MISUSE OF STATISTICS

This famous, but old book on statistics goes into detail about

[How to lie with statistics]

Number of children abused per 1,000 population in 1998 (National average is 12.9)*

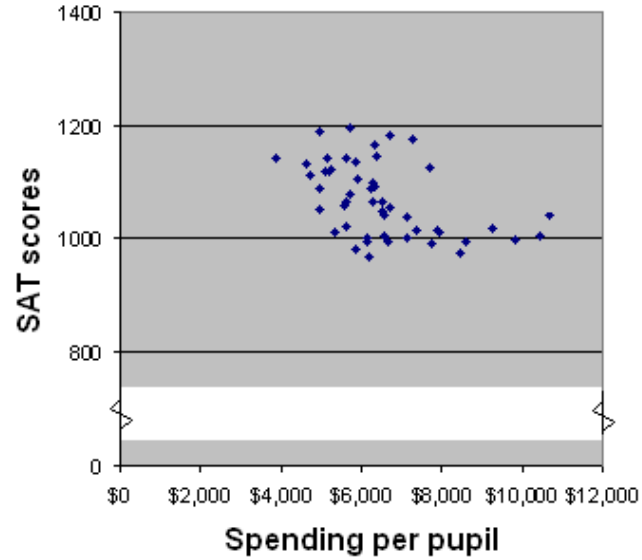
States with the highest rates		
1.	Alaska	37.1
2.	Florida	23.2
3.	Kentucky	23.1
4.	Idaho	22.6
5.	Connecticut	21.4

States with the lowest rates		
45.	Wisconsin	6.0
46.	Virginia	5.9
47.	New Jersey	4.9
48.	New Hampshire	3.9
49.	Pennsylvania	1.9

*North Dakota not reporting

Source: U.S Department of Health and Human Services, Children's Bureau

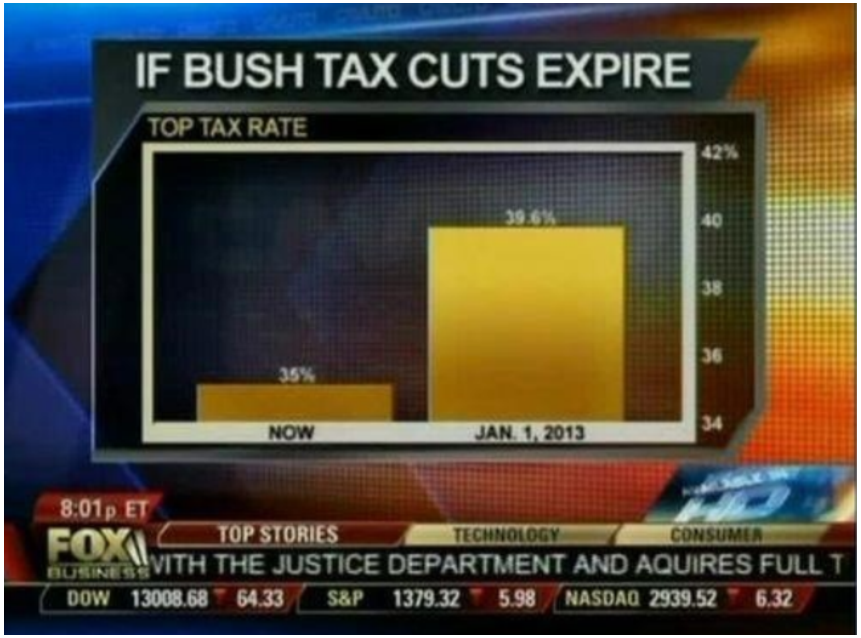
Spending per Pupil and SAT Scores by State, 1998

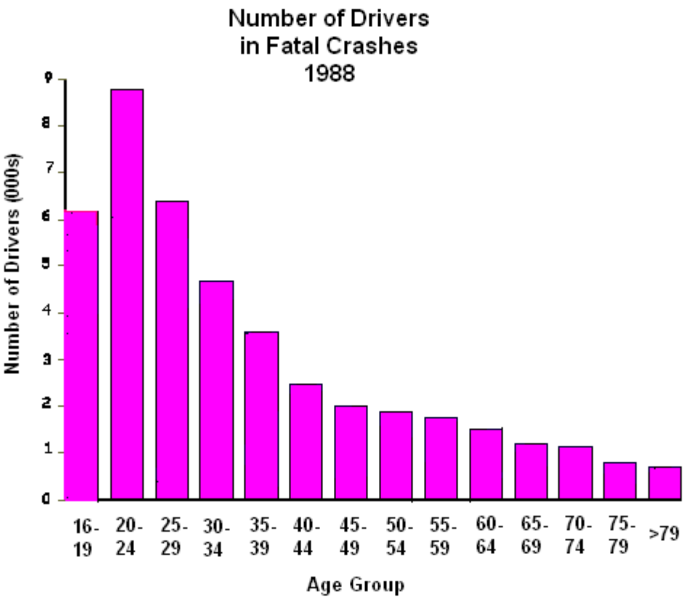


SAT Scores, 1998

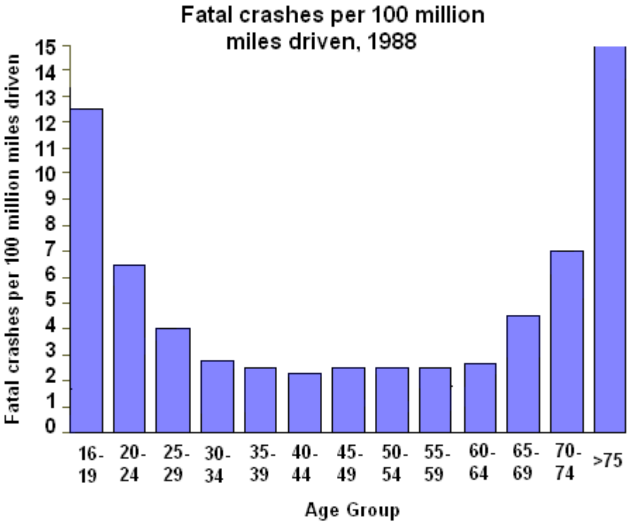
State	Verbal	Math	Participation Rate
North Dakota	590	599	5%
New Jersey	497	508	79%

