Introduction to Machine Learning

Fairness in Machine Learning

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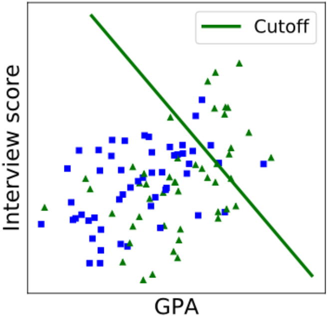
Outline

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 (FAccT 2018)
  - Machine Bias - COMPAS Study
  - Mehrabi, Ninareh, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. **"A survey on bias and fairness in machine learning."** ACM computing surveys (CSUR) 54, no. 6 (2021): 1-35.

Toy Example

- *Task*: Learn a ML based job hiring algorithm
- *Inputs*: GPA, Interview Score
- *Target*: Average performance review
- *Sensitive attribute*: Binary (denoted by □ 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

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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?

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- 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?

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
  - 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

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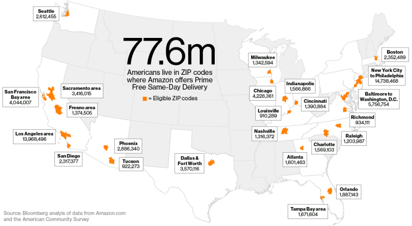
- Option 2: pick different thresholds for each sub-group
  - Model is no longer "blind"
- Option 3: add a diversity reward to the objective function
  - Could still result in poor accuracy

Why fairness?

- We want/expect everything to be fair and bias-free
- Machine learning driven systems are everywhere : admissions, job offers, bail granting, loan approvals
- Obviously we want them to be fair as well
  - Closely related are issues of ethics, trust, and accountability

- 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

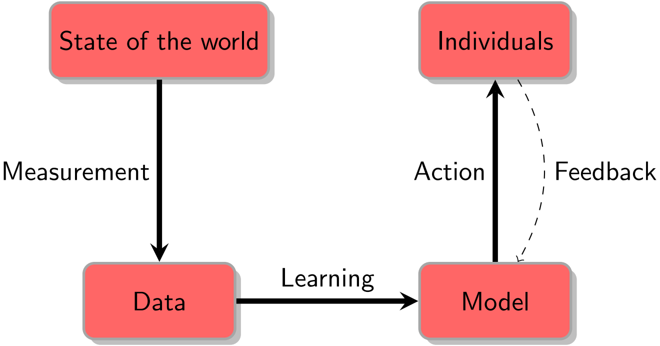
- Amazon claims that *race* was not a factor in their model (not a feature)
- Was designed based on efficiency and cost considerations
- Race was *implicitly* coded

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

How does an ML algorithm becomes unfair?

- The “ML for People” Pipeline



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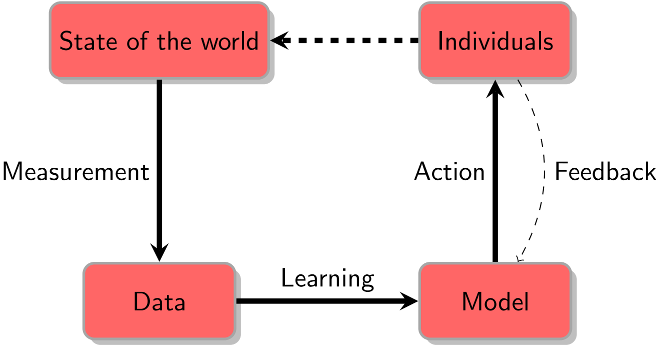
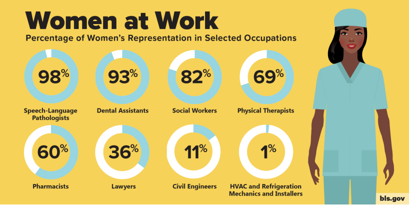
- The "ML for People" Pipeline



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** [3]



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)?

Measurement Issues

- Technical issues can often lead to bias
  - Default settings of cameras are usually optimized for lighter skin tones [5]

- 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?

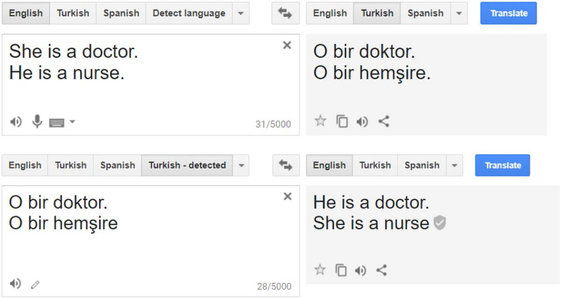
- Understand the provenance of the data
  - Even though you (ML practitioner) are working with data “given” to you
- “Clean” the data

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
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- Is that enough?

