Lecture 14

ML and the Real World

„The Algorithmic Foundations of Differential Privacy" by Dwork and Roth. Chapters: 2, 3.1 – 3.3
„Fairness and Machine Learning" by Barocas, Hardt, and Narayanan. Chapters: 3

Jilles Vreeken
Aleksandar Bojchevski

UNIVERSITÄT DES SAARLANDES

CISPA HELMHOLTZ CENTER FOR INFORMATION SECURITY

Overview

In the previous lectures we were focusing on models and algorithms and we were optimizing for simple metrics, e.g. misclassification rate, reconstruction error, etc

As ML/AI is becoming more widespread and is used in critical applications (e.g. algorithmic decision-making involving humans) we have to consider societal impacts

As ML models get deployed in the real-world they create feedback loops which can have potentially unintended consequences

We should always ask: ”Are we optimizing for the right thing?”

Beyond Accuracy we Have to Consider

- Privacy: how to avoid revealing (sensitive) information about the individuals in the training set (e.g. medical diagnosis)
- Fairness: how can we ensure that the system does not disadvantage particular individuals or (marginalized) groups
- Security: what if an attacker can "fool" the system with malicious input, poison the training data, "steal" the model, etc.?
- Explainability: people should be able to understand why and how a decision was made about them (GDPR)
- Uncertainty: we should be able to quantify how confident we are in our predictions
- Accountability: an outside auditor should be able to verify that the system is functioning as intended

Other important considerations: carbon footprint, fair and ethical data collection, etc.

Impact of AI/ML More Broadly

- How should self-driving cars trade off the safety of passengers, pedestrians, etc.? (Trolley problems)
- Face recognition and other surveillance-enabling technologies
- Autonomous weapons
- Risk of international AI arms races
- Long-term risks of super-intelligent AI
- Unemployment due to automation
- Bad side effects of optimizing for click-through

Disclaimer

These concepts sound "vague" and properly formalizing them is half the challenge

- most of today's topics are active areas of research with serious effort starting only around 5 years ago

Any "solution" can only be partly technical and tackling these issues must always involve social/legal/political aspects and must be an interdisciplinary effort

Given the above we will focus on two topics: privacy and fairness since they have well-established technical principles and techniques that address at least a part of the problem

Anonymization is Hard

US government releases a dataset of medical visits (Sweeney, '13)

- identifying info (names, addresses and SSNs) was removed
- data on zip code, birth date, and gender was left
- around 87% of Americans are uniquely identifiable from this triplet

Netflix Challenge: competition to improve movie recommendations

- dataset of 100 million movie ratings with anonymized user ID
- 99% of users who rated at least 6 movies could be identified by cross-referencing with IMDB reviews (associated with real names) (Narayanan & Smahtikov '08)

Re-Identifying 40% of anonymous volunteers in DNA Study (Sweeney, '13)

"A Face is Exposed for AOL Searcher No. 4417749" (Barrabo, '06)

Example of Why Anonymization is Hard

It is not sufficient to prevent unique identification of individuals

- if we know that Rebecca is 55 and is in this (fictional) database, then we know she has 1 of 2 diseases

Name	Age	Gender	Zip	Smoker	Diagnosis
*	60-70	Male	191**	Y	Heart disease
*	60-70	Female	191**	N	Arthritis
*	60-70	Male	191**	Y	Lung cancer
*	60-70	Female	191**	N	Crohn's disease
*	60-70	Male	191**	Y	Lung cancer
*****	**50-60**	**Female**	**191****	**N**	**HIV**
*	50-60	Male	191**	Y	Lyme disease
*	50-60	Male	191**	Y	Seasonal allergies
*****	**50-60**	**Female**	**191****	**N**	**Ulcerative colitis**

