

# Course Reminders

- Due Monday (11:59 PM)
  - Q2
- Due Wednesday (11:59 PM)
  - A1
  - Group signup
    - Self-assigned groups on canvas
    - GitHub user name survey
- Due Friday (11:59 PM)
  - D2

# Data Science Ethics

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<https://jgfleischer.com>

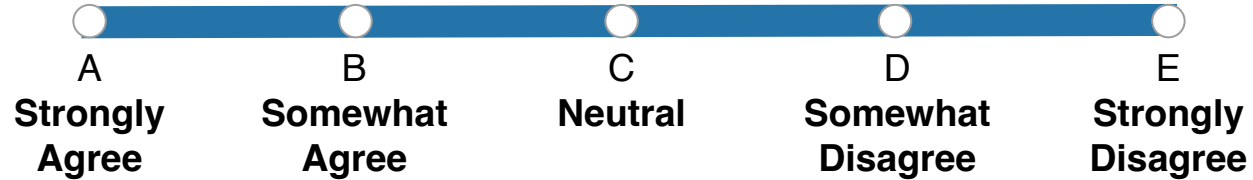


@jasongfleischer



# Data Science Ethics

When working on a data science project, data privacy is the primary ethical concern.



“Big data and analytics technology can reap huge benefits to both individuals and organizations – bringing personalized service, detection of fraud and abuse, efficient use of resources and prevention of failure or accident. So **why are there questions being raised about the ethics [of data science]?**”

**YouTube vows to recommend fewer  
conspiracy theory videos**

Site's move comes amid continuing pressure over i  
platform for misinformation and extremism

**The Reason This "Racist Soap  
Dispenser" Doesn't Work on  
Black Skin**

**Amazon Prime and the racist algorithms**

**MACHINES TAUGHT BY PHOTOS  
LEARN A SEXIST VIEW OF  
WOMEN**

**Facial recognition software  
is biased towards white  
men, researcher finds**

*Biases are seeping into software*

**YouTube's Restricted Mode Is Hiding  
Some LGBT Content [Update]**

**Google Translate's Gender  
Problem (And Bing Translate's,  
And Systran's...)**

# COGS 9 Examples

- Ashley Madison Hack [[link](#)]
- OKCupid Data Published [[link](#)]
- Equifax Hack [[link](#)]
- Google & Pentagon Team Up on Drones [[link](#)]
- Cambridge Analytica Data Breach To Influence US Elections [[link](#)]
- Amazon and Police Team Up on Facial Recognition & Surveillance [[link](#)]
- Amazon scraps secret AI recruiting tool biased against women [[link](#)]

## A few additional examples I've compiled in the last 2 years...

- Study of bias in AI [\[link\]](#)
- Pasco County Algorithmic Bias [\[link\]](#)
- Ethical issues (misogyny, racism) in large available datasets [\[link\]](#),[\[link\]](#)
- Florida COVID-19 dashboard data scientist debacle [\[link\]](#)
- Banjo surveillance via fake apps [\[link\]](#)
- Google fires AI ethics founder [\[link\]](#) & Timnit Gebru's firing [\[link\]](#)
- Twitter fires entire ethics & compliance team [\[link\]](#)
- MS lay off their entire ethics teams [\[link\]](#)
- ChatGPT is dumber than you think [\[link\]](#)
- Synthetic Media Creates New Social Engineering Threats [\[link\]](#)
- Generative AI art is a copyright nightmare [\[link\]](#)

