

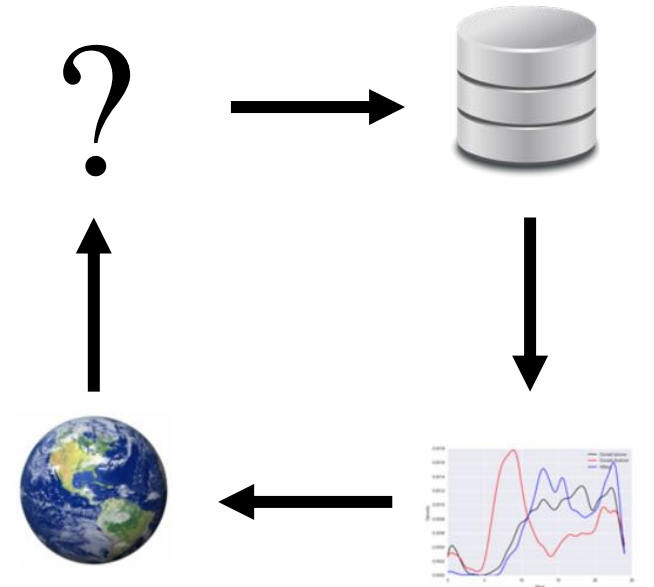
Data Science 100

Lecture 27: Ethics in Data Science

Slides by:

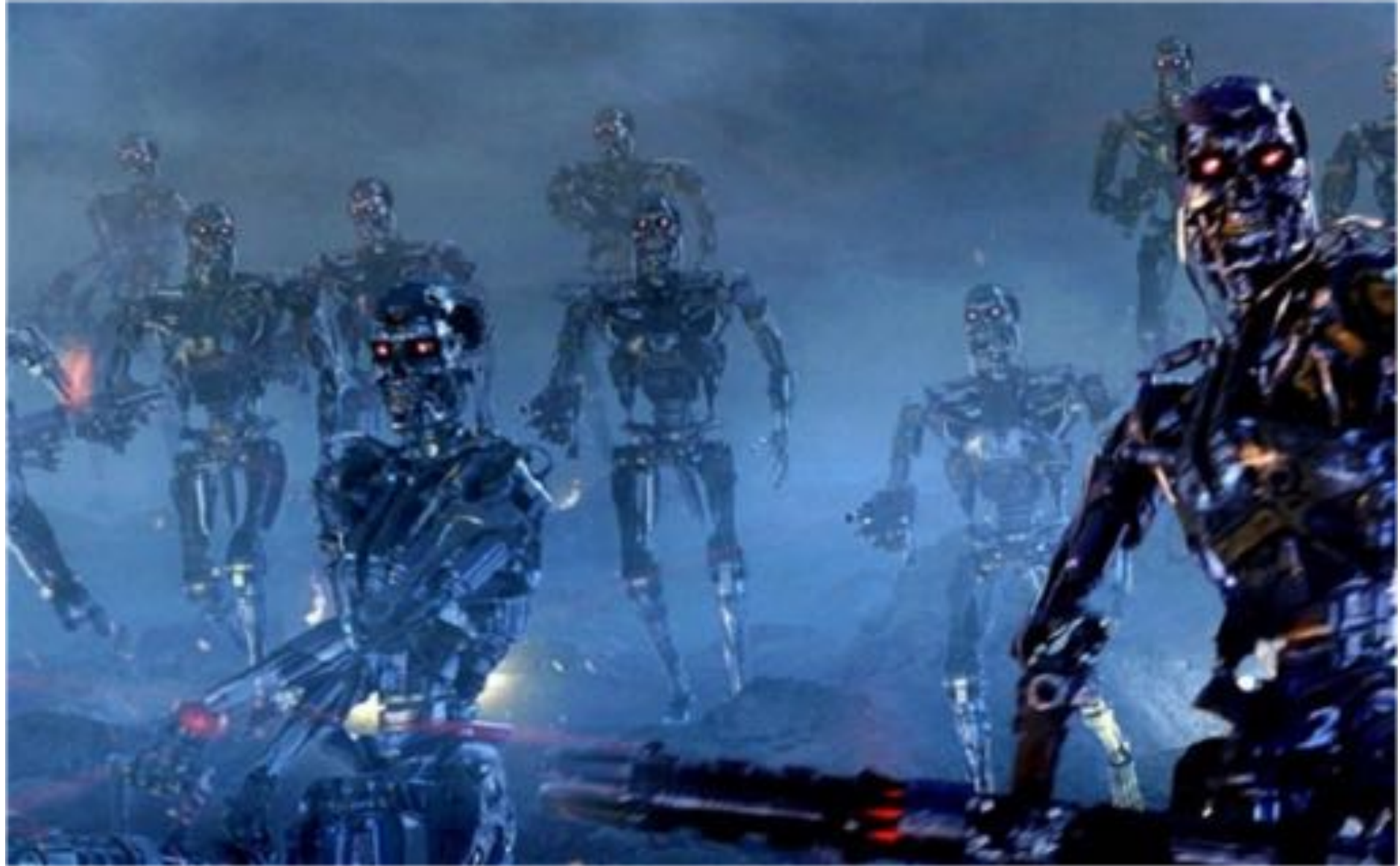
Joshua Kroll

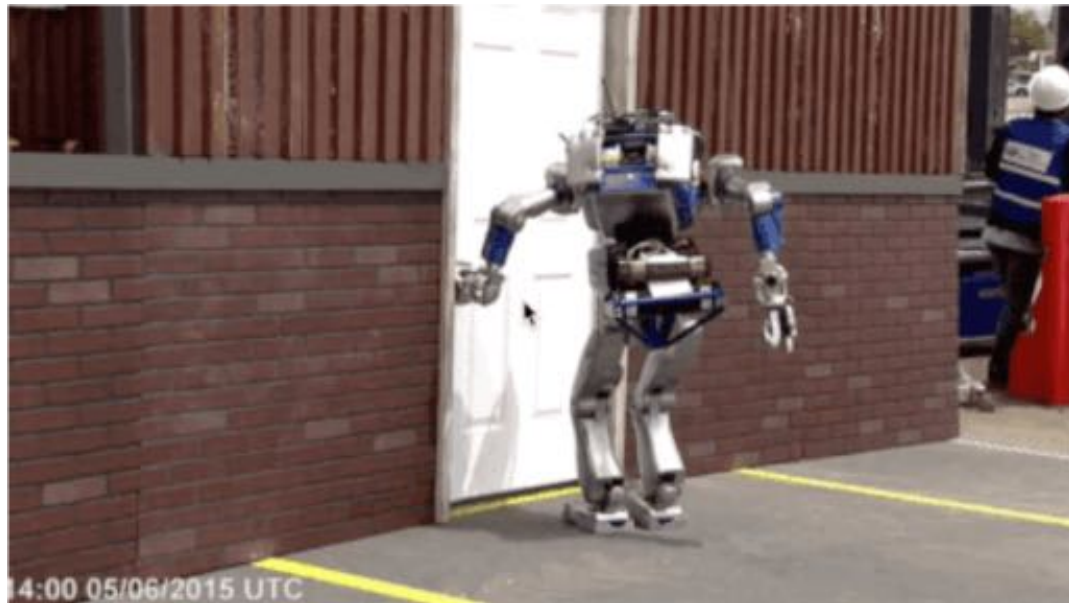
kroll@berkeley.edu







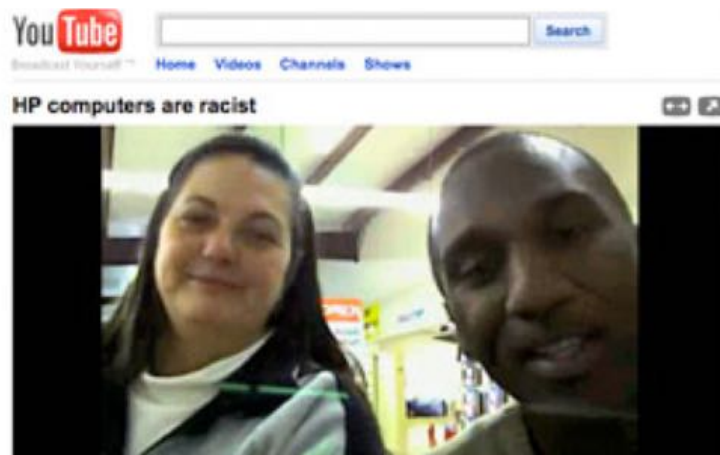




14:00 05/06/2015 UTC



14:01 05/06/2015 UTC



HP Face-Tracking Webcams Don't Recognize Black People



Adam Frucci

12/21/09 10:00am • Filed to: WEBCAMS ▾







154.6K 291  




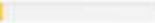



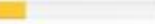



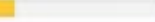


'A white mask worked better': why algorithms are not colour blind

When Joy Buolamwini found that a robot recognised her face better when she wore a white mask, she knew a problem needed fixing