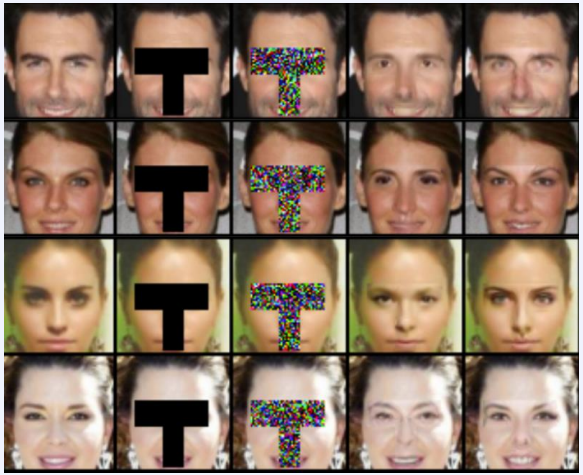
(Kearns & Roth, The Ethical Algorithm)

Sensitive Information in the Model

Even if you don't release the raw data, the weights of a trained network might reveal sensitive information

Model inversion attacks recover information about the training data from the trained model

Example 1: Reconstructing faces given a classifier trained on private data and a generative model trained on public data



reconstructing faces (Zhang et al., 2019)

Example 2: Email provider uses language models for email autocompletion, the model can remember (and spit out) sensitive info from past emails

The Main Question in Differential Privacy

How can we compute (statistical) queries and train ML models without leaking (too much) (sensitive) information about any individual?

Warmup: Randomized Response

Goal: Conduct a survey on a potentially incriminating or sensitive question with a binary (yes/no) answer

Examples

- Have you ever committed tax fraud?
- Does anyone in your family suffer from HIV?

We would like to motivate the participants to answer truthfully despite the sensitive nature of the question

Idea: introduce randomization to provide plausible deniability

Warmup: Randomized Response

Let each of the n participants follow the procedure (Warner, 1965)

- flip a coin
- if it lands tails answer truthfully
- else flip another coin. If it lands tails answer Yes, else answer No

What is the fraction of participants that answer Yes truthfully?

We can accurately estimate the population mean μ from the randomized responses by $\mu = \frac{1}{4}(1 - \hat{\mu}) + \frac{3}{4}(\hat{\mu})$, where $\hat{\mu}$ is the MLE (i.e. the counts)

- $P(\text{response} = \text{Yes} \mid \text{truth} = \text{Yes}) = \frac{3}{4}$
- $P(\text{response} = \text{Yes} \mid \text{truth} = \text{No}) = \frac{1}{4}$
- μ is an unbiased estimator of the non-randomized mean $\hat{\mu}$, the variance decays as $\frac{1}{n}$ but it is $4\times$ larger because of the randomization

Beyond Randomized Response

With **randomized response** we could compute useful queries (e.g. the fraction) in aggregate without learning the truthful answer for any individual

In general, randomness is a useful technique for preventing information leakage

Question: How to answer more complex (general) queries (e.g. computing arbitrary functions over data) with mathematical privacy guarantees?

Answer: **Differential Privacy**

Differential Privacy (DP)

- A (trusted) curator is given access to some input data $X \in \mathcal{X}$
- the curator computes some function $Y = f(x)$
- the curator wants to release the output $Y \in \mathcal{Y}$ to the public without leaking (too much) information

Example:

- let $\mathcal{X} = \{0,1\}^n$ is the set of binary vectors, e.g. containing the answers to a survey question for n users
- let f be the mean, thus $\mathcal{Y} \in [0,1]$
- let $X, X' \in \mathcal{X}$ be two "neighboring" input vectors, such that X' differs from X in only one position
  - they differ in the answer of a single participant

Informally, DP enforces that $f(X)$ and $f(X')$ also do not differ significantly preventing to leak the answer of the new participant

Differential Privacy

Given an input and output spaces $\mathcal{X}$ and $\mathcal{Y}$, a symmetric neighboring relation $\simeq$, a function of interest f, and a privacy parameter $\epsilon \geq 0$

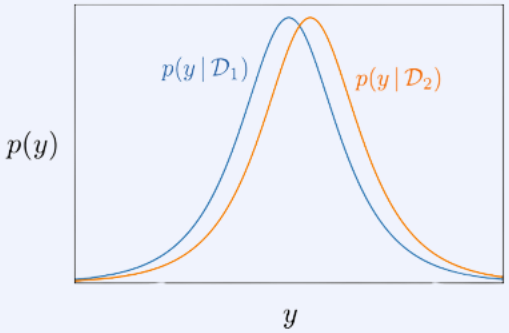
Definition: A randomized mechanism $\mathcal{M}_f: \mathcal{X} \to \mathcal{Y}$ is ϵ-differentially private if **for all** neighboring inputs $X \simeq X'$ and **for all** sets of outputs $\mathrm{Y} \subseteq \mathcal{Y}$ we have:

