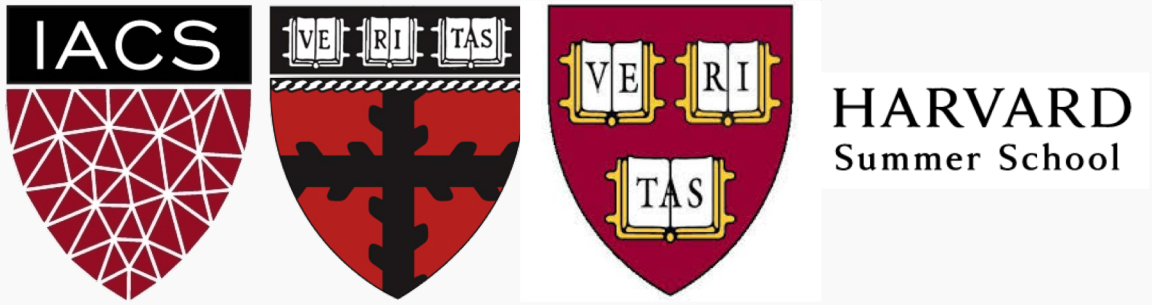
Lecture #12: Responsible Data Science and Wrap-Up

CS-S109A: Introduction to Data Science

Kevin Rader



ANNOUNCEMENTS

- The **Final Exam** (individual work) is available and due Monday, Aug. 3.
  - There is a 1% penalty if handed in up to 24 hours late (max = 99/100)

  A few clarifications:

  1. Unless specifically mentioned as departure delay, and reference to a delay should be assumed to be an arrival delay.
  2. Determining whether a flight is delayed or not it always whether the actual time of departure/arrival is 15 minutes or more after it's scheduled time.
- **Friday's lab** will include general review: both conceptual and technical (partially based on today's **quiz**)

Outline

- Ethical Data Science
- Case Study: Bias in the COMPAS algorithm
- Wrap-Up

Ethical Data Science

*slides modified by CS 109's guest speaker in Fall 2018:

Julia Stoyanovich, NYU

https://engineering.nyu.edu/faculty/julia-stoyanovich

Online price discrimination

THE WALL STREET JOURNAL.

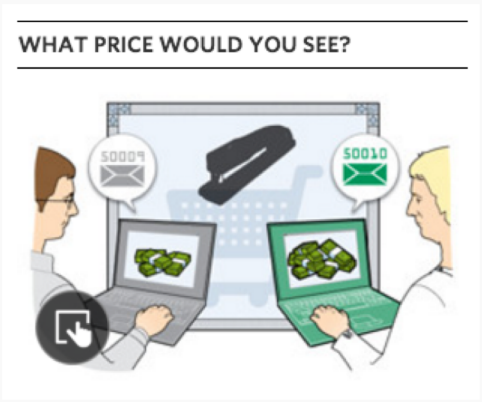
WHAT THEY KNOW

Websites Vary Prices, Deals Based on Users' Information

By JENNIFER VALENTINO-DEVRIES, JEREMY SINGER-VINE and ASHKAN SOLTANI
December 24, 2012

It was the same Swingline stapler, on the same Staples.com website. But for Kim Wamble, the price was $15.79, while the price on Trude Frizzell's screen, just a few miles away, was $14.29.

A key difference: where Staples seemed to think they were located.



lower prices offered to buyers who live in more affluent neighborhoods

https://www.wsj.com/articles/SB10001424127887323777204578189391813881534

Online job ads

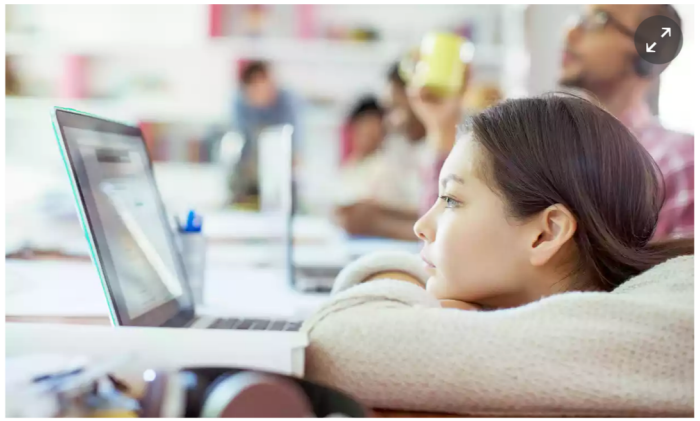
theguardian

Samuel Gibbs

Wednesday 8 July 2015 11.29 BST

Women less likely to be shown ads for high-paid jobs on Google, study shows

Automated testing and analysis of company's advertising system reveals male job seekers are shown far more adverts for high-paying executive jobs



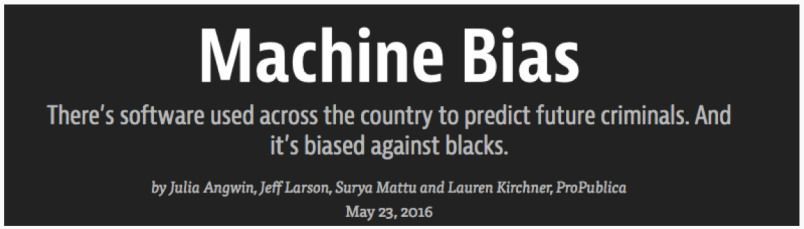
One experiment showed that Google displayed adverts for a career coaching service for executive jobs 1,852 times to the male group and only 318 times to the female group. Photograph: Alamy

The AdFisher tool simulated job seekers that did not differ in browsing behavior, preferences or demographic characteristics, except in gender.

One experiment showed that Google displayed ads for a career coaching service for "$200k+" executive jobs 1,852 times to the male group and only 318 times to the female group. Another experiment, in July 2014, showed a similar trend but was not statistically significant.

https://www.theguardian.com/technology/2015/jul/08/women-less-likely-ads-high-paid-jobs-google-study

Racial bias in criminal sentencing



A commercial tool COMPAS automatically predicts some categories of future crime to assist in bail and sentencing decisions. It is used in courts in the US.

The tool correctly predicts recidivism 61% of the time.

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Blacks are almost twice as likely as whites to be labeled

Is data science impartial?