BEWARE OF CHART





Graph is based on data from this study: Williams, Allan F., Ph.D., and Oliver Carston, Ph.D., "Driver Age and Crash Involvement," Am J Public Health 1989; 79: 326-327.



Graph is based on data from this study: Williams, Allan F., Ph.D., and Oliver Carston, Ph.D., "Driver Age and Crash Involvement," Am J Public Health 1989; 79: 326-327.

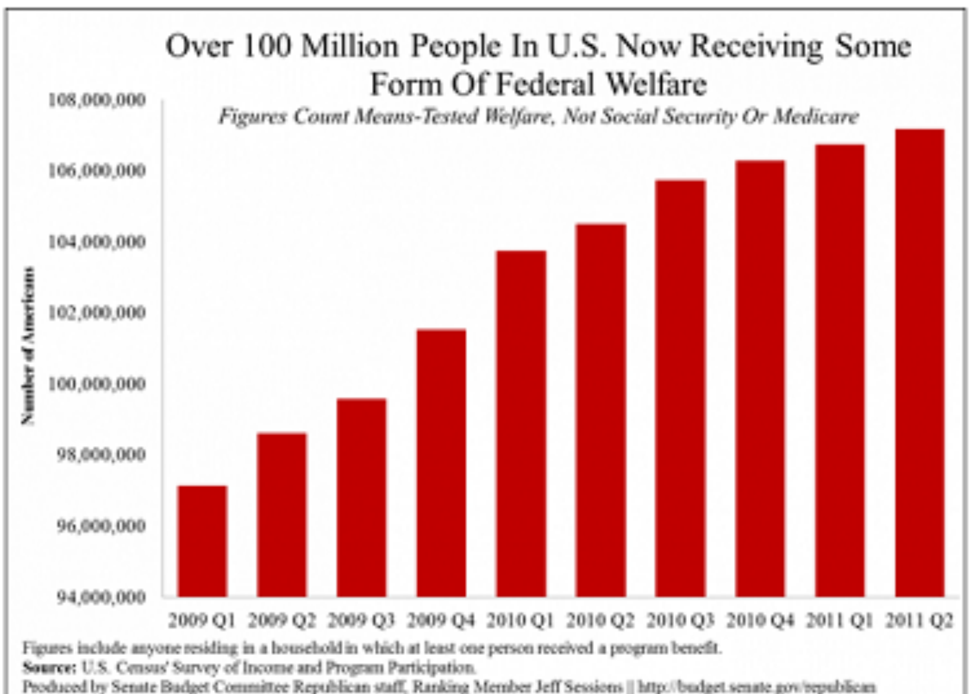
BEWARE OF CHARTS !

THE BLOG

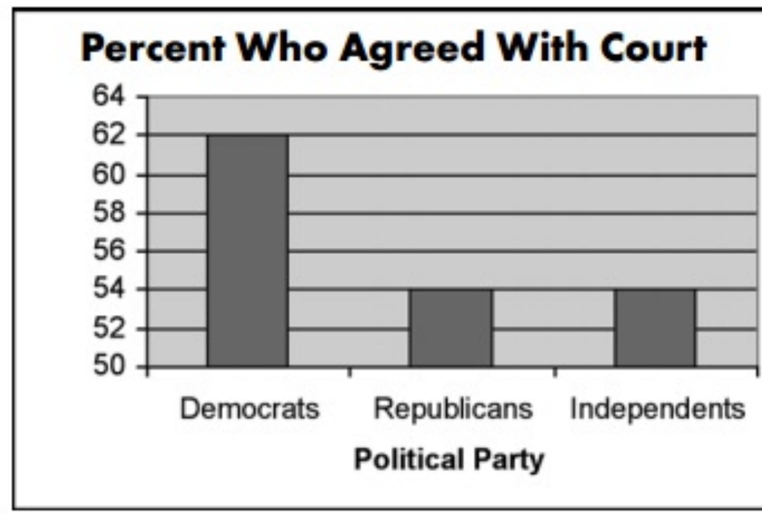
Over 100 Million Now Receiving Federal Welfare

2:40 PM, AUG 8, 2012 • BY DANIEL HALPER

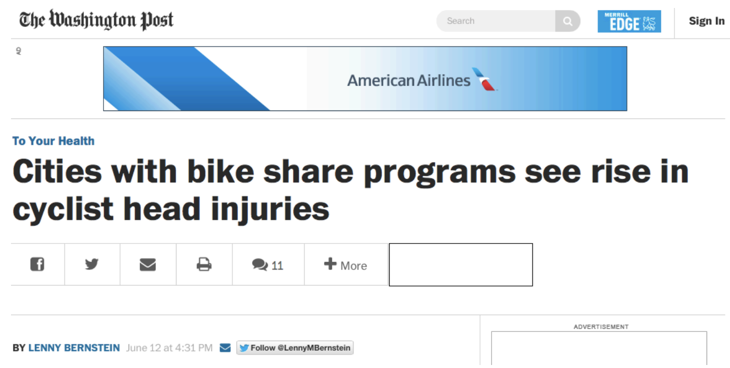
A new chart set to be released later today by the Republican side of the Senate Budget Committee details a startling statistic: "Over 100 Million People in U.S. Now Receiving Some Form Of Federal Welfare."