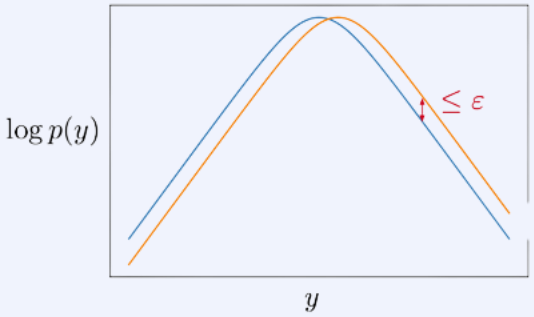
$$e^{-\epsilon} \leq \frac{P\left(\mathcal{M}_f(X) \in Y\right)}{P\left(\mathcal{M}_f(X') \in Y\right)} \leq e^{\epsilon}$$

$\mathcal{M}_f$ includes the function f we want to compute, it is not useful to output random numbers

Differential Privacy Intuition

The outcome should not change by much if we modify the information of a single instance





difference between two neighboring datasets

- $\simeq$ captures what is protected, e.g. two different vectors X and X' that differ in a single coordinate, or two different datasets $\mathcal{D}$ and $\mathcal{D}'$ that differ in single instance
- if the mechanism $\mathcal{M}_f$ behaves nearly identically X and X' an attacker can't tell whether X or X' was used and thus can't learn much about the individual

Laplace Mechanism (Output Perturbation)

Define the global sensitivity of a function $f: X \to \mathbb{R}^d$ as $\Delta = \max_{X \simeq X'} \|f(X) - f(X')\|_1$

- it measures the magnitude by which a single instance can change the output of f in the worst case

Output perturbation with Laplace noise:

- a curator holds data X
- the curator computes the function $f(X)$
- they sample Laplace noise $Z \sim \mathbf{Lap}\left(0, \frac{\Delta}{\epsilon}\right)^d$ i.i.d. for each dimension
- they reveal the noisy value $f(X) + Z$

We can prove that this mechanism is ϵ-differentially private

Example: Laplace Mechanism for the Mean

Computing the mean $\mu = f(X) = f(x_1, \dots, x_n) = \frac{1}{n}\sum x_i$ where $x_i \in \{0, 1\}$ are binary

The global sensitivity is $\Delta = \frac{1}{n}$

- changing the value of a single instance can change the output by at most $\frac{1}{n}$

Sample noisy $Z \sim \mathbf{Lap}\left(0, \frac{1}{\epsilon n}\right)$ and release the noisy mean $\hat{\mu} = \mu + Z$

In this case we can also say something about the utility of this mechanism

- $|\hat{\mu} - \mu| = \mathbf{Exponential}(\epsilon n)$ which has a mean of $\frac{1}{\epsilon n}$
- the true mean is not going to differ by much from the randomized mean and this difference decreases with the size of the data
- in general, computing the sensitivity of a function is challenging, and showing something about the utility is even more challenging

Differential Privacy for Machine Learning

Perturb input: perturb $\mathcal{D}$ and directly and rely on the post-processing property

- **robustness to post-processing**: if $\mathcal{M}$ is ϵ-DP then $\mathbf{g} \circ \mathcal{M}$ is ϵ-DP for any function g
- you can apply any function g on an output from a DP mechanism and the new output remains DP, as long as you don't touch again the data

Perturb weights: compute the optimal param θ^* and perturb them with Laplace noise

- need to calculate the global sensitivity of the optimization procedure which can be extremely difficult

Perturb objective: optimize $\mathcal{L}(\mathcal{D}, \theta) + \theta^T Z$ where Z is some carefully selected noise

Perturb gradients: perturb and release the gradient of $\mathcal{L}$ w.r.t. a mini-batch of the data