Data science is algorithmic, therefore it cannot be biased! And yet…

- All traditional evils of discrimination, and many new ones, exhibit themselves in the data science eco system
- Bias that is inherent in the data or in the process, and that is often due to systemic discrimination, is propelled and amplified
- Transparency helps prevent discrimination, enable public debate, establish trust
- Technology alone won't do: also need policy, user involvement and education

Data, responsibly

Because of its power, data science must be used responsibly

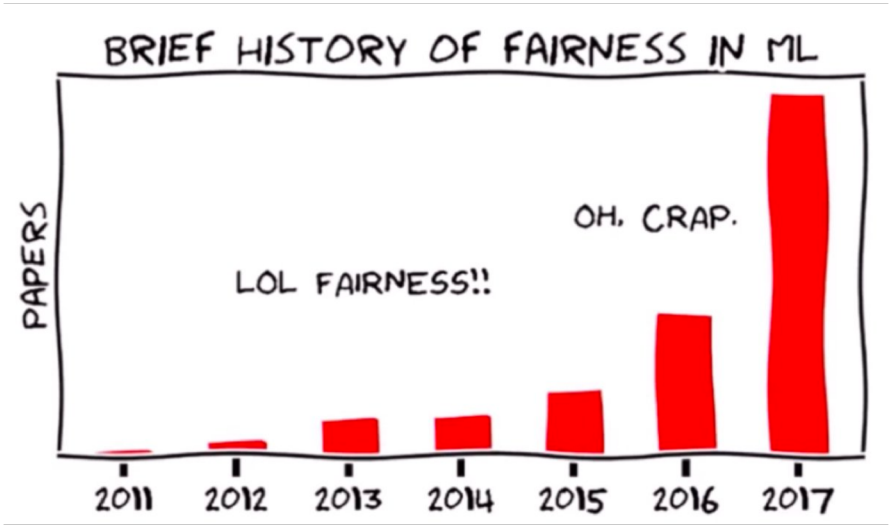
fairness

transparency

diversity

data protection

Fairness in ML



by Moritz Hardt

Fairness: a lack of "bias"

What are the tasks we are interested in?

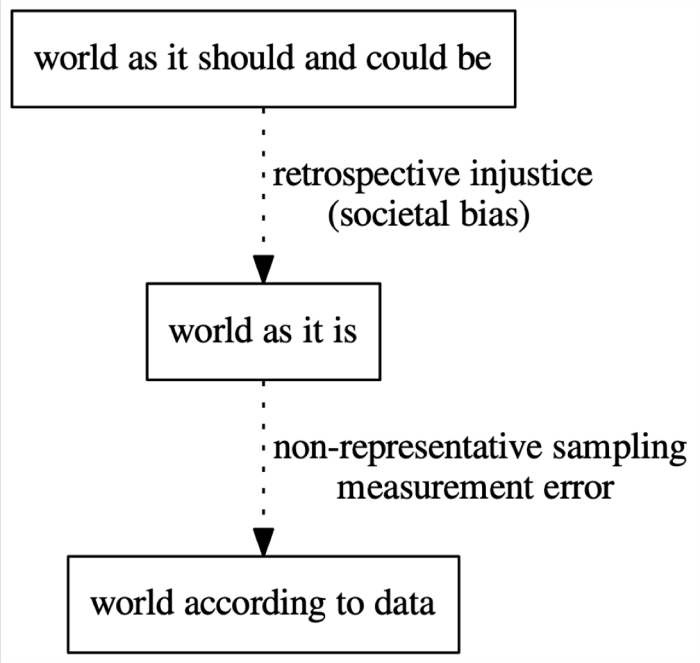
- predictive analytics and inferential interpretations

What do we mean by bias?

- **statistical bias**: a model is biased if it doesn't summarize the data correctly
- **societal bias**: a dataset or a model is biased if it does not represent the world "correctly", e.g., data is not representative, there is measurement error, or the world is "incorrect"

Depends on your perspective: the world as it is or as it should be?

“Biased data”



from “Prediction-Based Decisions and Fairness” by Mitchell, Potash and Barocas, 2018

when data is about people, bias can lead to discrimination

The evils of discrimination

Disparate treatment is the illegal practice of treating an entity, such as a creditor or employee, differently based on a protected characteristic such as race, gender, age, religion, sexual orientation, or national origin.

Disparate impact is the result of systematic disparate treatment, where disproportionate adverse impact is observed on members of a protected class.

- In the US, disparate impact measured by comparing the rate of positive outcomes for the protected class divided by rate of positive outcomes for the population as a whole.
- If that ratio is less than 80%, it is considered discriminatory

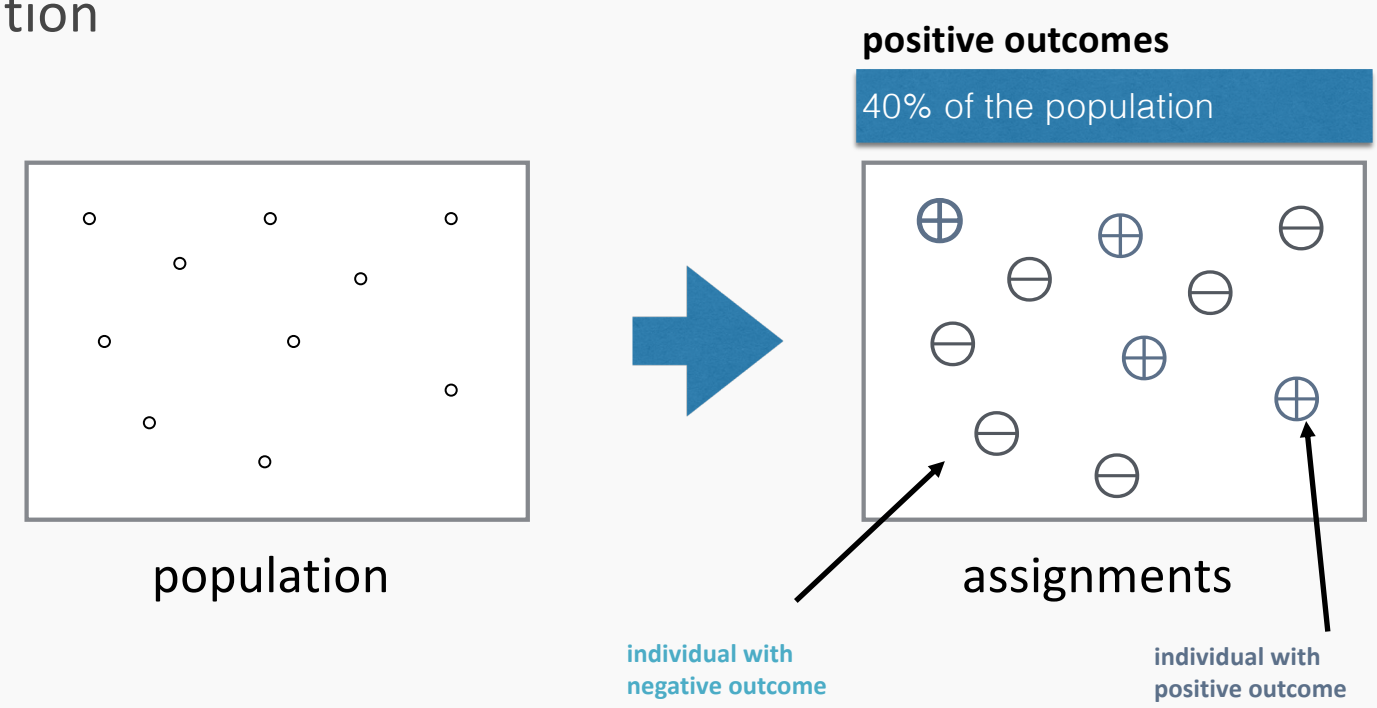
Vendors and outcomes

Consider a vendor assigning positive or negative outcomes to individuals.