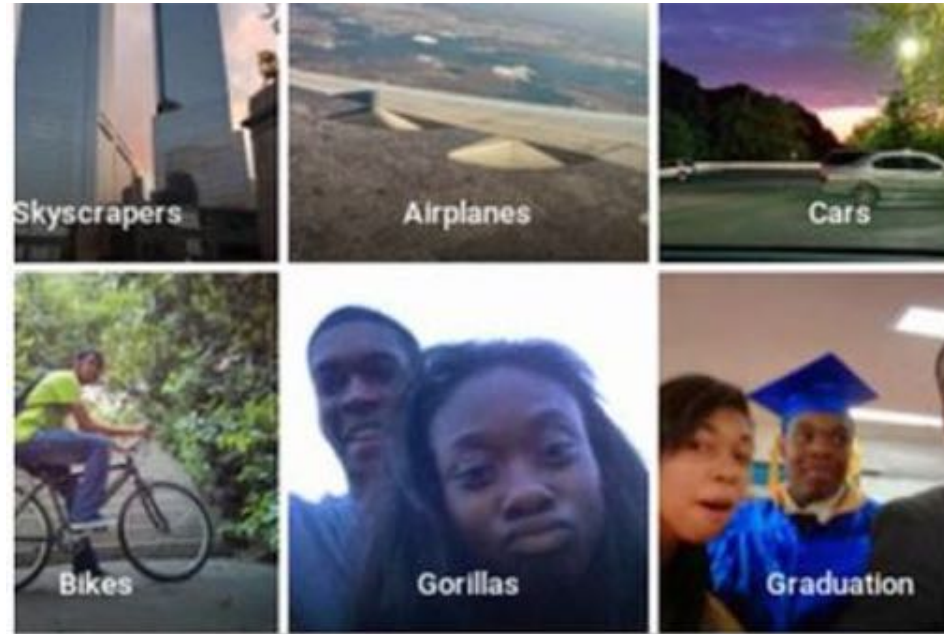
Gender Shades

Gender Classifier	Overall Accuracy on all Subjects in Pilot Parliaments Benchmark (2017)
 Microsoft	93.7% 
 FACE++	90.0% 
 IBM	87.9% 

Gender Classifier	Female Subjects Accuracy	Male Subjects Accuracy	Error Rate Diff.
 Microsoft	89.3% 	97.4% 	8.1% 
 FACE++	78.7% 	99.3% 	20.6% 
 IBM	79.7% 	94.4% 	14.7% 

Gender Classifier	Darker Subjects Accuracy	Lighter Subjects Accuracy	Error Rate Diff.
 Microsoft	87.1% 	99.3% 	12.2% 
 FACE++	83.5% 	95.3% 	11.8% 
 IBM	77.6% 	96.8% 	19.2% 

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
 Microsoft	94.0% 	79.2% 	100% 	98.3% 	20.8% 
 FACE++	99.3% 	65.5% 	99.2% 	94.0% 	33.8% 
 IBM	88.0% 	65.3% 	99.7% 	92.9% 	34.4% 



Google Photos Mistakenly Labels Black People 'Gorillas'

BY CONOR DOUGHERTY JULY 1, 2015 7:01 PM 41



physicist



Sign in

All

Images

News

Videos

Books

More

Settings

Tools

View saved

SafeSearch

famous

work

isaac newton

einstein

quantum

john ellis

hot

theoretical

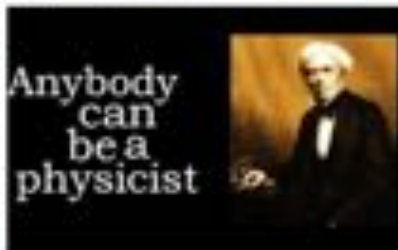
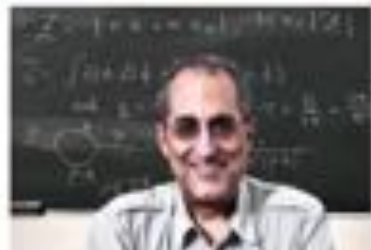
lab

medical

engineering

mathematical

research





professional hairstyles



Sign in

All Images Videos Shopping News More

Settings Tools

View saved SafeSearch

job interview

long hair

natural

medium length

simple

formal

low maintenance

classy

short hair

medium hair

shoulder length hair



Data science is everywhere...

Scoring Systems



Lotteries



Criminal Justice & National Security



News

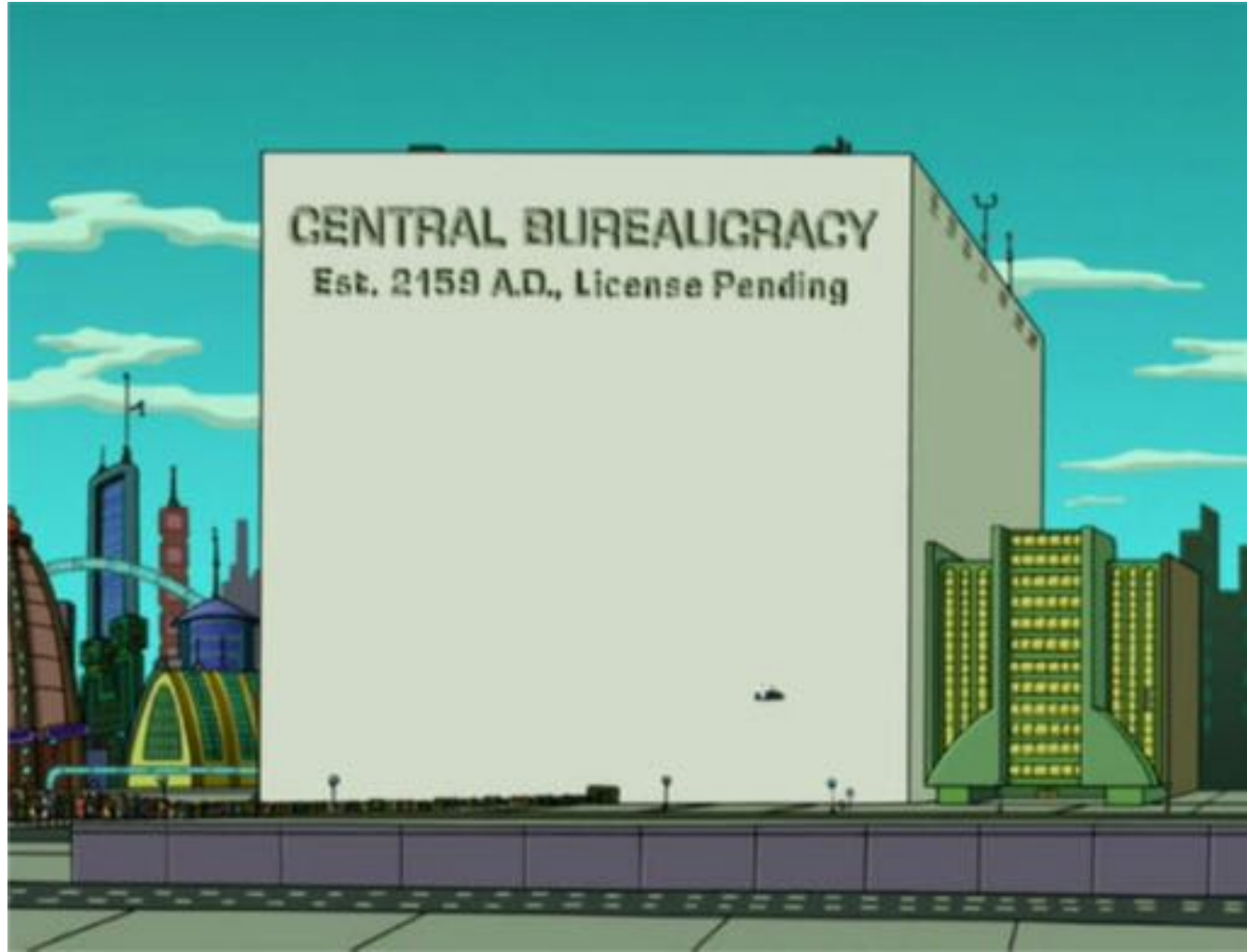


Lending



Hiring







Data Science Life Cycle

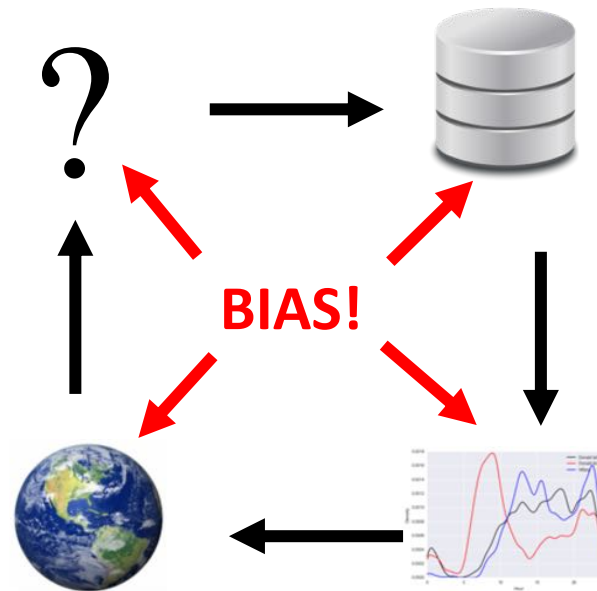
Context

Question

Refine Question to an one answerable with data

Model evaluation

Prediction error



Design

Data Collection

Data Cleaning

Modeling

Test-train split

Loss function choice

Feature engineering

Transformations,

Dummy Variables

Model selection

Best subset regression

Cross-Validation



Context & Refinement

Extreme Digital Vetting of Visitors to the U.S. Moves Forward Under a New Name

ICE officials have invited tech companies, including Microsoft, to develop algorithms that will track visa holders' social media activity.

by **George Joseph**, Nov. 22, 8 a.m. EST

Context & Refinement



A Stanford scientist says he built a gaydar using "the lamest" AI to prove a point

