CSE 417T
Introduction to Machine Learning

Lecture 13
Instructor: Chien-Ju (CJ) Ho

Logistics: Reminders

- Return of HW1
  - You can submit regrade requests till this Sat (within 7 days of homework return).
  - Please be respectful and polite when submitting requests.
  - We might review the entire piece of work, so the grades might go up/down.

- Exam 1: March 3, 2020 (Tuesday)
  - In-class exam (the same time/location as the lecture)
  - Exam duration: **75 minutes**
  - Planned exam content: **LFD Chapter 1 to 5**
  - Check seat assignments on Piazza the night before the exam
  - More details in the Slides on Feb 18

Logistics: Exam Preparations

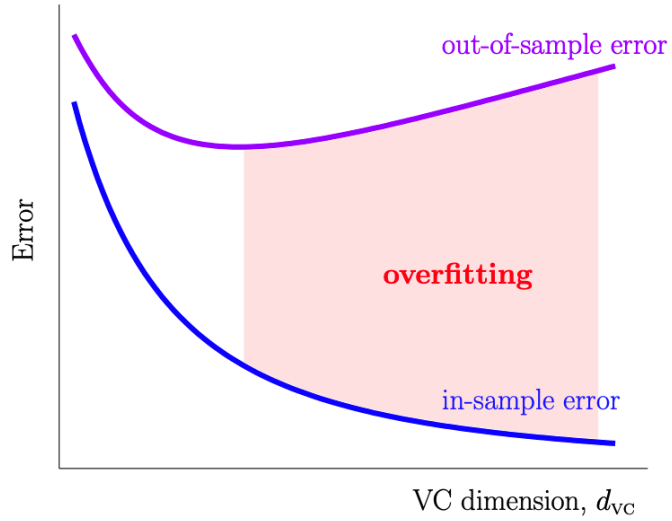
- We will post practice questions on Piazza by tonight.

- Next lecture will be the review session.
  - A summary of what we taught so far.
  - Discussion of practice questions.
  - Discussion of any other questions you might have.
  - Discussion on the exam logistics.

Recap

Overfitting and Its Cures

- Overfitting
  - Fitting the data more than is warranted
  - Fitting the noise instead of the pattern of the data
  - Decreasing E_{in} but getting larger E_{out}
  - When H is too strong, but N is not large enough



- Regularization
  - Intuition: Constraining H to make overfitting less likely to happen

- Validation
  - Intuition: Reserve data to estimate E_{out}

Regularization

- Constraining H
  - Example: Weight decay $H(C) = \{h \in H_Q \text{ and } \vec{w}^T\vec{w} \leq C\}$
  - Finding g => Constrained optimization

minimize $E_{in}(\vec{w})$

subject to $\vec{w}^T\vec{w} \leq C$

- Defining augmented error
  - $E_{aug}(h, \lambda, \Omega) = E_{in}(\vec{w}) + \frac{\lambda}{N}\Omega(h)$
  - Finding g => Unconstrained optimization

minimize $E_{in}(\vec{w}) + \frac{\lambda_C}{N}\vec{w}^T\vec{w}$

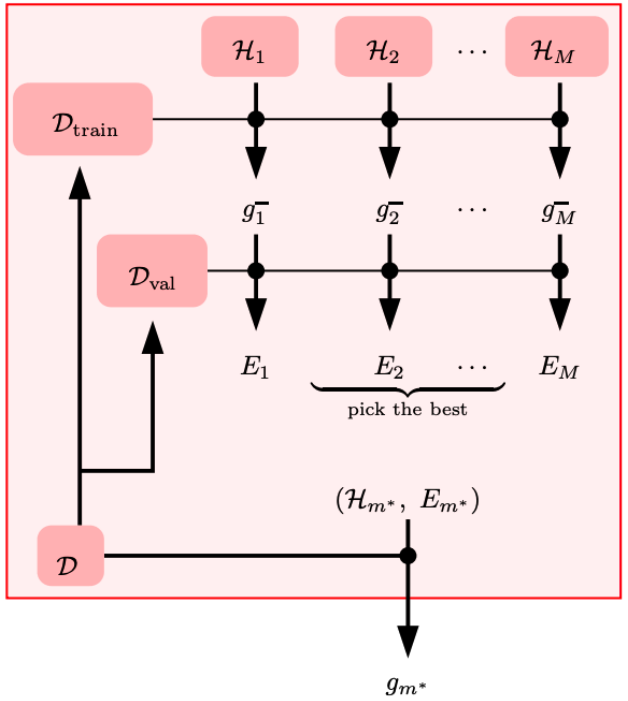
- The two interpretations are conceptually equivalent in a lot of cases.

- Understand the impacts of choosing Ω and λ

Validations

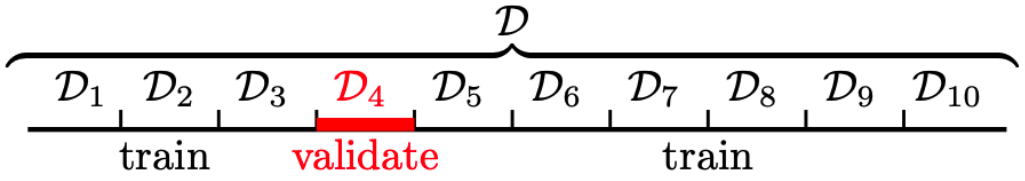
- Reserving data to estimate E_{out}

Model Selection



	Outlook	Relationship to E_{out}
E_{in}	Incredibly optimistic	VC-bound
E_{val}	Slightly optimistic	Hoeffding's bound (multiple hypotheses)
E_{test}	Unbiased	Hoeffding's bound (single hypothesis)

- Cross Validation



Brief Lecture Notes Today

The notes are not intended to be comprehensive. They should be accompanied by lectures and/or textbook.

Let me know if you spot errors.

Occam’s Razor

Sampling Bias

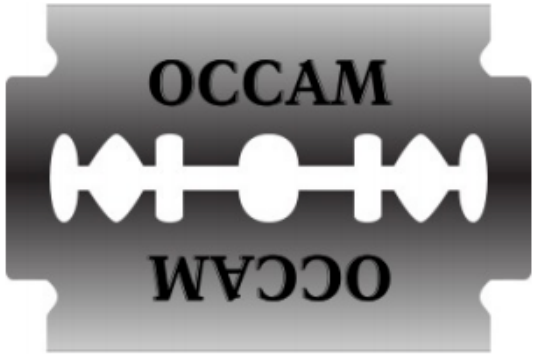
Data Snooping

Occam's Razor

"An explanation of the data should be made as simple as possible, but no simpler."
-- Einstein?

"entia non sunt multiplicanda praeter necessitatem"
(entities must not be multiplied beyond necessity)
-- William of Occam

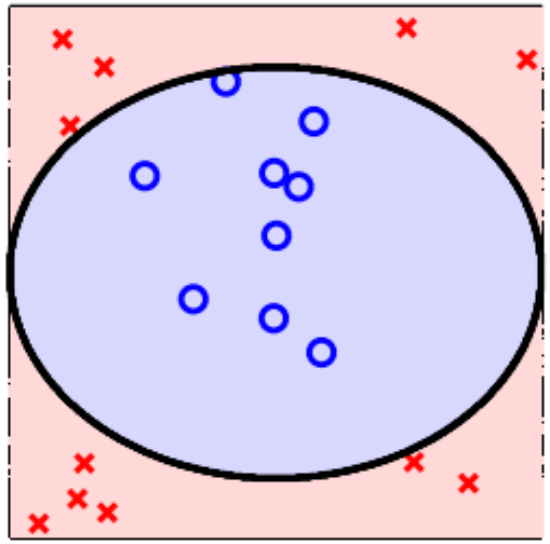
"trimming down"
unnecessary explanation

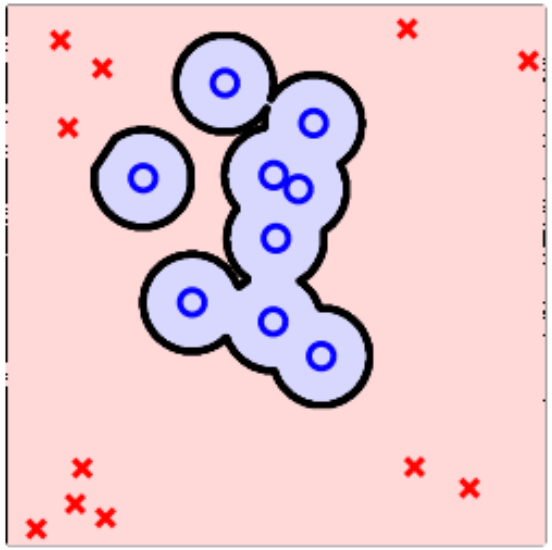


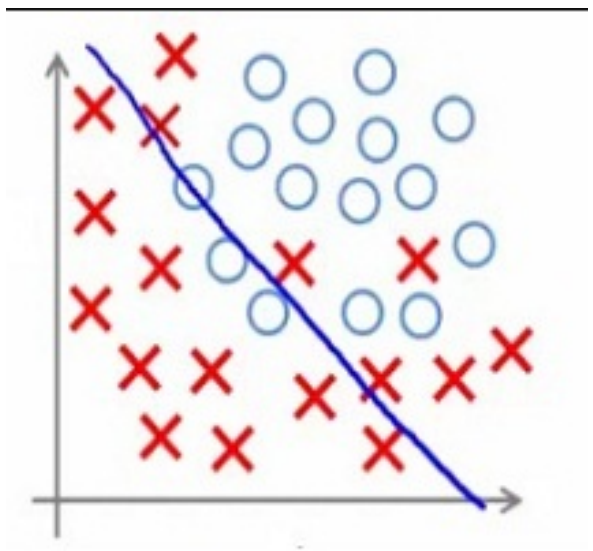
The simplest model that fits the data is also the most plausible

