Week 7: Ethics i

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Ethics in algorithm
it mean?

Ethics in algorithms mean?

"Ethics in algorithms" Data ethics is the branch of ethics that we only need to consider when we are writing algorithms.

Last week we discussed data anonymisation (and de-identification) a lot of our conversation was about ethical data collection

Data ethics includes,

- How data is collected
- How data is shared
- How data is processed
- How data is consumed and services
- How data is released

> Is it ethical for data about us to be collected without our knowledge?

Companies are hiring droves.

Data ethics... you mean machine le

Machine learning, big data and AI are all tremendously exciting and de always seem to be in the media.[1]

But data ethics is important every time we're dealing with sensitive and/or private data.

Even if we've got survey data about attitudes to green spaces during the pandemic.

In this course when we talk about data ethics we're also talking about the ethics of algorithms.

Ethics & Moral

Ethics & Moral Philo

Moral philosophy and the history of ethics is fascinating.

We're just going to it.

Right to priv

Right to privacy

The Universal Declaration of Human Rights[2] provides universal right to privacy

Article 12

No one shall be subjected to interference, with his privacy, family, home or correspondence, nor to attacks upon his honour and reputation. Everyone has the right to the protection of the law against such interference or attacks.

We're going to extend this to include right to privacy in data collection and sharing of data.

But let's look at algorithms a little bit more

Self-driving

Self-driving cars (I

There's a continuum of "self-driving car technology". For discussion purposes, let's define the tech as follows:

> A car on public roads under the control of an automated driving system that controls acceleration, breaking and driving direction. The driver does not have active control of the car, but can disengage the automated driving system and resume control.

- Who is responsible for a self-driving car collision?
- How does the automate
  respond to trolley p
  - Does the car priori
    the driver or a ped
  - Does the car priori
    other vehicles or p

What ethical questions does the addition of self-driving cars to existing road networks raise?