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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
- Ensure equal error rate for all sub-groups

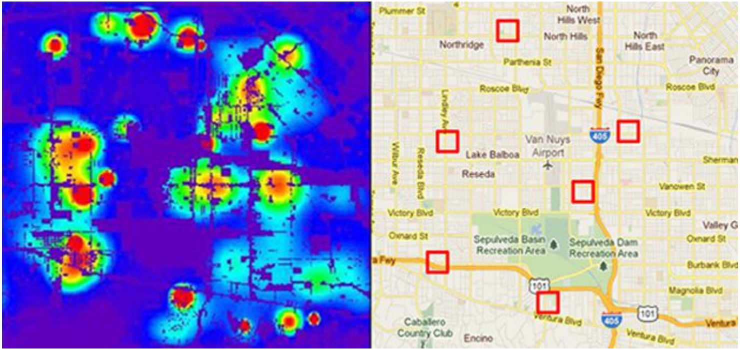
The Nymwars Controversy

- 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**

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

Problem Setup

Notation

- Predict Y given $\mathbf{X}$
- Y is our target class $Y \in \{0, 1\}$
- $\mathbf{X}$ represents the input feature vector

Example

- Y - Will an applicant pay the loan back?
- $\mathbf{X}$ - Applicant characteristics - credit history, income, etc.

Supervised Learning

- Given training data: $(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)$
- Either learn a function f, such that:

$$y^* = f(\mathbf{x}^*)$$

- Or, assume that the data was drawn from a probability distribution
- In either case, we can consider the classification output as a random variable $\hat{Y}$
- Now we have three random variables:

$$\mathbf{X}, Y, \hat{Y}$$

- We are going to ignore how we get $\hat{Y}$ from $\mathbf{X}$ for these discussions

How do we measure the quality of a classifier?

- So far we have been looking at accuracy

A different way to look at accuracy

$$\text{Accuracy} \equiv P(Y = \hat{Y})$$

- Probability of the predicted label to be equal to the true label
- How do we calculate this?

Accuracy is not everyting!

- Consider a test data set with 90 examples with true class 1 and 10 examples with true class 0
- A *degenerate* classifier that classifies everything as label 1, would still have a 90% accuracy on this data set

Other evaluation criteria

Event	**Condition**	**Metric**
$\hat{Y} = 1$	$Y = 1$	True positive rate (recall on positive class)
$\hat{Y} = 0$	$Y = 1$	False negative rate
$\hat{Y} = 1$	$Y = 0$	False positive rate
$\hat{Y} = 0$	$Y = 0$	True negative rate (recall on negative class)

- Here we are treating class label 1 as the positive class and class label 0 as the negative class.

We can swap the condition and the event

Event	**Condition**	**Metric**
$Y = 1$	$\hat{Y} = 1$	precision (on positive class)
$Y = 0$	$\hat{Y} = 0$	precision (on negative class)

Score Functions

- Often classification involves computing a **score** and then applying a threshold
- E.g., Logistic regression: first calculate $P(Y = 1|\mathbf{X} = \mathbf{x})$, then apply a threshold of 0.5
- Or, Support Vector Machine: first calculate $\mathbf{w}^\top \mathbf{x}$ and then apply a threshold of 0

Conditional Expectation

$$r(\mathbf{x}) = \mathbb{E}[Y|\mathbf{X} = \mathbf{x}]$$

- We can treat it as a random variable too $R = \mathbb{E}[Y|\mathbf{X}]$
- This is what logistic regression uses.

From scores to classification

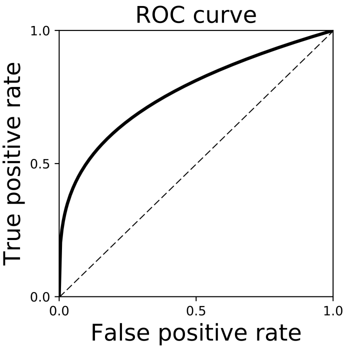
- Use a threshold t

$$y = \begin{cases} 1 & \text{if } r(\mathbf{x}) \geq t, \\ 0 & \text{otherwise} \end{cases}$$

- What threshold to choose?
  - If t is high, only few examples with very high score will be classified as 1 (accepted)
  - If t is low, only few examples with very low score will be classified as 0 (rejected)

The *Reciever Operating Characteristic* (ROC) Curve

- Exploring the entire range of t
- Each point on the plot is the FPR and TPR for a given value of t
- Area under the ROC curve or AUC is a quantitative metric derived from ROC curve