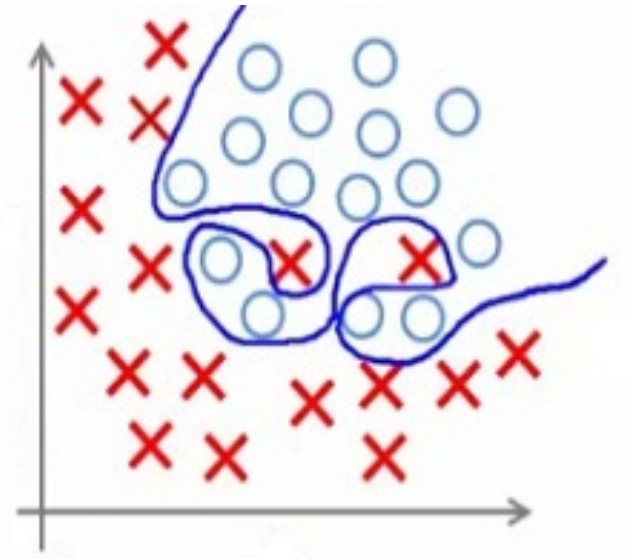
What does it mean to be simple?

Why is simple better?









Simple Model?

- For a hypothesis set H to be simple
  - # dichotomies it can generate is small
  - VC Dimension is small

- For a hypothesis h to be simple
  - lower order polynomial
  - smaller weights (think about the regularization)
  - easy to describe?
  - fewer number of parameters (fewer bits to describe)

Simple Model?

Connection:

A hypothesis set with *simple* hypotheses should be *simple*

Consider a hypothesis h can be specified by ℓ bits

$\Rightarrow H$ contains all such h

$\Rightarrow$ The size of H is 2^{ℓ}

Simple: small model complexity / VC dimension / size of hypothesis set

Why is Simple Better?

simple -> small VC dimension -> good generalization, less overfitting, …

Simple $\mathcal{H}$

$\Rightarrow$ small growth function $m_{\mathcal{H}}(N)$

$\Rightarrow$ if data labels are generated randomly, the probability of fitting perfectly is?

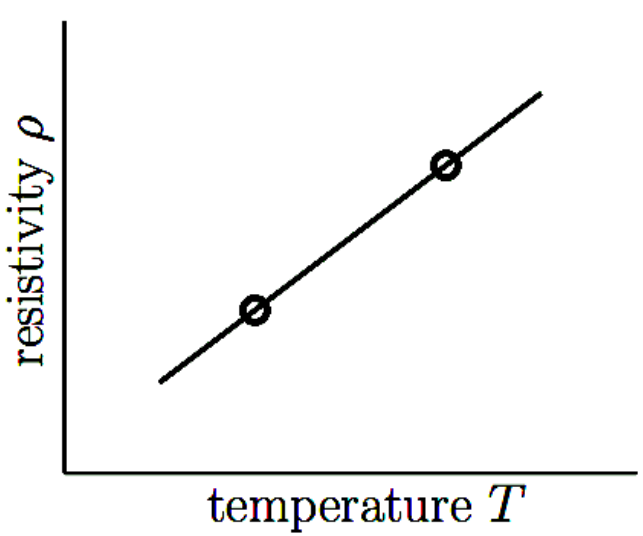
$$\frac{m_{\mathcal{H}}(N)}{2^N}$$

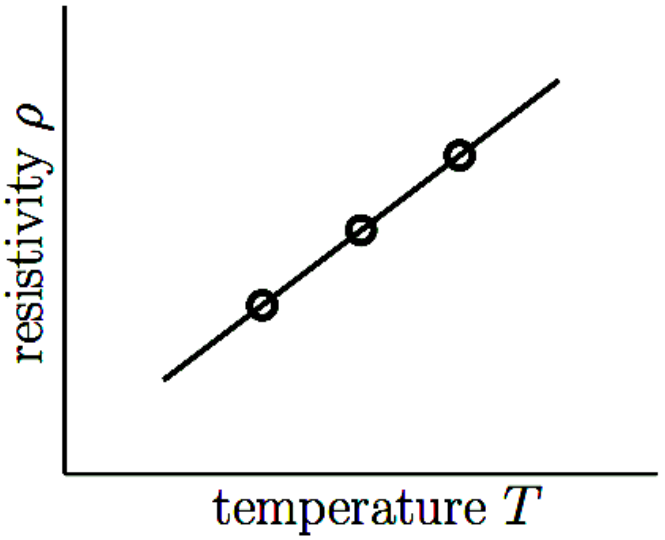
$\Rightarrow$ more significant when fit really happens

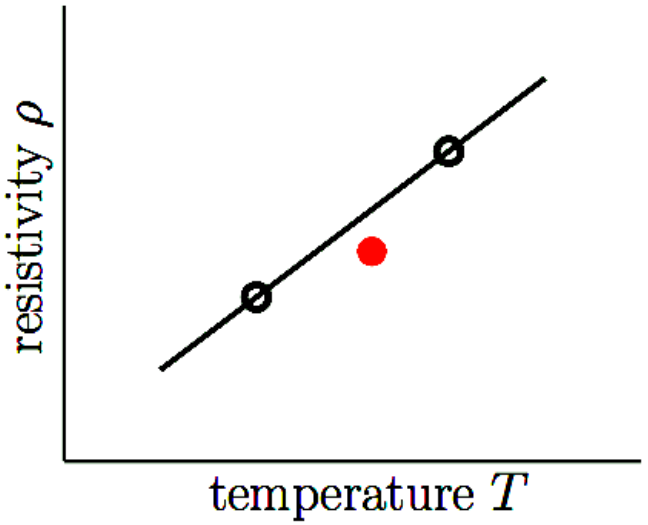
Falsifiability is important!

Falsifiability

Say you want to examine whether resistivity is linear in temperature (assume no measure error)







A Classical Puzzle

Imagine you got an email before each Cardinals game for the first 5 games.

Before Game 1: “Cardinals will win” -> Cardinals wins Game 1
Before Game 2: ”Cardinals will lose” -> Cardinals loses Game 2
….

Before Game 6:
If you pay me $50 dollars, I’ll tell you whether Cardinals will win or not

It’s not falsifiable:
Imagine if this person contacts 2^{10} persons, split them into two groups each game
2^5 persons will receive perfect prediction for the first 5 games

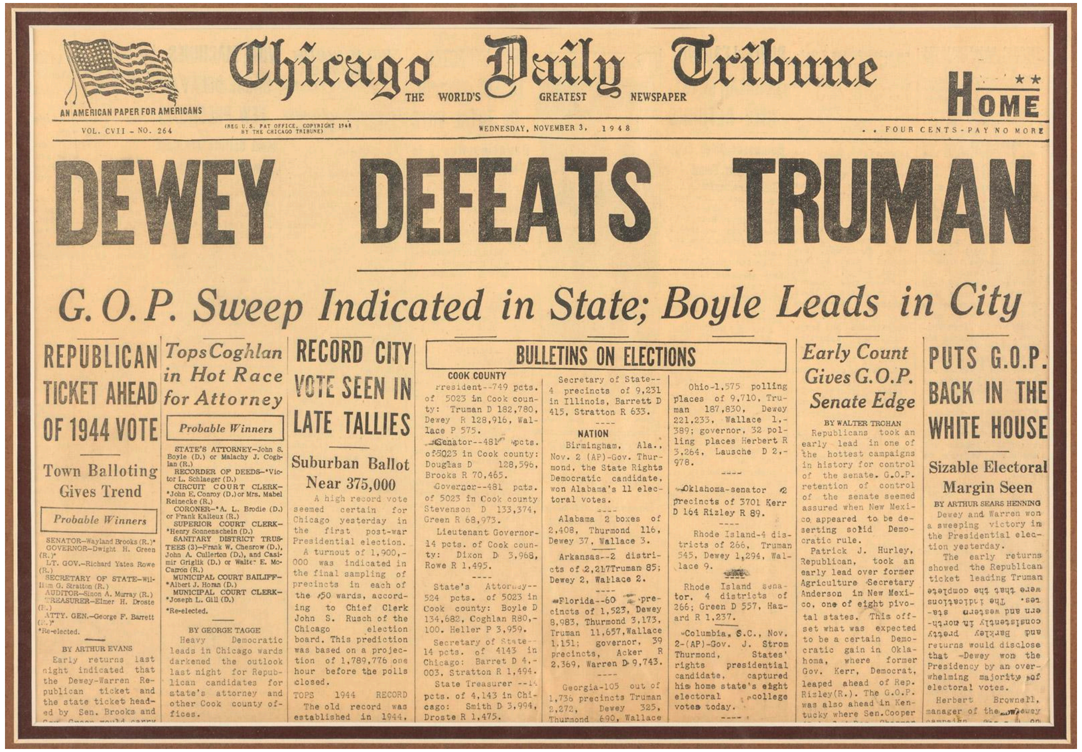
Occam’s Razor

Sampling Bias

Data Snooping

1948 US Presidential Election

- Truman vs. Dewey
- Chicago Daily Tribune decided to run a phone poll of how people voted



Chicago Daily Tribune
THE WORLD'S GREATEST NEWSPAPER
AN AMERICAN PAPER FOR AMERICANS
HOME

VOL. CVII - NO. 264 — WEDNESDAY, NOVEMBER 3, 1948 — FOUR CENTS-PAY NO MORE

DEWEY DEFEATS TRUMAN

G. O. P. Sweep Indicated in State; Boyle Leads in City

REPUBLICAN TICKET AHEAD OF 1944 VOTE

Town Balloting Gives Trend

Probable Winners

BY ARTHUR EVANS

Tops Coghlan in Hot Race for Attorney

Probable Winners

BY GEORGE TAGGE

RECORD CITY VOTE SEEN IN LATE TALLIES

Suburban Ballot Near 375,000

BULLETINS ON ELECTIONS

COOK COUNTY

NATION

Early Count Gives G.O.P. Senate Edge

BY WALTER TROHAN

PUTS G.O.P. BACK IN THE WHITE HOUSE

Sizable Electoral Margin Seen

BY ARTHUR SEARS HENNING

Truman


Chicago Daily Tribune
DEWEY DEFEATS TRUMAN
G.O.P. Sweep Indicated in State; Boyle Leads in

What happened?