Composite heterosexual faces

Composite gay faces

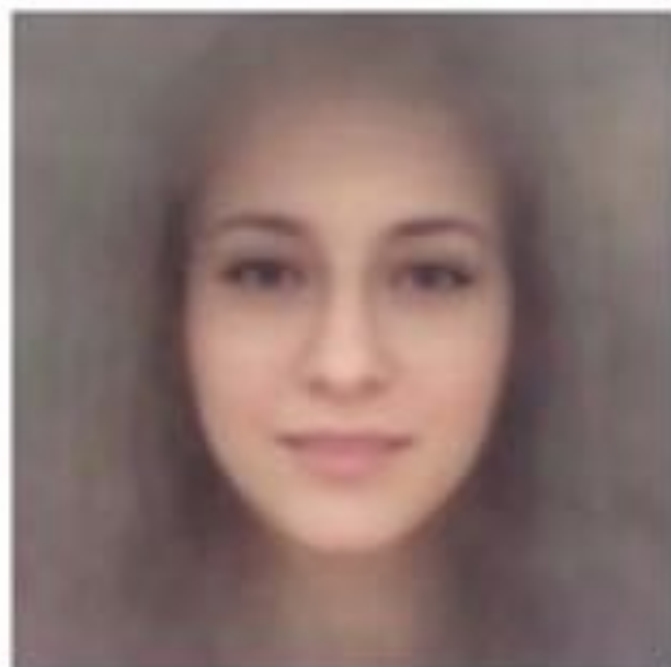
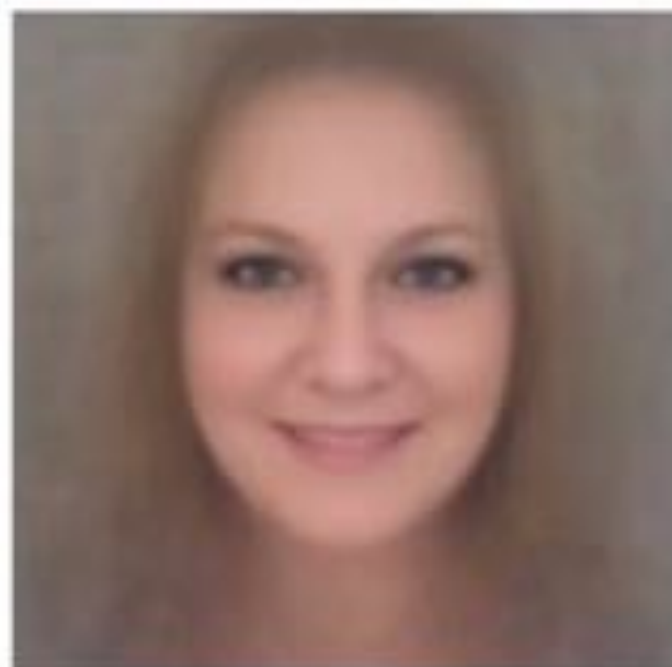
Average facial landmarks

Male



- gay
- straight

Female



Proxies

FACEPTION
HOW ARE WE DIFFERENT?

HIGH IQ
EXTROVERT
BRAND PROMOTER

FACEPTION is a facial analysis tool that uses facial landmarks to infer personality traits. The interface shows a woman's face with a grid of points and lines. Below the face is a bar chart with red and green segments, and a blue vertical line indicating a score. The traits listed are HIGH IQ, EXTROVERT, and BRAND PROMOTER.

Automated Inference on Criminality using Face Images

Xiaolin Wu
McMaster University
Shanghai Jiao Tong University
xwu510@gmail.com

Xi Zhang
Shanghai Jiao Tong University
zhangxi.19930818@sjtu.edu.cn



High IQ



Academic Researcher



Professional Poker
Player



Terrorist

Data Collection



Help keep your streets smooth

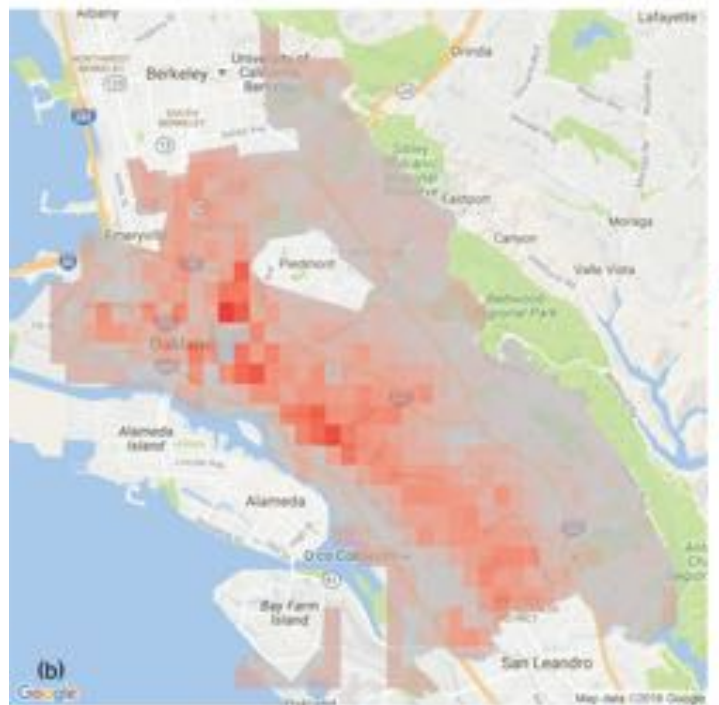
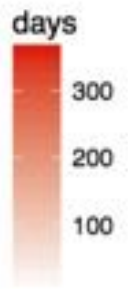
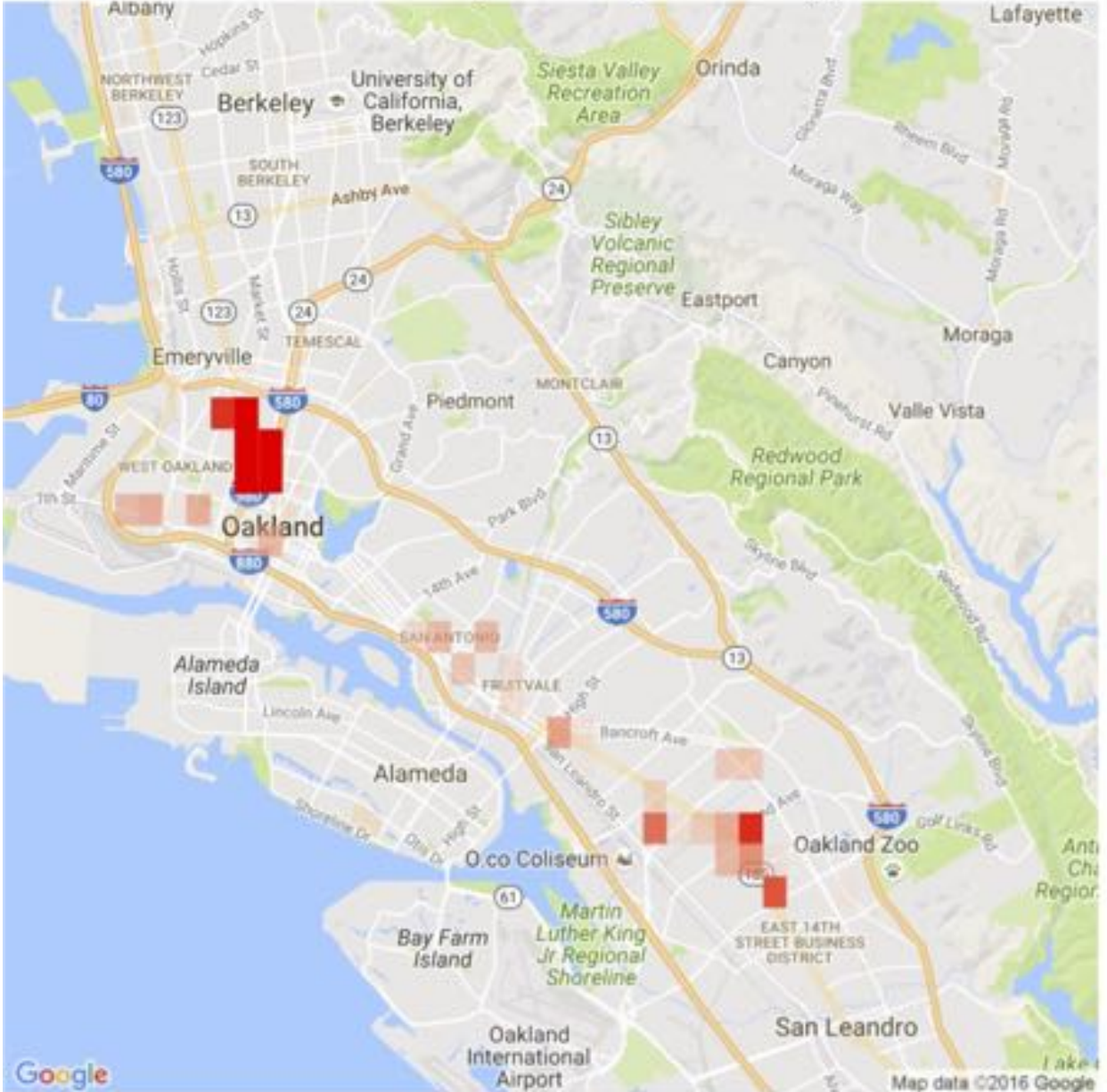


Data Collection



<http://bit.ly/ds100-sp18-eth>

Number of Days with Targeted Policing



From Lum, Kristian, and William Isaac. "To predict and serve?." Significance 13, no. 5 (2016): 14-19.

