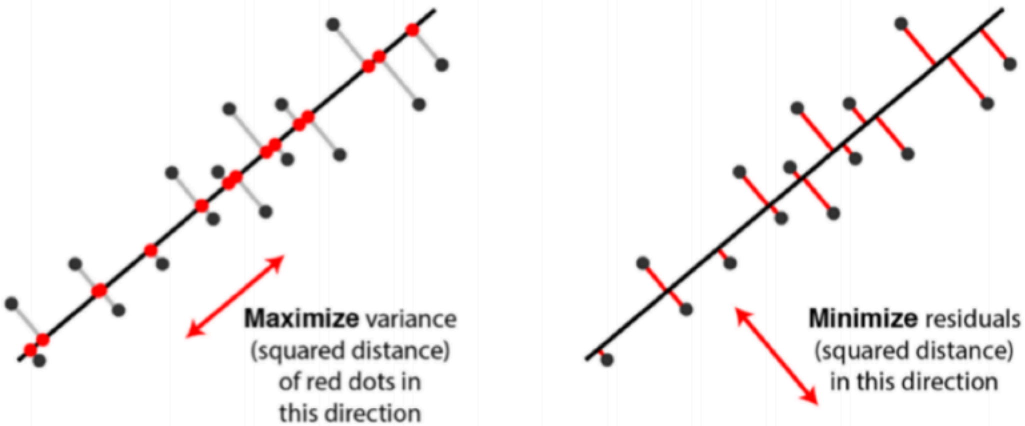
Privacy and Fairness in ML

UNIVERSITY of WASHINGTON

This course so far

How can one predict some value, find structure from data?



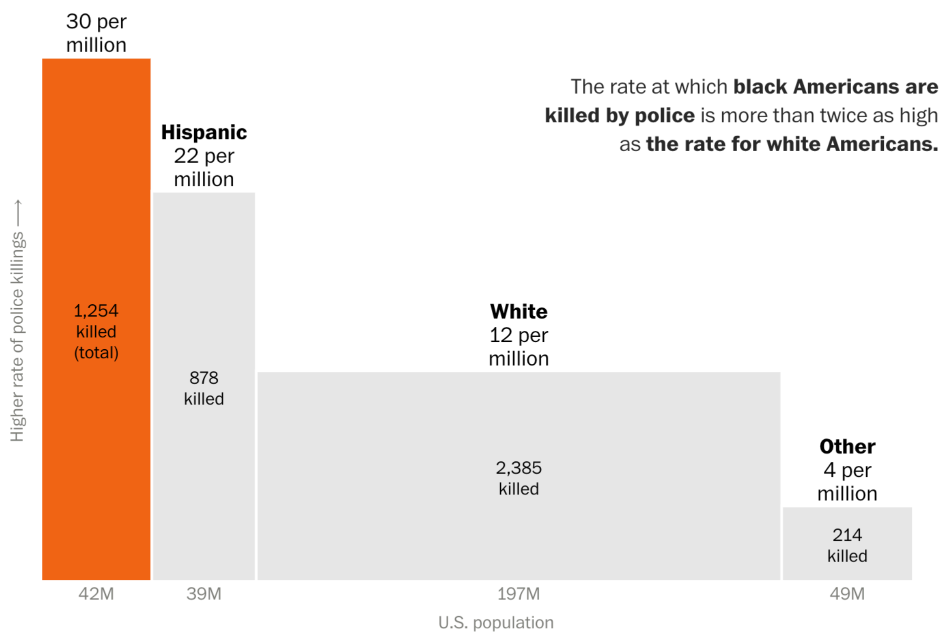
Two equivalent views of principal component analysis.

First, a moment of reflection

Some sobering statistics

Many, many people are killed by police every year (1,003 in the past 12 months)

> half of which aren't reported to the FBI (reporting is voluntary)



Source: an excellent Washington Post interactive database

Design choices

Model Class

Features to collect

Loss function

Regularization

Optimization Method

Constraints

…

Design choices affect your model

Model Class

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These will all affect what model you find, and how well and when that structure will generalize

… and that can have consequences "beyond" ML

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These will all affect what model you find, and how well and when that structure will generalize

Different models will have different kinds of errors, predictions, and failure modes

Consequence #1: Good predictions for whom?