One explanation: we cannot claim anything for certain.

However, there are bigger issues here…

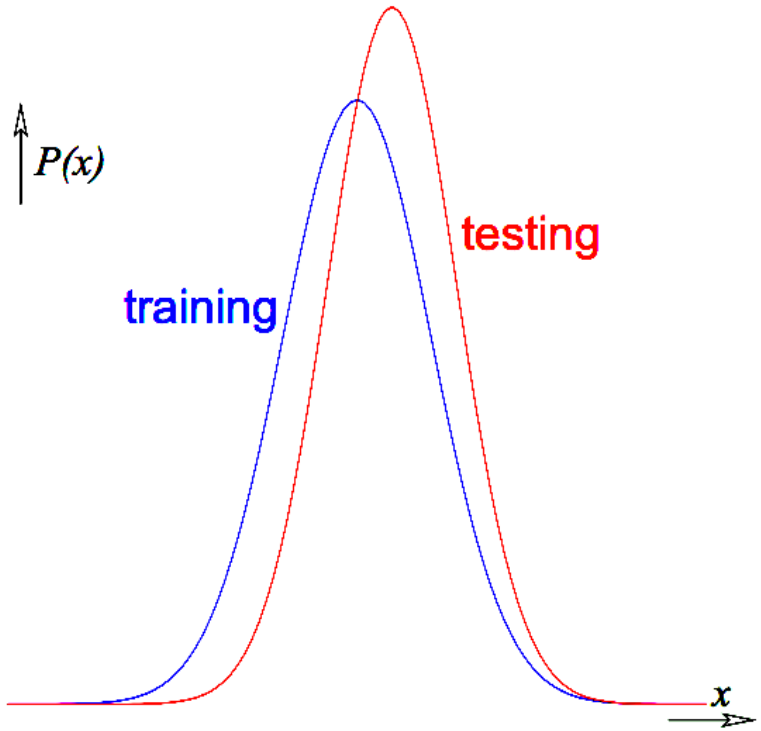
- Phones are expensive in 1948…
- Dewey was more favored in rich populations

- Imagine you are polling from people in DC/Texas/NY to predict who will win the presidential election…

Sampling Bias

If the data is sampled in a biased way, learning will produce a similarly biased outcome.

What can we do….

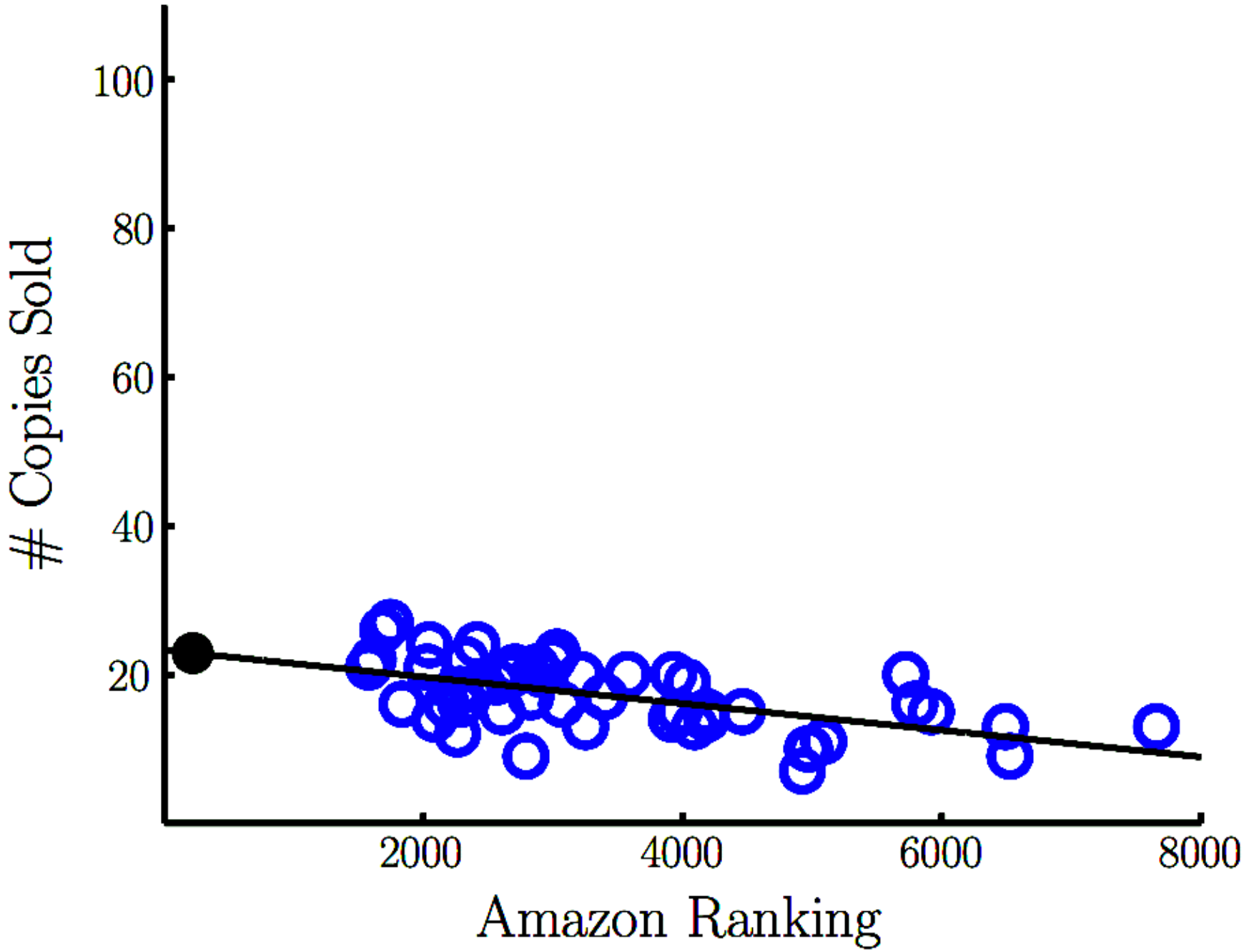


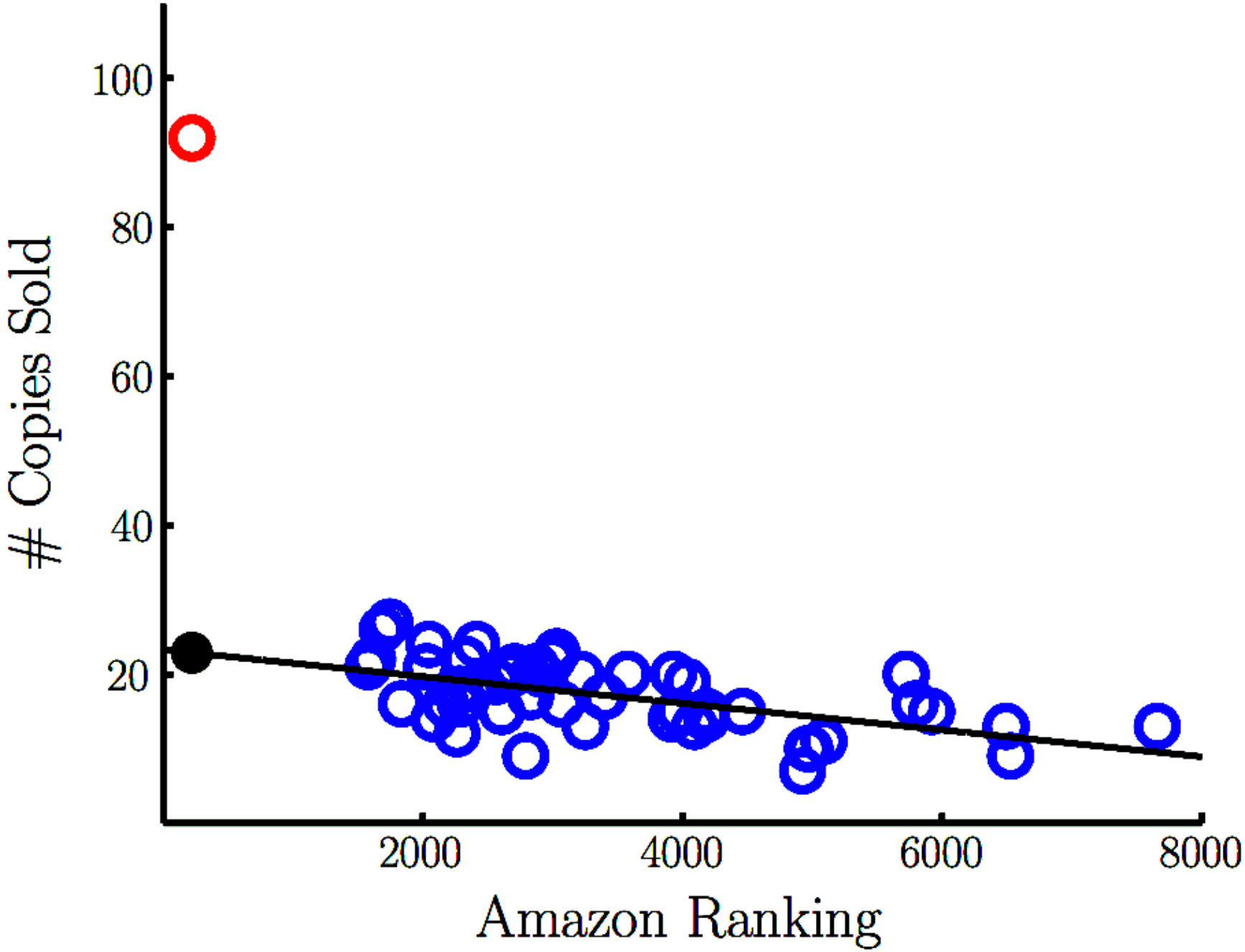
Make sure the training and test distributions are as close as possible…