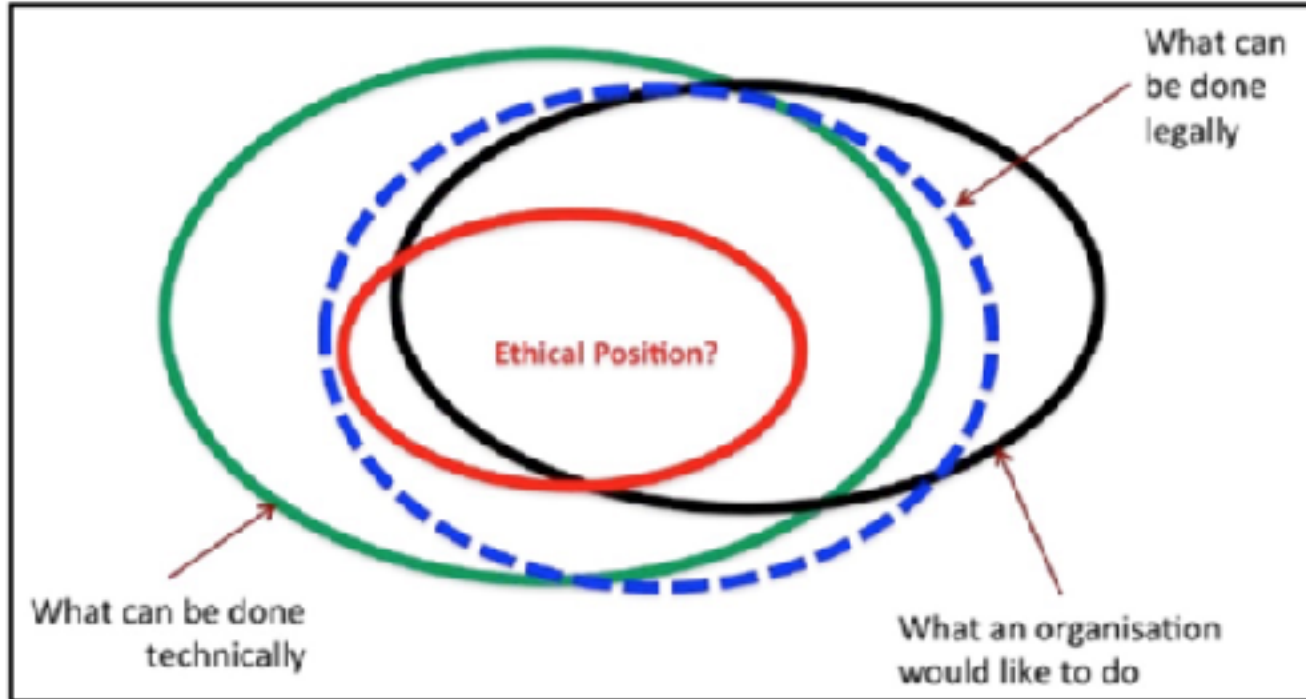
Always consider ethics.

## **ETHICS**

*“Moral principles that govern a person's behaviour or the conducting of an activity.”*



# Big Data Ethics



# Ethical Data Science

Data science pursued in a manner so that is equitable,  
with respect for privacy and consent, so as to ensure that  
it does not cause undue harm.

# On INTENT and OBJECTIVITY

- Intent is not required for harmful practices to occur
- Data, algorithms and analysis are not objective.
  - It is done by people, who have biases
  - It uses data, which have biases
- Data Science is powerful
- Bias & discrimination driven by data & algorithms can give new scale to pre-existing inequities

# NINE THINGS TO CONSIDER TO NOT RUIN PEOPLE'S LIVES WITH DATA SCIENCE

1. THE QUESTION
2. THE IMPLICATIONS
3. THE DATA
4. INFORMED CONSENT
5. PRIVACY
6. EVALUATION
7. ANALYSIS
8. TRANSPARENCY & APPEAL
9. CONTINUOUS MONITORING

# 1. THE QUESTION

- What is your question? Is it well-posed?
- Do you know something about the context and background of your question?
- What is the scope your investigation? What correlates might you inadvertently track? Is it possible to answer this question well?



# Case Study: Labelling Faces

Detecting criminality from faces [[link](#), [paper](#)]



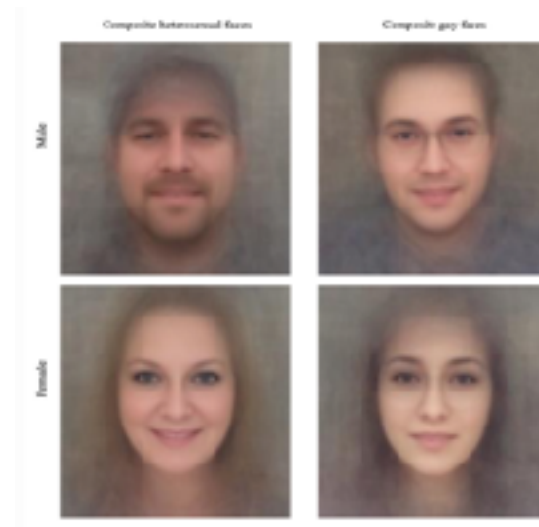
(a) Three samples in criminal ID photo set  $S_c$ .