Positive Outcomes	Negative Outcomes
offered employment	denied employment
accepted to school	rejected from school
offered a loan	denied a loan
offered a discount	not offered a discount

Assigning outcomes to populations

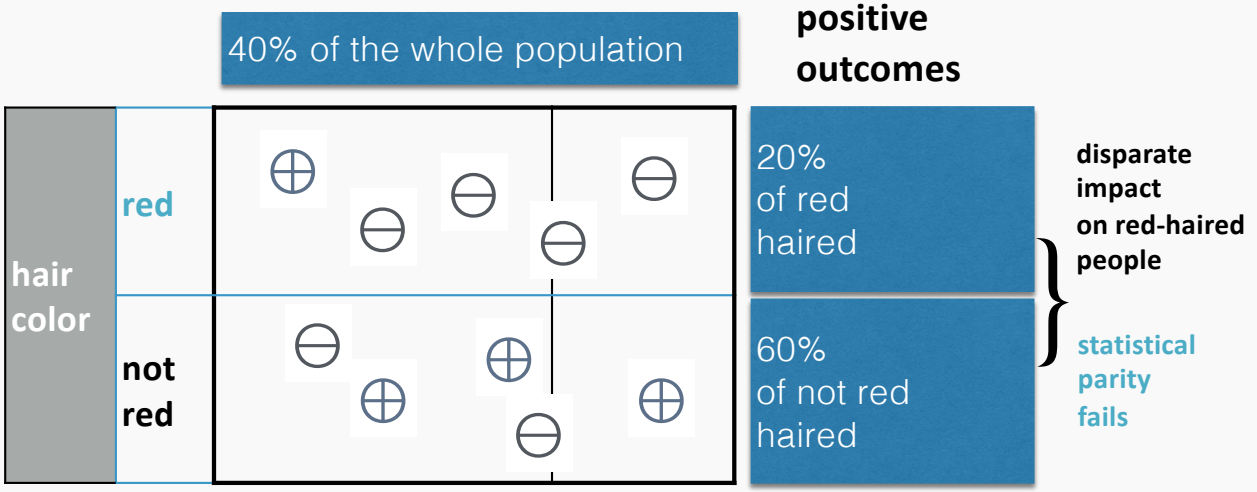
Fairness is concerned with how outcomes are assigned to a population



Sub-populations may be treated differently

Sub-population: those with red hair

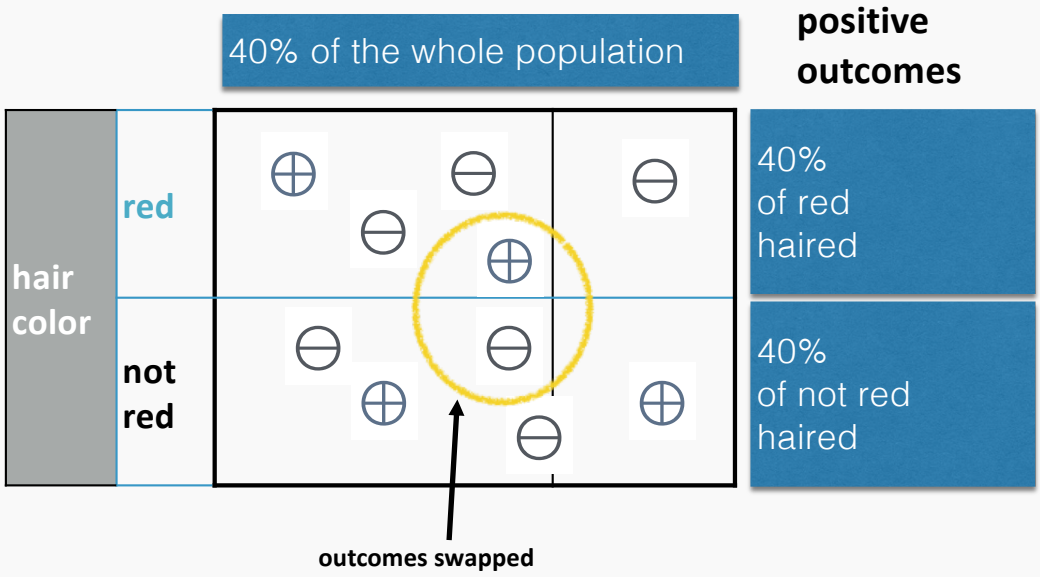
(under the same assignment of outcomes)



Statistical parity

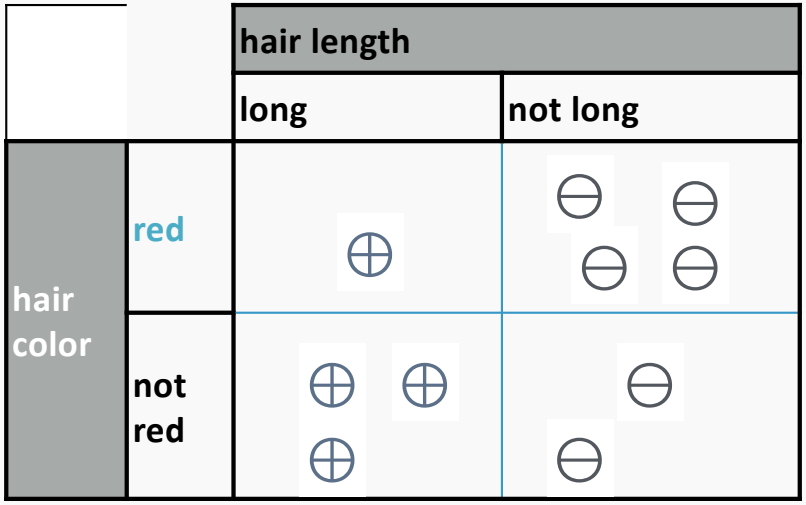
Statistical parity (a popular **group fairness** measure):

demographics of the individuals receiving any outcome are the same as demographics of the underlying population