- Example: importance weighting

Not always possible….

- If you don’t have access to some region of points in training, but they appear in the testing distribution


100
80
60
40
20
Copies Sold
2000
4000
6000
8000
Amazon Ranking


100
80
60
40
20
Copies Sold
2000
4000
6000
8000
Amazon Ranking

Credit card example

- Determine whether to approve credit cards given applicants' financial information
- Banks have lots of data:
  - Customer information
  - Whether they are good customers or not
- Are there any issues here?

age	32 years
gender	male
salary	40,000
debt	26,000
years in job	1 year
years at home	3 years
...	...

Approve for credit?

Occam’s Razor

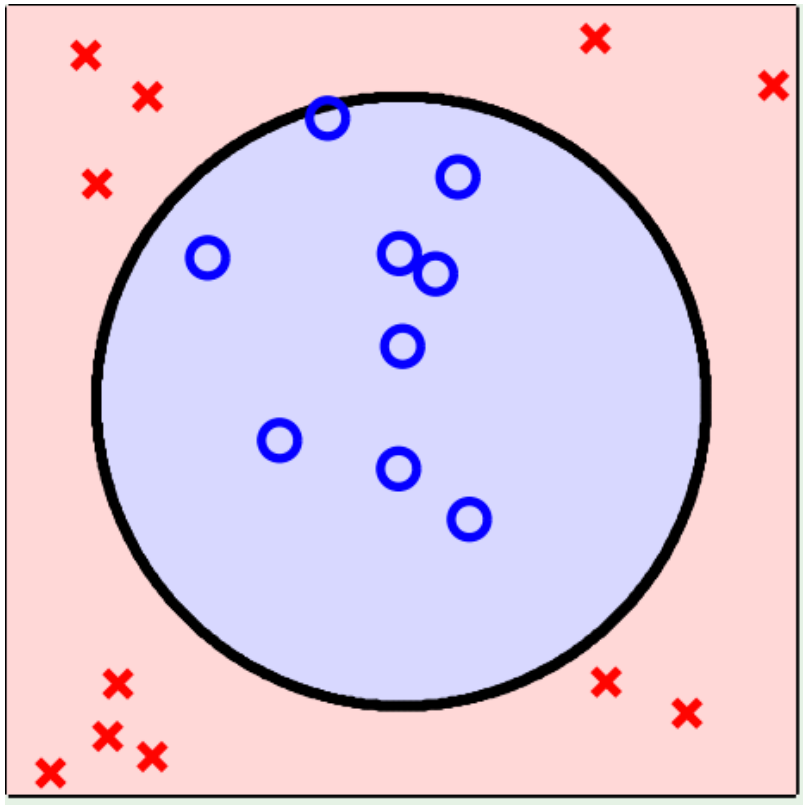
Sampling Bias

Data Snooping

Data Snooping

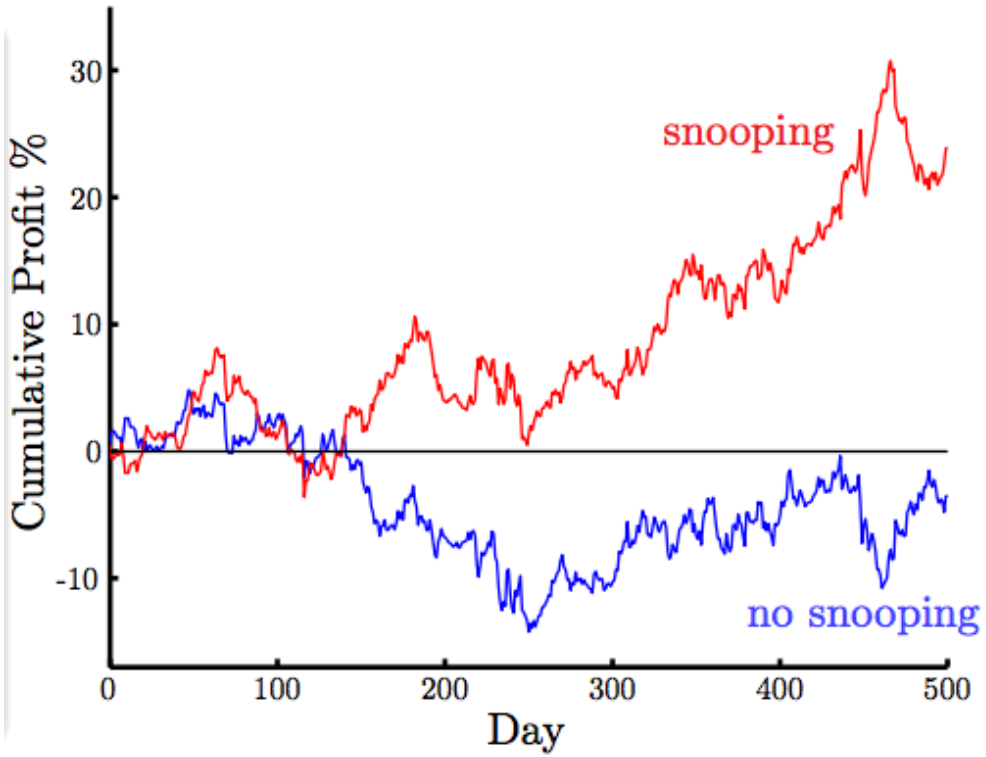
If a data set has affected any step in the learning process, its ability to assess the outcome has been compromised.

Shouldn’t looking at the data before selecting H



A Subtle Example

- Predict US Dollar vs. British Pound
  - $\vec{x}$: the change for the previous 20 days
  - y: the change in the 21th day
- Normalize data
- Randomly split D_{train} and D_{test}



- Where does snooping happen?
  - The normalization "looks at" D_{test}

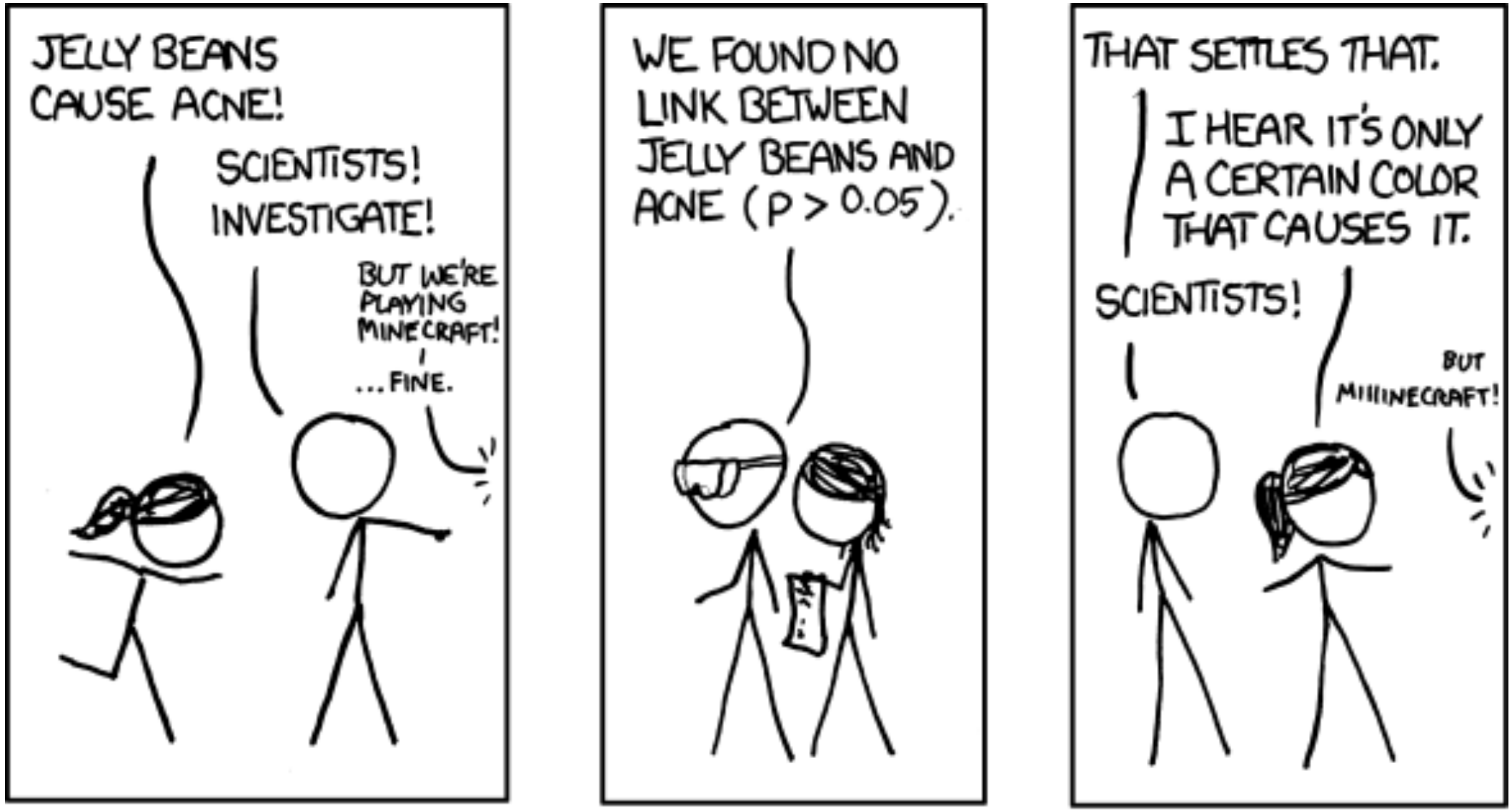
- How should you perform normalization in Q1 of HW2?