(b) Three samples in non-criminal ID photo set  $S_n$ .

Figure 1. Sample ID photos in our data set.

Detecting Sexual Orientation From Faces with computer vision [[link](#), [paper](#)]





This stuff just doesn't go away...



ARTICLE



<https://doi.org/10.1038/s41467-020-18566-7>

OPEN

# Tracking historical changes in trustworthiness using machine learning analyses of facial cues in paintings

Lou Safra <sup>1,2,3✉</sup>, Coralie Chevallier<sup>1</sup>, Julie Grèzes<sup>1</sup> & Nicolas Baumard <sup>2✉</sup>

Received: 19 May 2019; Accepted: 10 August 2020;  
Published online: 22 September 2020

## 2. THE IMPLICATIONS

- Who are the stakeholders? How does this affect them?
- Could the information you will gain and/or the tool you are building be co-opted for nefarious purposes?
  - a. If so, can you protect them from that?
- Have you considered potential unintended consequences?

# Case Study: Abuse of social networks

**The New York Times**

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***A Genocide Incited on Facebook,  
With Posts From Myanmar's Military***

Facebook has been co-opted by military personnel to spread misinformation, hate speech, and promote ethnic cleansing [[news link](#), [UN Report](#)]

### 3. THE DATA

- Is there data available? Is this data directly related to your question, or only potentially related through proxies?
- Who do you have data from?
- Do you have enough data to make reliable inferences?
- What biases does your data have?
- If you do not have, and can not get, enough good, appropriate data, you may just have to stop.

# Case Study: Biomedical Science



Biomedical research has often excluded female subjects

This was based on a (faulty) assumption that females would be more variable

These findings do not generalize as well

Sources: [link](#), [link](#), [link](#)

## 4. INFORMED CONSENT

INFORMED CONSENT: the voluntary agreement to participate in research, in which the subject has an understanding of the research and its risks

Informed consent can be withdrawn at any point in time



## 5. PRIVACY

- Can you guarantee privacy?
- What is the level of risk of your data, and how will you mitigate the risks? Are all subjects equally vulnerable?
- Anonymization: the process of removing personally identifiable information from datasets (PII)
- Use secure data storage, with appropriate access rights

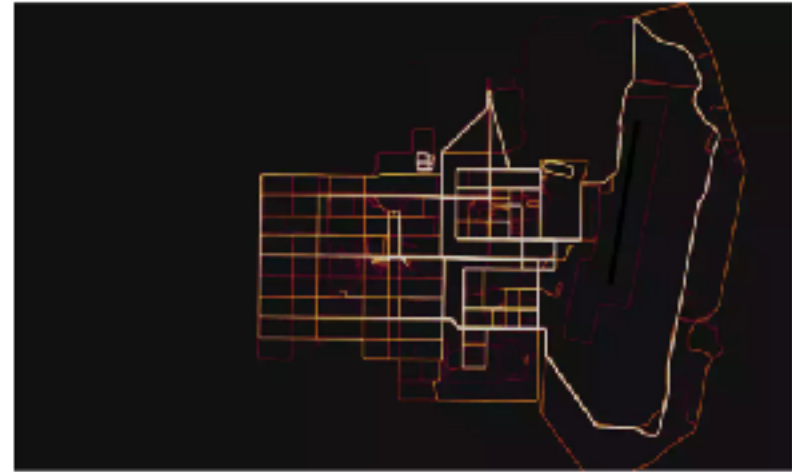
# Case Study: Running Data

Strava, a company who made an app that released running data, geotagged from around the world [[link](#)]

## Fitness tracking app Strava gives away location of secret US army bases

Data about exercise routes shared online by soldiers can be used to pinpoint overseas facilities

■ Latest: Strava suggests military users 'opt out' of heatmap as row deepens



▲ A military base in Herat Province, Afghanistan with route taken by joggers highlighted by Strava. Photograph: Strava/Heatmap



Consumer Tech

# Don't sell my data! We finally have a law for that

You're going to have to jump through some hoops, but you can ask companies to access, delete and stop selling your data using the new California Consumer Privacy Act - even if you don't live in California.