- useful in **federated learning** where we have no centralized entity that has access to all the data

Differential Privacy Summary

A lot of ML models are trained on datasets containing sensitive information about individuals, and database reconstruction attacks can be surprisingly effective

Differential privacy gives a way of provably preventing (much) information about individuals from leaking

The Laplace mechanism is an important building blocks of differential privacy

Differentially private algorithms can accurately answer queries for large populations

- The 2020 US Census used differential privacy

Motivation: The Influence of Biased Algorithms

- Selecting job applicants: XING ranks less qualified male candidates higher than more qualified female candidates (Lahoti et al. 2018)
- Recidivism prediction and predictive policing: COMPAS: high-risk FP: 23.5% for white vs. 44.9% for black, and low-risk FP: 47.7% for white vs. 28.0% for black (ProPublica article)
- Facial recognition: Commercial software has much lower accuracy on females with darker color (Buolamwini and Gebru, 2018)
- Search and recommendations: Search queries for African-American names more likely to return ads suggestive of an arrest (Sweeney, 2019)
- Bias found in word embeddings and translation: man-woman=surgeon-nurse (Bolukbasi et al. 2016)

What Causes the Bias?

- Tainted training data: any ML system maintains (and amplifies) the existing bias in the data caused by human bias, e.g. hiring decisions made by a (biased) manager used as labels, historic and systematic biases in the data collection process, etc.
- Skewed sample: initial predictions influence future observations, e.g. regions with initial high crime rate get more police attention (and thus higher recorded crime in the future), selection bias
- Proxies: even if we exclude legally protected features (e.g. race, gender, sexuality) other features may be highly correlated with these
- Sample size disparity: models will tend to fit the larger groups first (possibly) trading off accuracy for minority groups
- Limited features: features may be less informative or reliably collected for minority groups

Why Fairness is Hard

How to define fairness?

How can we formulate it so it can be considered in ML systems?

Two distinct notions from the law (Barocas and Selbst, 2016):

- **Disparate treatment:** decisions are (partly) based on the subject's sensitive attribute
- **Disparate impact:** disproportionately hurt (or benefit) people with certain sensitive attribute values

Currently, no consensus on the mathematical formulations of fairness

An Illustrating Example

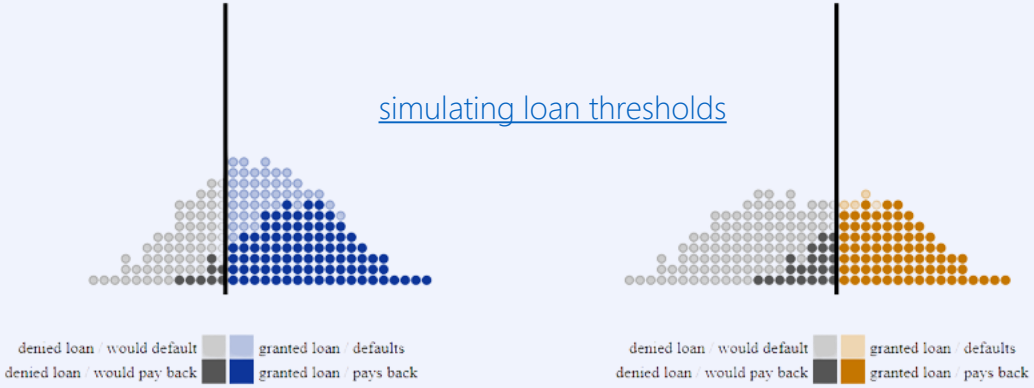
We are a bank trying to fairly decide who should get a loan

- i.e. predict which people will likely pay us back and which will default

We have two groups: blue and orange (the sensitive attribute)

- this is where discrimination could occur

simulating loan thresholds



Definitions of Fairness

How can we test if our (loan repay) classifier is fair?