Terry Schiavo Case



NEWSPAPERS EVEN MORE


The Washington Post

Sign In

American Airlines

To Your Health

Cities with bike share programs see rise in cyclist head injuries

11 More

BY LENNY BERNSTEIN June 12 at 4:31 PM Follow @LennyMBernstein

ADVERTISEMENT

Source

A Washington Post article says: In the first study of its kind, researchers from Washington State University and elsewhere found a 14 percent greater risk of head injuries to cyclists associated with cities that have bike share programs. In fact, when they compared raw head injury data for cyclists in five cities before and after they added bike share programs, the researchers found a 7.8 percent increase in the number of head injuries to cyclists.

Actually: head injuries declined from 319 to 273, and overall injuries declined from 757 to 545

- So the proportion of head injuries went up !!

CASE STUDY: FACEBOOK EMOTIONAL EXPERIMENT

Facebook routinely does A/B testing to test out new features (e.g., layouts, features, fonts, etc)

In 2014: intentionally manipulated news feeds of 700k users

- Changed the number of positive and negative stories the users saw
- Measured how the users themselves posted after that

Hypothesis: Emotions spread over the social media

Huge outcry

Facebook claims it gets the "consent" from the user agreement

OKCUPID EXPERIMENTS

Experiment 1: Love is Blind

- Turned off photos for a day
- Activity went way down, but deeper conversations, better responses
- Deeper analysis at the link below

Experiment 2:

- Turned off text or not – kept picture
- Strong support for the hypothesis that the words don't matter

Experiment 3: Power of Suggestion

- Told people opposite of what the algorithm suggested

https://theblog.okcupid.com/we-experiment-on-human-beings-5dd9fe280cd5

GDPR AND CONSENT

General Data Protection Regulation – new law in EU that recently went into play

Requires unambiguous consent

- data subjects are provided with a clear explanation of the processing to which they are consenting
- the consent mechanism is genuinely of a voluntary and "opt-in" nature
- data subjects are permitted to withdraw their consent easily
- the organisation does not rely on silence or inactivity to collect consent (e.g., pre-ticked boxes do not constitute valid consent);

DATA OWNERSHIP

Consider your "biography"

- About you, but is it yours?
- No, the authors owns the copyright – not much you can do

If someone takes your photo, they own it

- Limits on taking photos in private areas
- Can't use the photo in certain ways, e.g., as implied endorsement or implied libel

Intellectual Property Basics:

- Copyright vs Patent vs Trade Secret
- Derivative works

DATA OWNERSHIP

Data Collection and Curation takes a lot of effort, and whoever does this usually owns the data "asset"

Crowdsourced data typically belongs to the facilitator

- Rotten tomatoes, yelp, etc.

What about personal data though?

- e.g., videos of you walking around a store, etc?
- Written contracts in some cases, but not always

New regulations likely to come up allowing customers to have more control over what happens with their data (e.g., GDPR)

PRIVACY

First concern that comes to mind

- How to avoid the harms that can occur due to data being collected, linked, analyzed, and propagated?
- Reasonable rules ?
- Tradeoffs?

No option to exit

- In the past, could get a fresh start by moving to a new place, waiting till the past fades
- big data is universal and never forgets
- Data science results in major asymmetries in knowledge

WAYBACK MACHINES

Archives pages on the web (https://archive.org/web/ - 300 billion pages saved over time)

- almost everything that is accessible
- should be retained forever

If you have an unflattering page written about you, it will survive for ever in the archive (even if the original is removed)

RIGHT TO BE FORGOTTEN

Laws are often written to clear a person's record Law in EU and Argentina since 2006 after some years.

impacts search engines (not removed completely, but hard to find)

Collection vs Use

- Privacy usually harmed upon use of data
- Sometimes collection without use may be okay
- Survenillance:
    - By the time you know what you need, it is too late to go back and get it

WHY PRIVACY?

Data subjects have inherent right and expectation of privacy

"Privacy" is a complex concept

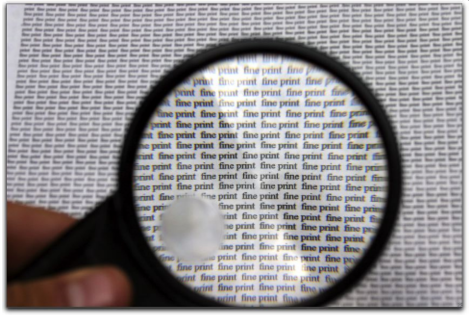
- What exactly does "privacy" mean? When does it apply?
- Could there exist societies without a concept of privacy?