UNIVERSITY of WASHINGTON

The US Criminal Justice System

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Any use of ML in the criminal justice system is just a tiny part of the larger CJ ecosystem.

Moreover, “reoffend” or “recidivate” are very, very, very far from precise terms in their use (in this lecture, and in industry).

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- arrested
- charged
- or being found guilty of a crime

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- arrested
- charged
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usually one which is violent.

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  Issue: race is strongly correlated with other features

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Pretrial release risk scale: 1-10
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Concern: not all errors are equally costly.

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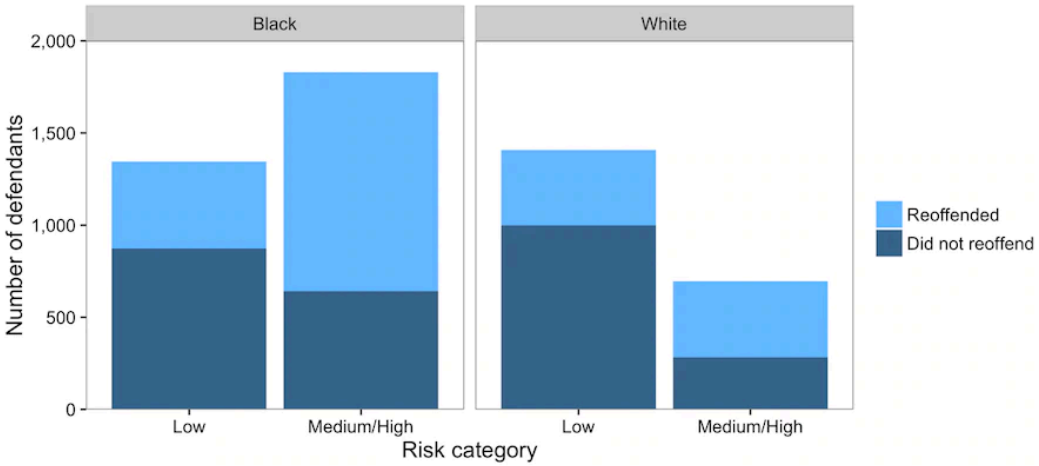

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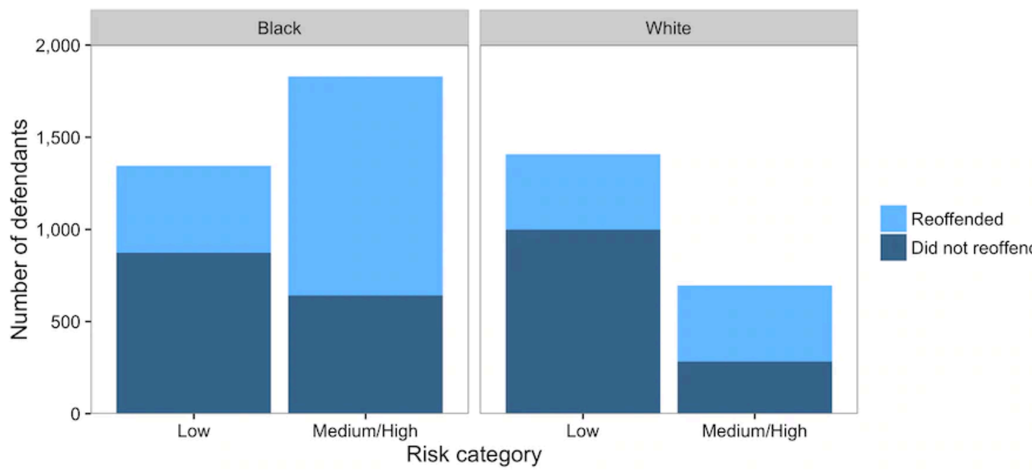

$$\mathbb{P}[\text{does not reoffend}|\text{predicted low risk, white}] <$$
$$\mathbb{P}[\text{does not reoffend}|\text{predicted low risk, black}]$$