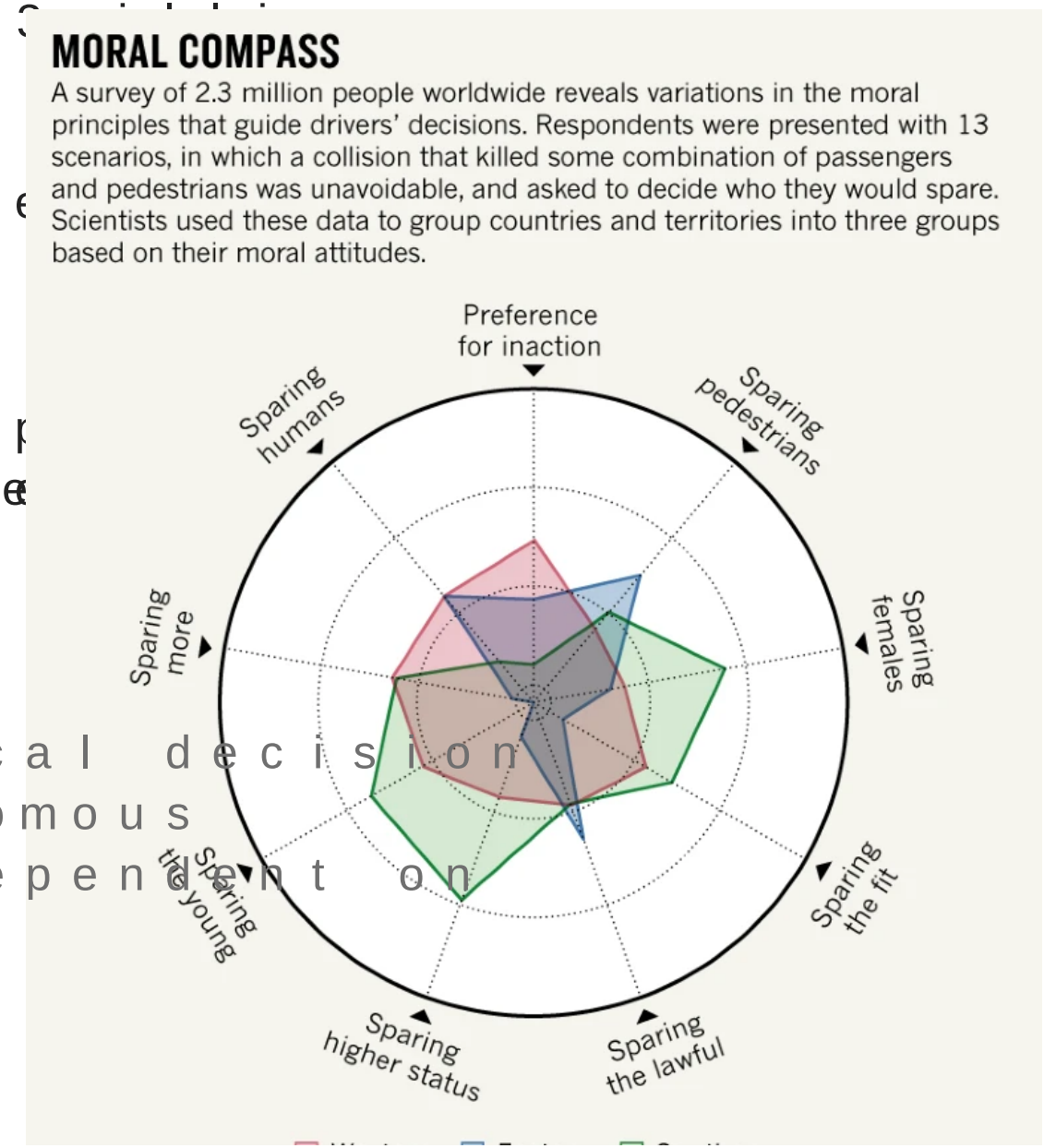
Self-driving cars (I

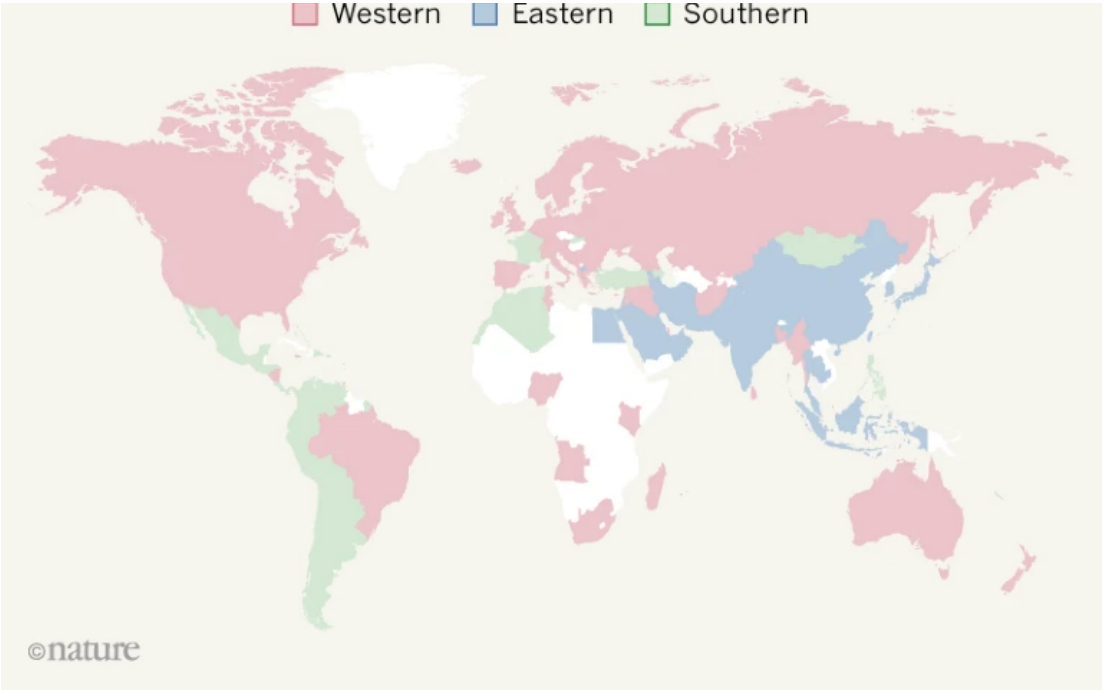
Awad et al surveyed 2.3 million people in 2018 to ... to moral dilemmas ... autonomous vehicle...

[3]

Attitudes vary by ... region of participa... demographics and ... victims

> Should the ethical decision-making of autonomous vehicles vary dependent on location?!





This data visualisation is derived from Awad et al[3] but appears in Maxmen 2018[4]

Self-driving cars (I

Reliable and unbiased estiTmhaitsi osntsa toifs taiuct oinsc
vehicle safety are difficult to find. ervperreytw.heevreen in 202

Self-driving car
an accident rate
crashes per mil
driven – which i
double that of r
vehicles.