Reuse of a data set

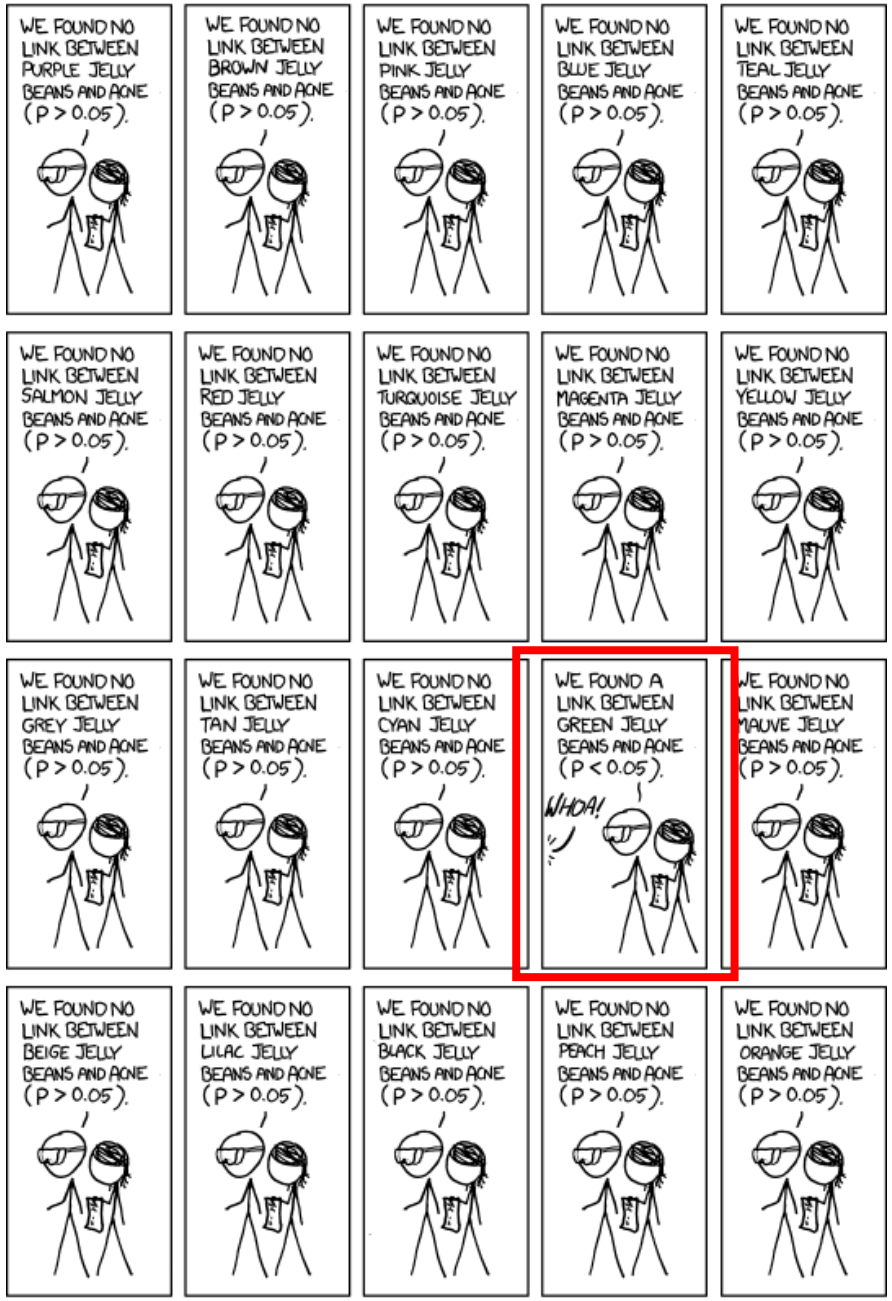
- Try one model after another **on the same data set**, you will eventually succeed.

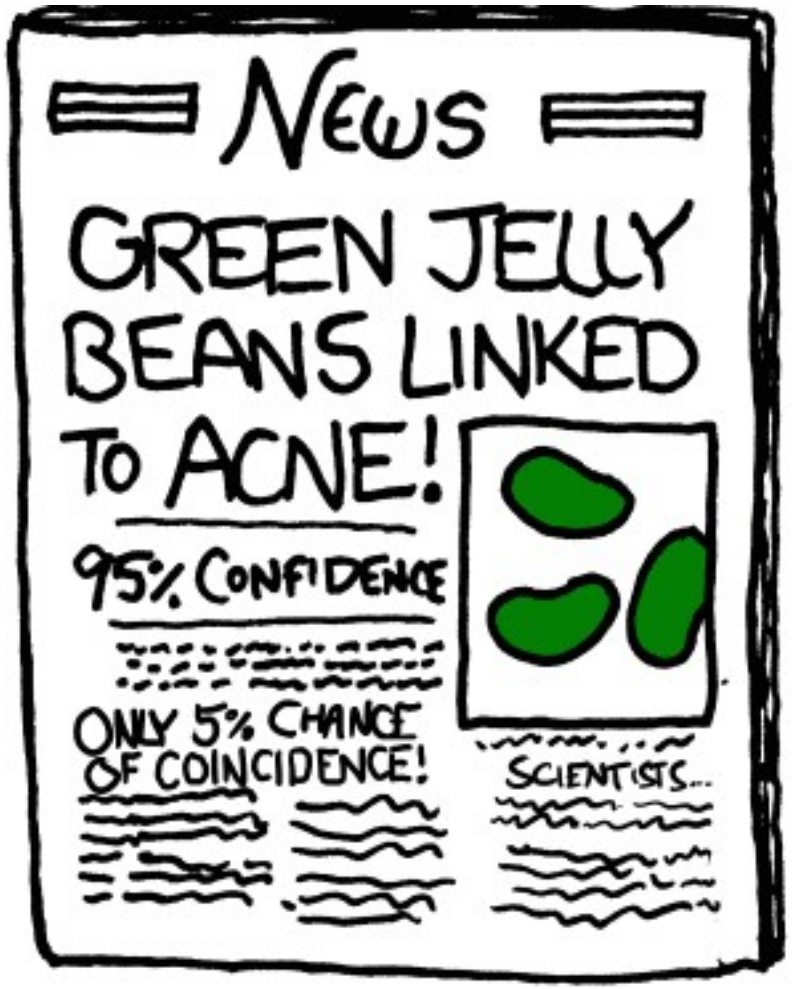
> "If you torture the data long enough, it will confess"

- VC dimension of the total learning models
- May even include what others tried (e.g., if you read their paper…)
- p-hacking…



From xkcd, by Randall Munroe: http://xkcd.com/882





From xkcd, by Randall Munroe: http://xkcd.com/882

What should we do…

Avoid data snooping

- Strict discipline
- E.g., be **honest** and lock the test data

Account for data snooping

- Measure how much data is contaminated
- E.g., what we discussed in validation

Occam’s Razor

Sampling Bias

Data Snooping

Course Plan

- Foundations
  - What's machine learning
  - Feasibility of learning
  - Generalization
  - Linear models
  - Non-linear transformations
  - Overfitting and how to avoid it
    - Regularization
    - Validation
- Techniques
  - Decision tree
  - Ensemble learning
    - Bagging and random forest
    - Boosting and Adaboost
  - Nearest neighbors
  - Support vector machine
  - Neural networks
  - …