Redundant encoding

Now consider the assignments under both
hair color (protected) and hair length (innocuous)



positive outcomes

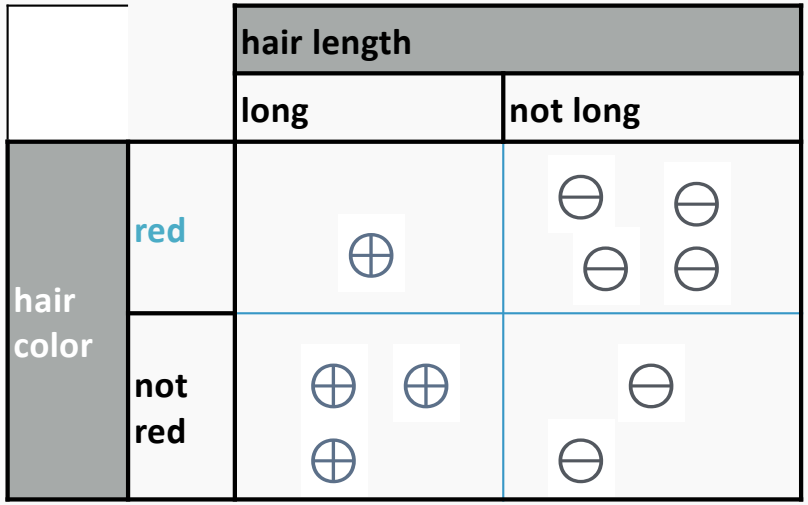
20% of red haired

60% of not red haired

Deniability
The vendor has adversely impacted red-haired people, but claims that outcomes are assigned according to hair length.

Blinding is not an excuse

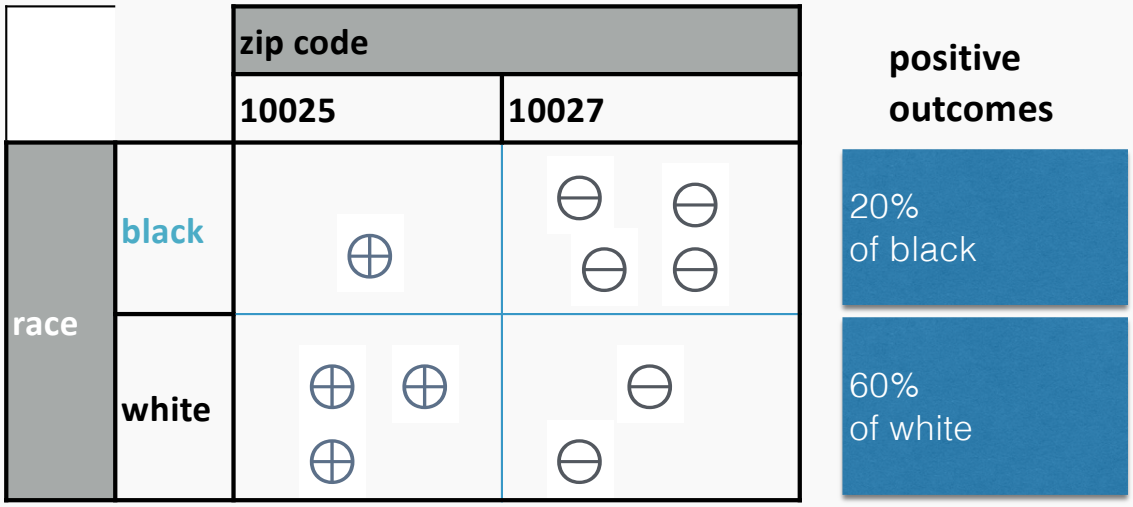
Removing **hair color** from the vendor's assignment process does not prevent discrimination! This is upheld in the legal system.



Assessing disparate impact
Discrimination is assessed by the effect on the protected sub-population, not by the input or by the process that lead to the effect.

Redundant encoding

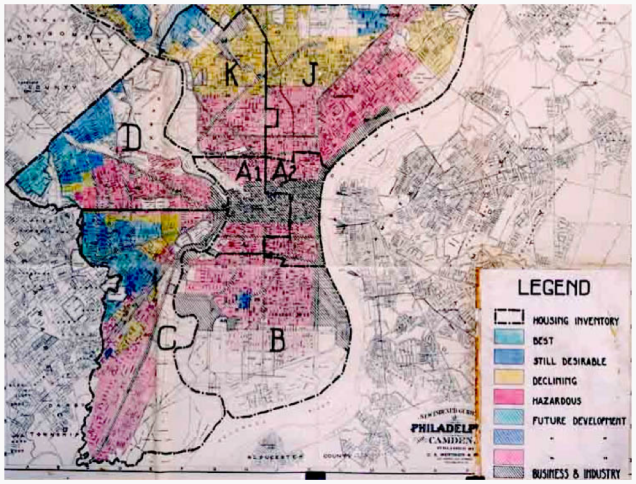
Let's replace hair color with race (protected), and hair length with zip code (innocuous)



Redlining

Redlining is the practice of arbitrarily denying or limiting financial services to specific neighborhoods, generally because its residents are people of color or are poor.

Philadelphia, 1936

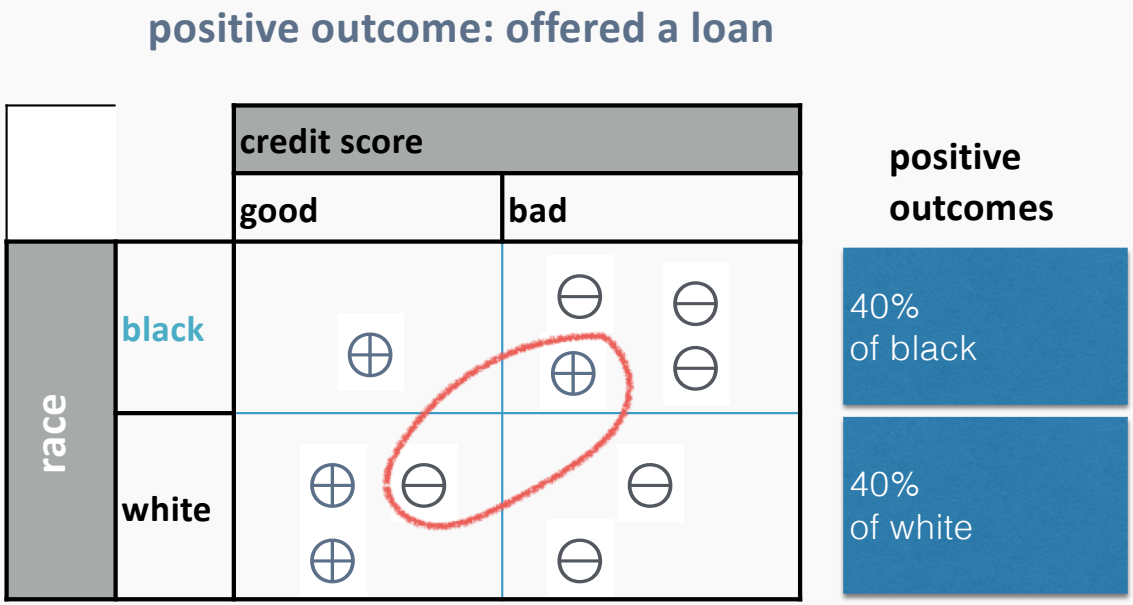


wikipedia

Households and businesses in the red zones could not get mortgages or business loans.