Concretely: at collection "small print" outlines privacy rules

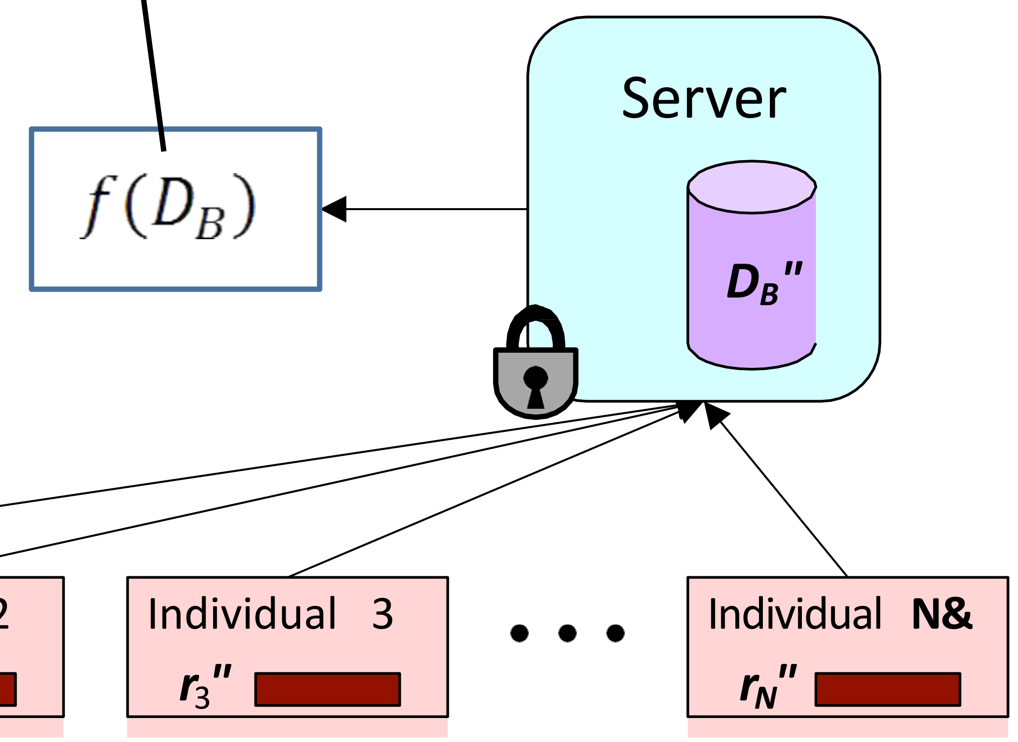
- Most companies have adopted a privacy policy
- E.g. AT&T privacy policy att.com/gen/privacy-policy?pid=2506

Significant legal framework relating to privacy

- UN Declaration of Human Rights, US Constitution
- HIPAA, Video Privacy Protection, Data Protection Acts



RELEASE THE DATA "ANONYMOUSLY" OR RELEASE A MODEL?



WHY ANONYMIZE?

For Data Sharing

- Give real(istic) data to others to study without compromising privacy of individuals in the data
- Allows third-parties to try new analysis and mining techniques not thought of by the data owner

For Data Retention and Usage

- Various requirements prevent companies from retaining customer information indefinitely
- E.g. Google progressively anonymizes IP addresses in search logs
- Internal sharing across departments (e.g. billing → marketing)

WHY ANONYMIZE?

2.1. Definitions in the EU Legal Context

Directive 95/46/EC refers to anonymisation in Recital 26 to exclude anonymised data from the scope of data protection legislation:

> *"Whereas the principles of protection must apply to any information concerning an identified or identifiable person; whereas, to determine whether a person is identifiable, account should be taken of all the means likely reasonably to be used either by the controller or by any other person to identify the said person; whereas the principles of protection shall not apply to data rendered anonymous in such a way that the data subject is no longer identifiable; whereas codes of conduct within the meaning of Article 27 may be a useful instrument for providing guidance as to the ways in which data may be rendered anonymous and retained in a form in which identification of the data subject is no longer possible;".*[1]

Releasing data is bad?

What if we ensure our names and other identifiers are never released?

CASE STUDY: US CENSUS

Raw data: information about every US household

- Who, where; age, gender, racial, income and educational data

Why released: determine representation, planning

How anonymized: aggregated to geographic areas (Zip code)

- Broken down by various combinations of dimensions
- Released in full after 72 years

Attacks: no reports of successful deanonymization

- Recent attempts by FBI to access raw data rebuffed

Consequences: greater understanding of US population

- Affects representation, funding of civil projects
- Rich source of data for future historians and genealogists

CASE STUDY: NETFLIX PRIZE

Raw data: 100M dated ratings from 480K users to 18K movies

Why released: improve predicting ratings of unlabeled examples

How anonymized: exact details not described by Netflix

- All direct customer information removed
- Only subset of full data; dates modified; some ratings deleted,
- Movie title and year published in full

Attacks: dataset is claimed vulnerable [Narayanan Shmatikov 08]