As more autonomous vehicles are used by untrained drivers in real-world circumstances, collect more information about their safety.

But it's important we throw and understand autonomous vehicles make their decisions.

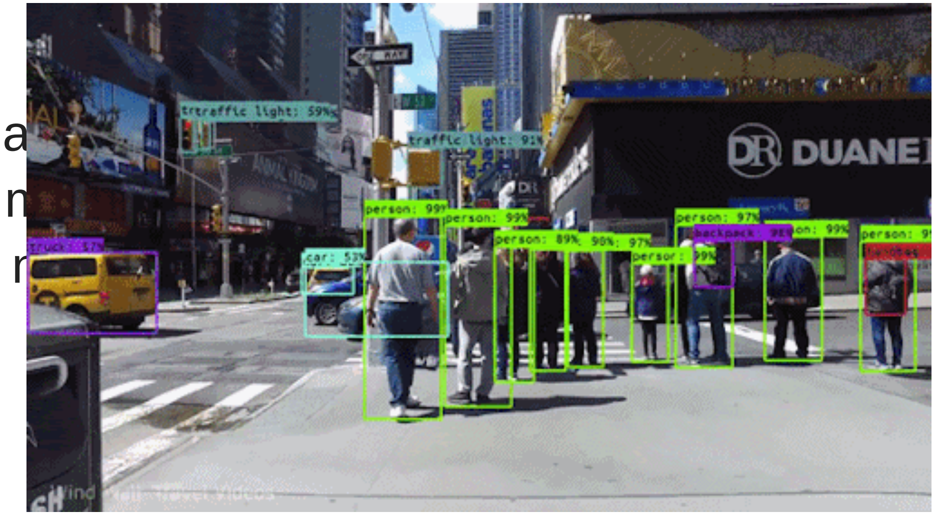
It's derived from a[5]
and a total of 10 ...

Self-driving cars (l

Self-driving vehicles use many tools for sensing and environment.

There's considerable debate [disputed] about two con technologies: LiDAR ar Vision.

- Computer vision uses and categorizes what measuring the



- LiDAR continuously pu measures reflection times a 3D visual map. This c clustered and classified it around the car.

Self-driving cars (I

As we question the eth... ns
autonomous vehicles it
understand how vehicles make
particularly during ac

Does the vehicle make a
and transparent decisions?

Thankfully LiDAR and
provide surprising

This table comes from
report[6] between an autonom
a pedestrian.

Time to Impact (seconds)	Speed (mph)	Classification and Path Prediction[a]	Vehicle and System Actions[b]
-9.9	35.1	--	Vehicle begins to accelerate from 35 mph in response to increased speed limit.
-5.8	44.1	--	Vehicle reaches 44 mph.
-5.6	44.3	Classification: *Vehicle*—by radar Path prediction: *None*; not on path of SUV	Radar makes first detection of pedestrian (classified as vehicle) and estimates speed.
-5.2	44.6	Classification: *Other*—by lidar Path prediction: *Static*; not on path of SUV	Lidar detects unknown object. Object is considered new, tracking history is unavailable, and velocity cannot be determined. ADS predicts object's path as static.
-4.2	44.8	Classification: *Vehicle*—by lidar Path prediction: *Static*; not on path of SUV	Lidar classifies detected object as *vehicle*; this is a changed classification of object and without a tracking history. ADS predicts object's path as static.
-3.9[c]	44.8	Classification: *Vehicle*—by lidar Path prediction: Left through lane (next to SUV); not on path of SUV	Lidar retains classification *vehicle*. Based on tracking history and assigned goal, ADS predicts object's path as traveling in left through lane.
-3.8 to -2.7	44.7	Classification: alternates between *vehicle* and *other*—by lidar Path prediction: alternates between *static* and left through lane; neither considered on path of SUV	Object's classification alternates several times between *vehicle* and *other*. At each change, tracking history is unavailable; ADS predicts object's path as static. When detected object's classification remains same, ADS predicts path as traveling in left through lane.
-2.6	44.6	Classification: *Bicycle*—by lidar Path prediction: *Static*; not on path of SUV	Lidar classifies detected object as *bicycle*; this is a changed classification of object and object is without a tracking history. ADS predicts bicycle's path as static.
-2.5	44.6	Classification: *Bicycle*—by lidar Path prediction: Left through lane (next to SUV); not on path of SUV	Lidar retains *bicycle* classification; based on tracking history and assigned goal, ADS predicts bicycle's path as traveling in left through lane.

We can see the autonomous vehicle repeatedly inconsistently misidenti... a pedestrian.