Source: Washington Post

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NORTHPOINTE

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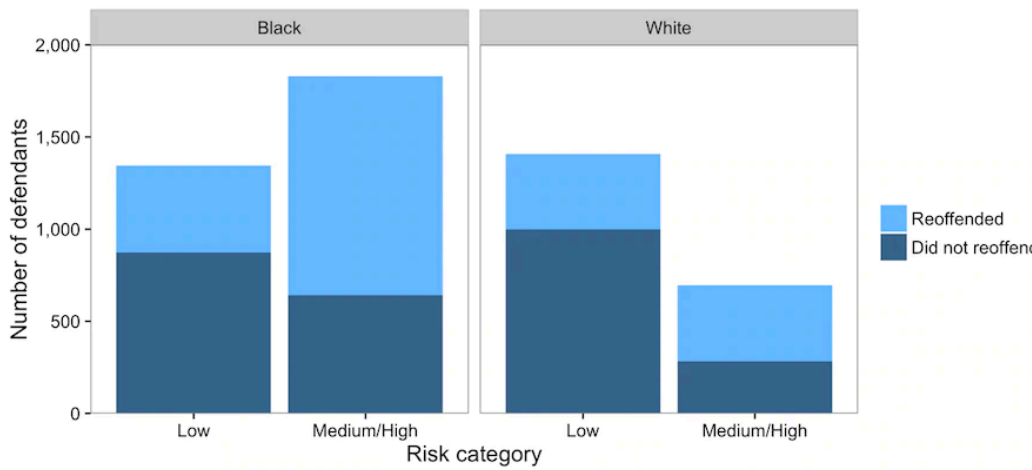

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False positive rate for black defendants higher than for white defendants.

Source: Washington Post

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Calibration of scores w.r.t. race

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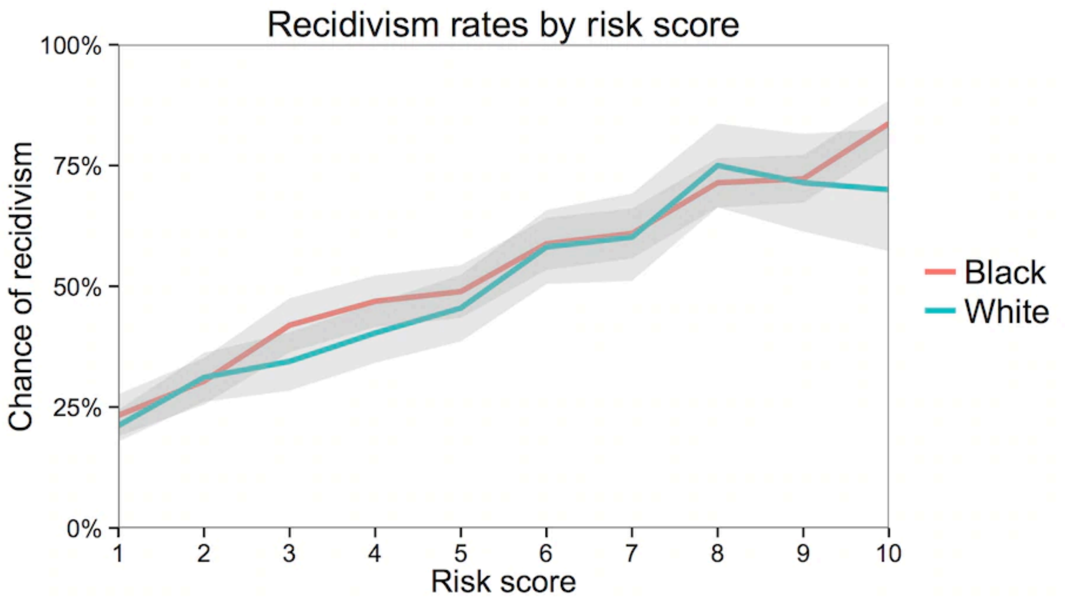

