Introduction to Machine Learning

Fairness in Machine Learning

Varun Chandola

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Outline

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1 Introduction to Fairness

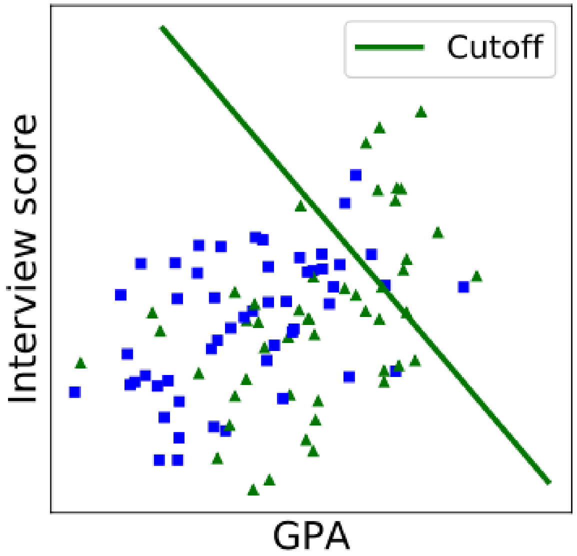
Introduction

- Main text - `https://fairmlbook.org` [1]
  - Solon Barocas, Moritz Hardt, Arvind Narayanan
- Other recommended resources:
  - Fairness in machine learning (NeurIPS 2017)
  - 21 fairness definitions and their politics (FAT* 2018)
  - Machine Bias - COMPAS Study
- Must read - The **Machine Learning Fairness Primer** by Dakota Handzlik
- Programming Assignment 3 and Gradiance Quiz #7
- Also see - The Mozilla Responsible Computer Science Challenge

2 Toy Example

Toy Example

- *Task*: Learn a ML based job hiring algorithm
- *Inputs*: GPA, Interview Score
- *Target*: Average performance review
- *Sensitive attribute*: Binary (denoted by $\square$ and Δ), represents some demographic group
  - We note that GPA is correlated with the sensitive attribute



Process

1. Regression model to predict target
2. Apply a threshold (denoted by green line) to select candidates

Toy Example

- ML models does not use sensitive attribute
- Does it mean it is fair?
- It depends on the definition of fairness

Fairness-as-blindness notion

- Two individuals with similar features get similar treatment
- This model is fair

What about a different definition of fairness?

- Are candidates from the two groups equally likely to be hired?
- No - triangles are more likely to be hired than squares
- Why did the model become unfair because of this definition?
  - In the training data, average performance review is lower for squares than triangles

Why this disparity in the data?

- Many factors could have led to this:
  - Managers who score employee's performance might have a bias
  - Workplace might be biased against one group
  - Socio-economic background of one group might have resulted in poor educational outcomes
  - Some intrinsic reason
  - Combination of these factors
- Let us assume that this disparity that was learnt by the ML model is unjustified
- How do we get rid of this?

Making ML model bias-free

- Option 1: ignore GPA as a feature
  - Might result in poor accuracy of the model
- Option 2: pick different thresholds for each sub-group

  - Model is no longer "blind"
- Option 3: add a diversity reward to the objective function
  - Could still result in poor accuracy

3 Why fairness?

Why fairness?

- We want/expect everything to be fair and bias-free
- Machine learning driven systems are everywhere
- Obviously we want them to be fair as well
  - Closely related are issues of ethics, trust, and accountability

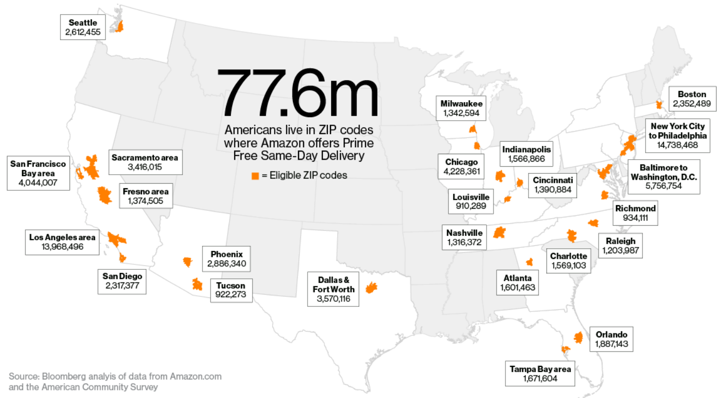
What does fairness mean?

