

# Responsible Data Science

Introduction and Overview

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**Prof. George Wood**

Center for Data Science



**course logistics**

# Instructor: George Wood

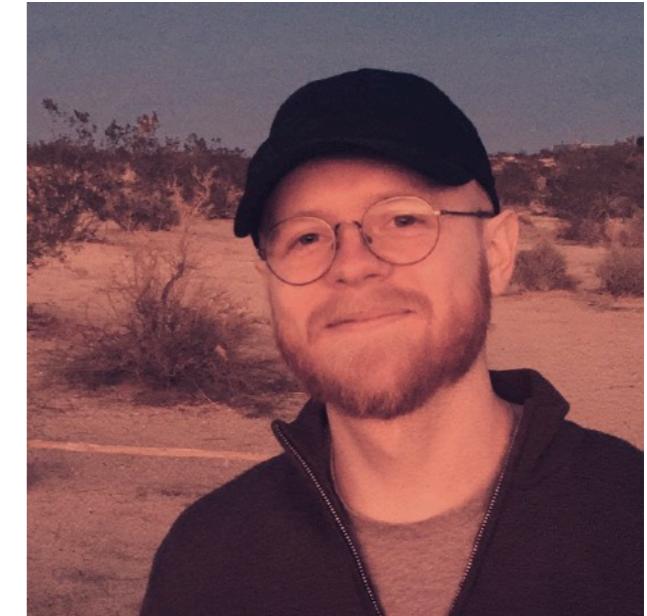
Moore-Sloan Faculty Fellow at the Center for Data Science

Ph.D. in Sociology from University of Oxford

Previously: Yale, Northwestern

Research:

- Discrimination in criminal justice
- Inequalities in public health
- Police behavior, police use of force, gunshot victimization
- Develop tools to enhance transparency and accountability in policing



**Office hours:** Wednesdays 11-noon EST and by appointment

# Course Staff

Section Leader & Grader: **Tamar Novetsky**  
Office hours: Thursdays 9–10am, via Zoom

Section Leader & Grader: **Yash Jajoo**  
Office hours: Fridays 4–5pm, via Zoom

Grader: **Jeewon Ha**

# Meeting times

**Lectures:** Mondays and Wednesdays, 8–9:15am

**Lab A:** Wednesdays, 2–2:50pm

**Lab B:** Thursdays, 8–8:50am

You have been assigned to either Lab A (Wednesdays) or Lab B (Thursdays)

**Online attendance** option will be offered throughout semester (subject to change based on NYU policy)

# Assignments and grading

**Grading:** homeworks:  $10\% \times 3 = 30\%$   
project: 30%  
final exam: 30%  
labs: 10%

**Late policy:** For homeworks, 2 late days over the term, no questions asked. If a homework is submitted a few hours late — a day is used in full. No credit for late submissions once your late days have been used up. No late days for project.

Assignment schedule posted to Brightspace, see calendar or assignments tab.

# Where to find information

**Website:** <https://dataresponsibly.github.io/rds/> slides, lab notebooks, reading

The screenshot shows a navigation bar with tabs: FAIRNESS (selected), DATA SCIENCE LIFECYCLE, DATA PROTECTION, and TRANSPARENCY AND INTERPRETABILITY. On the left, there's a vertical sidebar with 'WEEK 1' (play icon), 'WEEK 2' (star icon), 'WEEK 3' (star icon), and 'WEEK 4' (star icon). Below the sidebar, it says 'Next module: DATA SCIENCE LIFECYCLE ▶'. The main content area is titled 'Fairness' with a blue underline. It includes a 'Lecture' section with 'Introduction and Algorithmic Fairness', a 'Topics' section with a bulleted list, a 'Reading' section with a link 'See Introduction and Algorithmic Fairness' (which is highlighted with a red rounded rectangle), and a 'Lab' section with 'Intro to Google Colaboratory; ProPublica's Machine Bias'.

FAIRNESS

DATA SCIENCE LIFECYCLE   DATA PROTECTION   TRANSPARENCY AND INTERPRETABILITY

WEEK 1

WEEK 2

WEEK 3

WEEK 4

Next module:  
DATA SCIENCE  
LIFECYCLE ▶

## Fairness

Lecture: Introduction and Algorithmic Fairness

Topics:

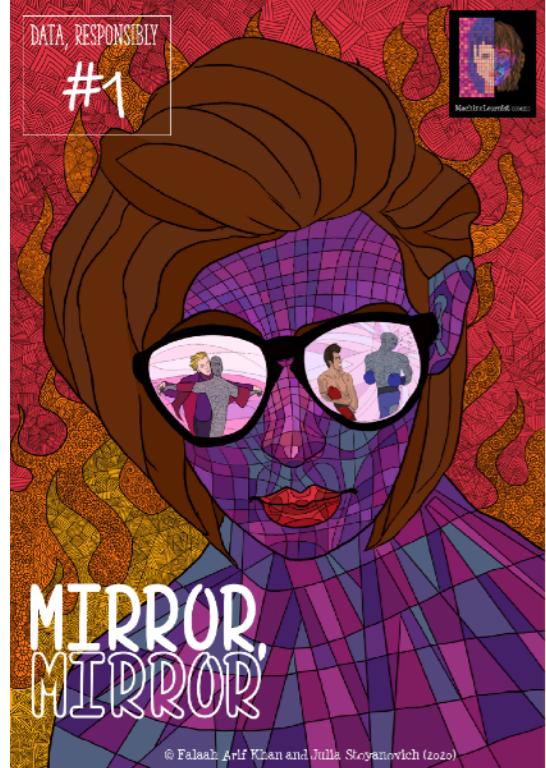
- Course outline
- Aspects of responsibility in data science through recent examples
- The importance of a socio-technical perspective: stakeholders and trade-offs
- Fairness in classification

Reading: See Introduction and Algorithmic Fairness

Lab: Intro to Google Colaboratory; ProPublica's Machine Bias

**Brightspace:** everything assignment-related, Zoom links for lectures and labs, announcements, discussion board

# This week's reading



DOI:10.1145/3376898

**A group of industry, academic, and government experts convene in Philadelphia to explore the roots of algorithmic bias.**

BY ALEXANDRA CHOLDECHOVA AND AARON ROTH

## A Snapshot of the Frontiers of Fairness in Machine Learning

**Machine Bias**

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016

PRO PUBLICA

Bernard Parker, left, was rated high risk; Dylan Faccett was rated low risk. (Josh Ritchie for ProPublica)

Comics by Professor Stoyanovich, Falaah Arif Khan, Mona Sloane

# Requirements of this course

This course will require that you:

- **Program in Python:** importing data, inspecting data, wrangling, visualization, writing technical programs
- **Don't leave homeworks and project to the last minute;** they are substantial pieces of work and you are given 3+ weeks for each homework
- **Work in partnerships:** the project is a joint submission with a fellow student



what is  
responsible DS?

# Algorithms, AI, ML, Data Science

## Algorithm

a step-by-step **set of instructions** that tell a computer what to do with a given input

## Data Science

Can involve AI, always involves algorithms. Usually covers the **pipeline** from data processing to modeling

## Artificial Intelligence (AI)

a **system** in which **algorithms** use **data** and make **decisions** on our behalf, or help us make decisions

**Machine learning (ML)** is a subset of AI in which a program learns patterns from data

[Kearns and Roth, 2019]