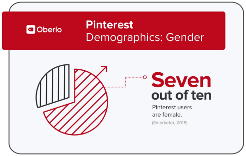


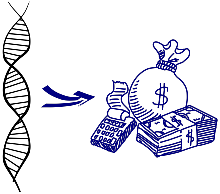
Sensitive Attributes

- Let A denote the attribute representing the sensitive characteristic of an individual
- There could be more than one sensitive attributes

Things to remember

- It is not always easy to identify A and differentiate it from $\mathbf{X}$
- Removing the sensitive attribute from $\mathbf{X}$ does not guarantee fairness
- Removing the sensitive attribute could make the classifier less accurate
- Not always a good idea to remove the impact of sensitive attributes





Quantifying Fairness

- Let us define some reasonable ways of measuring fairness
  - There are several ways to do this
  - All are debatable
- Three different categories

Independence	**Separation**	**Sufficiency**
$\hat{Y} \perp\!\!\!\perp A$	$\hat{Y} \perp\!\!\!\perp A \mid Y$	$Y \perp\!\!\!\perp A \mid \hat{Y}$

- Y - True label; $\hat{Y}$ - Predicted label; A - Sensitive attribute;

Conditional Independence

$$A \perp\!\!\!\perp B|C \Leftarrow P(A, B|C) = P(A|C)P(B|C)$$

- Amount of Speeding fine $\perp\!\!\!\perp$ Type of Car | Speed

Independence

$$P(\hat{Y} = 1 | A = a) = P(\hat{Y} = 1 | A = b), \forall a, b \in A$$

- Referred to as *demographic parity*, *statistical parity*, *group fairness*, *disparate impact*, etc.
- Probability of an individual to be assigned a class is equal for each group

Disparate Impact Law

$$\frac{P(\hat{Y} = 1 | A = a)}{P(\hat{Y} = 1 | A = b)} \geq 1 - \epsilon$$

For $\epsilon = 0.2$ - *80 percent rule*

Issues with independence measures

- *The self fulfilling prophecy* [2]
- Consider the hiring scenario where the model picks p excellent candidates from group a and p poor quality candidates from group b
  - Meets the independence criteria
  - However, it is still unfair

How to satisfy fairness criteria?

1. **Pre-processing phase**: Adjust the feature space to be uncorrelated with the sensitive attribute.
2. **Training phase**: Build the constraint into the optimization process for the classifier.
3. **Post-processing phase**: Adjust a learned classifier so that it is uncorrelated to the sensitive attribute

Separation

$$\hat{Y} \perp\!\!\!\perp A | Y$$

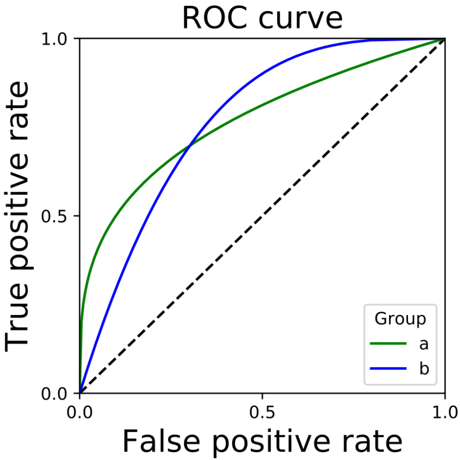
- Alternatively, the true positive rate and the false positive rate is equal for any pair of groups:

$$\begin{aligned} P(\hat{Y} = 1 | Y = 1, A = a) &= P(\hat{Y} = 1 | Y = 1, A = b) \\ P(\hat{Y} = 1 | Y = 0, A = a) &= P(\hat{Y} = 1 | Y = 0, A = b) \\ \forall a, b \in A \end{aligned}$$

- Can handle the discrepancy with the independence metric mentioned earlier

How to achieve separation

- Apply post-processing step using the ROC Curve
- Plot ROC curve for each group
- Within the constraint region (overlap), pick a classifier that minimizes the given cost



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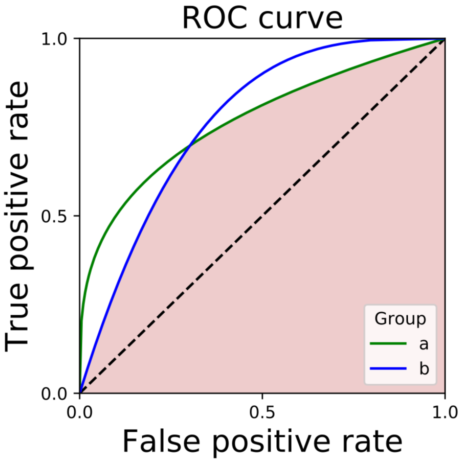


Sufficiency

$$Y \perp\!\!\!\perp A | R$$

- Alternatively, the precision is equal for any pair of groups:

$$P(Y = 1 | R = r, A = a) \quad = \quad P(Y = 1 | R = r, A = b)$$
$$\forall r \in dom(R) \text{ and } a, b \in A$$

Achieving sufficieny by calibration

What is calibration?