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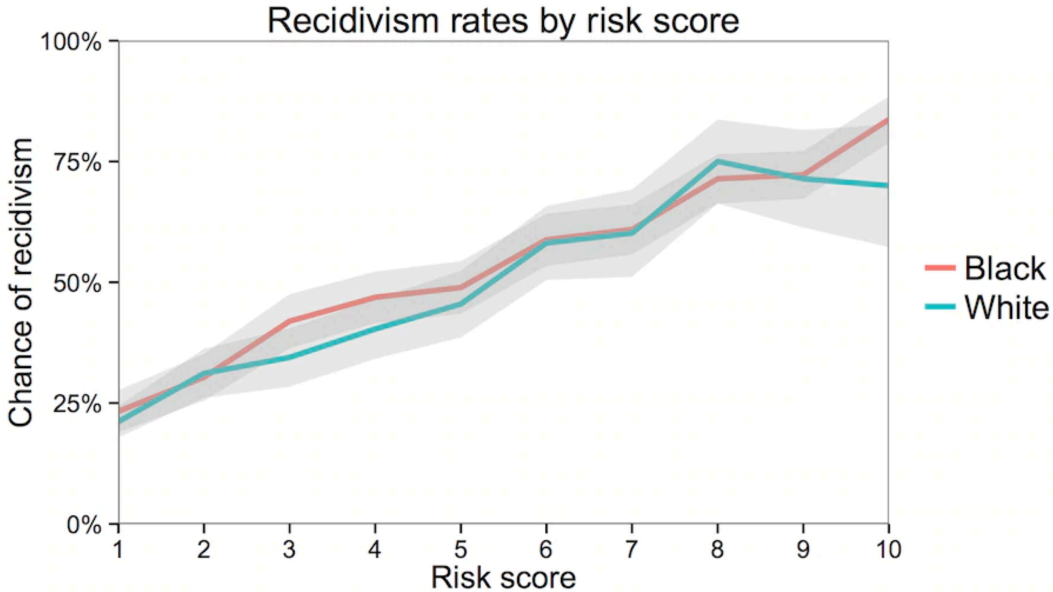

$$\mathbb{P}[\text{reoffend}|\text{prediction, white}] \approx \mathbb{P}[\text{reoffend}|\text{prediction, black}]$$

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Can any predictions be fair with respect to race?

$$\mathbb{P}[\text{does not reoffend}|\text{predicted low risk, white}] <$$
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while

$$\mathbb{P}[\text{reoffend}|\text{prediction, white}] \approx \mathbb{P}[\text{reoffend}|\text{prediction, black}]$$

How is this possible?

Is this avoidable?

Can any predictions be fair with respect to race?

False positives approximately equal and calibration are mutually exclusive, unless we have perfect predictions or the rate of what we are predicting is equal in every racial group.

… and this is true for more settings than just criminal justice.

Lending
Advertising
…

We are making a choice about how we allocate predictions.

Consequence #2: Leaking Sensitive information

Vignette 1: The Netflix Challenge

Given historical data on how users rated movies in past:

17,700 movies, 480,189 users, 99,072,112 ratings

(Sparsity: 1.2%)

Predict how the same users will rate movies in the future (for $1 million prize)

Alice	1	?	?	4	?	
Bob	?	2	5	?	?	
Carol	?	?	4	5	?	
Dave	5	?	?	?	4	
⋮						

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U2	?	2	5	?	?	
U3	?	?	4	5	?	
U4	5	?	?	?	4	
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De-anonymized records

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Conclusions:

Anonymization can be undone
linkage attacks help in de-anonymizing!

De-anonymized records

Vignette 2: Medical Records

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So dates of 2 hospital admissions will uniquely identify many, many people.

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Conclusions:

Anonymizing low dimensional data still isn’t safe… a small number of features can uniquely id people if those features take on many values

Large (#people) datasets aren’t enough to hide users either

A new approach to privacy

perfect privacy

No amount of analysis or linkage can tell you **anything** about **any** user in a database.

Issue: dataset/models learned from it will contain 0 information.

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Linkage attacks **will** happen

What should we mean when we say a dataset (or model) protects users’ privacy?

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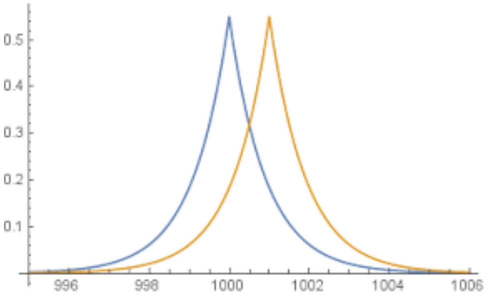

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Vignette 3: The Census

The History of Privacy for the Census