# The DS chef

**Data:** flour, sugar, baking powder, baking soda, butter, milk, eggs

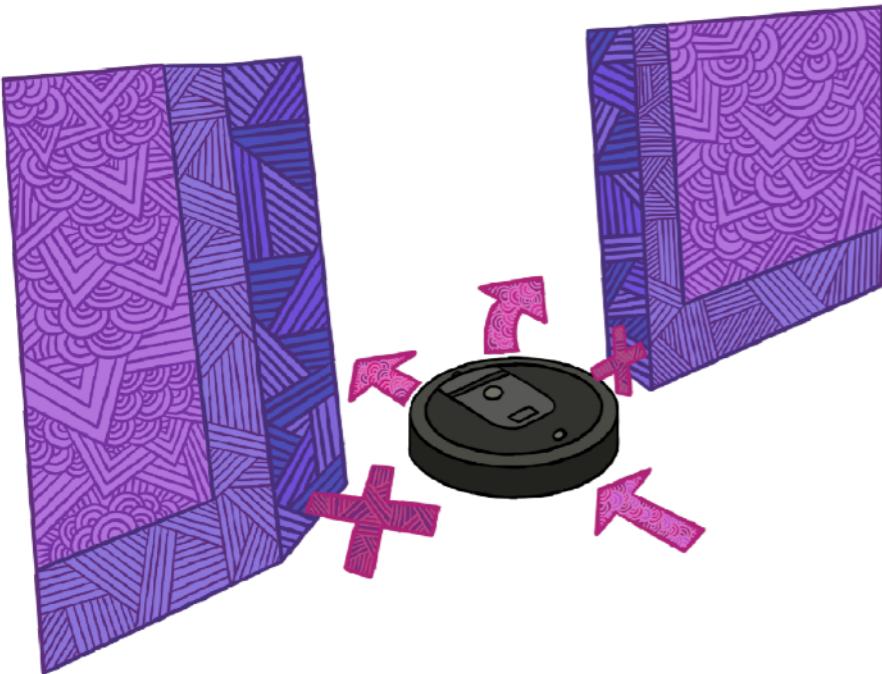
**Algorithm 1:** remove recipes that include ingredients not in data

**Algorithm 2 (AI, ML):** check if system recommended pancakes recently. If no: recommend pancakes. If yes: recommend waffles.

Does the **DS chef** have enough information to make good (or safe) recommendations?

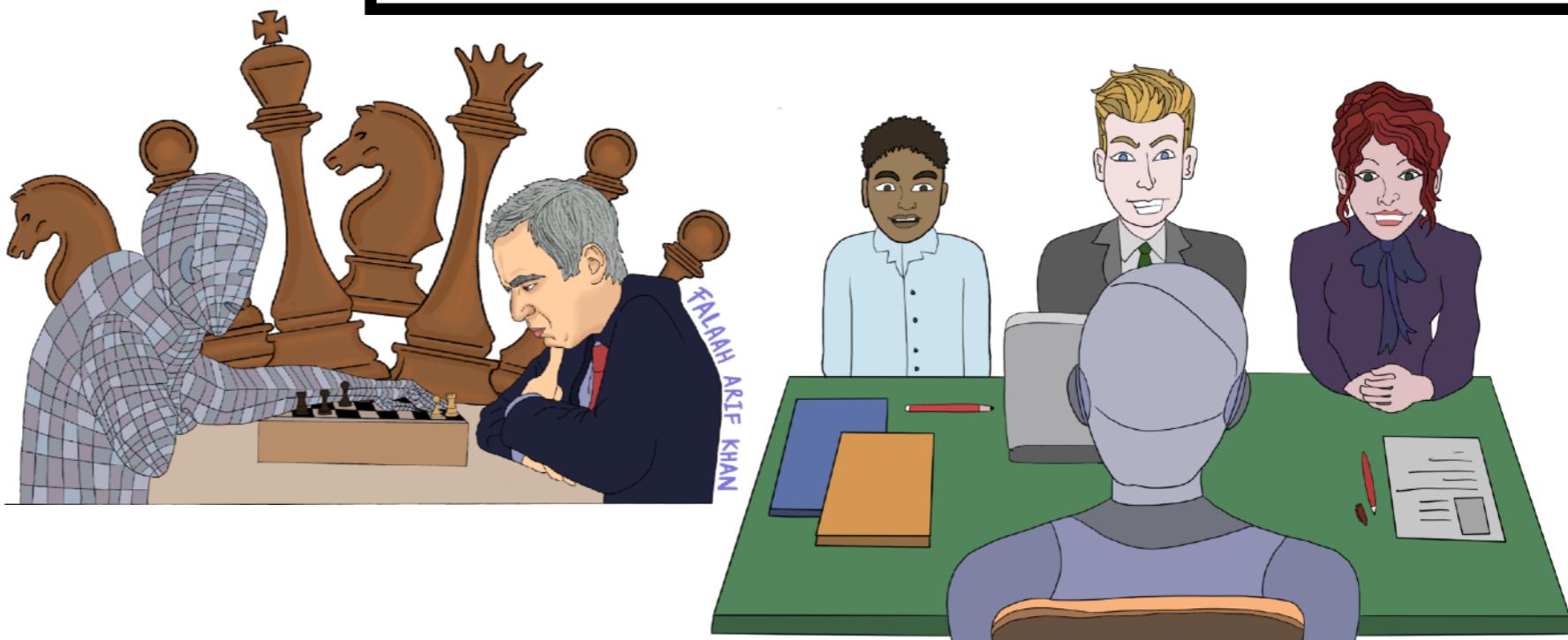
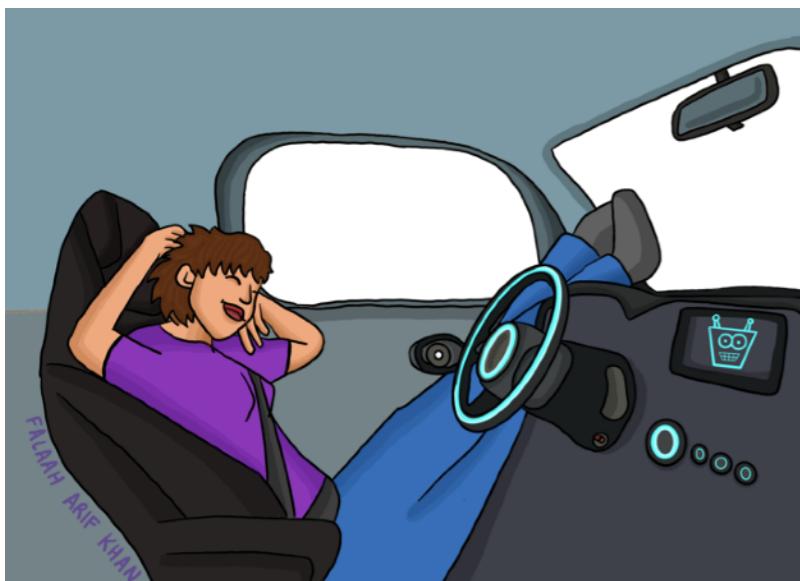


# AI: algorithms, data, decisions



## Artificial Intelligence (AI)

a **system** in which **algorithms** use **data** and make **decisions** on our behalf, or help us make decisions