Fairness in ML

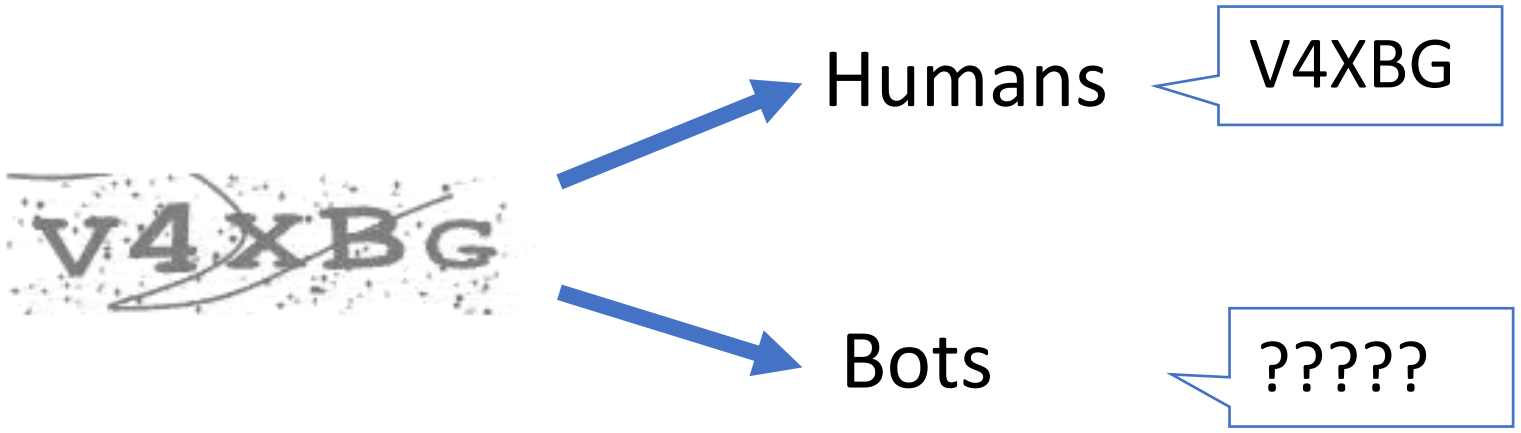
[The Remaining Lecture is Safe to Skip for Exam 1]

Modern ML is driven by data.

Where does data come from?

CAPTCHA

Completely **A**utomated **P**ublic **T**uring test to tell **C**omputers and **H**umans **A**part

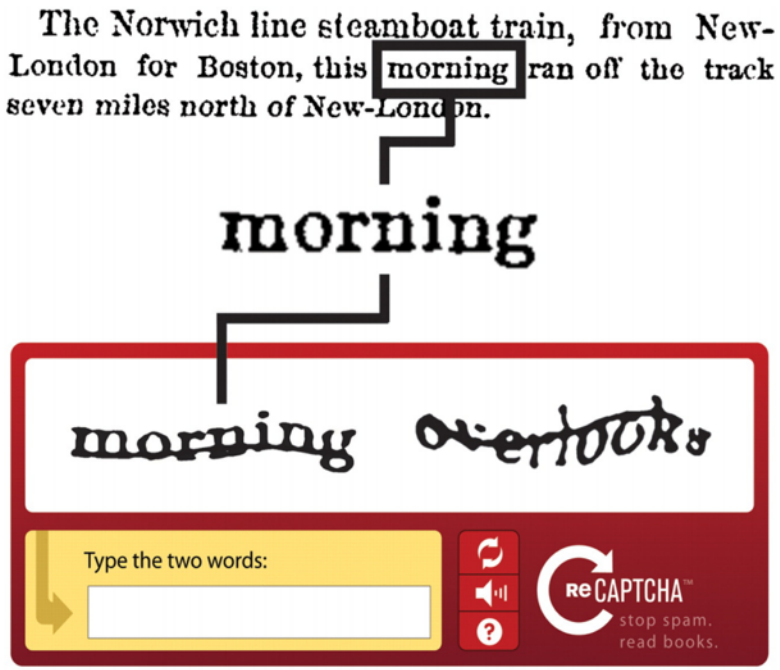


Roughly 200 million CAPTCHAs are typed every day*

10s of human time per CAPTCHA

Can we utilize this wasted human computation power?

*statistics around 2011



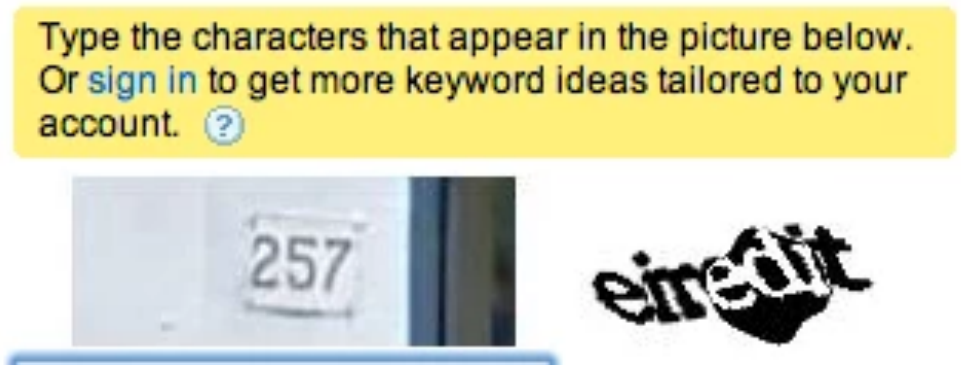
Word 1: an OCR task to solve
Word 2: tell apart humans and bots

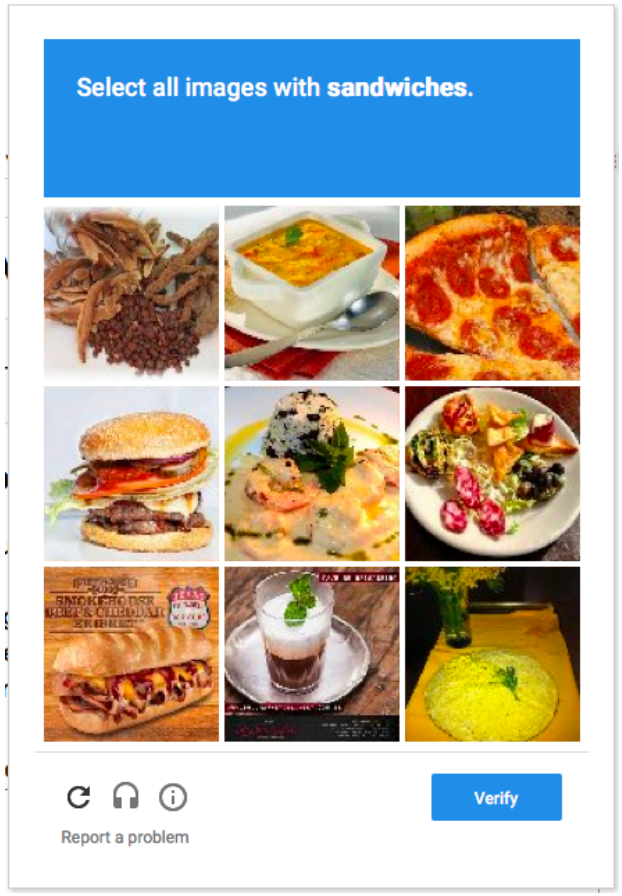
"reCAPTCHA has completely digitized the archives of The New York Times and books from Google Books, as of 2011"

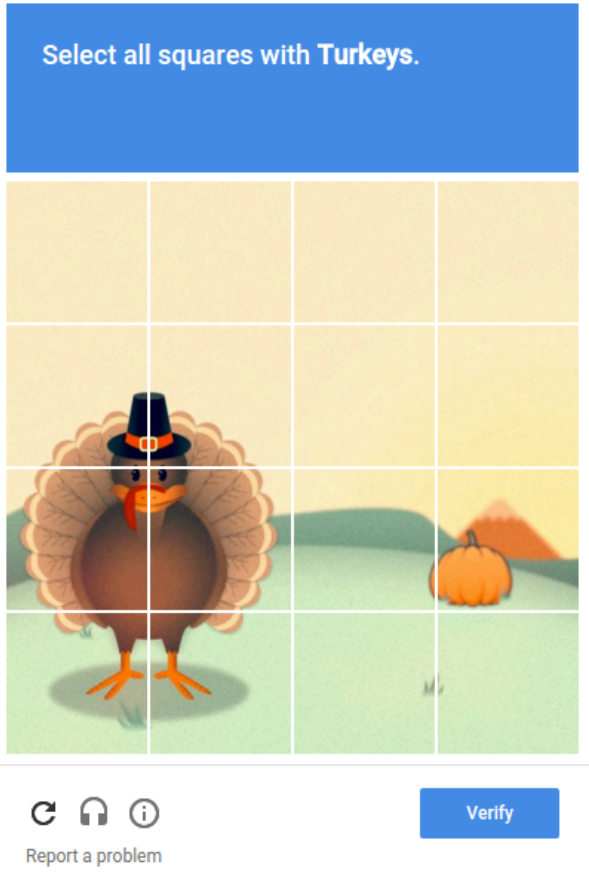
von Ahn et al. reCaptcha: Human-based Character Recognition via Web Security Measures. Science, September 2008

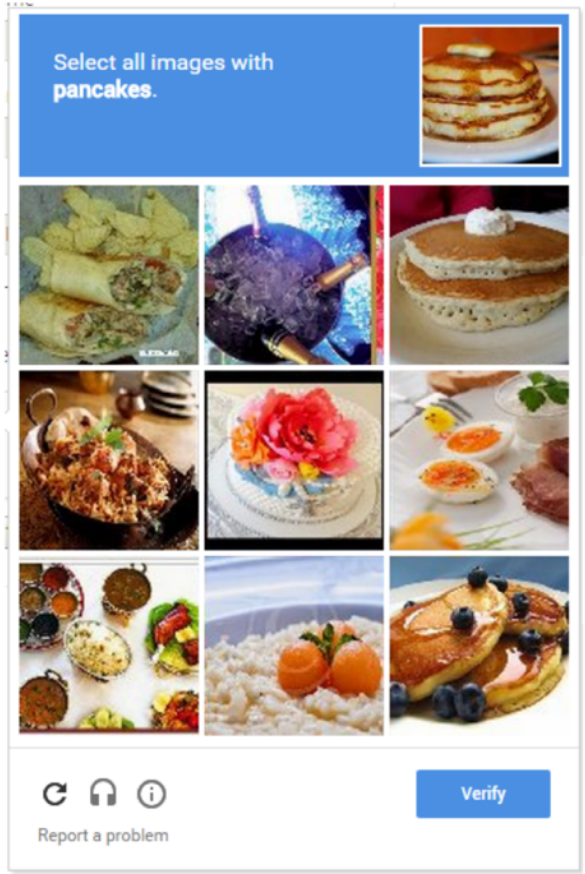
More than recognizing text

- Google acquired reCAPTCHA in 2009.