By **Geoffrey A. Fowler**

FEBRUARY 19, 2020

Our version of Europe's GDPR law

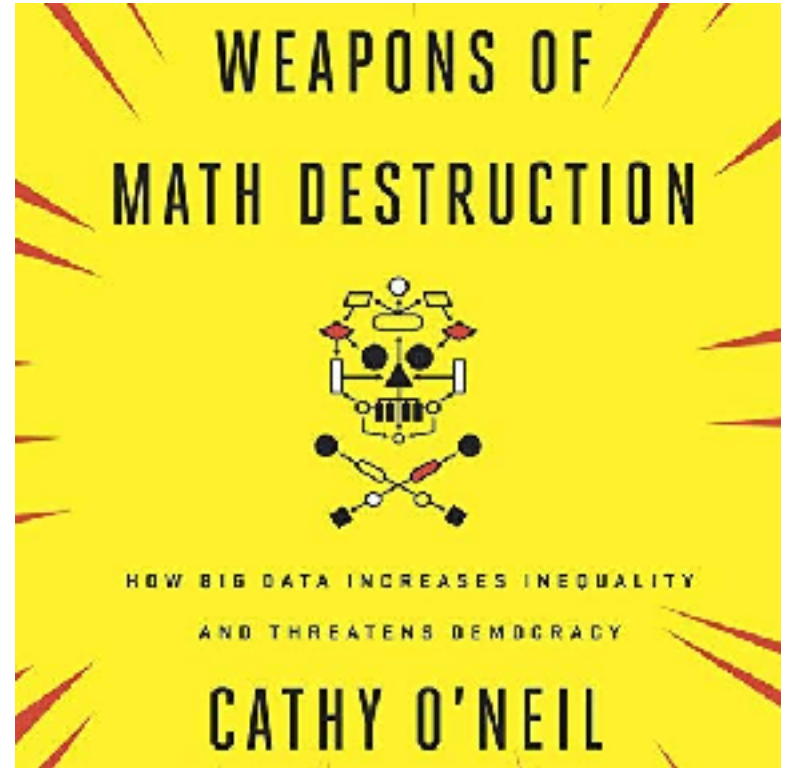
## 6. EVALUATION

- How will you evaluate the project?
  - a. Do you have a verifiable metric of success?
- Goodhart's Law: when a measure becomes a target, it ceases to be a good measure.

## Case Study: Teacher Rating

Washington, DC school district used an algorithm to rate teachers, based on test scores. Scores from this algorithm were used to fire 'low performers'

*They had no independent measure of whether this measure improved teaching*



## 7. ANALYSIS

- Do your analyses reflect spurious correlations?
  - a. Can you tease apart causation?
- What kind of covariates might you be tracking?
  - a. Are you inferring latent variables from proxies?

# Spurious correlations

US spending on science, space, and technology  
correlates with  
Suicides by hanging, strangulation and suffocation



Data sources: J.E. Office of Management and Budget and Centers for Disease Control & Prevention.

Number of people who drowned by falling into a pool  
correlates with  
Films Nicolas Cage appeared in