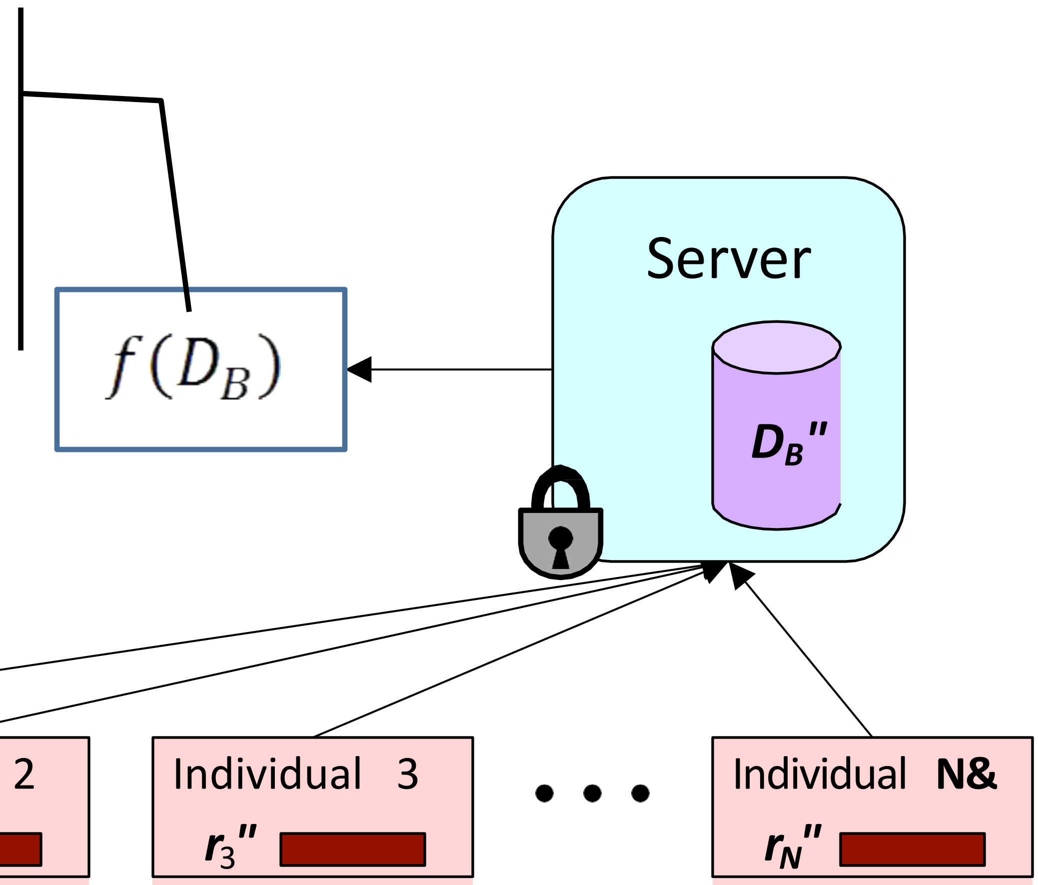
- Attack links data to IMDB where same users also rated movies
- Find matches based on similar ratings or dates in both

Consequences: rich source of user data for researchers

- unclear if attacks are a threat—no lawsuits or apologies yet

CAN WE RELEASE A MODEL ALONE?

Release the data “~~anonymously~~” or release a model



RELEASING A MODEL CAN ALSO BE BAD

[Korolova JPC 2011]

Facebook profile

+

Online Data

- who live in the **United States**
- who live within 50 miles of **Staten Island, NY**
- between the ages of **23** and **27** inclusive
- who are **female**
- who are connected to **DogAnd PonyShow**
- in one of the categories: **Pop Culture**, **Science Fiction/Fantasy**, **Alternative**, **Rock**, **Classic Rock** or **iPhone**

	Number of Impressions
+ Who are interested in **Men**	25
+ Who are interested in **Women**	0

Facebook's learning algorithm uses private information to predict match to ad

Model Inversion

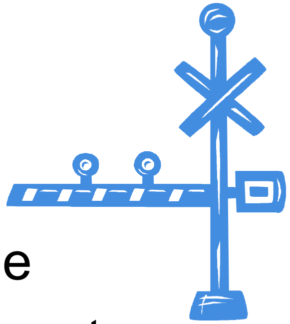
[Frederickson et al., USENIX Security 2014]

- An attacker, given the model and some demographic information about a patient, can predict the patient's genetic markers.

We show, however, that warfarin models do pose a privacy risk (Section 3). To do so, we provide a general model inversion algorithm that is optimal in the sense that it minimizes the attacker's *expected misprediction rate* given the available information. We find that when one knows a target patient's background and stable dosage, their genetic markers are predicted with significantly better accuracy (up to 22% better) than guessing based on marginal distributions. In fact, *it does almost as well as regression models specifically trained to predict these markers (only ~5% worse)*, suggesting that model inversion can be nearly as effective as learning in an "ideal" setting. Lastly, the inverted model performs measurably better for members of the training cohort than others (yielding an increased 4% accuracy) indicating a leak of information specifically about those patients.

MODELS OF ANONYMIZATION

Interactive Model (akin to statistical databases)



- Data owner acts as "gatekeeper" to data
- Researchers pose queries in some agreed language
- Gatekeeper gives an (anonymized) answer, or refuses to answer

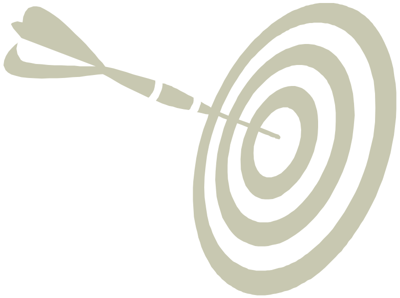
"Send me your code" model

- Data owner executes code on their system and reports result
- Cannot be sure that the code is not malicious

Offline, aka "publish and be damned" model

- Data owner somehow anonymizes data set
- Publishes the results to the world, and retires
- Our focus in this tutorial – seems to model most real releases

OBJECTIVES FOR ANONYMIZATION



Prevent (high confidence) inference of associations

- Prevent inference of salary for an individual in “census”
- Prevent inference of individual’s viewing history in “video”
- Prevent inference of individual’s search history in “search”
- All aim to prevent linking sensitive information to an individual

Prevent inference of presence of an individual in the data set

- Satisfying “presence” also satisfies “association” (not vice-versa)
- Presence in a data set can violate privacy (eg STD clinic patients)

Have to model what knowledge might be known to attacker

- Background knowledge: facts about the data set (X has salary Y)
- Domain knowledge: broad properties of data (illness Z rare in men)

UTILITY

Anonymization is meaningless if utility of data not considered

- The empty data set has perfect privacy, but no utility
- The original data has full utility, but no privacy

What is "utility"? Depends what the application is…

- For fixed query set, can look at max, average distortion
- Problem for publishing: want to support unknown applications!
- Need some way to quantify utility of alternate anonymizations

PRIVACY IS NOT ANONYMITY

- Bob's record is indistinguishable from records of other Cancer patients
  - We can infer Bob has Cancer !