Fairness, Accountability, Transparency

Fairness, Accountability, Transparency

Fairness

Fairness: 5 (or 6) S

> Frustratingly, finding the source for this! But this list has been around since at least 2014.[8]

Broadly in the literature (and in essays on the subject) there are 5 common sources of bias in training datasets.

These biases result in unfair treatment of individuals/groups by an algorithm.

Examples of unfair treatment include

- Refusal of service
- More expensive services
- Reduced range of services

When these services include healthcare the ramifications can be life threatening.

- Proxies
- Limited features
- Skewed sample
- Tainted examples
- Sample size disparity

The assessment limits its ... treatment of ...

Is it worthwhile mention... these bias, is knowledge left (or added) to a ...

This is masking.[8]

Fairness: Proxies

> Proxies are the easiest to identify and d…

When training our algorithms we want to re…
gender, age or religious belief - because we …
disadvantage or advantage a specific group

However, there are many other variables that act as proxies for these …
Can you think of any?

- Systemic racism means that income, neighbo… proxies for race.

> "Redlining is the practice of … financial services … neighborhoods, generally because its residents …"

- Facebook friendships can be a[11] strong proxy…

Fairness: Limited Fe

> This is a harder bias to address entirely (and more extremely down examples

Limited features is a consequence of having specific combinations of sensitive attributes.

Individuals in these groups with a low success (objec than other groups.

This article gives a theoretical example: h unintended-bias-in-training-data-be5b7f334

> Limited features is a pre-requisite for s

Fairness: Skewed sam

> It's kind of unfair this is collected togeth
> examples, sample size disparities

Skewed samples is a bias in your algorithm
results in an algorithm that becomes more skewed over time by
feedback[12]. Please do read the paper[12] from Ensign et al. 2017 as
really well.

> Given historical crime incident data for
> patrol officers to areas to detect crime
>
> ...
>
> Since such discovered incidents only occu
> sent to by the predictive policing algori
> bias to be compounded, causing a runaway

Fairness: Skewed sam

> Another really great example with an easy
> issues with spurious correlations

Lazer et al 2014[13]

In 2009 Google published results in Nature[14]
that used search queries to predict

The theory being that ill people search for
detected.

However, the whole thing is somewhat questiona

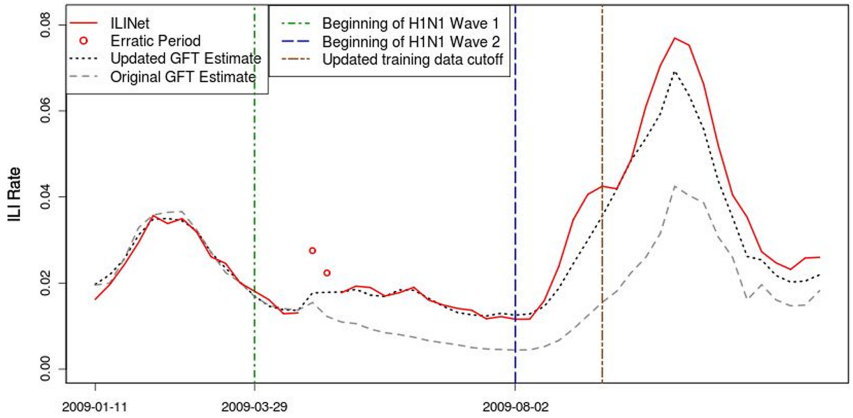
> GFT has never documented the 45 search te
> been released appear misleading[15]
>
> Source: Lazer et al 2014[13]

Fairness: Skewed sam (II)

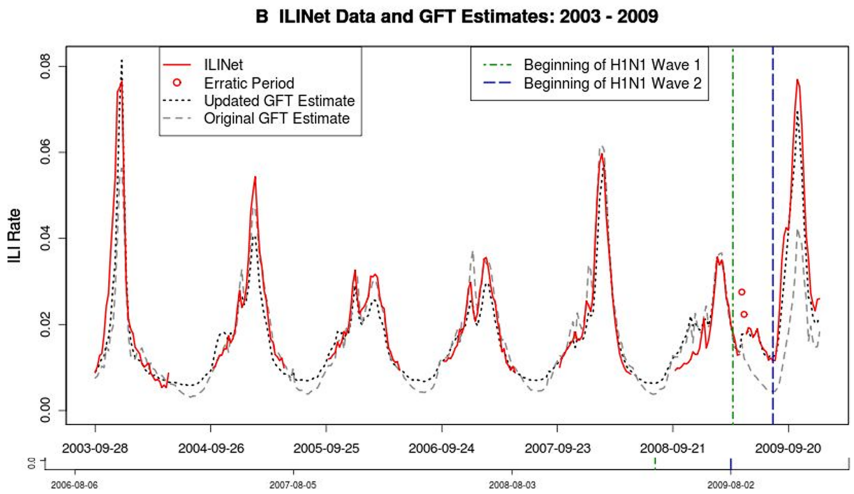
Coincidentally, the first big failure of the service was the 2009

15

The GFT didn't detect wave of H1N1 during t .