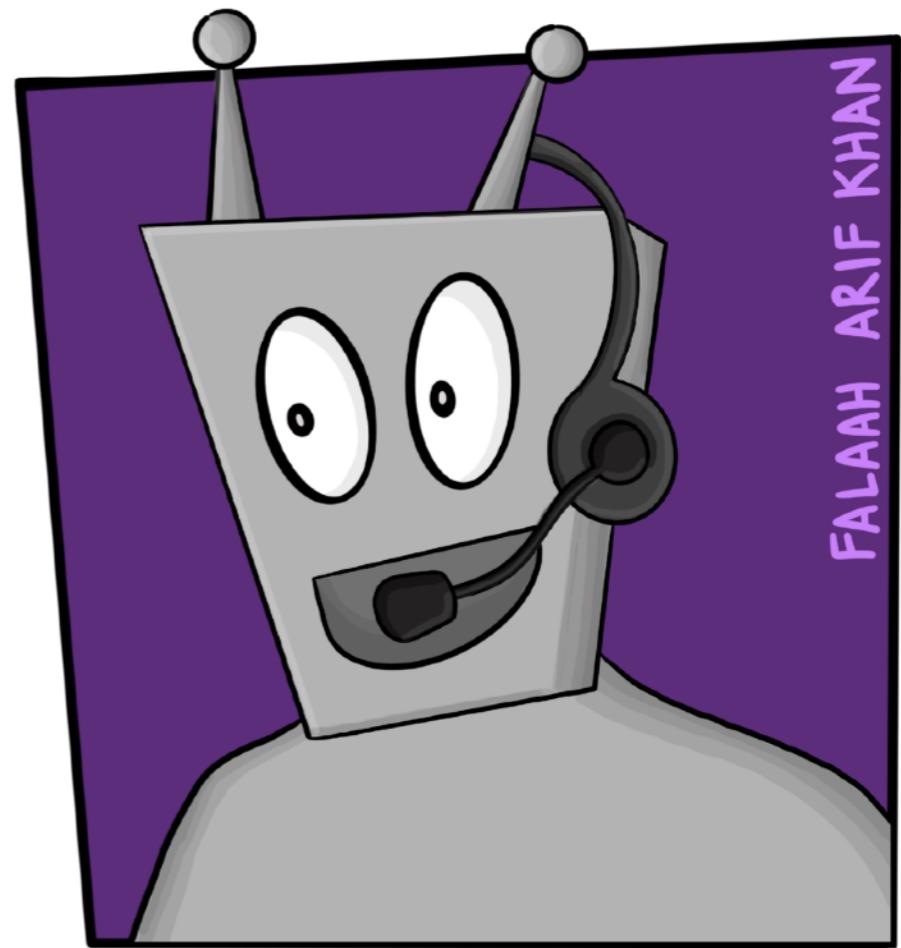
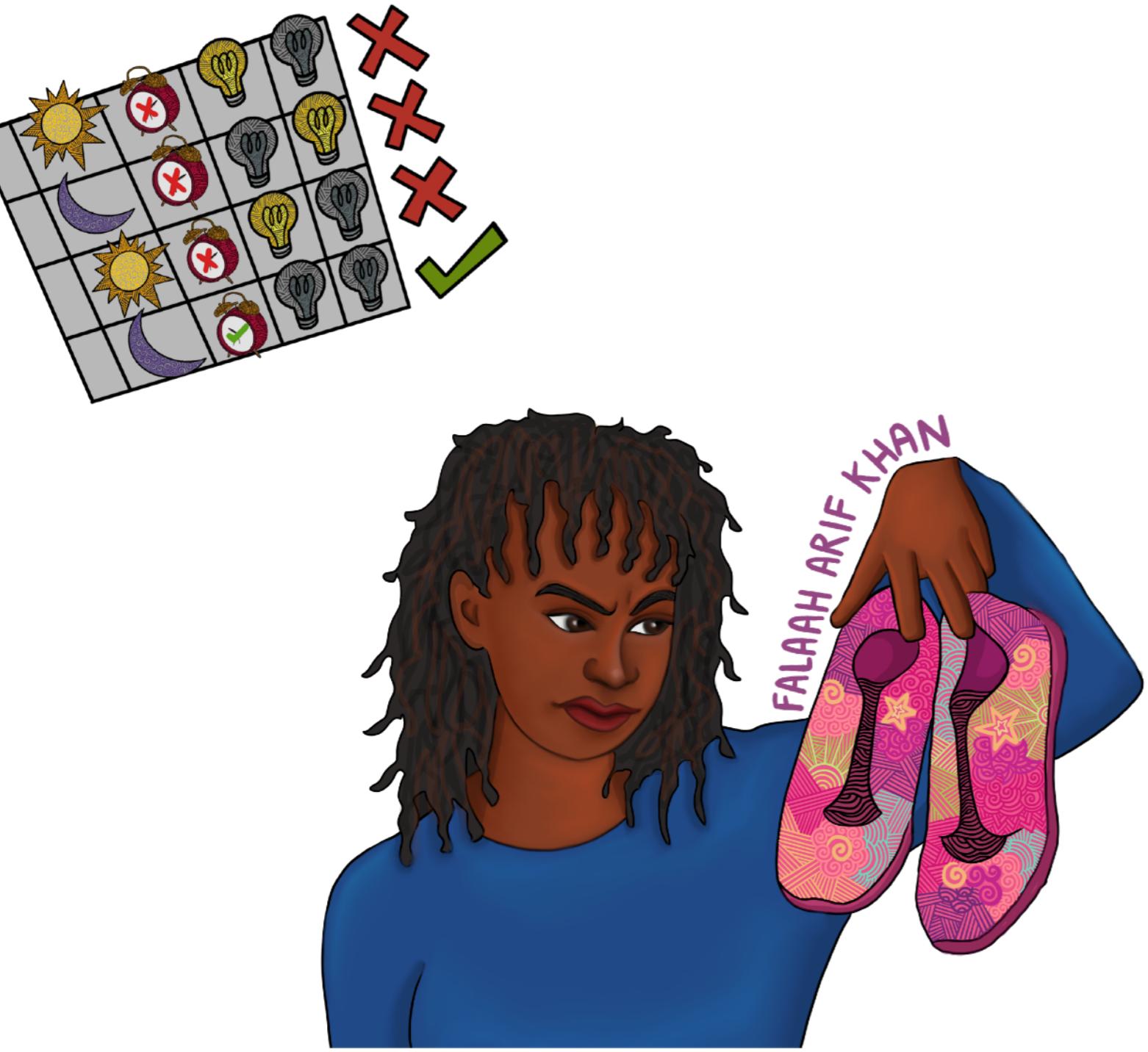
# The promise of AI

## Opportunity

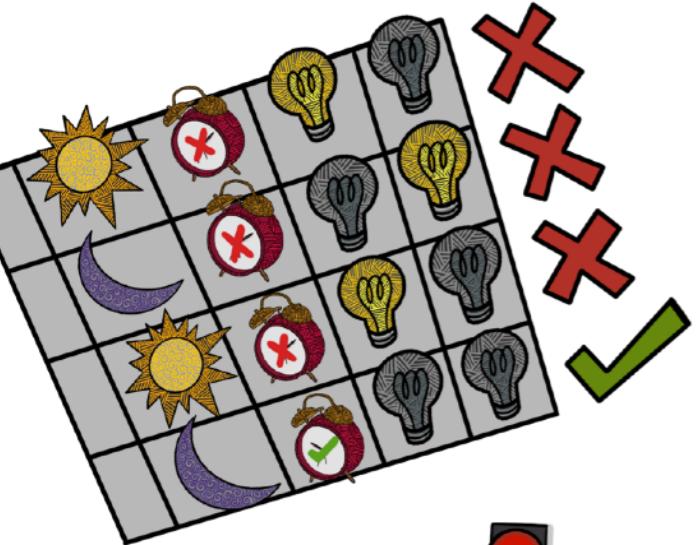
- make our lives convenient
- accelerate science
- boost innovation
- transform government