- "New Information" principle
  - Privacy is breached if releasing D (or f(D)) allows an adversary to learn sufficient new information.
  - *New Information = distance(adversary's prior belief, adversary's posterior belief after seeing D)*
  - *New Information* can't be 0 if the output D or f(D) should be useful.

PRIVACY DEFINITIONS

- Many privacy definitions
  - L-diversity, T-closeness, M-invariance, **ε- Differential privacy,** E- Privacy, …
- Definitions differs in
  - What information is considered sensitive
    - Specific attribute (disease) vs all possible properties of an individual
  - What is the adversary's prior
    - All values are equally likely vs Adversary knows everything about all but one individuals
  - How is new information measured
    - Information theoretic measures
    - Pointwise absolute distance
    - Pointwise relative distance

NO FREE LUNCH

- Why can't we have a single definition for privacy?
  - For every adversarial prior and every property about an individual, new information is bounded by some constant.
- No Free Lunch Theorem: For every algorithm that outputs a D with even a sliver of utility, there is some adversary with a prior such that privacy is not guaranteed.

RANDOMIZED RESPONSE MODEL

- N respondents asked a sensitive “yes/no” question.
- Surveyor wants to compute fraction π who answer “yes”.
- Respondents don't trust the surveyor.
- What should the respondents do?

RANDOMIZED RESPONSE MODEL

- Flip a coin
  - heads with probability p, and
  - tails with probability 1-p ($p > ½$)

- Answer question according to the following table:

	True Answer = Yes	True Answer = No
Heads	Yes	No
Tails	No	Yes

DIFFERENTIAL PRIVACY

- **Typically achieved by adding controlled noise (e.g., Laplace Mechanism)**

- **Some adoption in the wild:**
  - US Census Bureau
  - Google, Apple, and some others have used this for collecting data

- **Issues:**
  - Effectiveness in general still unclear

THE DREAM

You run your ML algorithm(s) and it works well (?!)

Still: be skeptical …

Very easy to accidentally let your ML algorithm cheat:

- Peaking (train/test bleedover)
- Including output as an input feature explicitly
- Including output as an input feature implicitly

Try to solve the problem by hand;

Try to interpret the ML algorithm / output

Continue being skeptical. Always be skeptical.

DATA SCIENCE LIFECYCLE: AN ALTERNATE VIEW

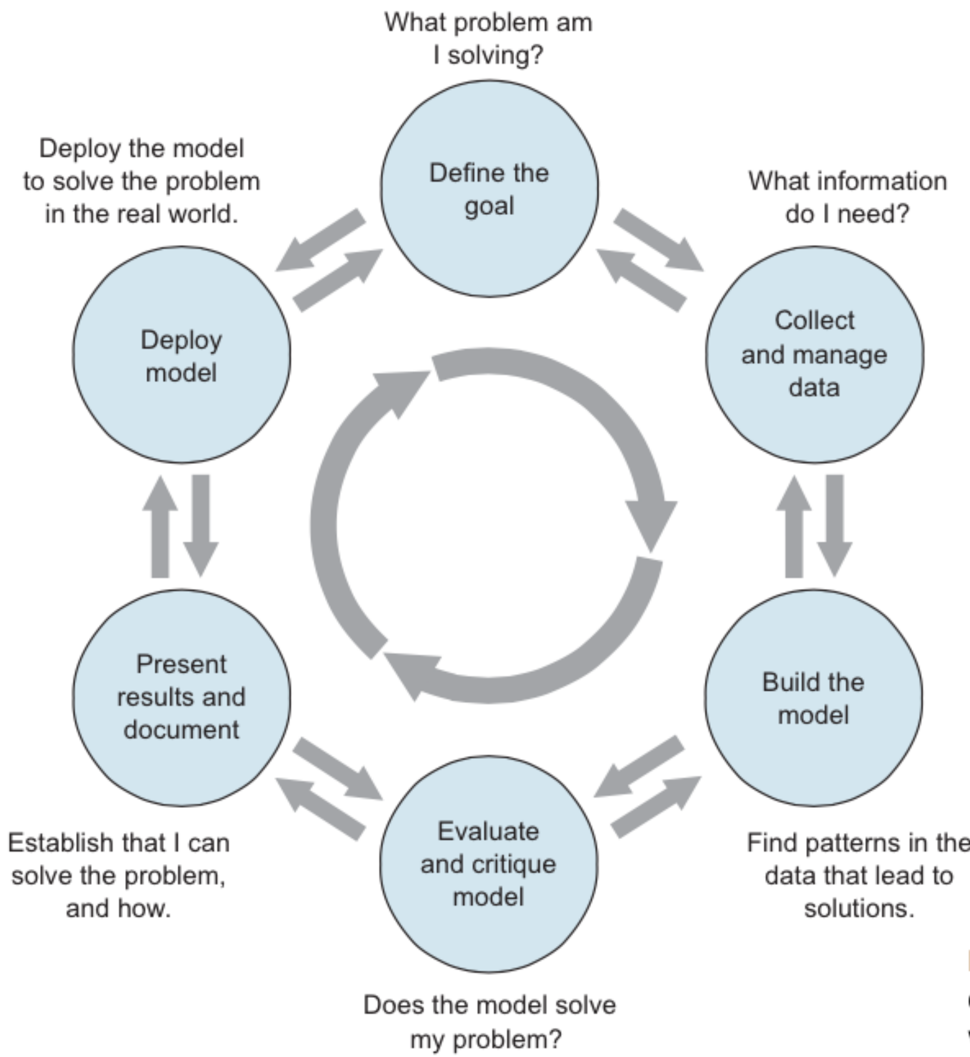


Figure 1.1 The lifecycle of a data science project: loops within loops

COMBATING BIAS

Fairness through blindness:

- Don’t let an algorithm look at protected attributes

Examples currently in use ??????????