Group fairness: aim to treat all groups equally

- e.g. we can require that the same percentage of blue and orange receive loans
- or equal false negative rates $P(\text{no loan} \mid \text{would repay}, \text{orange}) = P(\text{no loan} \mid \text{would repay}, \text{blue})$

Individual fairness: treat similar examples similarly for an appropriate definition of similarity

Counterfactual fairness: same decision in the actual world and a counterfactual world where the individual belongs to a different group

Group Fairness Setup

Consider binary classification with single sensitive attribute for simplicity:

- X are the features of an individual (e.g. credit history)
- $A = \{a, b, c, \dots\}$ is the sensitive attribute (gender, race, etc.)
- $R = r(X, A) \in \{0, 1\}$ is the binary predictor (e.g. to grant a loan or not) which makes a decision
- $Y \in \{0, 1\}$ is the target variable representing the ground truth

Assume that $(X, A, Y) \sim \mathcal{D}$ are generated from an underlying data distribution
Then X, A, Y and R are all random variables

Shortcut notation for the probability conditional on group a: $P_a(R) = P(R \mid A = a)$

Naive Approach: Fairness Through Unawareness

We should not include the sensitive attribute as a feature in the training data

$R = r(X)$ instead of $R = r(X, A)$

Pros/Cons:

- intuitive, easy to use and implement
- consistent with disparate treatment which has legal support (e.g. the "General Equal Treatment Act" in Germany)
- however, there can be many highly correlated features (e.g. neighborhood) that are proxies of the sensitive attribute (e.g. race)

First Criterion: Independence

Require: R independent of A, denoted $R \perp A$

- also called Demographic Parity, Statistical Parity, Group Fairness, Darlington Criterion (4)

In case of binary classification for all groups a, b it has to hold $P_a(R = 1) = P_b(R = 1)$

- there are also approximate version where we allow the probabilities to be approximately equal $(\pm\epsilon)$

In our example, this means that the acceptance rates of the applicants from the two groups must be equal, i.e. same percentage of applications receive loans

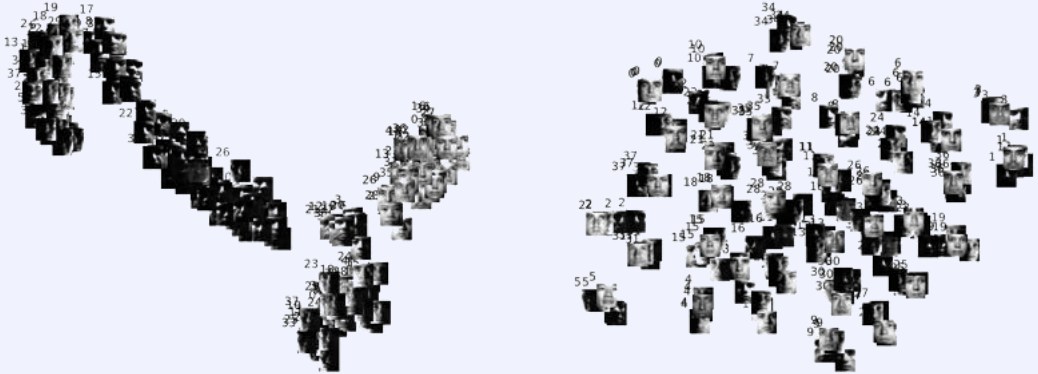
How to Achieve Independence?

Post-processing: adjust a learned classifier so as to be uncorrelated with the sensitive attribute

Training time constraint: include the exact/approximate constraints in the optimization

Pre-processing: e.g. via representation learning

- map the instances into some space where information about A is destroyed (e.g. fair PCA)
- example representations learned by a variational fair autoencoder (Louizos et al., 2016)



Pros/Cons of Independence

Legal support: "four-fifth rule" prescribes that a selection rate for any disadvantaged group that is less than four-fifths of that for the group with the highest rate must be justified

What if 83% of Blue is likely to repay, but only 43% of Orange is?

