality**: $FPR_p = FPR_u$ (equivalent with $TNR_p = TNR_u$)
3. **Equalised Odds**: both previous
4. **Predictive Parity** or outcome test: $Prec_p = Prec_u$ (equal positive predictive value or precision ($Prec = \frac{TP}{TP+FP}$))
5. **Demographic Parity**: membership of S has no correlation with favourable outcome ($\hat{Y}$).

Visual Biases are systematic miss-interpretations





Origin and Types of Bias

General Causes of Bias in Data

- **Confirmation Bias**: bias governs what we search for and we find what we search for (e.g. belief preservation via social media)

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- **Outlier Bias**: thinking about a startup one things of Google, Amazon, Facebook, etc. These are the outliers. (use median instead of average, identify outliers, etc.)

Process Related Bias

- **Reporting bias**: selective reporting of some data: citation bias, language bias (ignore reports in other languages), duplicate publication bias (copied data found twice), location bias (some studies are hard to find), publication bias (secret or not popular data is hard to find), outcome reporting bias (e.g. company does not report with much bravo when results are bad), time lag bias
- **Automation bias**: we prefer automated systems to provide data
- **Selection bias**: data is not representative (e.g. sampling bias, convergence bias (only people who got a loan are in our database), participation bias, etc.)
- **Over-generalisation bias**: no black swans in the data
- **Group Attribution bias**: generalisation of stereotypes, in-group bias (preference for members in the group), out-group bias (stereotype for other groups), etc.
- **Implicit bias**: search for conforming information

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3. the model development process (including selection of algorithm, variables, etc.)
4. the particulars of model implementation

Conclusions

Fairness is a matter of perspective

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Bias is learnt

Case Study

Case study on addressing bias: car insurance