Transparancy, Causality & Fairness

Finnian Lattimore
Australian National University
finnlattimore@gmail.com

Introduction

long vs short regressions
The rise of machine learning and big data is accompanied by increasing concerns over transparency and fairness [1]. A recent EU directive requires automated decision systems used to profile individuals must provide *"meaningful information about the logic involved."* and *"shall not be based on special categories of personal data"* [3]

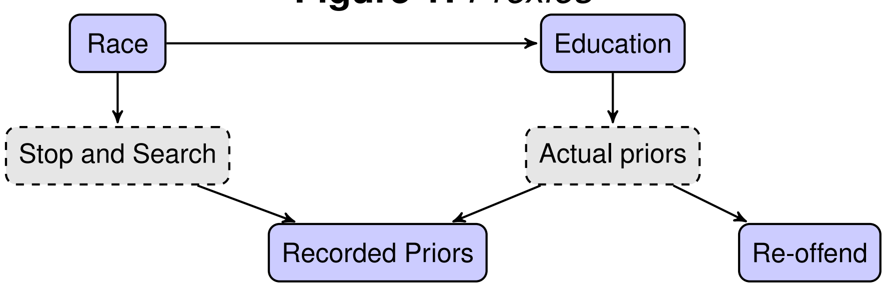
Fairness & Discrimination

Consider a binary outcome of interest Y, protected variable X, other covariates Z and a model f that outputs the probability of a positive Y for each individual.

1. *disparate treatment* Two people with otherwise identical attributes should be treated the same. $f(x,z) = f(x',z) \; \forall \; x, x', z$.
2. *disparate impact* The distribution of the outcome should be the same for all values of the protected variable. $\sum_z f(x,z)P(z|x) = C \; \forall \; x$

Disparate treatment can be trivially avoided by excluding the protected variable from the model. However, this is deeply unsatisfying given the presence of proxy variables and can increase bias (figure 1)
Avoiding *disparate impact* may be be expensive in terms of predictive accuracy and/or require *disparate treatment*.

Figure 1: *Proxies*



Transparancy/Interpretability

A desire for interpretability implies a miss-match between the real world goal and the optimisation problem presented to a machine learning algorithm [4].

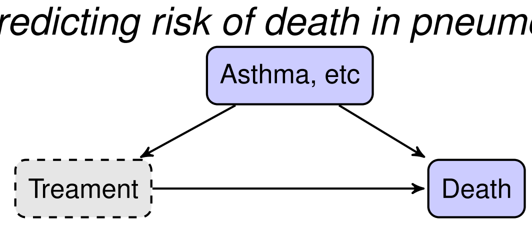
1. situations where the true objective is hard to measure or quantify. (model can be assessed in multiple different ways for hard to define characteristics such as *fairness*)
2. integration with human decision making
3. improved generalizability (users can detect and eliminate features that are irrelevant/artefacts of training data)
4. increased *trust* due to the ability to validate the model for problems such as data leaks & feedback, where acting on model predictions changes the system.
5. user *trust* leading to increased adherence to the model (irrespective of any actual advantages).

Causal Models

We define a causal model as a model which can be used to predict the outcome of an intervention or change to a system.

1. Causal models explicitly predict the outcome of an intervention. If taking actions based on the outcome of the model significantly changes the system, a causal model is required.
2. Interpretable models can mitigate some, but not all problems associated with not building a causal model eg [2] (figure 2).
3. If a model is non-causal making it transparent can lead to changes in people's behaviour that reduce the predictive accuracy of the model: Consider making the details of an automated essay marking system public.
4. If membership of a protected class, X, is not causally related to the outcome of interest, Y, then there exits a set of variables, Z, such that $X \perp\!\!\!\perp Y|Z$.

Figure 2: *Predicting risk of death in pneumonia patients*



References

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[2] Rich Caruana, Yin Lou, Johannes Gehrke, Paul Koch, Marc Sturm, and Noemie Elhadad. Intelligible Models for HealthCare. *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '15*, pages 1721–1730, 2015.

[3] Bryce Goodman and Seth Flaxman. EU regulations on algorithmic decision-making and a ”right to explanation”. In *ICML Workshop on Human Interpretability in Machine Learning*, 2016.

[4] Zachary C Lipton. The Mythos of Model Interpretability. In *ICML Workshop on Human Interpretability in Machine Learning*, pages 96–100, 2016.