- **Consequential decision making**: ML system makes a decision that impacts individuals
  - admissions, job offers, bail granting, loan approvals
- Should use factors that are *relevant* to the outcome of interest

Amazon same-day delivery

- A data-driven system to determine neighborhoods to offer *same-day delivery* service

- In many U.S. cities, white residents were more than twice as likely as black residents to live in one of the qualifying neighborhoods.
- *Src:* - `https://www.bloomberg.com/graphics/2016-amazon-same-day/`



ML - Antithesis to fairness

- Machine learning algorithms are based on *generalization*
- Trained on historical data which can be unfair
  - Our society has always been unfair
- Can perpetuate historical prejudices

Continuing with the Amazon example

- Amazon claims that *race* was not a factor in their model (not a feature)
- Was designed based on efficiency and cost considerations
- Race was *implicitly* coded

3.1 Defining Fairness

When is there a fairness issue?

- What if the Amazon system was such that zip codes ending in an odd digit are selected for same-day delivery?

- It is biased and maybe unfair to individuals living in the even numbered zipcodes
- But will that trigger a similar reaction?
- Is the system unfair?

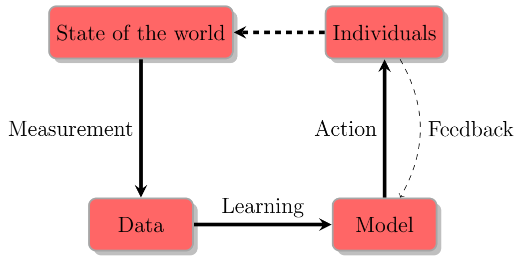
What do we want to do?

- Make machine learning algorithms fair
- Need a quantifiable fairness metric
  - Similar to other performance metrics such as precision, recall, accuracy, etc.
- Incorporate the fairness metric in the learning process
- Often leads to a tension with other metrics

Copied verbatim from the book - The attention to demographic criteria in statistics and machine learning is a relatively new direction. This reflects a change in how we conceptualize machine learning systems and the responsibilities of those building them. Is our goal to faithfully reflect the data? Or do we have an obligation to question the data, and to design our systems to conform to some notion of equitable behavior, regardless of whether or not that's supported by the data currently available to us? These perspectives are often in tension, and the difference between them will become clearer when we delve into stages of machine learning.

How does an ML algorithm becomes unfair?

- The "ML for People" Pipeline

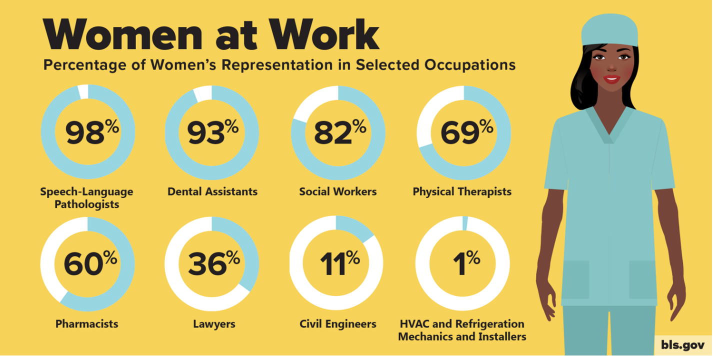


Issues with the state of the society

- Most ML applications are about people
  - Even a pothole identification algorithm
- Demographic disparities exist in society
- These get embedded into the training data
- As ML practitioners we are not focused on removing these disparities
- We do not want ML to reinforce these disparities
- The dreaded **feedback loops** [2]

Feedback loops in ML: If outcomes of the ML model are used to drive policies that can influence societal behavior, which can then bias the data and the resulting models.

The *pothold example* refers to smartphone app called "Speed Bump", which was deployed in the city of Boston, MA, to identify potholes from user uploaded images that would then trigger a maintainence request to the city. While the data-driven algorithm was about potholes, one can argue that the data reflects patterns of smartphone ownership, which is higher in wealthier parts of the city compared to low-income areas and areas with elderly people.



Measurement Issues

- Measurement of data is fraught with subjectivity and technical issues
- Measuring race, or any categorical variable, depends on how the categories are defined
- Most critical - defining the target variable
  - Often this is "made up" rather than measured objectively
  - credit-worthiness of a loan applicant
  - attractiveness of a face (beauty.ai, FaceApp)

Criminal Risk Assessment

1. Target variable - bail or not?
2. Target variable - will commit a crime later or not (recidivism)?

Clearly if the target variable is "bail or not", then this would carry the bias of the judges in the training data. "Committing a crime later" is a measurable quantity and might appear to have less risk of bias. But there is a big issue here as well – we do not really know who commits a crime, unless they are caught doing so. In that cas, this target variable might be subjected to the biases of policing.