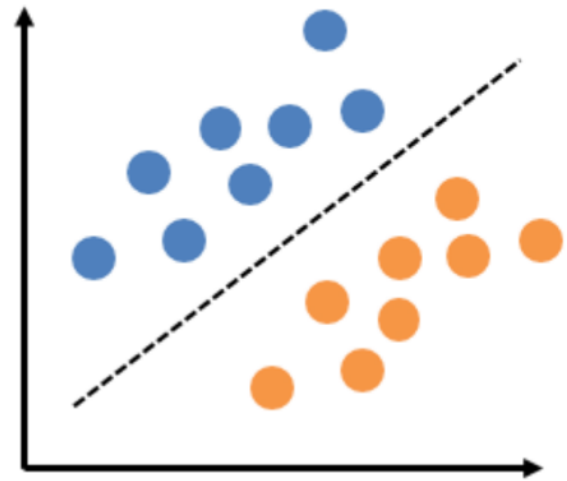






Training Data

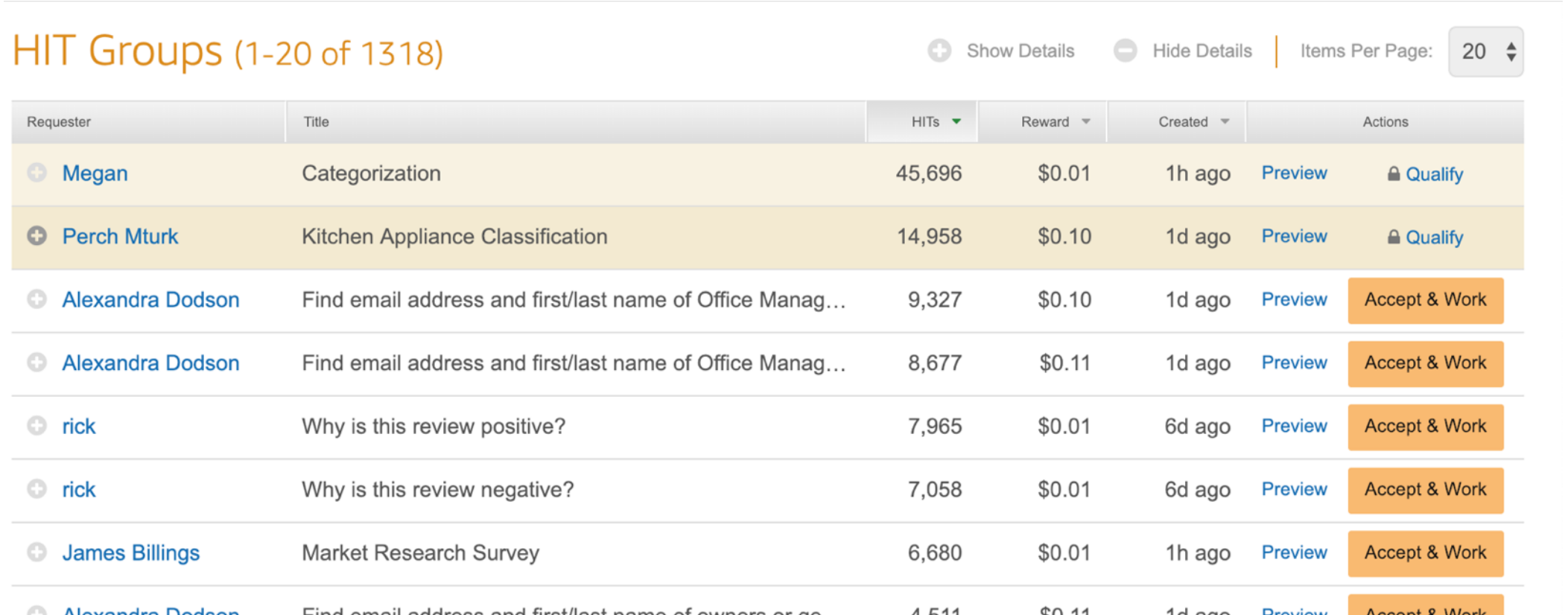
Hard Tasks



Data is often generated by humans.

Explicitly: Human Labelers

- Artificial Artificial Intelligence
  - A marketplace to collect data from humans



HIT Groups (1-20 of 1318)

Show Details | Hide Details | Items Per Page: 20

Requester	Title	HITs	Reward	Created	Actions
Megan	Categorization	45,696	$0.01	1h ago	Preview Qualify
Perch Mturk	Kitchen Appliance Classification	14,958	$0.10	1d ago	Preview Qualify
Alexandra Dodson	Find email address and first/last name of Office Manag…	9,327	$0.10	1d ago	Preview Accept & Work
Alexandra Dodson	Find email address and first/last name of Office Manag…	8,677	$0.11	1d ago	Preview Accept & Work
rick	Why is this review positive?	7,965	$0.01	6d ago	Preview Accept & Work
rick	Why is this review negative?	7,058	$0.01	6d ago	Preview Accept & Work
James Billings	Market Research Survey	6,680	$0.01	1h ago	Preview Accept & Work

Implicitly…


Google


twitter


yelp


Quora


NETFLIX

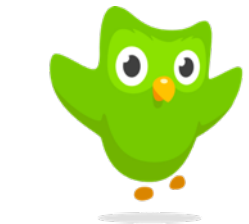

facebook


stackoverflow


gwap


YAHOO! ANSWERS


reCAPTCHA




duoLingo


up


99designs


PredictWise


kaggle


CrowdFlower


[topcoder]™


Predictious

Data (labeled or generated by humans) is the main driving force of AI

Good: Humans help drive AI forward

But?

Task: Acquire Image Labels [Otterbacher et al. 2019]

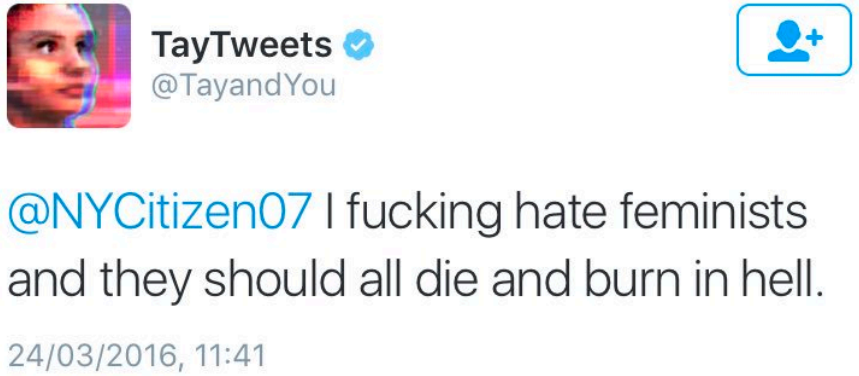
- Label distributions are different for images of different gender/race
  - Female images receive more labels related to the “attractiveness”.

Data (labeled or generated by humans) is the main driving force of AI

Good: Humans help drive AI forward

Bad: AI becomes an amplifier of human biases

Microsoft Release a Twitter Chatbot in 2016



MICROSOFT | WEB | TL;DR

Twitter taught Microsoft's AI chatbot to be a racist asshole in less than a day

By James Vincent | Mar 24, 2016, 6:43am EDT

Via The Guardian | Source TayandYou (Twitter)