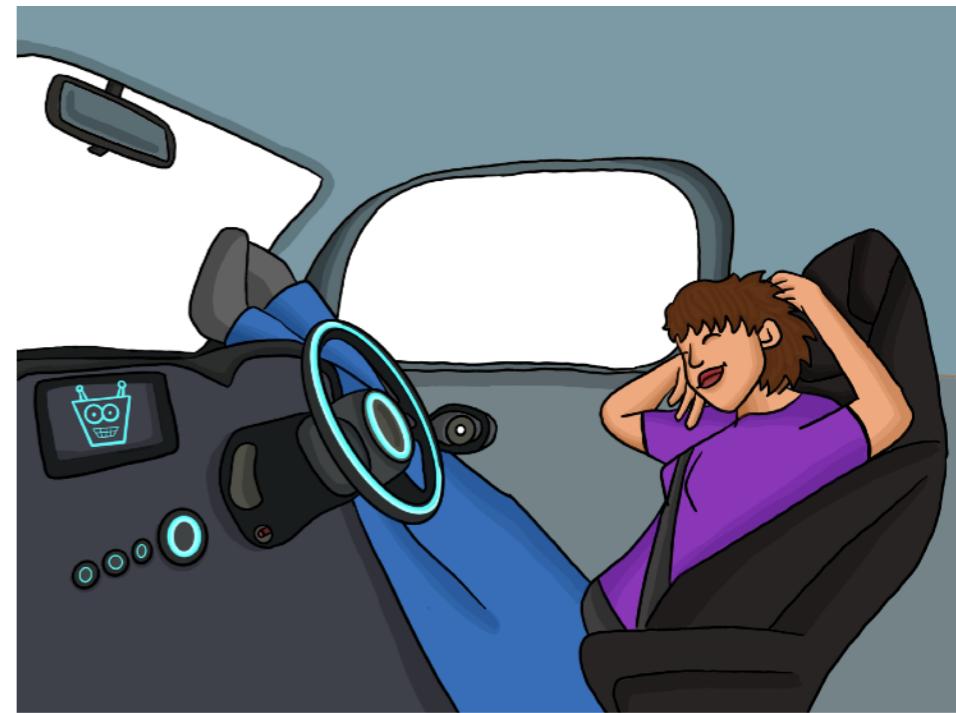
# Machines make mistakes



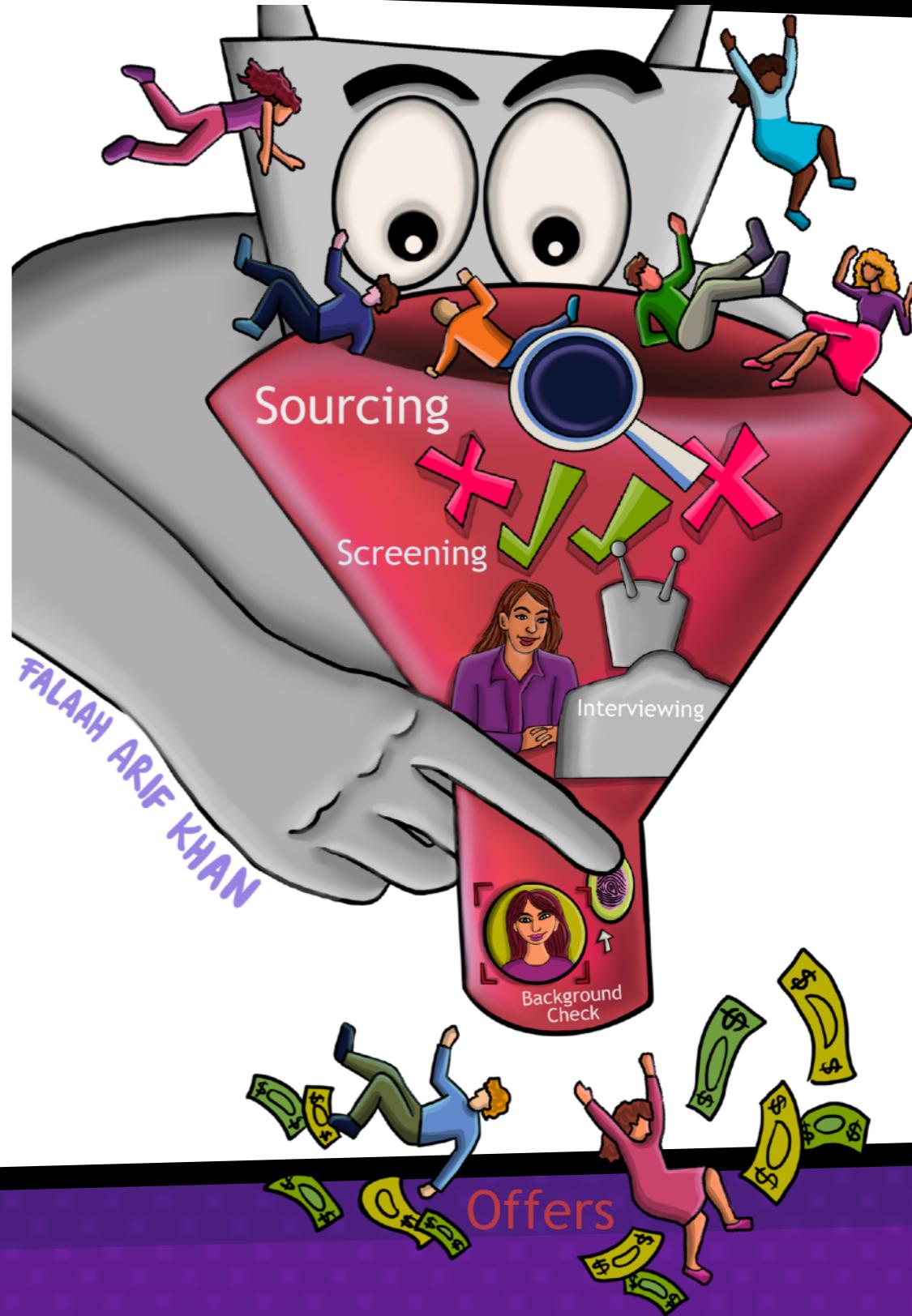
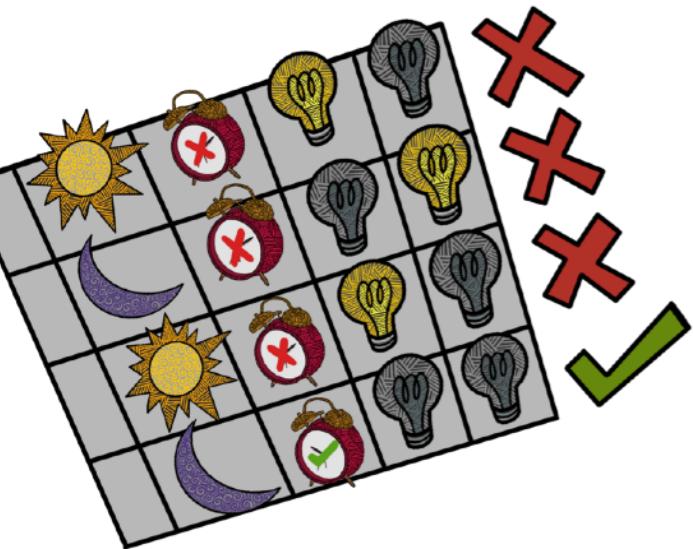
# Mistakes lead to harms



FALAAH ARIF KHAN



# Harms can be cumulative





what is  
responsible DS?



more examples

# Medical imaging

FACEBOOK AI



## fastMRI

Accelerating MR Imaging

### What is fastMRI?

fastMRI is a collaborative research project between Facebook AI Research and NYU Langone Health. The aim is to investigate the use of AI to make MRI scans up to 10 times faster.

By producing accurate images from undersampled data, AI image reconstruction has the potential to improve the patient's experience and to make MRIs accessible for more people.

### Positive factors

clear need for improvement

can validate predictions

technical readiness

decision-maker readiness

raw data and image dataset repository, which contains baseline reconstruction models and PyTorch data loaders for the fastMRI dataset.