- then independence is too strong
- rules out perfect predictor $R = Y$ when the base rates are different

Laziness: we can trivially satisfy the criterion if we give loan to qualified people from one group and random people from the other

Second Criterion: Separation

Require: R and A to be independent **conditional** on the target Y, denoted $R \perp A \mid Y$

- also called Equalized Odds, Conditional Procedure Accuracy, Avoiding Disparate Mistreatment

In case of binary classification for all groups a, b it has to hold

$P_a(R = 1 \mid Y = 1) = P_b(R = 1 \mid Y = 1)$ equal true positive (TP)

$P_a(R = 1 \mid Y = 0) = P_b(R = 1 \mid Y = 0)$ equal false positive (FP)

Equality of opportunity is a commonly used relaxation where we only match TP

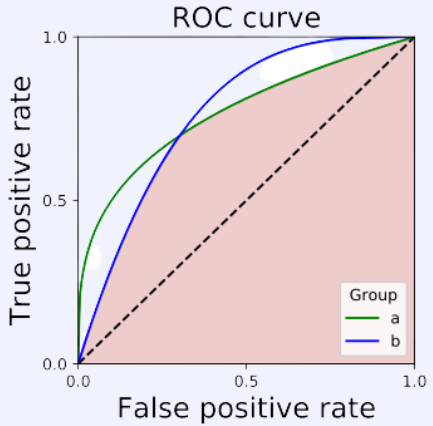
- in our example, this means we should give loan to equal proportion of individuals who would repay

Achieving Separation

Area under the ROC (Receiver Operating Characteristic) curve

- each point on the solid curves is realized by thresholding the predicted score at some value
- i.e. predict $r(X, A) > t$ for some threshold t

Pick a classifier that minimizes the given cost (e.g. maximizes profit)



intersection of areas under the curves for two groups

Pros/Cons of Separation

Optimal predictor not ruled out: $R = Y$ is now allowed

Penalizes laziness: it provides incentive to reduce errors uniformly in all groups

It may not help closing the gap between two groups

- granting more loans to the group that is more likely to repay **now** makes the groups more likely to have better living conditions and thus even more likely to repay in the **future**, thus widening the gap

Third Criterion: Sufficiency

Require Y and A to be independent conditional on R, denoted $Y \perp A \mid R$

- also called Cleary model, Conditional Use Accuracy, Calibration Within Groups

In case of binary classification for all groups a, b and all output probabilities r it has to hold

$$P_a(Y = 1 \mid R = r) = P_b(Y = 1 \mid R = r)$$

In our example, the score used to determine if a candidate would repay should reflect the candidate's real/actual capability of repaying

Achieving Sufficiency

In general a classifier R is calibrated if for all $r \in [0, 1]$ we have $P(Y = 1 \mid R = r) = r$

- of all instances assigned a probability or score value r an r fraction of them should be positive

Calibration for each group implies sufficiency: $P_a(Y = 1 \mid R = r) = r$ for all groups a

We can apply standard calibration techniques to each group (if necessary)

- Platt scalling: given an uncalibrated score treat it as a single feature and fit a one variable regression model against Y

Pros/Cons of Sufficiency

Satisfied by the Bayes optimal classifier

For predicting Y we do not need to see A when we have R

Equal chance of success ($Y = 1$) given acceptance ($R = 1$)

Similar to before it may not help closing the gap between the groups

Fairness Summary: Growing List of Criteria

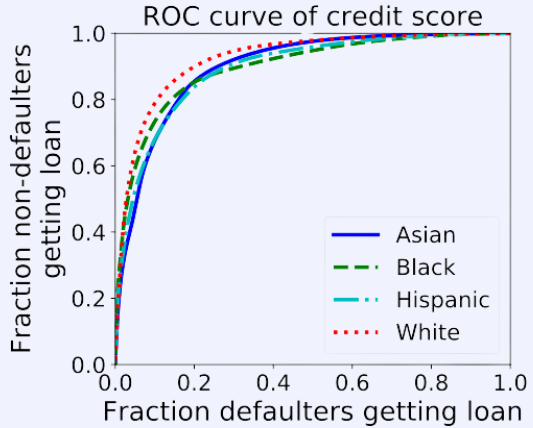
- Independence: $R \perp A$
- Separation: $R \perp A \mid Y$
- Equality of opportunity: $R \perp A \mid Y = 1$
- Sufficiency: $\mathrm{Y} \perp A \mid R$
- … and many many more