Google quickly update hm later in 2009 and the hm d a better job of predi k.

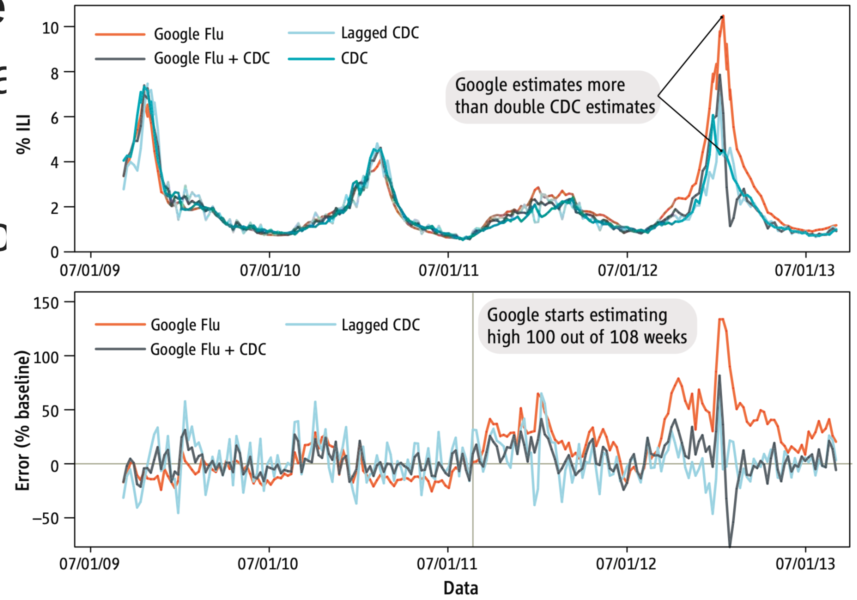


Fairness: Skewed sam (III)

However, from 2011 onwards the
consistently overestimated flu
and became increasing
Lazer[13] points to two reaso

- Big data hubris

Was the algorithm a detector?!



Source: Lazer[13] et al

- Algorithm dynamic

Google has many competing algorithms that shows potentially interesting (or use

Fairness: Two examples

We need to talk about learning.

Do you know the difference between supervised and unsupervised...

In supervised learning ... categories and ass... these categories.

The algorithm will ... as belonging to one...

That's all well and g... something like the titanic survival dataset

... but often our ca... absolute, eg

- Google's flu has t...
- Rating's a driver's likelihood of an accident
- Rating a "good jo...

> Let's look into the example more

Fairness issues: Tech examples in HR

Algorithms are used to sometimes aggressively exclude applicants during recruitment. Fraij and Laval's literature review[16] on technologies in 2021

These algorithms are often software to filter automatically

The algorithms are celebrated for being fast, efficient and allowing recruiters to focus on more interesting and human-required tasks.

> This couldn't possibly create issues

These algorithms are often heavily criticised for categorising "good CVs".

- Who gets hired. And what "shocking levels of discrimination"[17] for being hiring
- Work evaluation scores people's performance[18]

Fairness: Sample Size Dis

> Unfortunately, never hyperfectly balanced [untainte
> untainted categories can have bias. Sampl
> this.

Sample size disparity Tehxei smtoss twhweindely cited
completely balanced daetxaasmeptlse hoafvet his is1s -th
disparity in the size hotft pssu:b/g/reonu.pwsi.kipe.dia.

This disparity results in unfair behaviour
the algorithm when applied to real-world
datasets.

Fairness: Sample Size Dis

In 2011 Google implemented a real name policy for Google+.

There are significant privacy issues with this policy.

But users also found their names rejected as “not real”.

Folks with names that don’t last name pattern - e found their names rej

This is widely blamed datasets having sampl there were fewer inst forms.