Data Cleaning



PAUL
REUBENS



PETER PAUL
RUBENS



ZAREK



SAREK



ZAREK

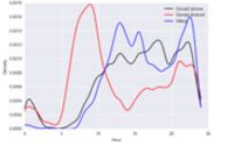
Data Cleaning



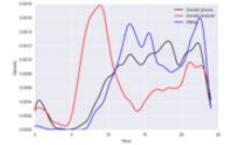
Data Cleaning



Test-Train Split



Loss Function Choice

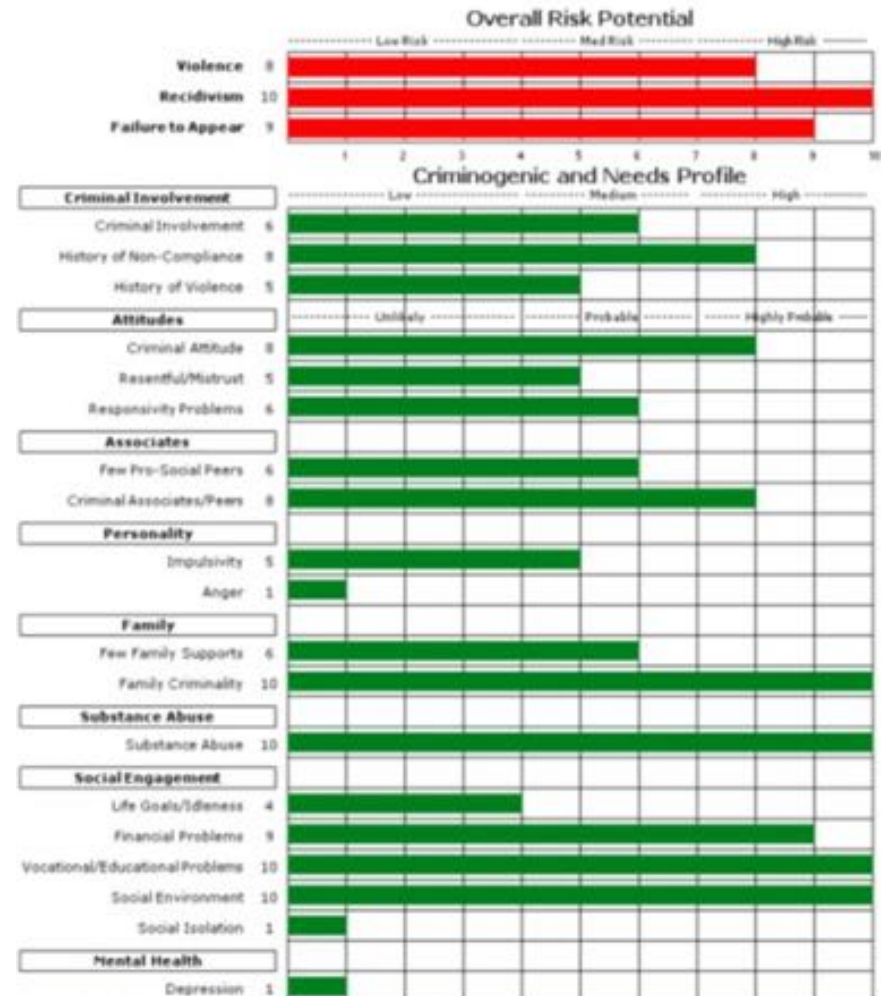


DOES UNCONSCIOUS RACIAL BIAS AFFECT TRIAL JUDGES?

Jeffrey J. Rachlinski, Sheri Lynn Johnson,† Andrew J. Wistrich,‡ & Chris Guthrie††*

COMPAS Probation Risk Assessment

Offender: **Justin Example** DOB: **1/1/1982** Gender: **Male**
 Screening Date: **10/15/2007** Screener: **Rose, Susanne** Ethnicity: **Asian**
 Scale Set: **All with PSI** Case: **66677789-1015200** Marital Status: **Divorced**



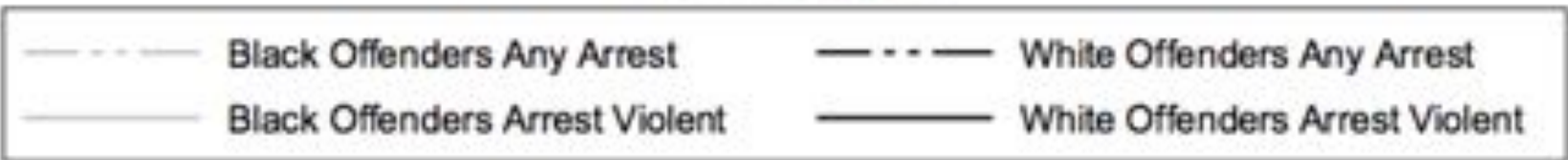
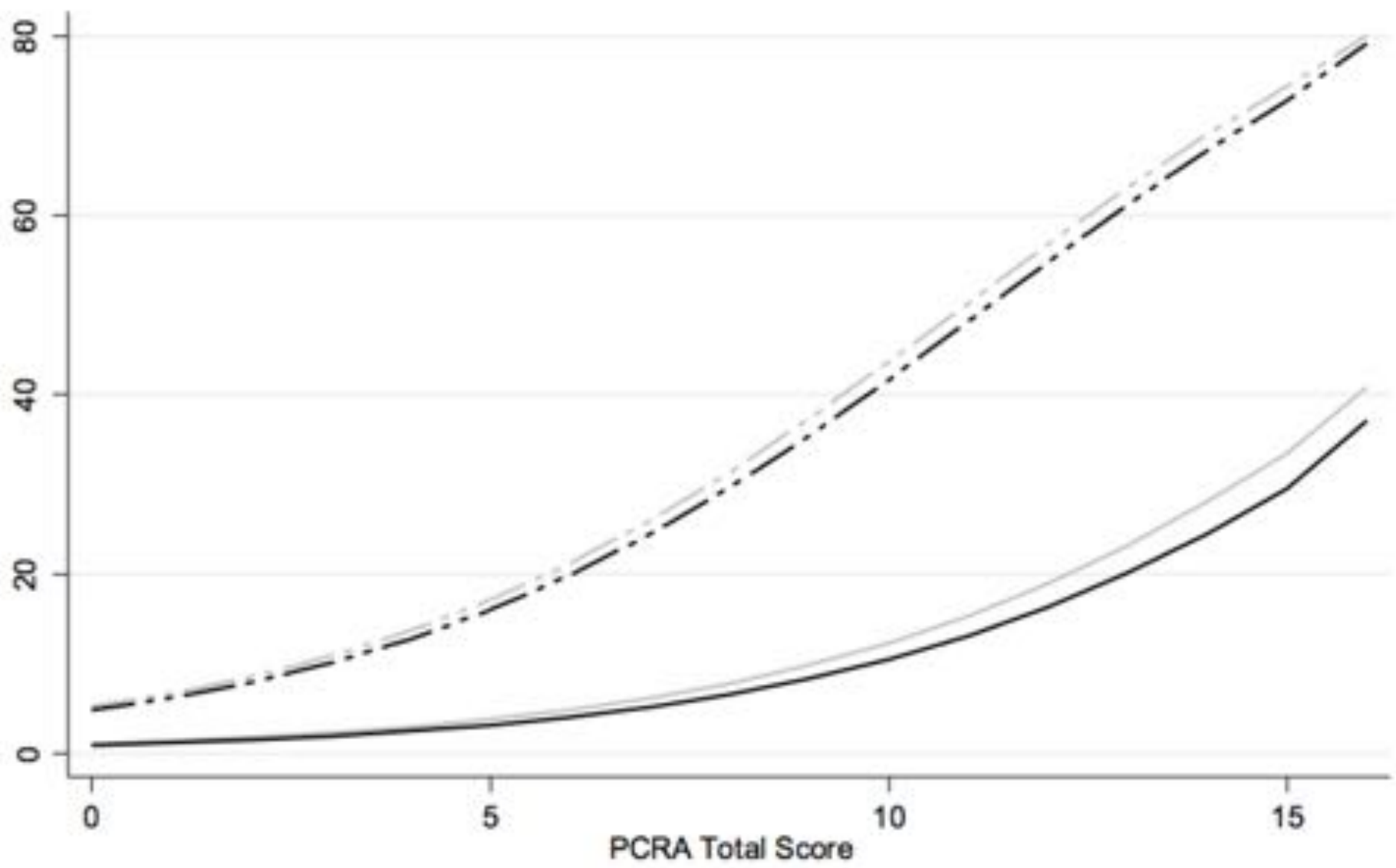
Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

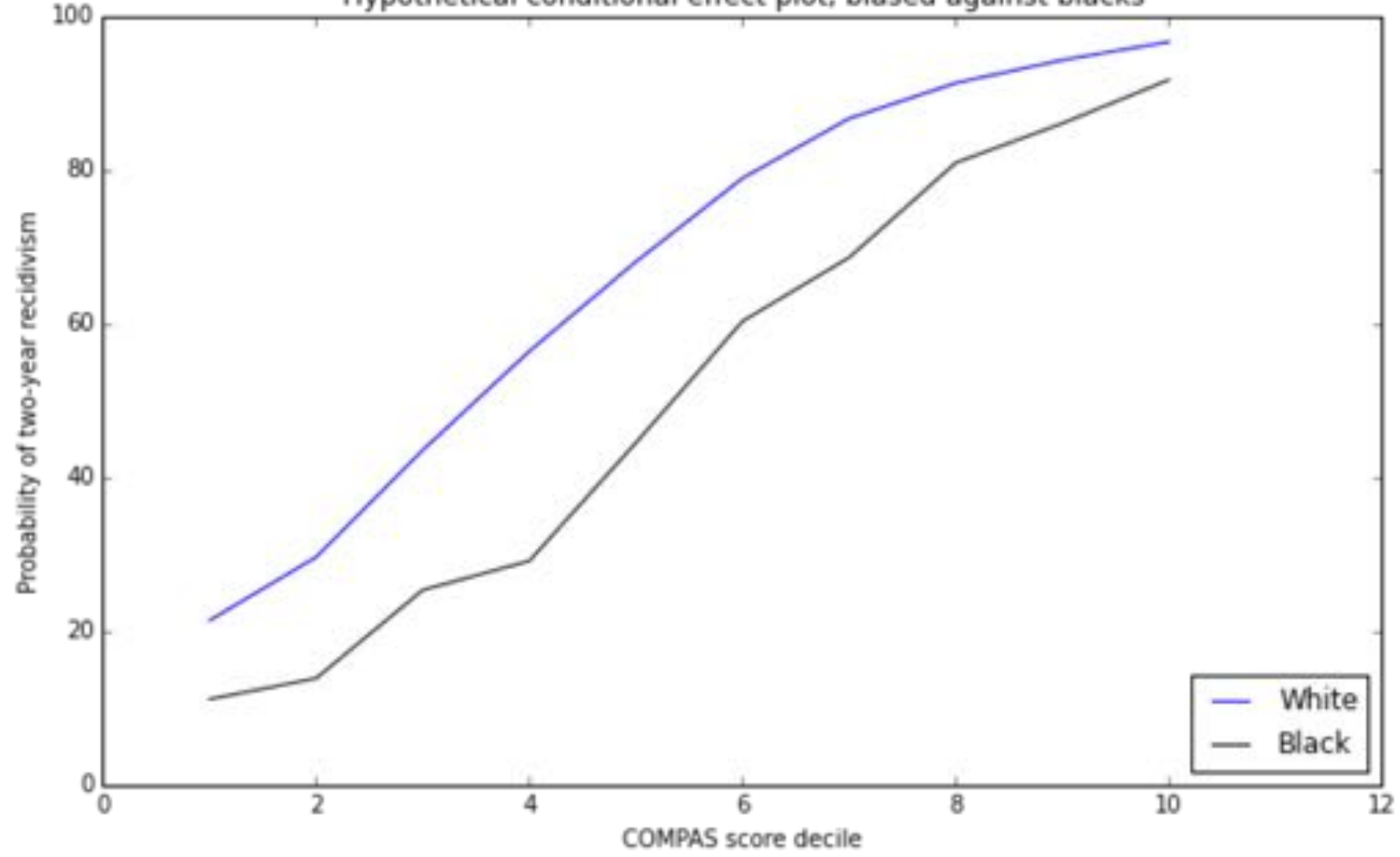
by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