- Race
- Gender
- Sexuality
- Disability
- Religion

Problems with this approach ?????????

COMBATING BIAS

"After all, as the former CPD [Chicago Police Department] computer experts point out, the algorithms in themselves are neutral. 'This program had absolutely nothing to do with race… but multi-variable equations,' argues Goldstein. Meanwhile, the potential benefits of predictive policing are profound."

COMBATING BIAS

If there is bias in the training data, the algorithm/ML technique will pick it up

- Especially social biases against minorities
- Even if the the protected attributes are not used

Sample sizes tend to vary drastically across groups

- Models for the groups with less representation are less accurate
- Hard to correct this, and so fundamentally unfair
- e.g., a classifier that performs no better than coin toss on a minority group, but does very well on a majority group

COMBATING BIAS

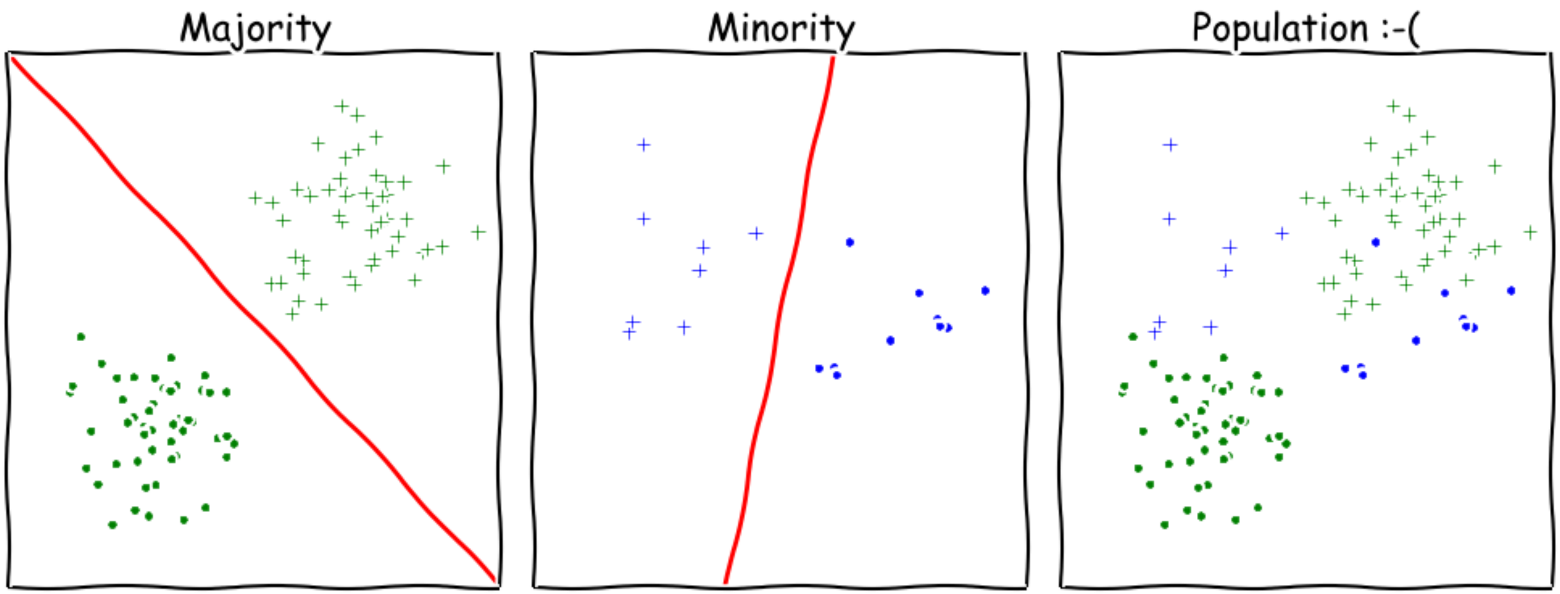
Cultural Differences

- Consider a social network that tried to classify user names into real and fake
- Diversity in names differs a lot – in some cases, short common names are ‘real’, in others long unique names are ‘real’

COMBATING BIAS

Undesired complexity

- Learning combinations of linear classifiers much harder than learning linear classifiers



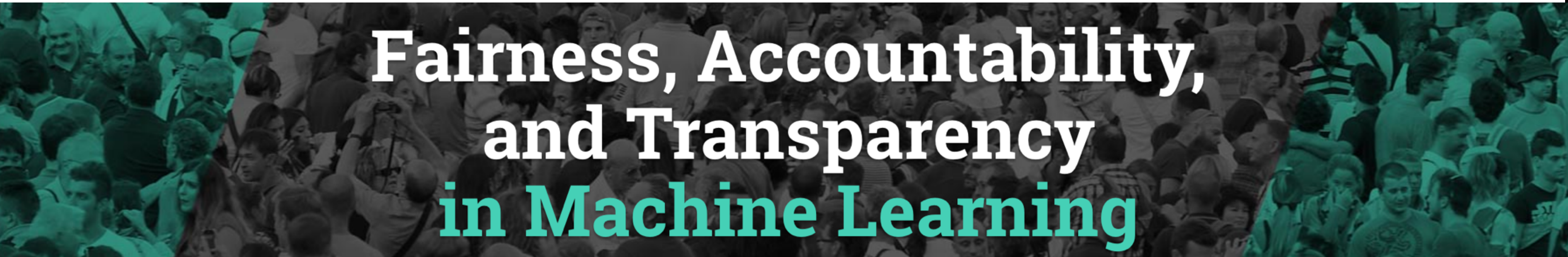
FATML

This stuff is really tricky (and really important).