I recommend reading t Falsehoods Programmer Names – With Examples

... some more cas

“Man is to computer programmer a
(I)

In 2016 Bolukbasi et al.[20] demonstrated how the extremely common word2vec algorithm shows gender bias.

word2vec is a patented algorithm[21] that - when trained on a given text - will find similar/synonymous words given input.

Google provides a useful interaction on how the system works.

For example, if you
distance will displa
words and their dist
which should look li

“Man is to computer programmer a
(II)

“Man is to computer programmer a (III)

What sources of bias are present in this example?

- Proxies
- Limited features
- Skewed sample
- Tainted examples
- Sample size disparit

Racial bias in photo

Smartphone manufacturers [illegible] started advertising how t[illegible] accurately photograph the [illegible] skin tones.[22]

This has been known as an issue in photography, for many decades in different situations.

Figure 1
Polaroid Shirley card (Printed with permission of Polaroid)

In pre-digital photograph[illegible]k issued "Shirley cards" fo[illegible]ancing images. These cards exclu[illegible] contained Caucasian model[illegible] until the 1990s.

Source: Lorna Roth[23]

Racial bias in photo

This issue has also be[en pervasive in]
digital photography.

TABLE 1 Fitzpatrick Classification of Skin Types I through VI

Type I	Type II	Type III	Type IV	Type V	Type VI
White skin. Always burns, never tans.	Fair skin. Always burns, tans with difficulty.	Average skin color. Sometimes mild burn, tan about average.	Light-brown skin. Rarely burns. Tans easily.	Brown skin. Never burns. Tans very easily.	Black skin. Heavily pigmented. Never burns, tans very easily.

The continued use of t[he ... ski]n tone scale is largely to blame.

Source: Ward et al[25]

Dr Ellis Monk's research[24] culminated in the Monk Skin Tone with evidence improvements in processing of images compared to the Fitzpatrick scale.

Racial bias in photo

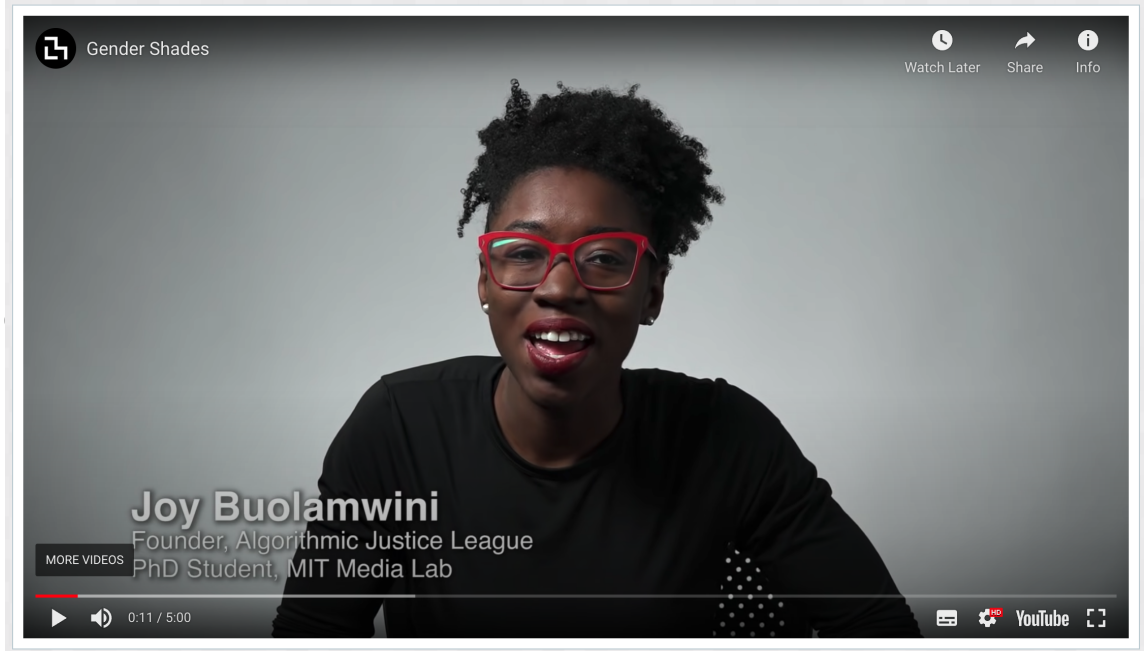
I'd like to recommend some additional resou

- Vox Media's video "Colorism was built for white skin."[26]
- The Racial Bias Built Into Photography[27]
- Lorna Roth's research on Shirley Cards[28]
- Google's Skin Tone Research Team with Dr. Ellis Monk.