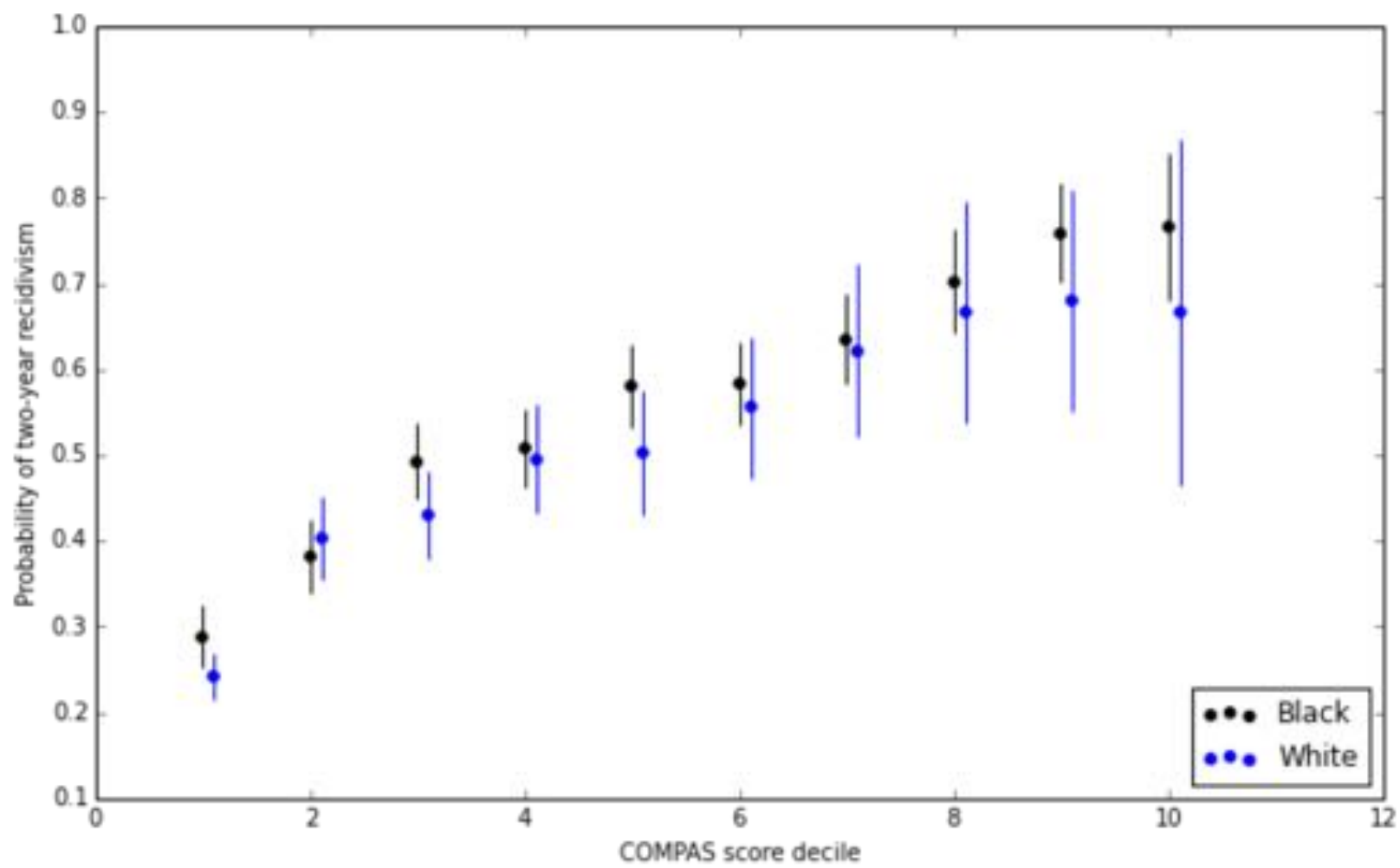
May 23, 2016

ON A SPRING AFTERNOON IN 2014, Brisha Borden was running late to pick up her god-sister from school when she spotted an unlocked kid's blue Huffy bicycle and a silver Razor scooter. Borden and a friend grabbed the bike and scooter and tried to ride them down the street in the Fort Lauderdale suburb of Coral Springs.



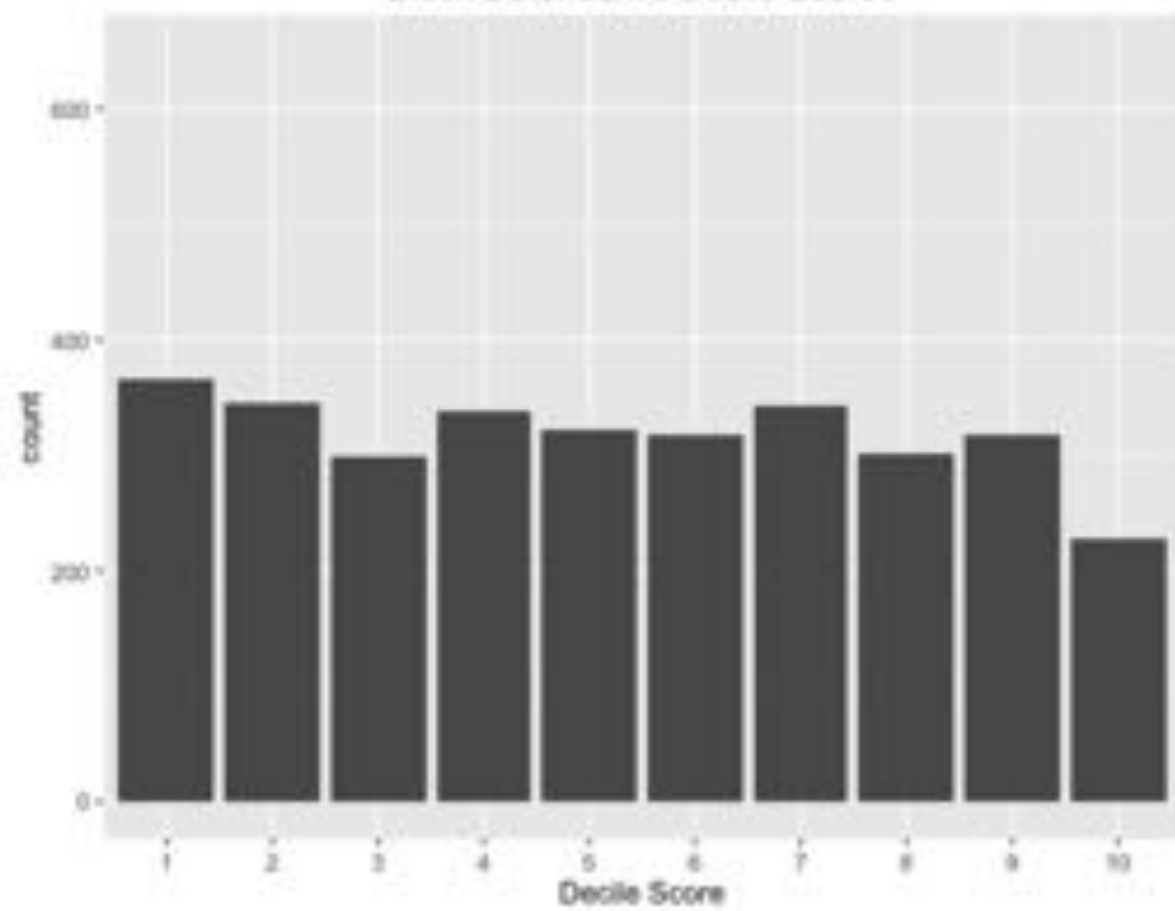
Hypothetical conditional effect plot, biased against blacks