<https://fastmri.org/>

# Automated hiring systems

MIT

Technology Review February 2013

Racism is Poisoning Online Ad Delivery, Says Harvard Professor



REUTERS

Amazon scraps secret AI recruiting tool that showed bias against women

The New York Times

March 2021

We Need Laws to Take On Racism and Sexism in Hiring Technology

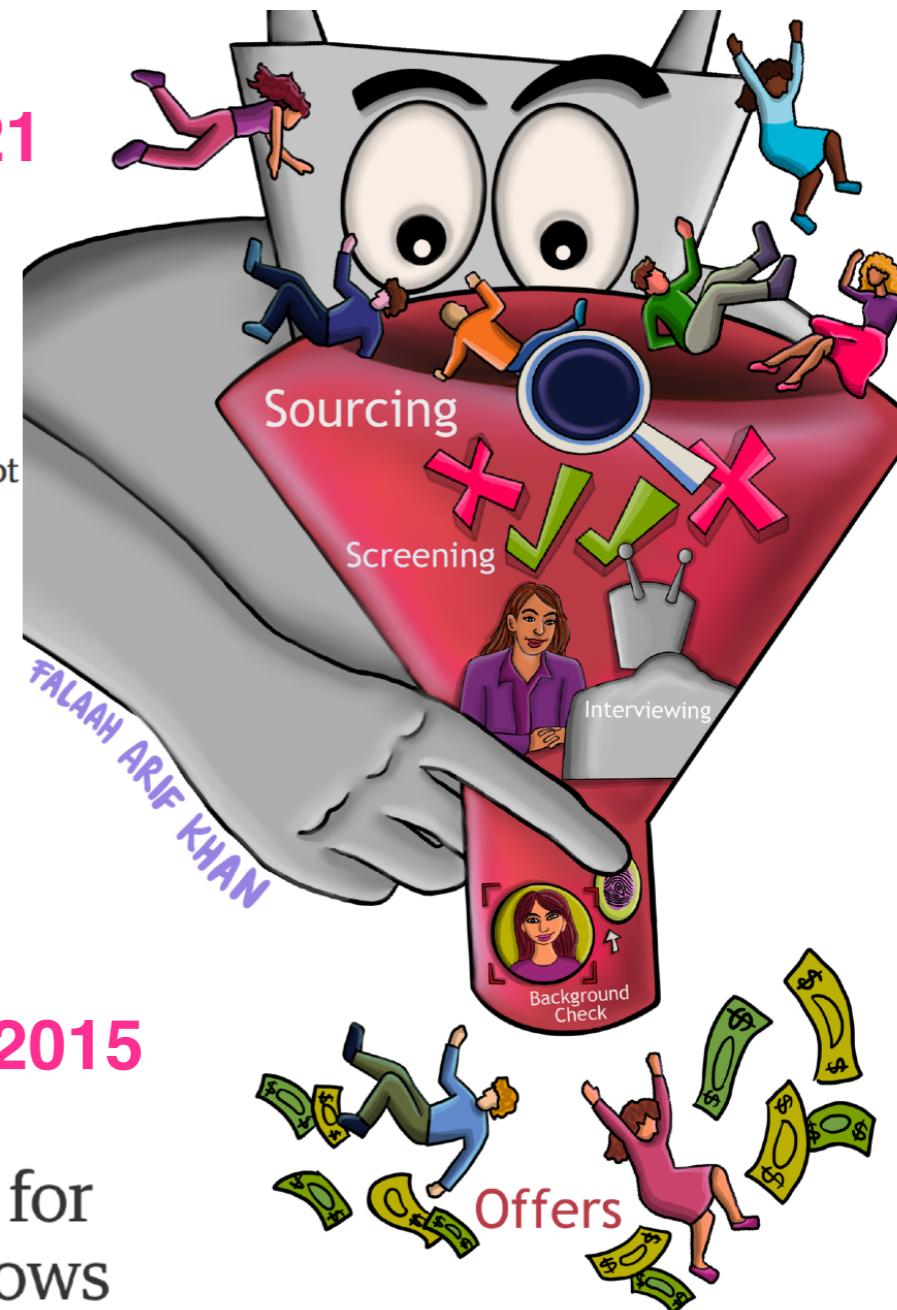
Artificial intelligence used to evaluate job candidates must not become a tool that exacerbates discrimination.

October 2018

the guardian

July 2015

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



# Hiring before automation

## Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination

September 2004

Marianne Bertrand

Sendhil Mullainathan

AMERICAN ECONOMIC REVIEW  
VOL. 94, NO. 4, SEPTEMBER 2004  
(pp. 991-1013)

**We study race in the labor market by sending fictitious resumes to help-wanted ads in Boston and Chicago newspapers.** To manipulate perceived race, resumes are randomly assigned African-American- or White-sounding names. **White names receive 50 percent more callbacks for interviews.** Callbacks are also more responsive to resume quality for White names than for African-American ones. The racial gap is uniform across occupation, industry, and employer size. We also find little evidence that employers are inferring social class from the names. Differential treatment by race still appears to still be prominent in the U. S. labor market.

# discussion

## Describe a use case

what are the **goals** of the DS system?

what are the **benefits** and to **whom**?

what are the **harms** and to **whom**?

# Use case: Staples discounts

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

### WHAT PRICE WOULD YOU SEE?



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

December 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.

A Wall Street Journal investigation found that the Staples Inc. website displays different prices to people after estimating their locations. More than that, **Staples appeared to consider the person's distance from a rival brick-and-mortar store**, either OfficeMax Inc. or Office Depot Inc. If rival stores were within 20 miles or so, Staples.com usually showed a discounted price.

# Use case: AdFisher

the guardian

July 2015

Samuel Gibbs

Wednesday 8 July 2015 11.29 BST

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

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

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>

# Use case: Resume screening



Jeffrey Dastin

BUSINESS NEWS OCTOBER 9, 2018 / 11:12 PM / 6 MONTHS AGO

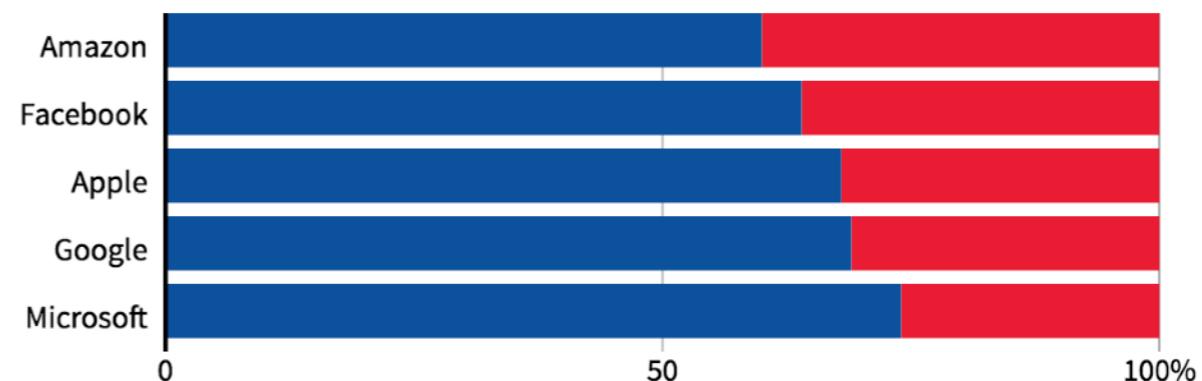
October 2018

## Amazon scraps secret AI recruiting tool that showed bias against women

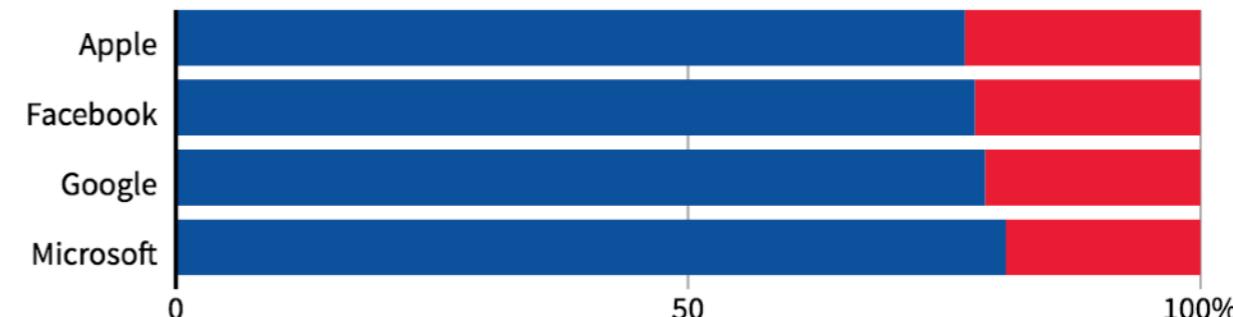
"In effect, **Amazon's system taught itself that male candidates were preferable**. It penalized resumes that included the word "women's," as in "women's chess club captain." And it **downgraded graduates of two all-women's colleges**, according to people familiar with the matter. They did not specify the names of the schools."

### GLOBAL HEADCOUNT

■ Male ■ Female



### EMPLOYEES IN TECHNICAL ROLES



"Note: Amazon does not disclose the gender breakdown of its technical workforce."

<https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scaps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G>

# Use case: Instant Checkmate



Ads by Google

[Latanya Sweeney, Arrested?](#)

1) Enter Name and State. 2) Access F  
Checks Instantly.

[www.instantcheckmate.com/](http://www.instantcheckmate.com/)

[Latanya Sweeney](#)

Public Records Found For: Latanya S  
[www.publicrecords.com/](http://www.publicrecords.com/)

Tanya

arrest

www.

com

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# Use case: Amazon self-day delivery

Bloomberg

## Amazon Doesn't Consider the Race of Its Customers. Should It?

“... In six major same-day delivery cities, however, **the service area excludes predominantly black ZIP codes** to varying degrees, according to a Bloomberg analysis that compared Amazon same-day delivery areas with U.S. Census Bureau data.”