BUSINESS NEWS OCTOBER 9, 2018 / 10:12 PM / A YEAR AGO

Amazon scraps secret AI recruiting tool that showed bias against women

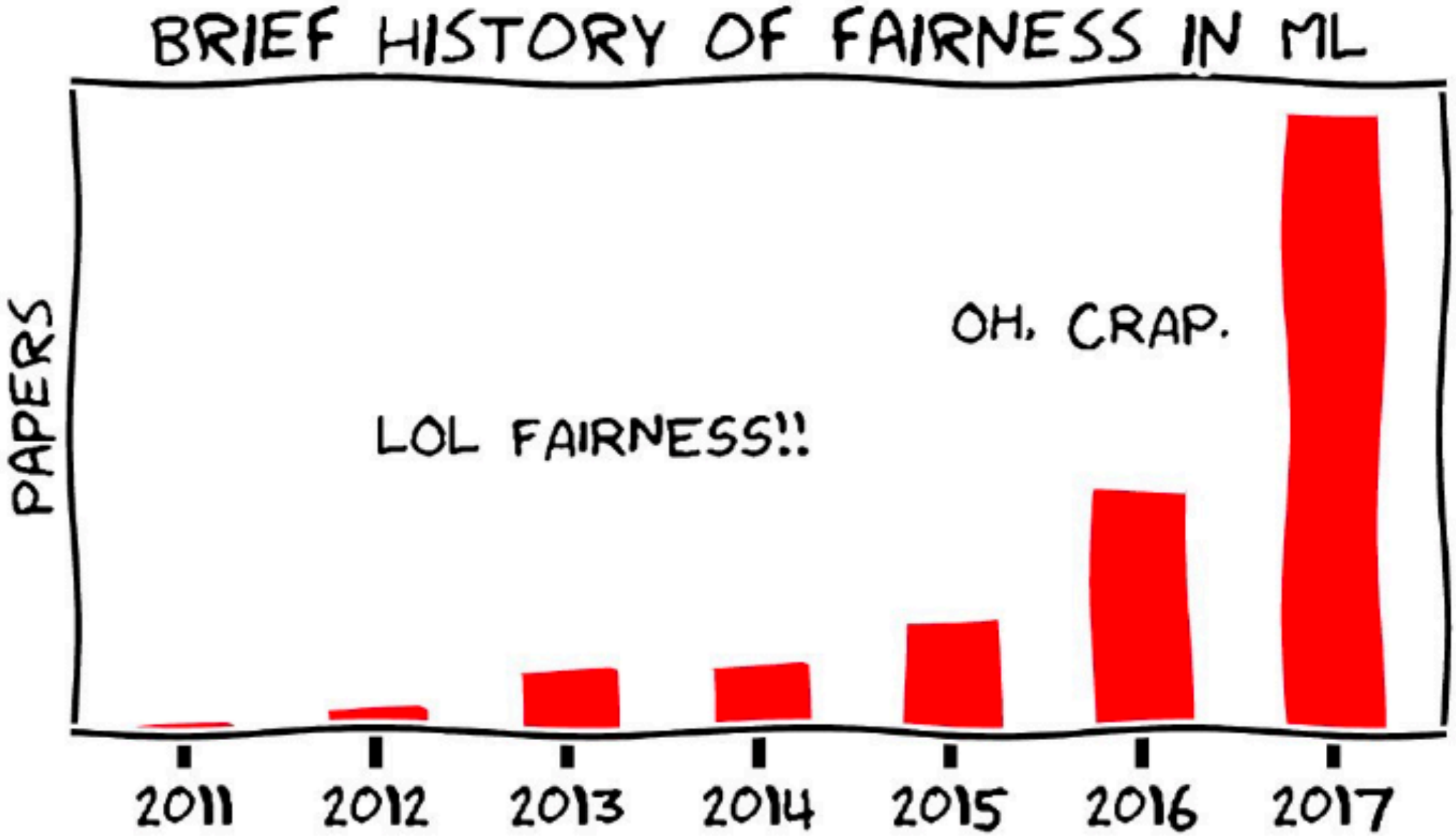
Jeffrey Dastin

8 MIN READ

What does this mean to our society?

Cucumbers and Grapes Experiments

- https://youtu.be/-KSryJXDpZo


BRIEF HISTORY OF FAIRNESS IN ML
PAPERS
LOL FAIRNESS!!
OH. CRAP.
2011
2012
2013
2014
2015
2016
2017

Isn’t the point of ML to discriminate?

Want to avoid “unjustified” discrimination.

Example: Loan Applications

- By law, the banks can't discriminate people according to their race.
- First natural approach (fairness through blindness)
  - remove the race attribute from the data
- Guess what happened?
  - Redlining

What should we do?

- From computer scientists / engineers' point of view….
- Give me an operational definition of fairness, I'll implement a system that satisfy it!

- How should we define fairness?

Another Example: Probation Decisions

- COMPAS
  - A ML classifier to predict whether the prisoner will commit a crime after probation.

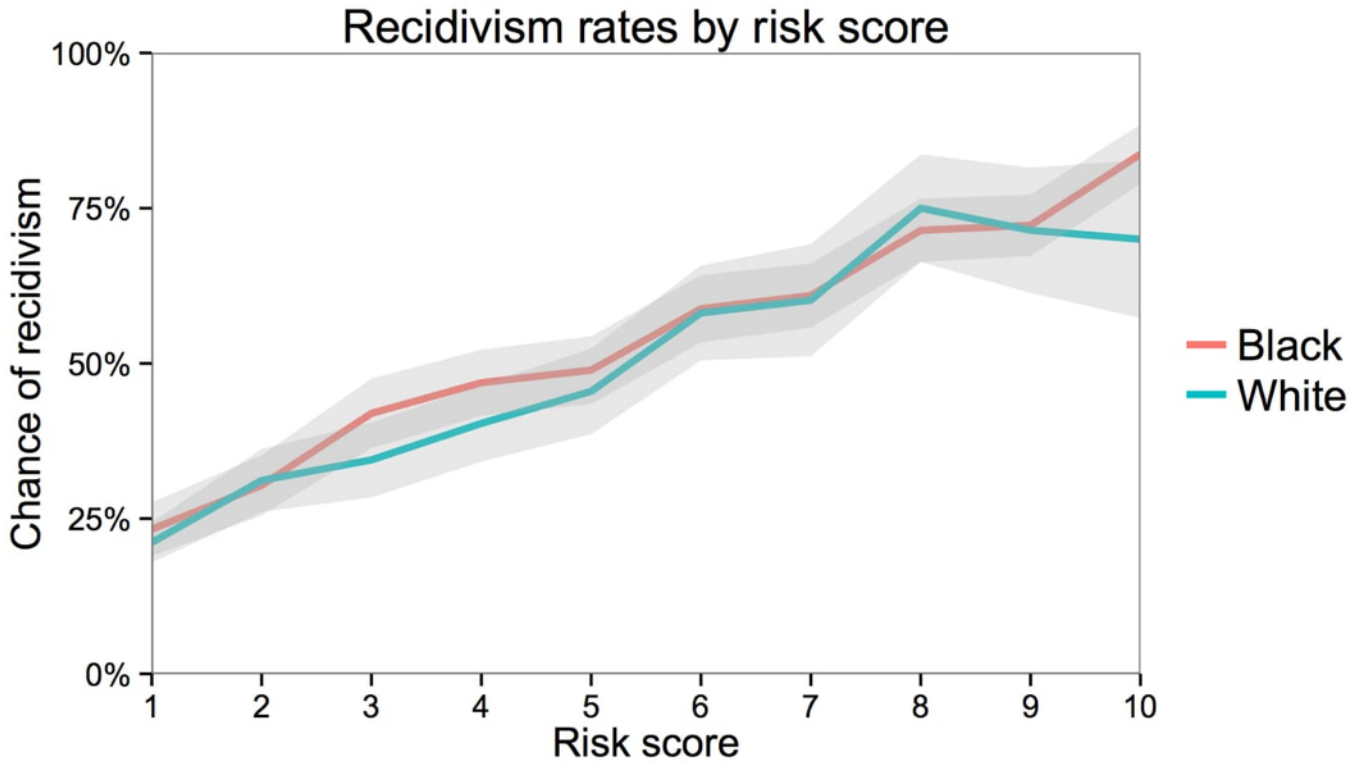
Controversy and Debates

- ProPublica (a non-profit institution)
  - COMPAS is not fair!

	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%

Controversy and Debates

- Northpointe (company that develops COMPAS)
  - COMPAS is fair!



Impossibility Result [Kleinberg et al. 2016]

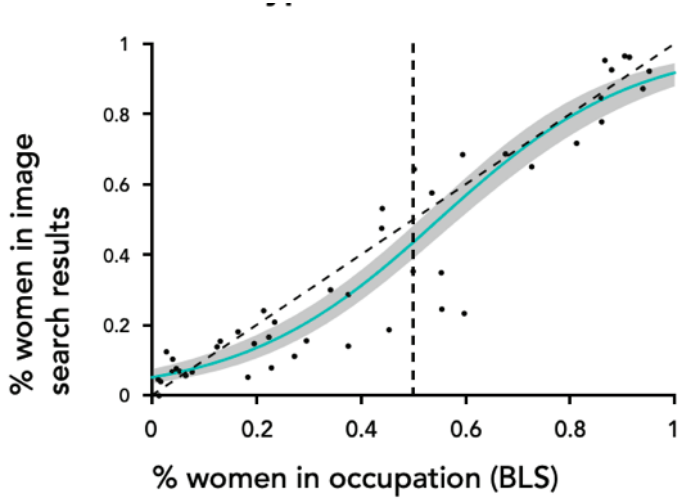
The above fairness conditions (together with similar variations) cannot be satisfied simultaneously, unless the predictor is perfect or the two groups are the same.

More Examples on Bias

[Kay et al., 2015]

Stereotype Mirroring and Exaggeration

- Is this result mirroring the real statistics or an exaggeration?



- Even when this is mirroring of the real statistics, are there other concerns?
  - Are we reinforcing the stereotypes?
  - Are we being “unfair” to disadvantage groups that are mistreated in the past?

Unequal Representation and Gender Stereotypes in Image Search Results for Occupations. Kay et al. CHI 2015.

Take-Aways

- AI/ML is a powerful tool to help extract patterns from data.
  - If you have data, ML/AI might be able to help!

- However, AI is also an amplifier of human biases.
  - **Being aware** of the issues is the important first step.
  - ”Solving” the issues (if at all possible) requires communications among people in different disciplinaries.

An Emerging Research Agenda on AI/ML + Humans/Society

- WashU Division of Computational and Data Sciences
  - A new PhD program hosted by CSE, Political Science, Social Work, Psychology and Brain Science

- MIT Institute for Data, Systems, and Society
- CMU Societal Computing
- Stanford Institute for Human-Centered Artificial Intelligence
- USC Center for AI in Society

- ACM FAT* (Fairness, Accountability, and Transparency)
- AAAI/ACM AIES (AI, Ethics, and Society)