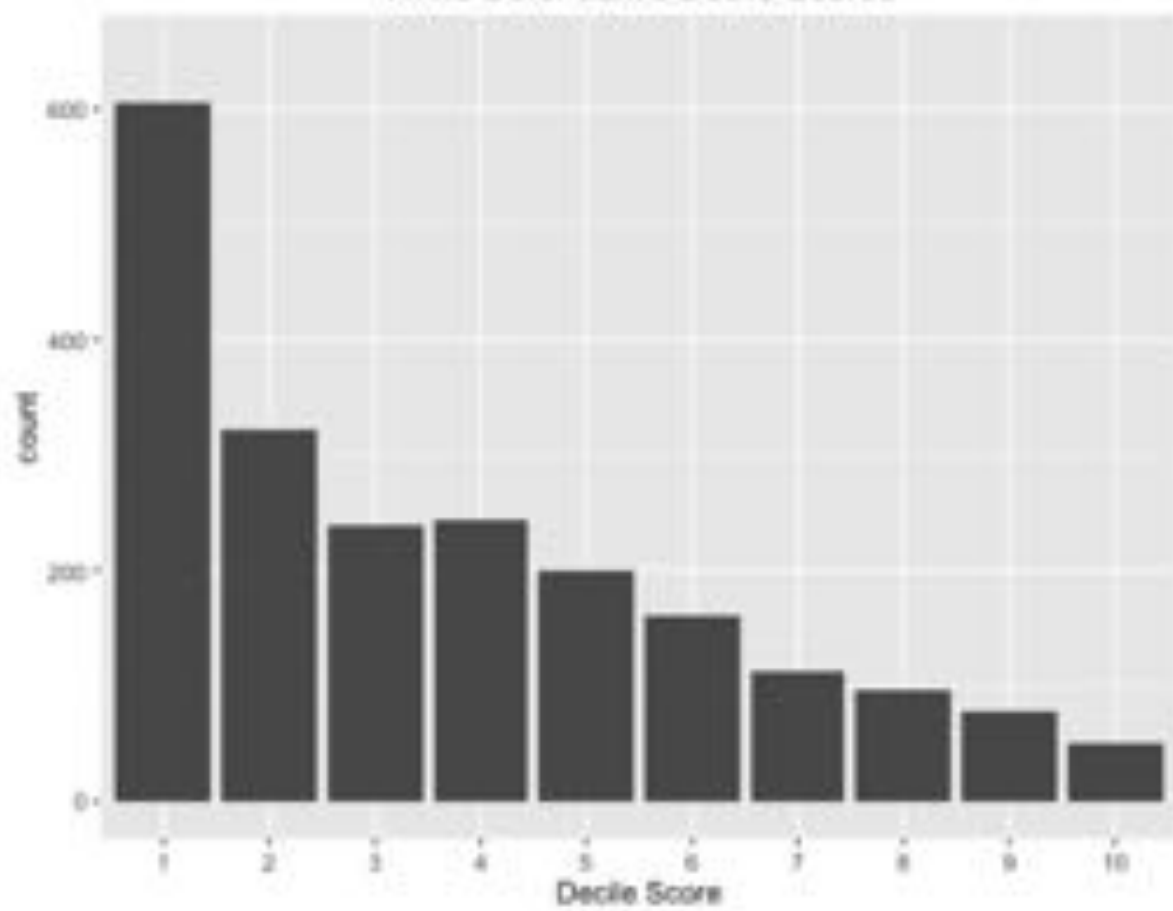


So why does ProPublica think
COMPAS is biased?

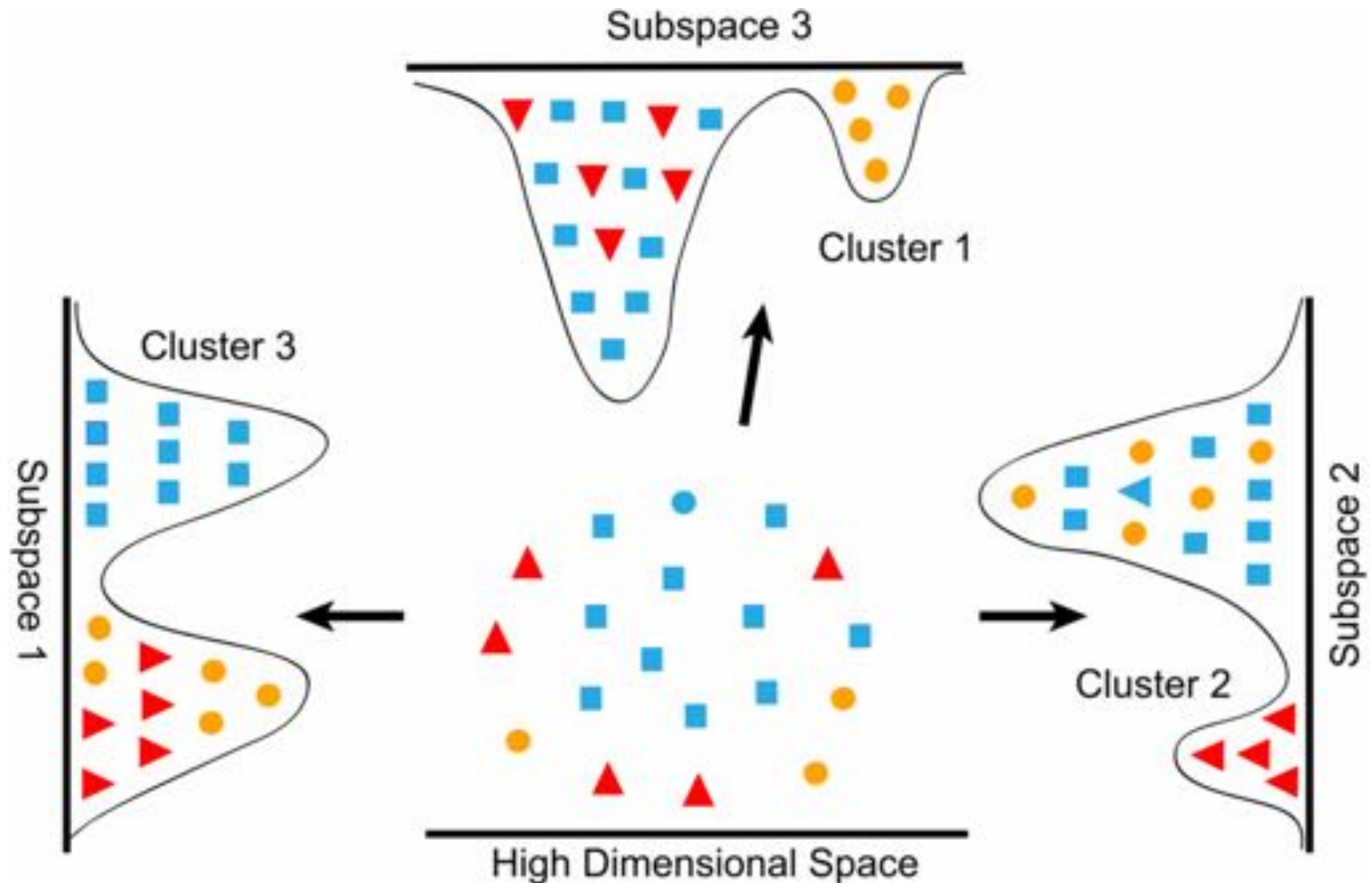
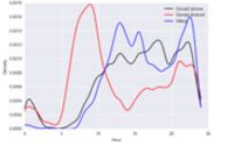
Black Defendant's Decile Scores



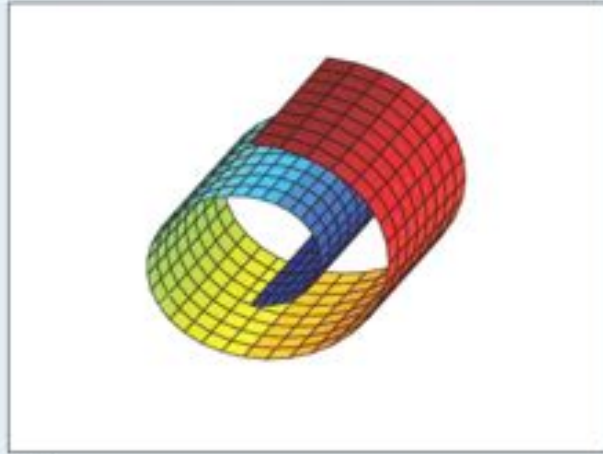
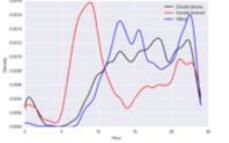
White Defendant's Decile Scores