Racial bias in face

This is a fundamental problem in all face analysis software.

Joy Buolamwini was a mu
better job of exp
minutes than I ca



Source: gendershades.org[28]

Racial bias in face photography

What sources of bias are present in this example?

- Proxies
- Limited features
- Skewed sample
- Tainted examples
- Sample size disparit

Accountabrialnistpya&e

Accountability & Transparency

These two terms are used interchangeably ... Thankfully ... discuss how these two concepts relate to one ...

There's a really useful EU "governance framework ... accountability[29] and transparency"

> The primary role of transparency is ... not known what an organisation is doing, ... regulated.
>
> ...
>
> An important difference between transparency and a... is primarily a legal and ethical obligation ... for its activities, accept responsibility ... transparent manner.

... but the rest of the document is very hea...

Accountability

For a more thorough exploration of accounta

Transparency and gami

Is it worthwhile mentioning that transparency algorithm is applied:

> Also, in some cases, transparency may lea system." For example, even the minimal op feature weighting surfaces topics has allowed i certain topics by bots and coordinated gr contexts may create illusions of transparency

Source: Caplan et al 2018[30]

- How else could we game algorithms?

Other sources of

Other sources of unf

Earlier we tried to categorize some of the sources of bias:

- Proxies
- Limited features
- Skewed sample
- Tainted examples
- Sample size disparities

These are almost always concerned with the training data behind algorithms.

These are a whole universe of ways we can bias an algorithm by how it is applied

Fairness and Abstraction Systems

Selbst et al published in 2019 "abstraction traps" [31]. In the next several slides we'll provide context for one of these traps and how it can help us account for the interactions between the technical systems behind our algorithms and the social world in which they're applied.

Selbst Abstraction Trap:

> Failure to model the entire system over w
> be enforced

Example:

In the US criminal justice pipeline algori
predict the “risk” of a defendant and dete

<br

However - usually this is the risk the defe
Reoffending is only occassionally considered

These risk assessment tools are presented
not account for[31]) the interaction betwe

> The intended appliction of the algorithm
> into account their use by judges and ther
> measured

Selbst Abstraction trap

> Failure to understand how repurposing algorithmic solutions designed for one social context may be misleading, inaccurate, or otherwise do harm when applied to a different context

Here's a really nice quote

> Within computer science, it is considered good practice for a system to be used for different tasks in different contexts. "But what that ignores is that social context," says Selbst. "You can't have a system designed in Utah and then applied in Kentucky directly because different communities have different versions of fairness. Or you can't have a system that you apply for 'fair' criminal justice results then applied to employment. How we think about fairness in those contexts is just totally different."
>
> Source: Karen Hao[32]

Selbst Abstraction: ap

Failure to account for the full meaning o
be procedural, contextual, and contestabl
mathematical formalisms

I did promise we would ... recrui
philosophy important for ... don't particularly mi
moment.

positives (candidates
fit) because ... re
them out.

Fairness and discrimination are complex concepts that philosophers, sociologists, and lawyers have long debated. They are at times procedural, contextual, and politically contestable, and each of those properties is a core part of the concepts themselves[31]

However the justicial r
mentioned earlier mig
opposite treatment. F
result in parole bein

Selbst Abstraction Trap

> Failure to understand how the insertion o
> changes the behaviors and embedded values

Selbst et al.[31] define and entirely on the justicial ris
increased use focuses the intent of the jus

Selbst Abstraction: Trap

- Failure to recognize the possibility that technology
- Modeling requires fixing definitions in Code. When fairness is politically contested, movable issue, a m how it moves

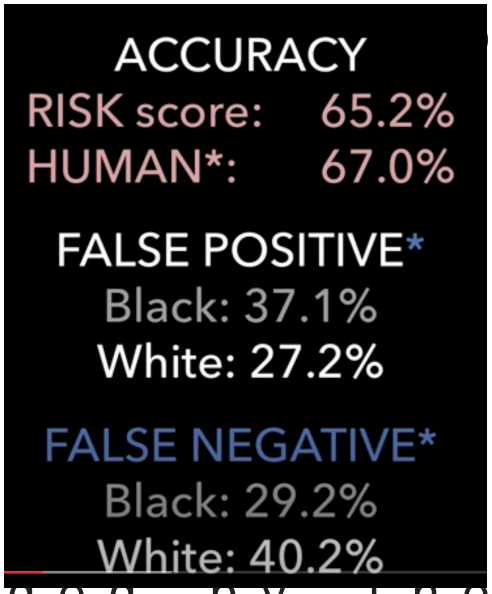
COMP3: Algorithmic assessments

COMPAS: Algorithmic risk assessments

The algorithmic risk assessment algorithm we've discussed is called COMPAS.