New York City



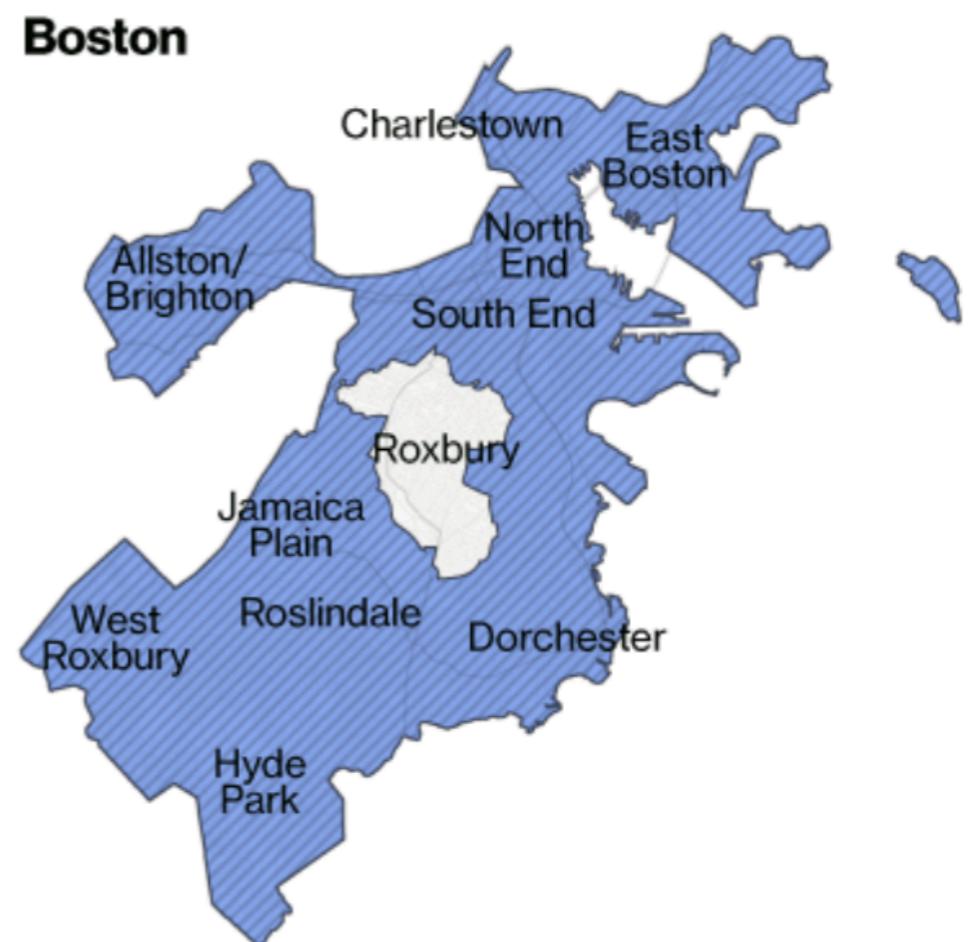
<https://www.bloomberg.com/graphics/2016-amazon-same-day/>

# Use case: Amazon self-day delivery

Bloomberg

## Amazon Doesn't Consider the Race of Its Customers. Should It?

"The most striking gap in Amazon's same-day service is in Boston, where **three ZIP codes encompassing the primarily black neighborhood of Roxbury are excluded** from same-day service, while the neighborhoods that surround it on all sides are eligible."

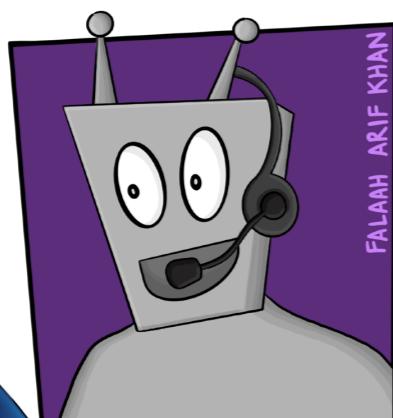
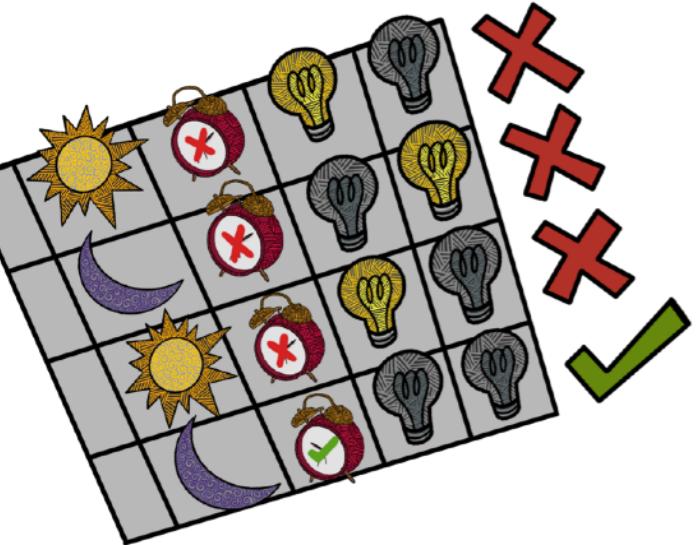


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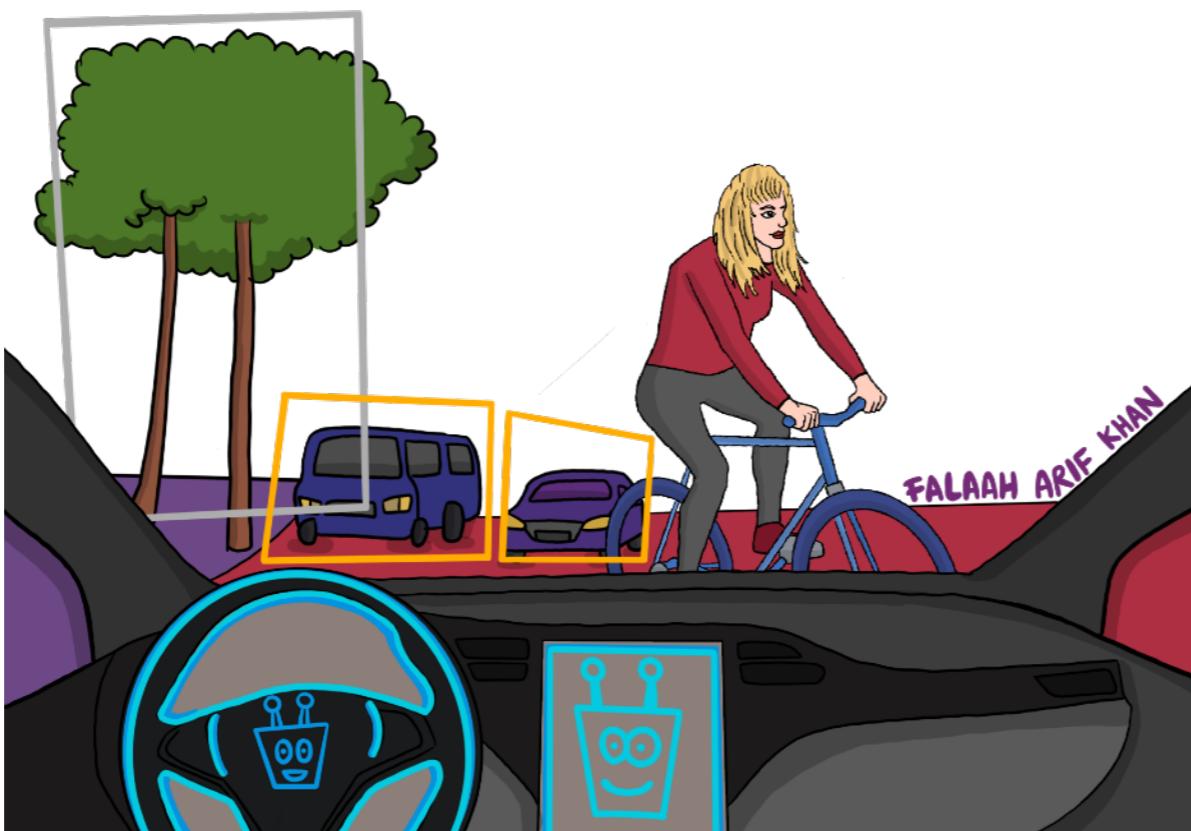
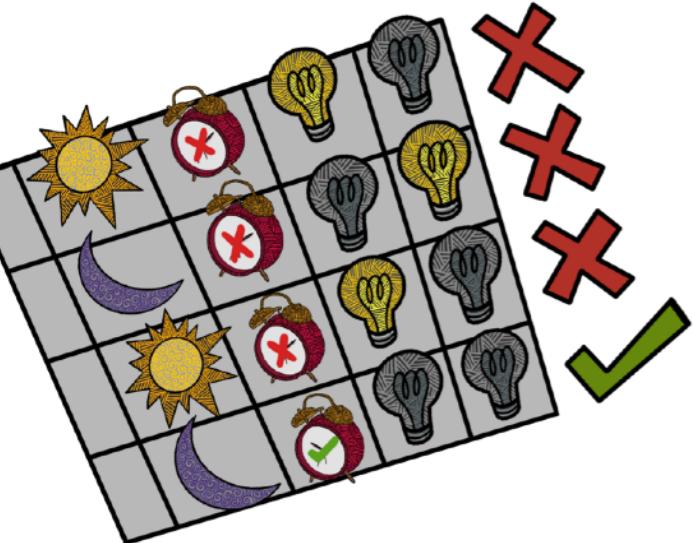