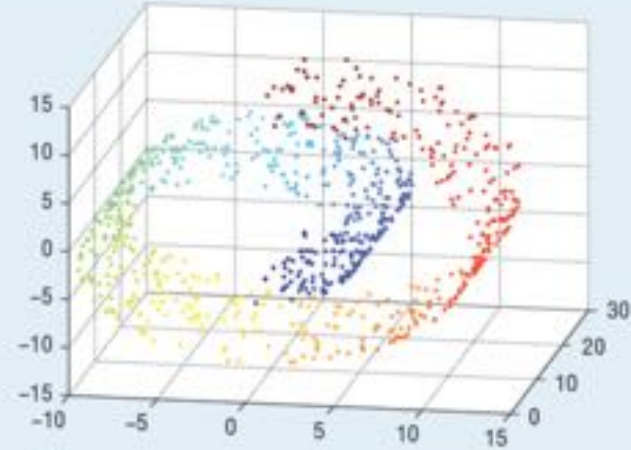
Feature Engineering



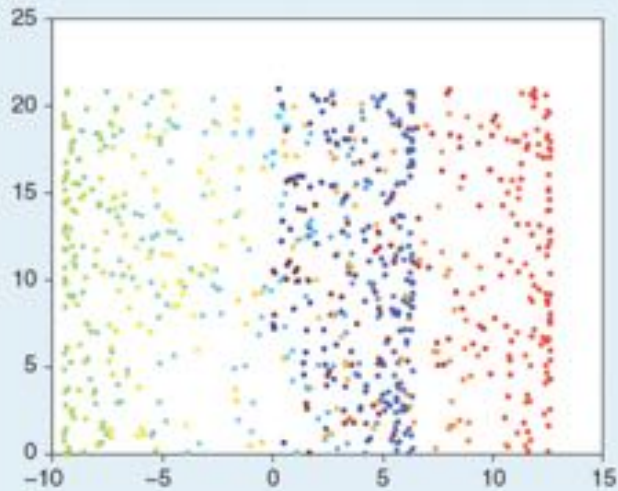
Feature Engineering



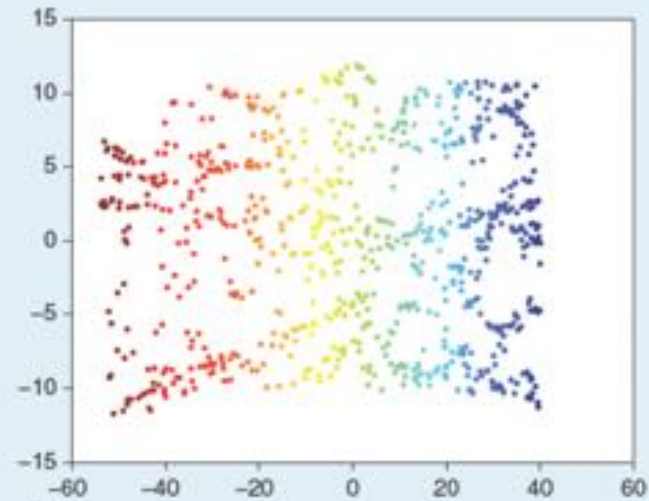
(a)



(b)

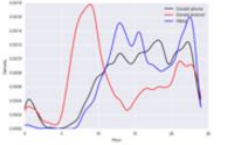


(c)

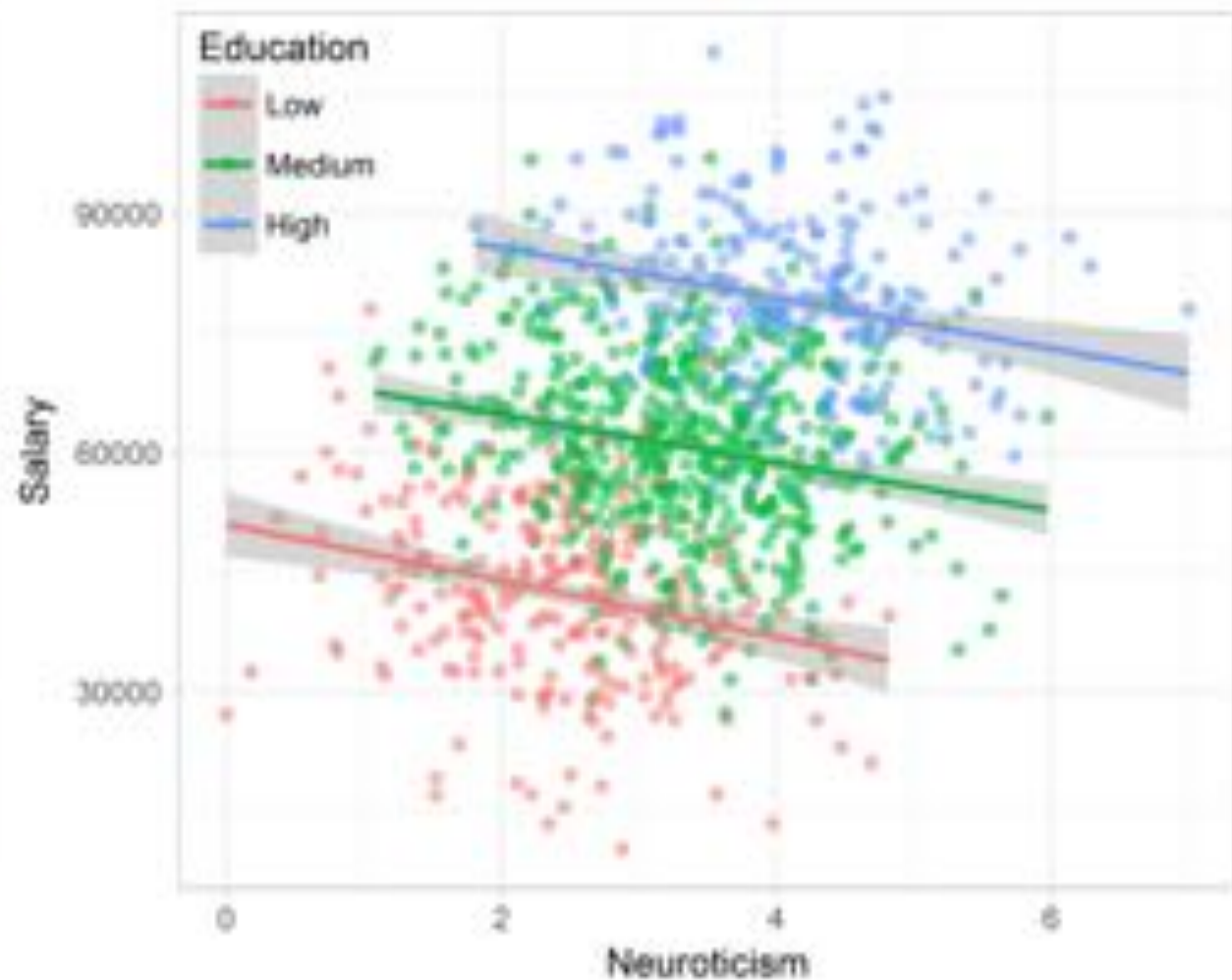
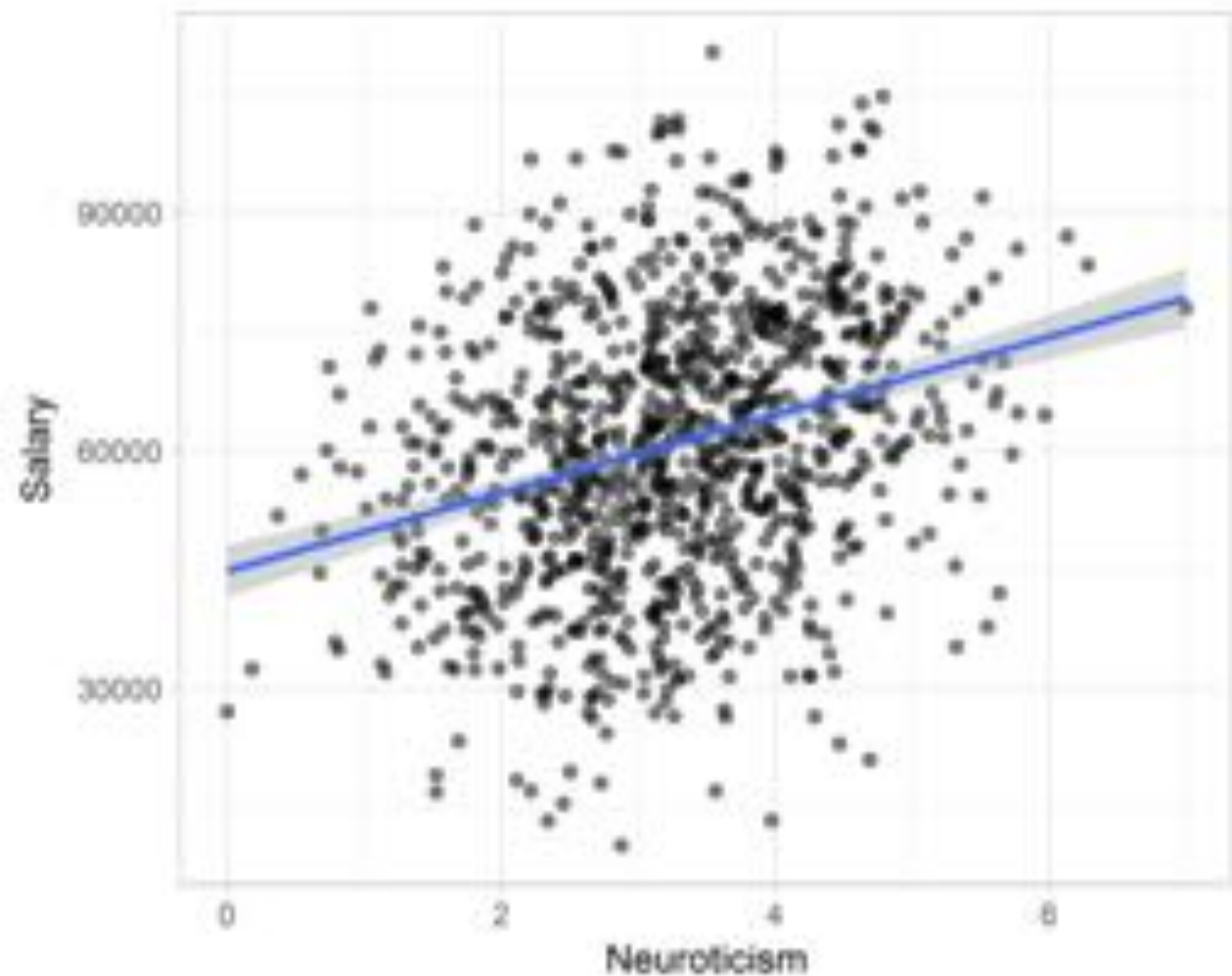
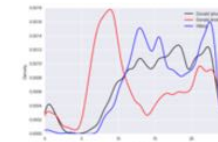


(d)