- It's also not solved, even remotely, yet!

New community: Fairness, Accountability, and Transparency in Machine Learning (aka **FATML**)

"… policymakers, regulators, and advocates have expressed fears about the potentially discriminatory impact of machine learning, with many calling for further technical research into the dangers of inadvertently encoding bias into automated decisions."



F IS FOR FAIRNESS

In large data sets, there is always proportionally less data available about minorities.

Statistical patterns that hold for the majority may be invalid for a given minority group.

Fairness can be viewed as a measure of diversity in the combinatorial space of sensitive attributes, as opposed to the geometric space of features.

Thanks to: Faez Ahmed

A IS FOR ACCOUNTABILITY

Accountability of a mechanism implies an obligation to report, explain, or justify algorithmic decision-making as well as mitigate any negative social impacts or potential harms.

- Current accountability tools were developed to oversee human decision makers
- They often fail when applied to algorithms and mechanisms instead

Example, no established methods exist to judge the intent of a piece of software. Because automated decision systems can return potentially incorrect, unjustified or unfair results, additional approaches are needed to make such systems accountable and governable.

Thanks to: Faez Ahmed

T IS FOR TRANSPARENCY

Automated ML-based algorithms make many important decisions in life.

- Decision-making process is opaque, hard to audit

A transparent mechanism should be:

- understandable;
- more meaningful;
- more accessible; and
- more measurable.

Thanks to: Faez Ahmed

DATA COLLECTION

What data should (not) be collected

Who owns the data

Whose data can (not) be shared

What technology for collecting, storing, managing data

Whose data can (not) be traded

What data can (not) be merged

What to do with prejudicial data

Thanks to: Kaiser Fung

DATA MODELING

Data is biased (known/unknown)

- Invalid assumptions
- Confirmation bias

Publication bias

- WSDM 2017: https://arxiv.org/abs/1702.00502

Badly handling missing values

Thanks to: Kaiser Fung

DEPLOYMENT

Spurious correlation / over-generalization

Using “black-box” methods that cannot be explained

Using heuristics that are not well understood

Releasing untested code

Extrapolating

Not measuring lifecycle performance (concept drift in ML)

We will go over ways to counter this in the ML/stats/hypothesis testing portion of the course

Thanks to: Kaiser Fung

GUIDING PRINCIPLES

Start with clear user need and public benefit

Use data and tools which have minimum intrusion necessary

Create robust data science models

Be alert to public perceptions

Be as open and accountable as possible

Keep data secure

GOV.UK

Thanks to: UK cabinet office

SOME REFERENCES

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FINDING A JOB

Make a personal website.

- Free hosting options: GitHub Pages, Google Sites
- Pay for your own URL (but not the hosting).
- Make a clean website, and make sure it renders on mobile:
    - Bootstrap: https://getbootstrap.com/
    - Foundation: http://foundation.zurb.com/

Highlight relevant coursework, open source projects, tangible work experience, etc

Highlight tools that you know (not just programming languages, but also frameworks like TensorFlow and general tech skills)

“REQUIREMENTS”

Data science job postings – and, honestly, CS postings in general – often have completely nonsense requirements

1. The group is filtering out some noise from the applicant pool
2. Somebody wrote the posting and went buzzword crazy

In most cases (unless the position is a team lead, pure R&D, or a very senior role) you can work around requirements:

- A good, simple website with good, clean projects can work wonders here …
- Reach out and speak directly with team members
- Alumni network, internship network, online forums

INTERVIEWING

We saw that there is no standard for being a "data scientist" – and there is also no standard interview style …

… but, generally, you'll be asked about the five "chunks" we covered in this class, plus core CS stuff:

- Software engineering questions
- Data collection and management questions (SQL, APIs, scraping, newer DB stuff like NoSQL, Graph DBs, etc)
- General "how would you approach …" EDA questions
- Machine learning questions ("general" best practices, but you should be able to describe DTs, RFs, SVM, basic neural nets, KNN, OLS, boosting, PCA, feature selection, clustering)
- Basic "best practices" for statistics, e.g., hypothesis testing

Take-home data analysis project (YMMV)

GRADUATE SCHOOL, ACADEMIA, R&D, …

Data science isn't really an academic discipline by itself, but it comes up everywhere within and without CS

- **Modern science is built on a "CS and Statistics stack" …**

Academic work in the area:

- **Outside of CS, using techniques from this class to help fundamental research in that field**
- **Within CS, fundamental research in:**
  - Machine learning
  - Statistics (non-pure theory)
  - Databases and data management
  - Incentives, game theory, mechanism design
- **Within CS, trying to automate data science (e.g., Google Cloud's Predictive Analytics, "Automatic Statistician," …)**

Final Thoughts

1. No easy answers
2. Play, explore, think
3. Use off-the-shelf technologies wherever possible
4. Think about possible introduction of biases and be skeptical of ‘clear’ results