data science  
ethics teaser

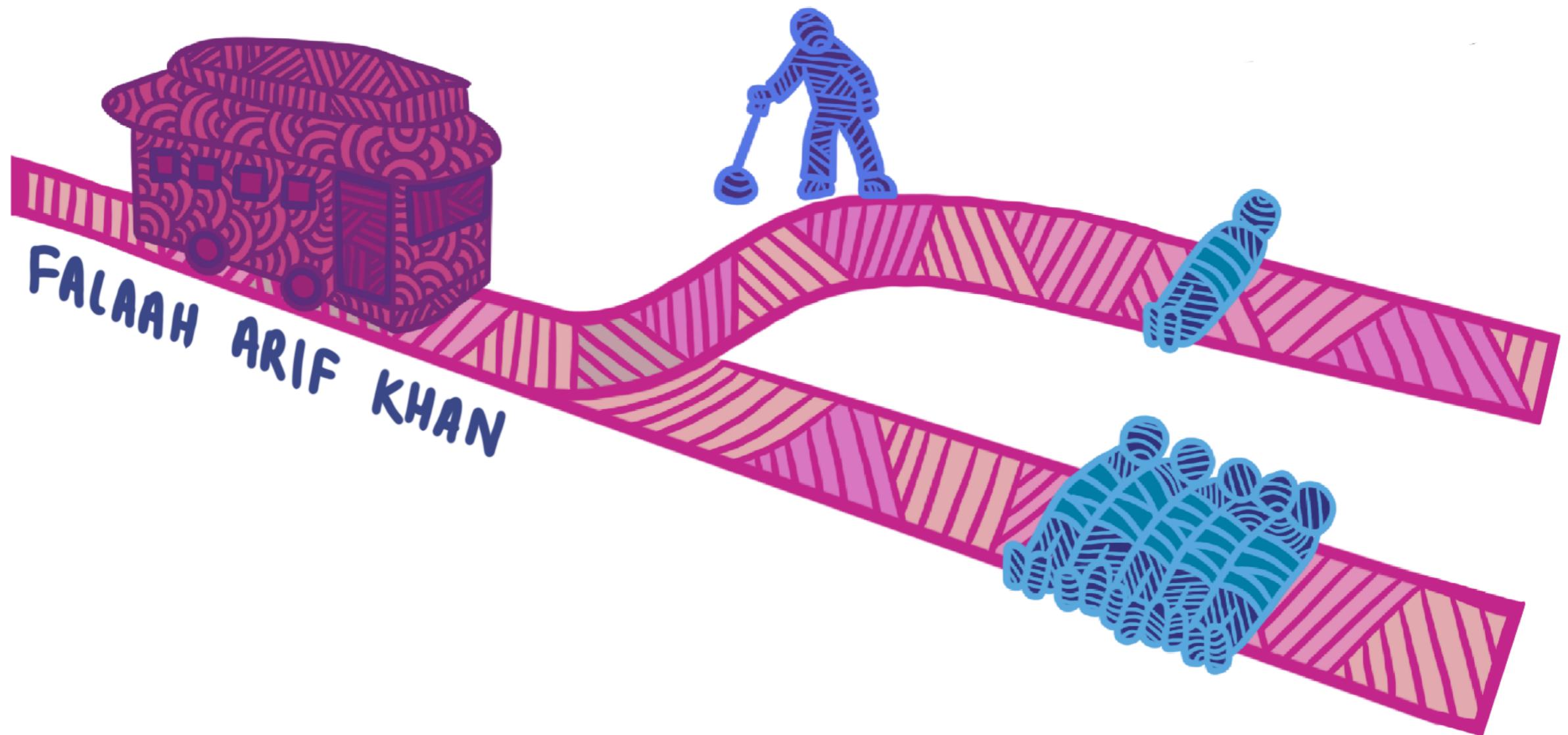
# Mistakes lead to harms



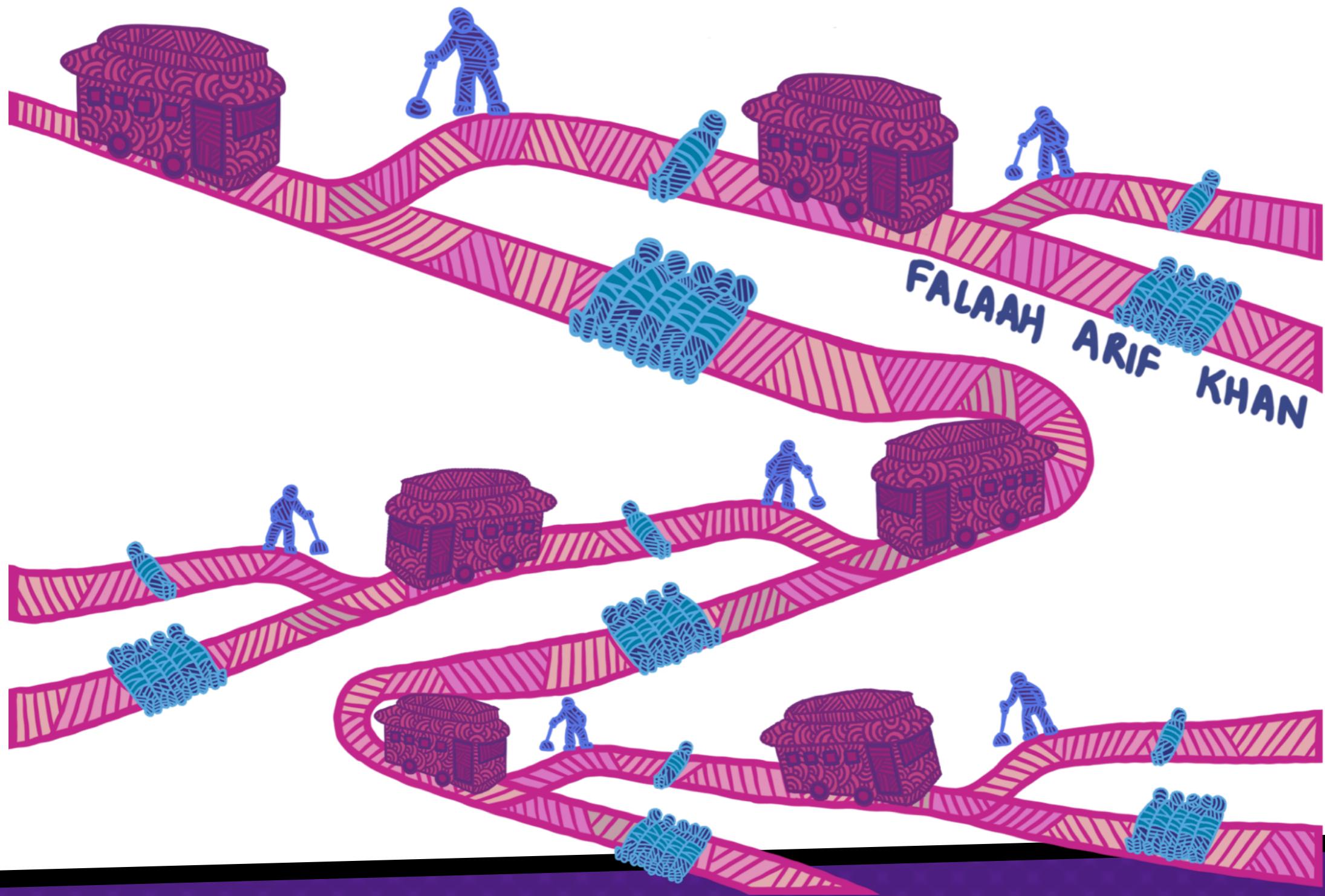
# Mistakes lead to harms



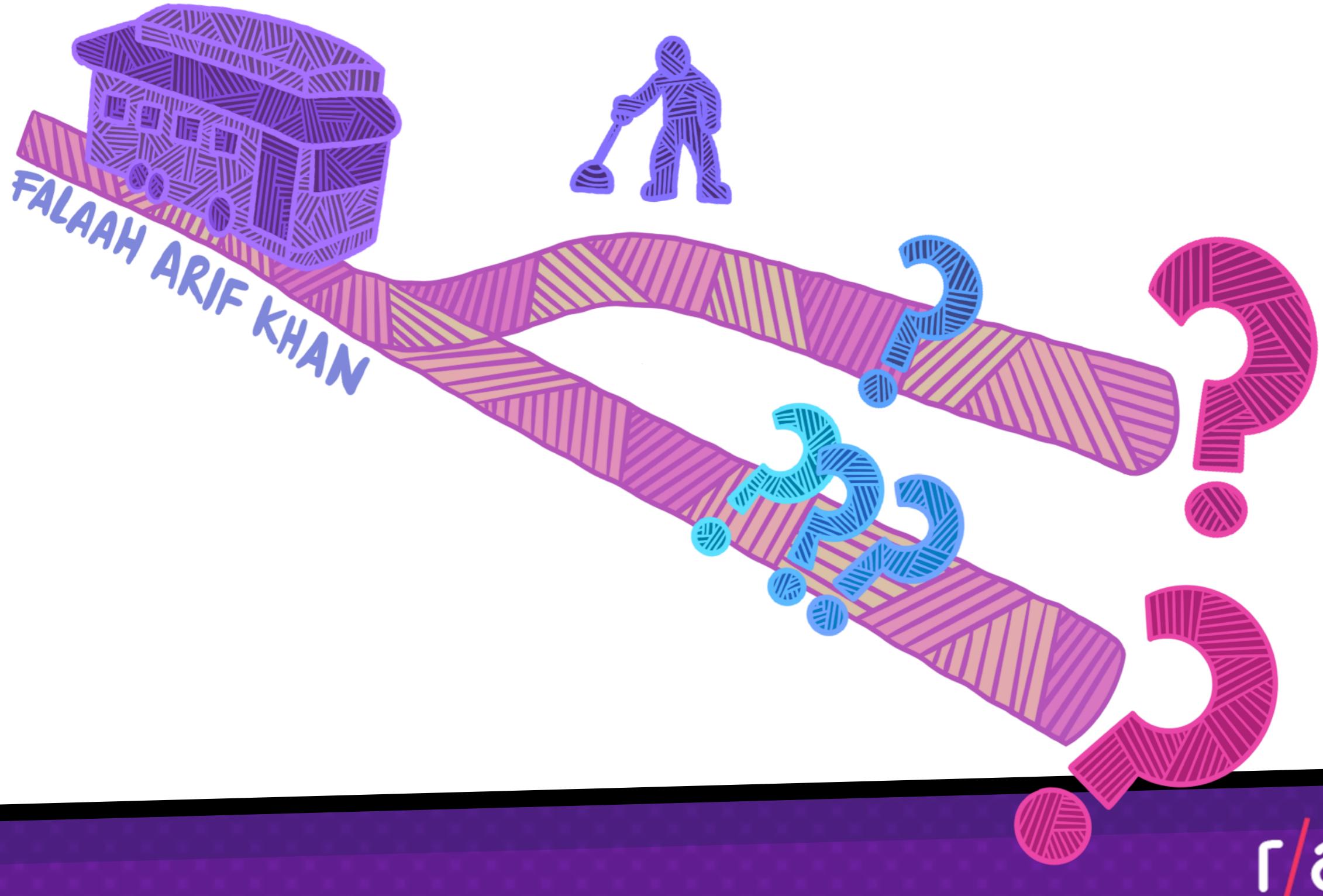