Measurement Issues

- Technical issues can often lead to bias
  - Default settings of cameras are usually optimized for lighter skin tones [3]

- Most images data sets used to train object recognition systems are biased relative to each other

– http://people.csail.mit.edu/torralba/research/bias/

How to fix the measurement bias?

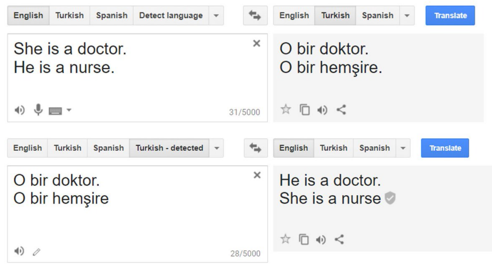
- Understand the provenance of the data
  - Even though you (ML practitioner) are working with data "given" to you
- "Clean" the data

Issues with models

- We know the training data can have biases
- Will the ML model preserve, mitigate or exacerbate these biases?
- ML model will learn a pattern in the data that assists in optimizing the objective function
- Some patterns are useful - *smoking is associated with cancer*, some are not - *girls like pink and boys like blue*
- But ML algorithm has not way of distinguishing between these two types of patterns
  - established by social norms and moral judgements
- Without a specific intervention, the ML algorithm will extract stereotypes

An Example

- Machine translation



How to make the ML model more fair

- Model reflects biases in the data
- Withold sensitive attributes (gender, race, ...)
- Is that enough?

Unfortunately not

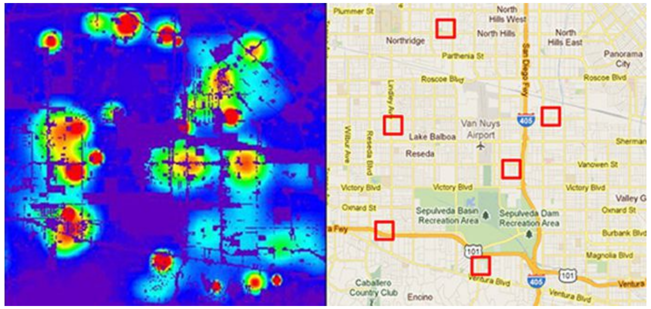
- There could be *proxies* or *redundant encodings*
- Example - Using "programming experience in years" might indirectly encode gender bias
  - Age at which someone starts programming is well-known to be correlated with gender

How to make the ML model more fair

- Better objective functions that are fair to all sub-groups
  - More about this in next lecture
- Ensure equal error rate for all sub-groups

  The Nymwars Controversy

  - Google, Facebook and other companies blocking users with uncommon names (presumably *fake*)
  - Higher error rate for cultures with a diverse set of names



The pitfalls of action

- While as ML practitioners our world ends after we have trained a *good* model
- But this model will impact people
- Need to understand that impact in the larger socio-technical system
  - Are there disparities in the error across different sub-groups?
  - How do these disparities change over time (drift)?
  - What is the perception of society about the model?
    - Ethics, trustworthiness, accountability
    - Explainability and interpretability
    - **Correlation is not causation**

Correlation is not causation is an extremely important concept when trying to explain and interpret machine learning models. ML models only pick up correlations between the inputs and outputs. But that does not mean that we can claim that the input *causes* the output.

The perils of feedback loops

- The "actions" made by individuals based on the predictions of the ML model could be fed back into the system, either explicitly or implicitly

  - Self-fulfilling predictions
  - Predictions impacting the training data
  - Predictions impacting the society

4 References

References

[1] S. Barocas, M. Hardt, and A. Narayanan. *Fairness and Machine Learning*. fairmlbook.org, 2019. `http://www.fairmlbook.org`.

[2] D. Ensign, S. A. Friedler, S. Neville, C. Scheidegger, and S. Venkatasubramanian. Runaway feedback loops in predictive policing. In *Conference on Fairness, Accountability and Transparency, FAT 2018, 23-24 February 2018, New York, NY, USA*, volume 81 of *Proceedings of Machine Learning Research*, pages 160–171. PMLR, 2018.

[3] L. Roth. Looking at shirley, the ultimate norm: Colour balance, image technologies, and cognitive equity. *Canadian Journal of Communication*, 34:111–136, 2009.