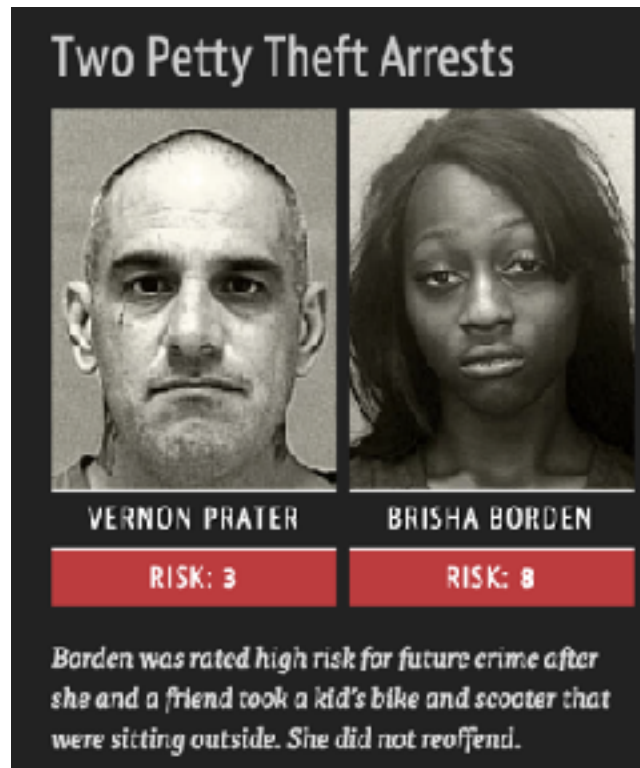


## 8. TRANSPARENCY & APPEAL

- Is your model a black box?
  - a. Is it interpretable as to how it came to any particular decision?
- Is there a way to appeal a model decision?
  - a. What kind of evidence would you need to refute a decision?

# Case Study: Predictive Policing

- Predictive policing uses algorithms to predict crime, and recidivism
- Input data can be highly correlated [\[link\]](#) with race & SES, reflecting spurious correlations and leading to discriminatory decisions.
- These algorithms and decisions are often opaque and un-appealable.



## 9. CONTINUOUS MONITORING

- Healthy models maintain a back and forth with the thing(s) in the world they are trying to understand.
- Are you tracking for changes related to your data, assumptions, and evaluation metrics?
- Are you proactively looking for potential unintended side effects of your model itself or harmful outputs?
- Do you have a mechanism to fix and update your algorithm?



# Case Study: Fake news and video recs

- Companies are continuously making predictions about what you are going to do, which it uses to try to influence behaviour and then update its models based on the results
- Models optimize for engagement and sharing - can promote the spreading of misinformation



13.5% of U.K. teen girls in one survey say their suicidal thoughts became more frequent after starting on Instagram.

Another leaked study found 17% of teen girls say their eating disorders got worse after using Instagram.

About 32% of teen girls said that when they felt bad about their bodies, Instagram made them feel worse

## TECHNOLOGY

## Here are 4 key points from the Facebook whistleblower's testimony on Capitol Hill

Updated: October 5, 2021 - 9:13 AM ET

by BOBBY ALLEN



Former Facebook public affairs officer Frances Haugen speaks during a hearing of the Senate Commerce, Science and Transportation Subcommittee on Consumer Protection, Product Safety and Data Security on Capitol Hill on Tuesday. Alex Brandon/UP

# ON SYSTEMS & INCENTIVE STRUCTURES

- Novel systems are not, *de facto*, equalizers. They will tend toward propagating existing inequalities.
- Companies working on these systems may have conflicts of interest with respect to the incentive structures imposed by the system and/or the business

# ON PERPETUATING INEQUALITY

- Data & Algorithms can & will entrench social disparities
- Errors and bias typically target the disenfranchised
- The combination of damage, scale, and opacity can be incredibly destructive
- They can introduce feedback in such a way as to enact self-fulfilling prophecies

# PUTTING IT ALL TOGETHER (GOOD)

- well-posed question that you know something about
- have considered implications of work
- adequate data, covering population of interest, with known and manageable biases
- allowed to use the data
- have de-identified data, stored securely
- defined metrics for success, objectively measured
- if suggesting causality, have actually established causality
- model is understandable, has procedure for appeal
- will monitor system for changes, have way & plan to update

# HOW TO BE BAD WITH DATA SCIENCE

- ill-posed question you know nothing about
- don't consider implications
- haphazardly collected biased data
- didn't check or are not allowed to use data for this purpose
- un-anonymized, identifiable data, stored insecurely
- no clear metric for success (meh, it 'seems to work')
- present spurious correlations as meaningful
- model is a black box, no method for appeal in place
- no monitoring, no way to identify biases or update model



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