- Let us revert back to the score R
  - Recall that $\hat{Y}$ was obtained by applying a threshold on R
- R is *calibrated*, if for all r in the domain of R:

$$P(Y = 1|R = r) = r$$

- Of course, this means that R should be between 0 and 1
- *Platt Scaling*: Converts an uncalibrated score to a calibrated score [4]

- Calibration by group implies sufficiency
  - Apply Platt scaling to each group defined by the sensitive attribute

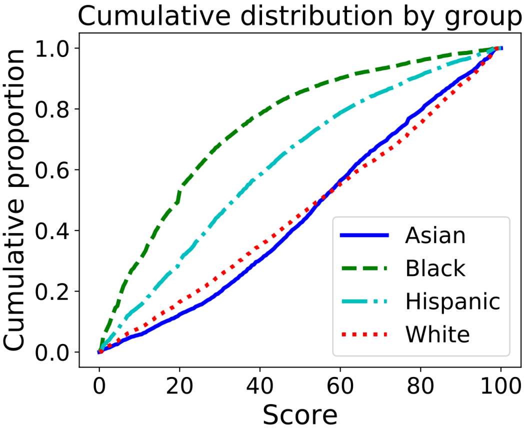
Case Study: Credit Scoring

- Extend loan or not - based on the risk that a loan applicant will default on a loan
- Data from the *Federal Reserve*
  - A - Demographic information (race)
  - R - Credit score
  - Y - Default or not (defined by credit bureau)

Table: Credit score distribution by race

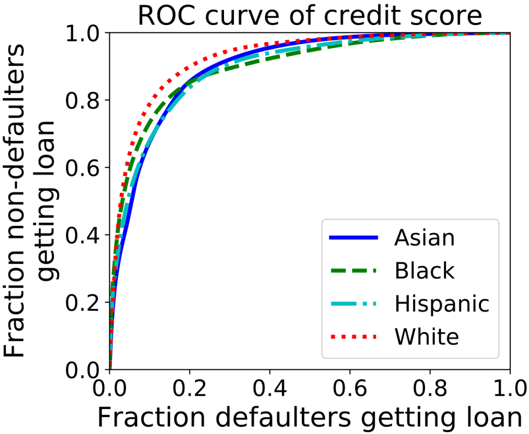
Race or ethnicity	Samples with both score and outcome
White	133,165
Black	18,274
Hispanic	14,702
Asian	7,906
Total	174,047

Group-wise distribution of credit score



- Strongly depends on the group

Using credit score for classification



- How make the classifier fair?

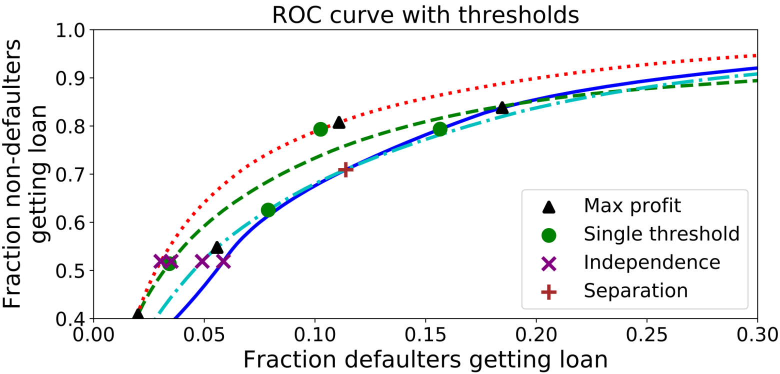
Four Strategies

1. *Maximum profit*: Pick group-dependent score thresholds in a way that maximizes profit
2. *Single threshold*: Pick a single uniform score threshold for all groups in a way that maximizes profit
3. *Separation*: Achieve an equal true/false positive rate in all groups. Subject to this constraint, maximize profit.
4. *Independence*: Achieve an equal acceptance rate in all groups. Subject to this constraint, maximize profit.

What is the profit?

- Need to assume a reward for a true positive classification and a cost/penalty for a false positive classification
- We will assume that cost of a false positive is 6 times greater than the reward for a true positive.

Comparing different criteria



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