Feature Engineering



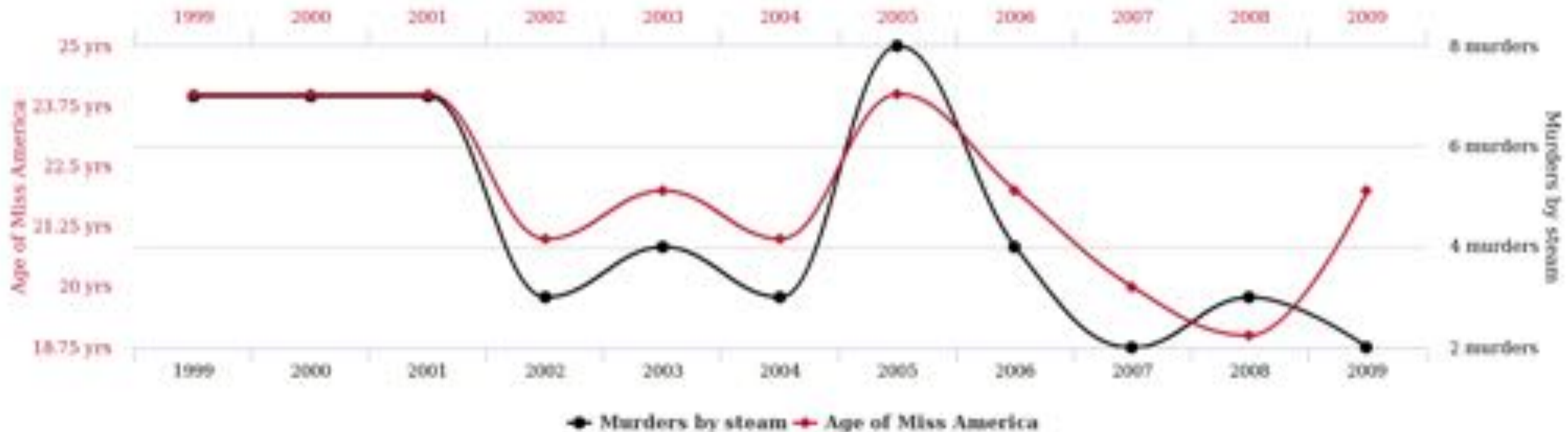
Model Selection





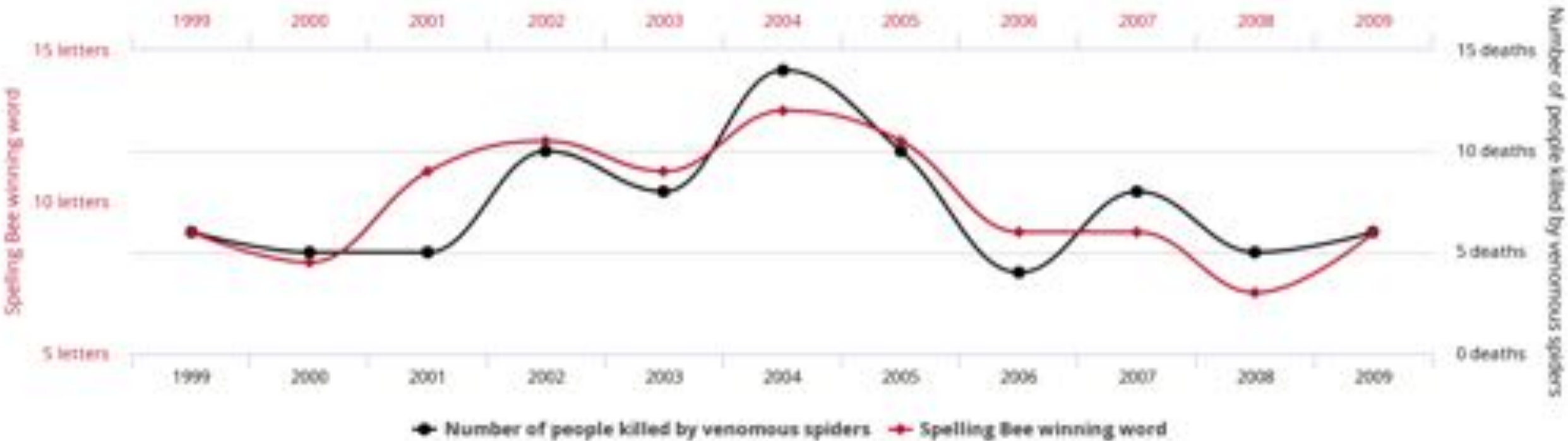
Model Evaluation

Age of Miss America correlates with Murders by steam, hot vapours and hot objects



Model Evaluation

Letters in Winning Word of Scripps National Spelling Bee
correlates with
Number of people killed by venomous spiders



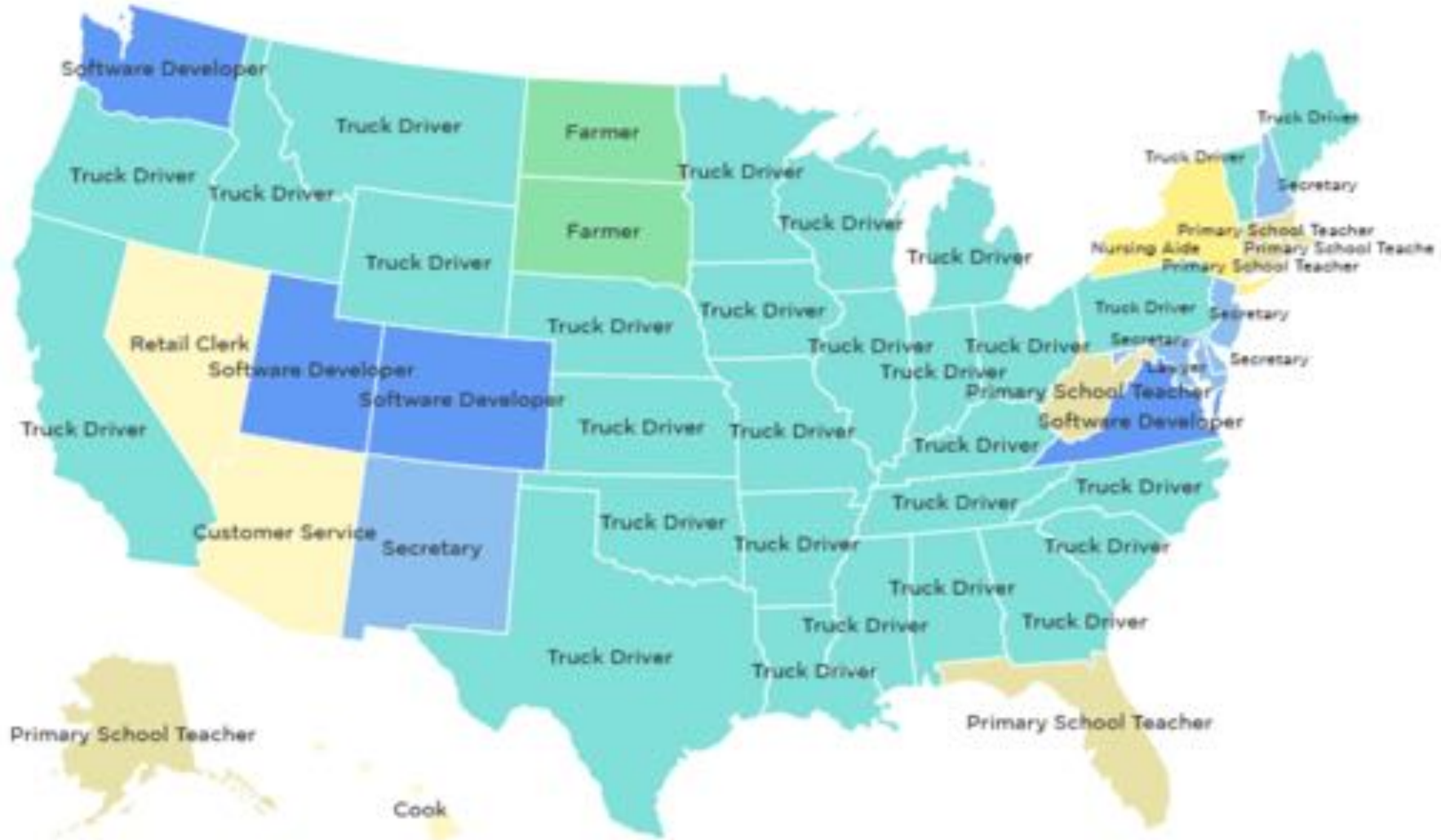
So what do we do about this?

Ethical Lessons

1. Know what the data are telling you
 - Understand your model, and validate it
 - Involve domain experts; “raw data” is an oxymoron
 - Communicate not just model *capabilities*, but also *limits* and *assumptions*
2. Data about people are about people
 - The data do not exist on their own, someone made them
3. *Always* consider why your model might be wrong in systematic ways
 - Don't just **trust** the technology, make it **trustworthy**
 - **Close** the data science lifecycle: the world changes, and so should your models

Ethics beyond the Data Science Lifecycle

Should we deploy technology at all?



When is it ethical to collect data?



RYAN SINGEL · SECURITY 02.17.12 03:02 PM

GOOGLE BUSTED WITH HAND IN SAFARI-BROWSER COOKIE JAR



When is it ethical to collect *sensitive* data?

- Without knowing sensitive attributes, it's not possible to know how to make good decisions.
 - E.g., in a credit-granting context, there's no reason to believe that qualified minority applicants will be similar to qualified members of the majority
- But having sensitive data means it can be repurposed for other uses

Inclusion and Representation



Resources

- Take a course at Berkeley on people and technology
- Visit <https://fatml.org> and <https://fatconference.org>
 - Reading list
 - Principles for Accountable Algorithms
- Books
 - *Weapons of Math Destruction*, by Cathy O'Neil
 - *How to Lie With Statistics*, by Darrell Huff
- Courses around the world: tinyurl.com/ethics-classes

*“Remember that all models are wrong;
the practical question is how wrong do
they have to be to not be useful.”*

-George E. P. Box