Imposing statistical parity

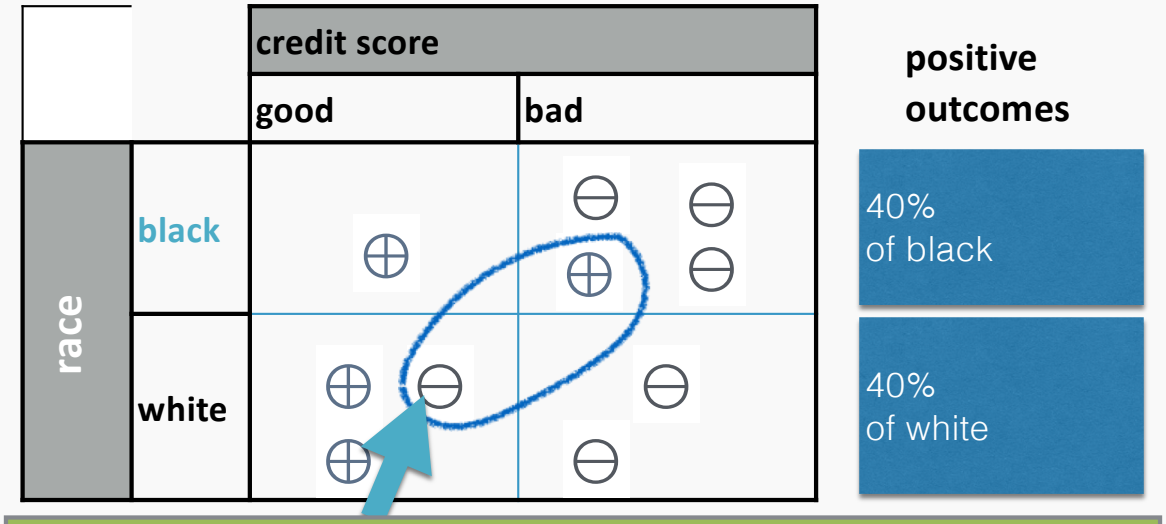
May be contrary to the goals of the vendor



Impossible to predict loan payback accurately.
Use past information, which may itself be biased.

Is statistical parity sufficient?

Statistical parity (a popular **group fairness** measure)
demographics of the individuals receiving any outcome are the same as demographics of the underlying population



Individual fairness
any two individuals who are similar w.r.t. a particular task should receive similar outcomes

Ricci v. DeStefano (2009)

Supreme Court Finds Bias Against White Firefighters

By **ADAM LIPTAK** JUNE 29, 2009

The New York Times

Karen Lee Torre, left, a lawyer who represented the New Haven firefighters in their lawsuit, with her clients Monday at the federal courthouse in New Haven. Christopher Capozziello for The New York Times

Case opinions	
Majority	Kennedy, joined by Roberts, Scalia, Thomas, Alito
Concurrence	Scalia
Concurrence	Alito, joined by Scalia, Thomas
Dissent	Ginsburg, joined by Stevens, Souter, Breyer

Laws applied

Title VII of the Civil Rights Act of 1964, 42 U.S.C. § 2000e et seq.

Two notions of fairness

individual fairness

equality

group fairness

equity

two intrinsically different world views

On the (im)possibility of fairness

2 intrinsically different worlds views

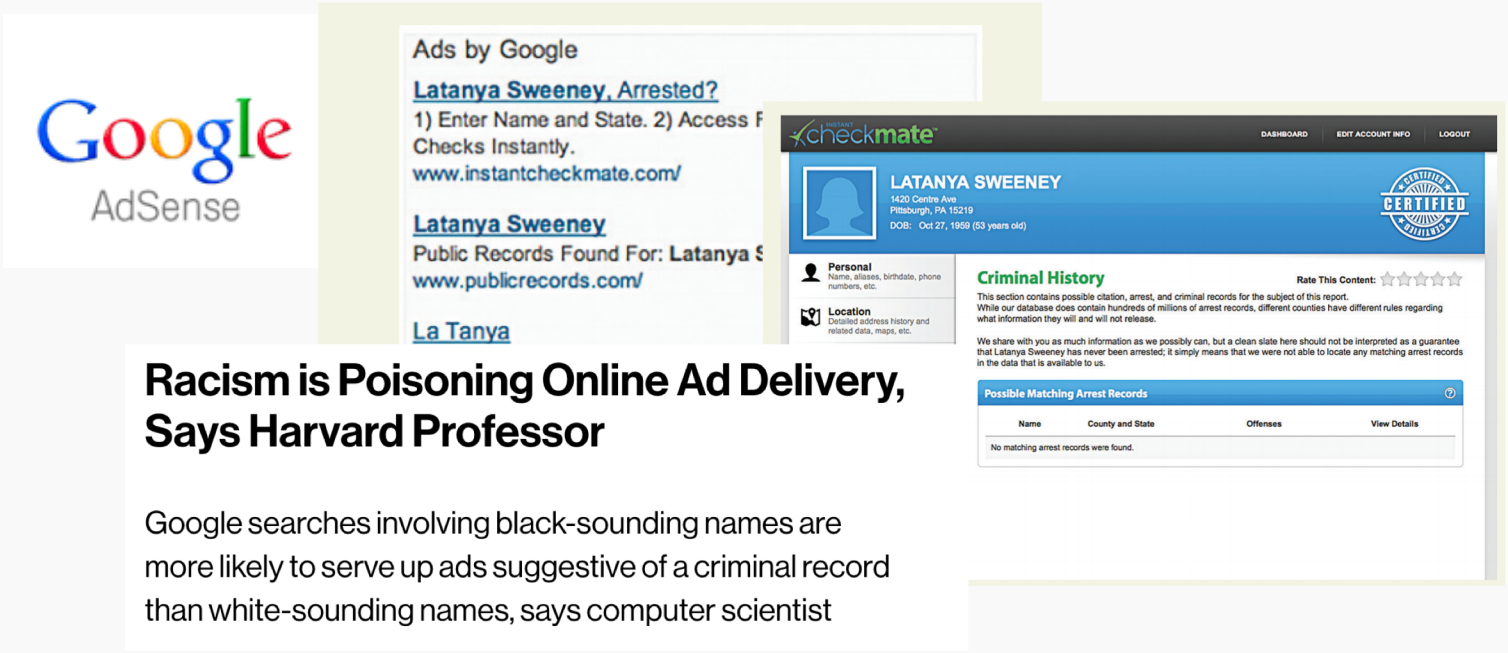
- What you see is what you get (WYSIWYG) - individual fairness
- We are all equal (WAE) - group fairness