It's been subject to intense scrutiny.

ProPublica did a study[33] in 2016 that was one of the first investigations. A technical breakdown of this is provided by the same authors[34]



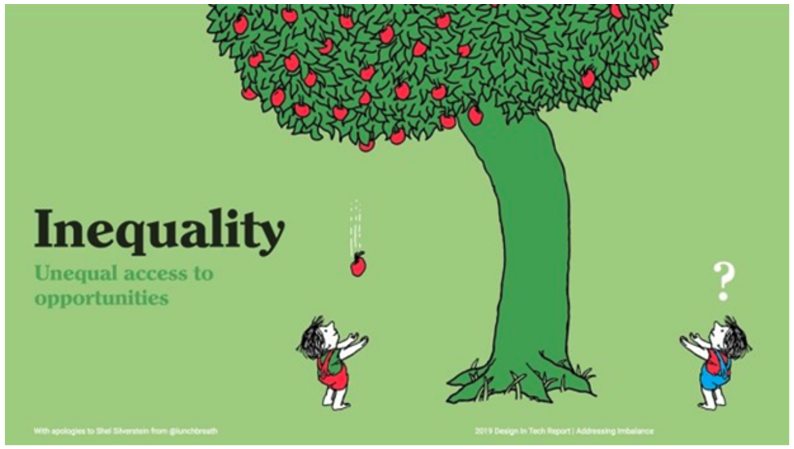
The algorithm performs worse than random Mechanical Turk workers[35]

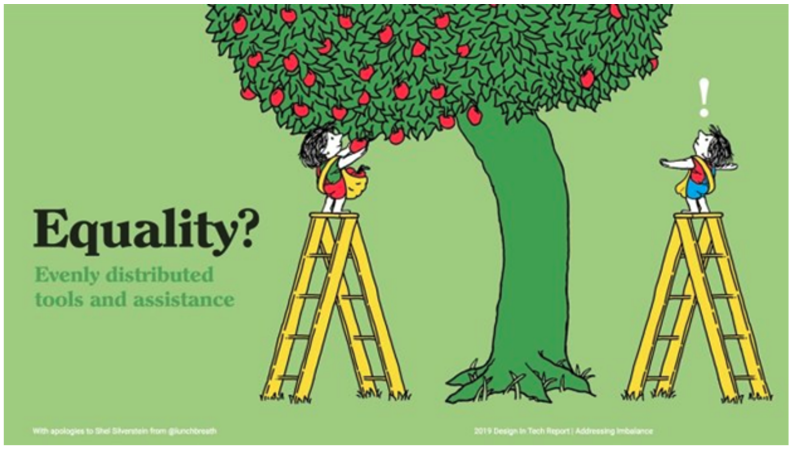
I'd like to hear your thoughts on this topic[36]

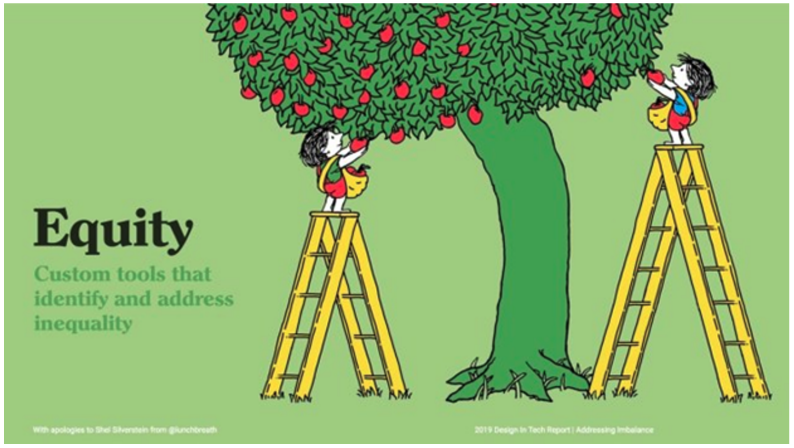
Inequality vs Jus

Inequality vs Justic

I thought it was important to not skip over
These cartoons are from Design in Tech Report 2019
designed by Tony Ruth







We have to stop

We have to stop some

We've covered more than enough for your ass
complexities of ethics in algorithms.

We didn't really discuss data privacy very
Fair Information Practices.

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