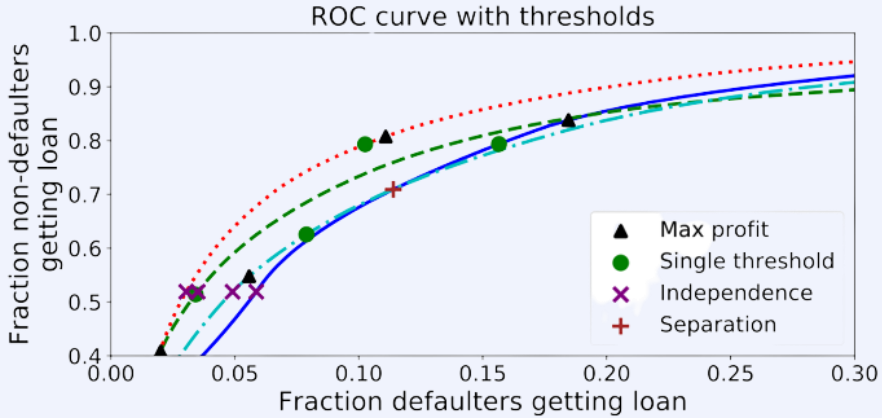
Many of these definitions are **provably incompatible**, i.e. they are mutually exclusive except in degenerate cases

Comparing Different Criteria

The cost of FP is typically much greater than the profit for TP

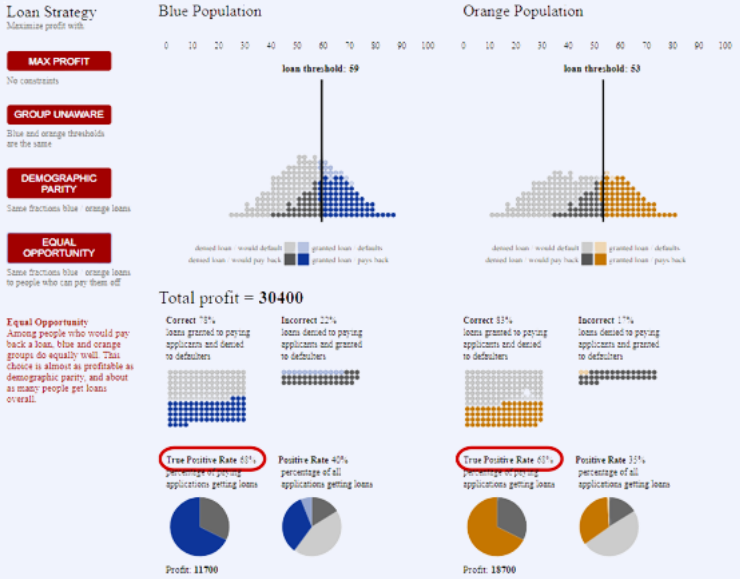
- example: different thresholds induced by different criteria (Hardt et al., 2016)





Visualizing the Trade-offs

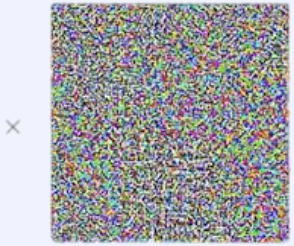
[Attacking discrimination with smarter machine learning]



Bonus: Robustness to Adversarial Examples

Deliberate data perturbations designed to achieve a specific malicious goal (misclassification)

predicted: panda



(Goodfellow et. al, 2014)

predicted: gibbon

adversarial glasses fool facial recognition systems into classifying the wearer as someone else (Sharif et al., 2016)

the ML system classifies the adversarially modified stop sign as a speed limit sign (Eykholt et al., 2018)

Summary

Decisions based on data are not always accurate, reliable, or fair

DP allows us to compute arbitrary queries on (sensitive) data with provable guarantees

- there are no absolute privacy guarantees, your neighbor's habits are correlated with your habits

Fairness criteria require (and enforce) some invariances w.r.t. sensitive attributes

- algorithmic fairness ≠ actual fairness, social/legal/political effort is also needed
- without a model of long-term impact it is difficult to foresee the effects of a fairness criterion

Accuracy, Fairness, Privacy, Robustness, and other aspects are non-trivially related

Algorithmic solutions are only (small) part of the puzzle