Construct Space (CS)	Observed Space (OS)	Decision Space (DS)
intelligence	SAT score	performance in college
grit	high-school GPA	
propensity to commit crime	family history	recidivism
risk-averseness	age	

Goal: tease out the difference between beliefs about fairness and mechanisms that logically follow from those beliefs.

Racially identifying names

[Latanya Sweeney; *CACM 2013*]



racially identifying names trigger ads suggestive of a criminal record

https://www.technologyreview.com/s/510646/racism-is-poisoning-online-ad-delivery-says-harvard-professor/

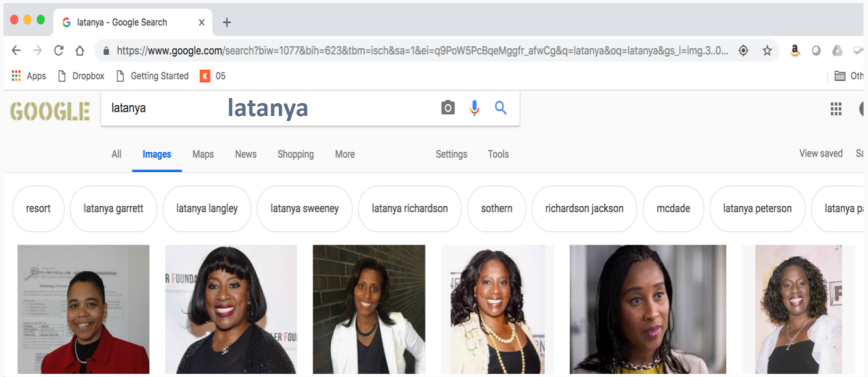
Observations

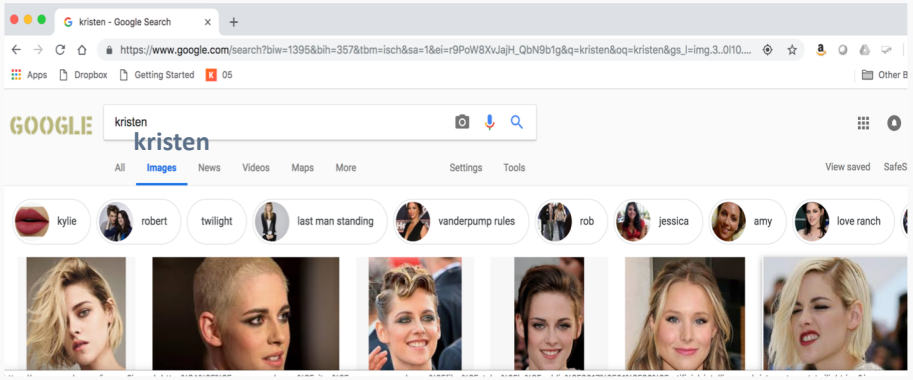
[Latanya Sweeney; *CACM 2013*]

Ads suggestive of a criminal record, linking to Instant Checkmate, appear on google.com and reuters.com in response to searches for "Latanya Sweeney", "Latanya Farrell"and "Latanya Lockett"*

No Instant Checkmate ads when searching for "Kristen Haring", "Kristen Sparrow"* and "Kristen Lindquist"*

* next to a name associated with an actual arrest record





Why is this happening?

[Latanya Sweeney; *CACM 2013*]

Possible explanations (from Latanya Sweeney):

- Does Instant Checkmate serve ads specifically for black-identifying names?
- Is Google's Adsense explicitly biased in this way?
- Does Google's Adsense learn racial bias based on click-through rates?

How do we know which explanation is right?

We need transparency!

Codes of ethics

Association for Computing Machinery

Advancing Computing as a Science & Profession

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Home > Code Of Ethics

ACM Code of Ethics and Professional Conduct

ACM Code of Ethics and Professional Conduct

PDF of the ACM Code of Ethics

Preamble

Computing professionals' actions change the world. To act responsibly, they should reflect upon the wider impacts of their work, consistently supporting the public good. The ACM Code of Ethics and Professional Conduct ("the Code") expresses the conscience of the profession.

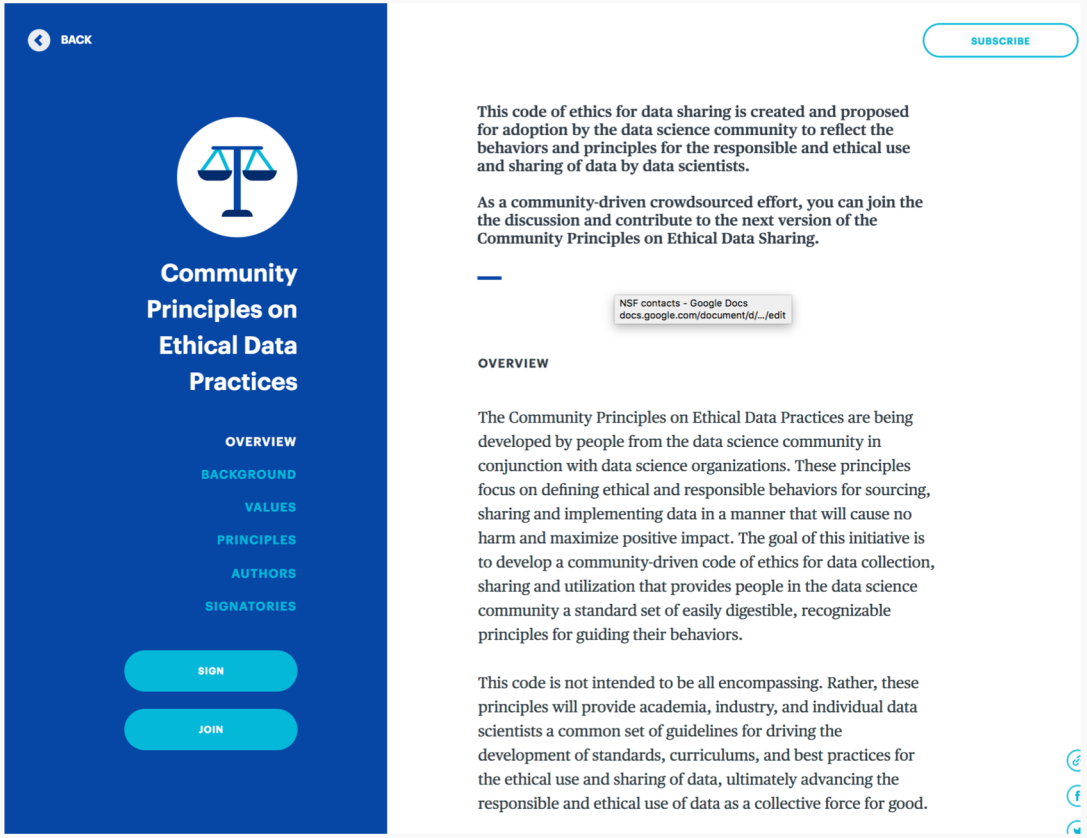
The Code is designed to inspire and guide the ethical conduct of all computing professionals, including current and aspiring practitioners, instructors, students, influencers, and anyone who uses computing technology in an impactful way. Additionally, the Code serves as a basis for remediation when violations occur. The Code includes principles formulated as statements of responsibility, based on the understanding that the public good is always the primary consideration. Each principle is supplemented by guidelines, which provide explanations to assist computing professionals in understanding and applying the principle.

Section 1 outlines fundamental ethical principles that form the basis for the remainder of the Code. Section 2 addresses additional, more specific considerations of professional responsibility. Section 3 guides individuals who have a leadership role, whether in the workplace or in a volunteer professional capacity. Commitment to ethical conduct is required of every ACM member, and principles involving compliance with the Code are given in Section 4.

The Code as a whole is concerned with how fundamental ethical principles apply to a computing professional's conduct. The Code is not an algorithm for solving ethical problems; rather it serves as a basis for ethical decision-making. When thinking through a particular issue, a computing professional may find that multiple principles should be taken into account, and that different principles will have different relevance to the issue. Questions related to these kinds of issues can best be answered by thoughtful consideration of the fundamental ethical principles, understanding that the public good is the paramount consideration. The entire computing profession benefits when the ethical decision-making process is accountable to and transparent to all stakeholders. Open discussions about ethical issues promote this accountability and transparency.

On This Page

Codes of ethics



Case Study: Bias in the COMPAS algorithm

Racial bias in criminal sentencing

ProPublica is "an independent, non-profit newsroom that produces investigative journalism in the public interest."

ProPublica investigated COMPAS, a commercial tool that automatically predicts some categories of future crime to assist in bail and sentencing decisions. It is used in courts in the US.

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Automated risk assessment

Goal: predict the likelihood of some category of future crime

Used by judges to assist in (1) assigning bail amounts and (2) sentencing

Intended use of the algorithm was **different** - to provide supportive interventions!

Algorithm

Input: attributes of individuals, based on a 137-question questionnaire answered by defendants. Questions are from the following categories:

- current charges, criminal history, non-compliance history, family criminality, peers, substance abuse, residence/stability, social environment, education, vocation, leisure/recreation, social isolation, criminal personality, anger, criminal attitudes
- race is not a feature!

Example questions

- "Was one of your parents ever sent to jail or prison?"
- "How many of your friends/acquaintances are taking drugs illegally?"
- "How often did you get into fights while at school?"
- Agree or disagree with statements such as:
  - "A hungry person has a right to steal." and
  - "If people make me angry or lose my temper, I can be dangerous."

Training Data

The original training data were based on a subset of Michigan and New York inmates and parolees. Even though it was trained on mostly male observations, the score is said to be "gender-neutral."

The algorithm/score was revised and tuned to a new training group:

"normative data were sampled from over 30,000 COMPAS Core assessments conducted between January 2004 and November 2005 at prison, parole, jail and probation sites across the United States." This is the normative group that the risk assessments are based on today.

Output: risk score [1,10]

- risk for general recidivism
- risk for violent recidivism

Output Score

Output: risk score [1,10]

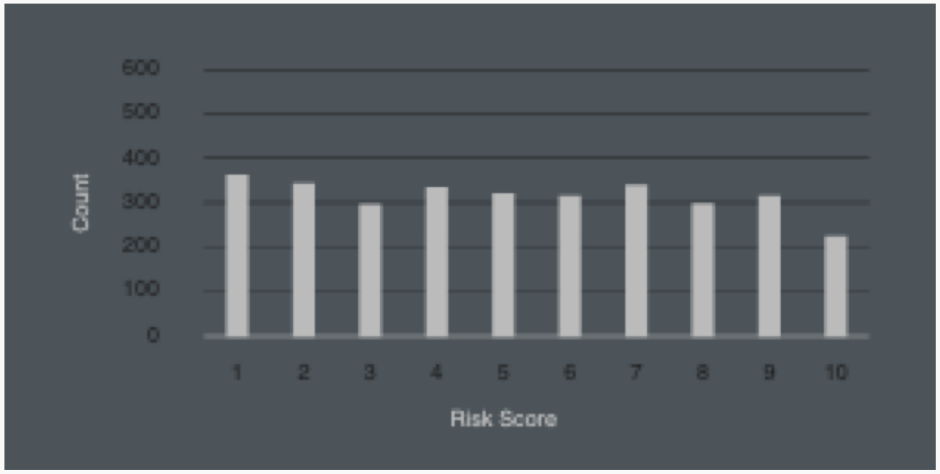
- risk for general recidivism
- risk for violent recidivism

These scores are often put into 2 or 3 categories of low-risk, medium-risk, and high-risk of recidivism.

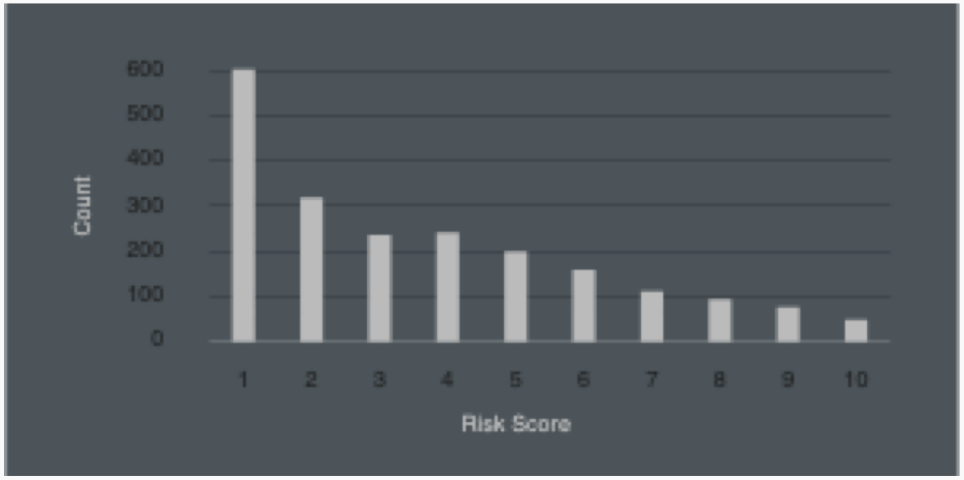
The predicted risk groups are then assessed via the standard false positive and false negative rates, and the AUC score is used to tune the output and compare to other predictive models.

Risk Assessment Results (in Broward County, Fla.)

Black Defendants' Risk Scores



White Defendants' Risk Scores



Recidivism Results (in Broward County, Fla.)

Prediction Fails Differently for Black Defendants

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Discussion Questions:

1. Is COMPAS a fair algorithm? Think about this from both the individual and group perspective.

2. How can the COMPAS algorithm predict different rates of recidivism for racial groups even though race was not an input into the prediction model? (How) can this be corrected?

3. What factors could be causing the observed differences

Course Wrap-Up

Modules

The semester has been organized into 4 major 'modules':

- Module 0: Intro to Data and Data Science (and Python)
- Module 1: Regression
- Module 2: Classification
- Module 3: Ensemble Methods

We have learned various approaches to perform both predictions and inferences within each of these frameworks.

Module 1: Regression Methods

When is it appropriate to perform a regression method? What regression models have we learned?

1. Linear Regression (simple, multiple, polynomial, interactions, model selection, Ridge & Lasso, etc...)
2. *k*-NN
3. Regression Trees

What is the main difference between these types of models?

Module 2: Classification Methods

When is it appropriate to perform a classification method? What classification models have we learned?

1. Logistic Regression: same details as linear regression apply
2. *k*-NN
3. Classification Trees

What is the main difference between these types of models (advantages and disadvantages)? When should you use each method?

Module 3: Ensemble Methods

What does it mean for a model to be an ensemble method?

1. Bagging Trees
2. Random Forests
3. Boosting Models
4. Stacking Models
5. Neural Networks

What approach does each model take to improve prediction accuracy?

Choosing between Models

How can we choose between our various methods/models to answer a question at hand? What approaches/measures can we use to make this determination?

1. In-sample: AIC, BIC (barely mentioned)
2. Out-of-sample: Cross-Validation

What measure(s) should we use when we perform cross-validation?

Dealing with Data Issues

What issues have arisen when dealing with real data? How have we handled them?

1. Categorical Predictors: might make sense to one-hot encode
2. Missing Data: might make sense to impute
3. High Dimensionality: might make sense to use a data reduction technique.
4. Too many observations: do preliminary analysis on a subset

How are predictions affected? How are inferences affected?

Dealing with High Dimensionality

What does 'high dimensionality' mean? What issues arise when this happens? How can we handle it?

1. Model Selection: subset variable selection
2. Regularization: LASSO and Ridge like approaches (penalize the loss function)
3. PCA: create new predictor variables that encapsulate the 'essence' of all your predictor data with a minimal number of variables.

How can we compare methods to determine which approach is best?

Other things we've learned

- Scraping, Data Gathering, Data Wrangling
- EDA: Visualization and Summary Statistics
- *t*-tests and *p*-values: probabilistic/ approaches to perform inferences
- Bootstrapping: empirical approach to perform inferences
- Misclassification Rates, Types of Errors, Confusion Matrices/Tables, and ROC Curves
- Bias-Variance Trade-off
- Train vs. Test vs. Validation
- Standardization vs. Normalization. When should we do it?
- Data Ethics

Anything lingering questions or thoughts?

Other things we haven't discussed

There are lots of topics we have not covered in one semester…some are covered in 109B in the Spring:

- AB testing and Causal Inference
- Unsupervised Classification/Clustering
- Smoothers
- Bayesian Data Analysis
- Reinforcement Learning
- Other versions of Neural Networks (and 'Deep Learning')
- Interactive Visualizations
- Database Management (SQL, etc.)
- Cloud Computing and Scaling (AWS)
- And much, much more…

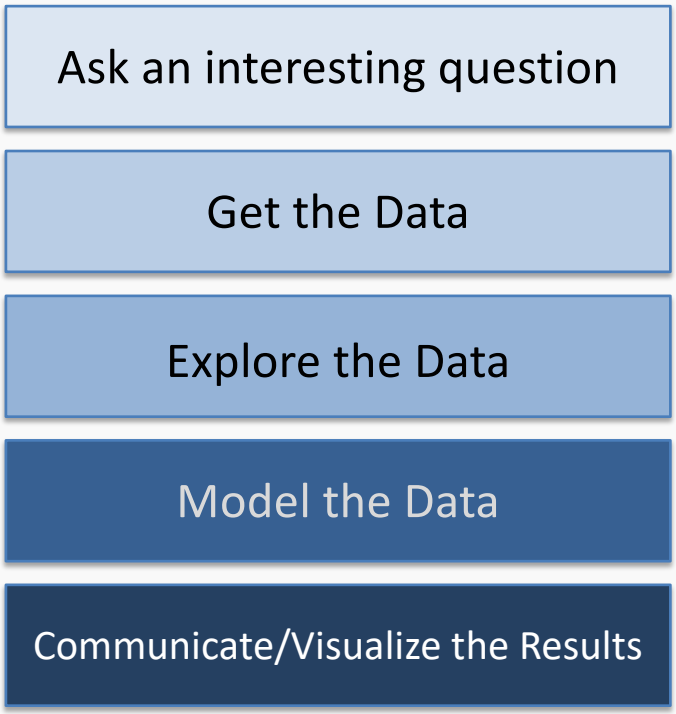
Courses Related to Data Science

- CS 109B: Advanced Topics in Data Science
- CS 171: Visualizations
- CS 181/281: Machine Learning
- CS 182: Artificial Intelligence (AI)
- CS 205: Distributive Computing
- Stat 110/210: Probability Theory
- Stat 111/211: Statistical Inference
- Stat 139: Linear Models
- Stat 149: Generalized Linear Models
- Stat 195: Intro to Statistical Machine Learning

This list is not exhaustive!

What?

The Data Science Process



Thanks for all your hard work!

It's been a long semester for everyone involved. Thank you for your patience, your hard work, and your commitment to data science!

It's sad to see you go...