# The trolley problem



# The trolley problem



# Dealing with uncertainty



# Utilitarianism

“It is the greatest happiness of the greatest number that is the measure of right and wrong.”

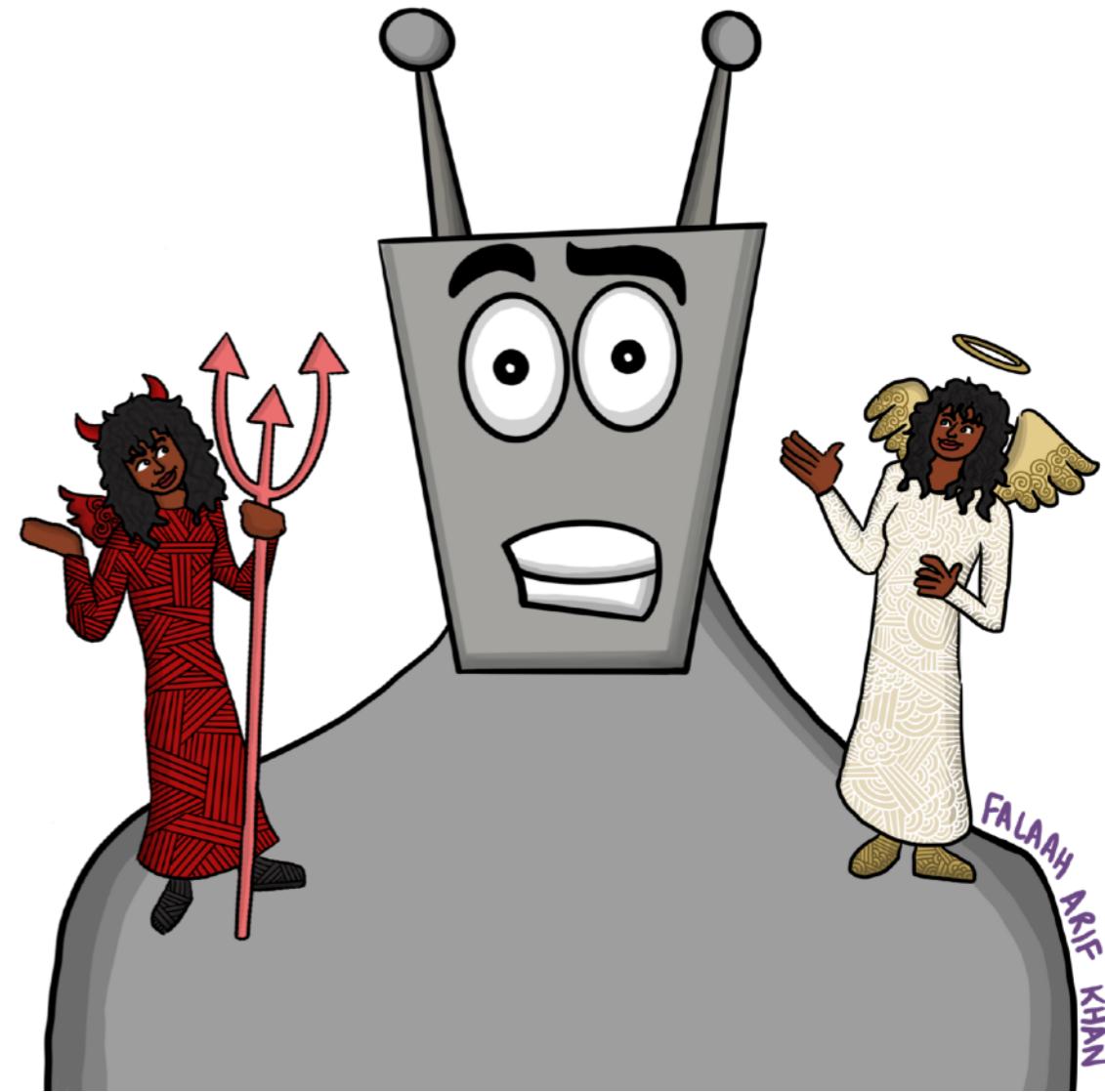
*Jeremy Bentham*



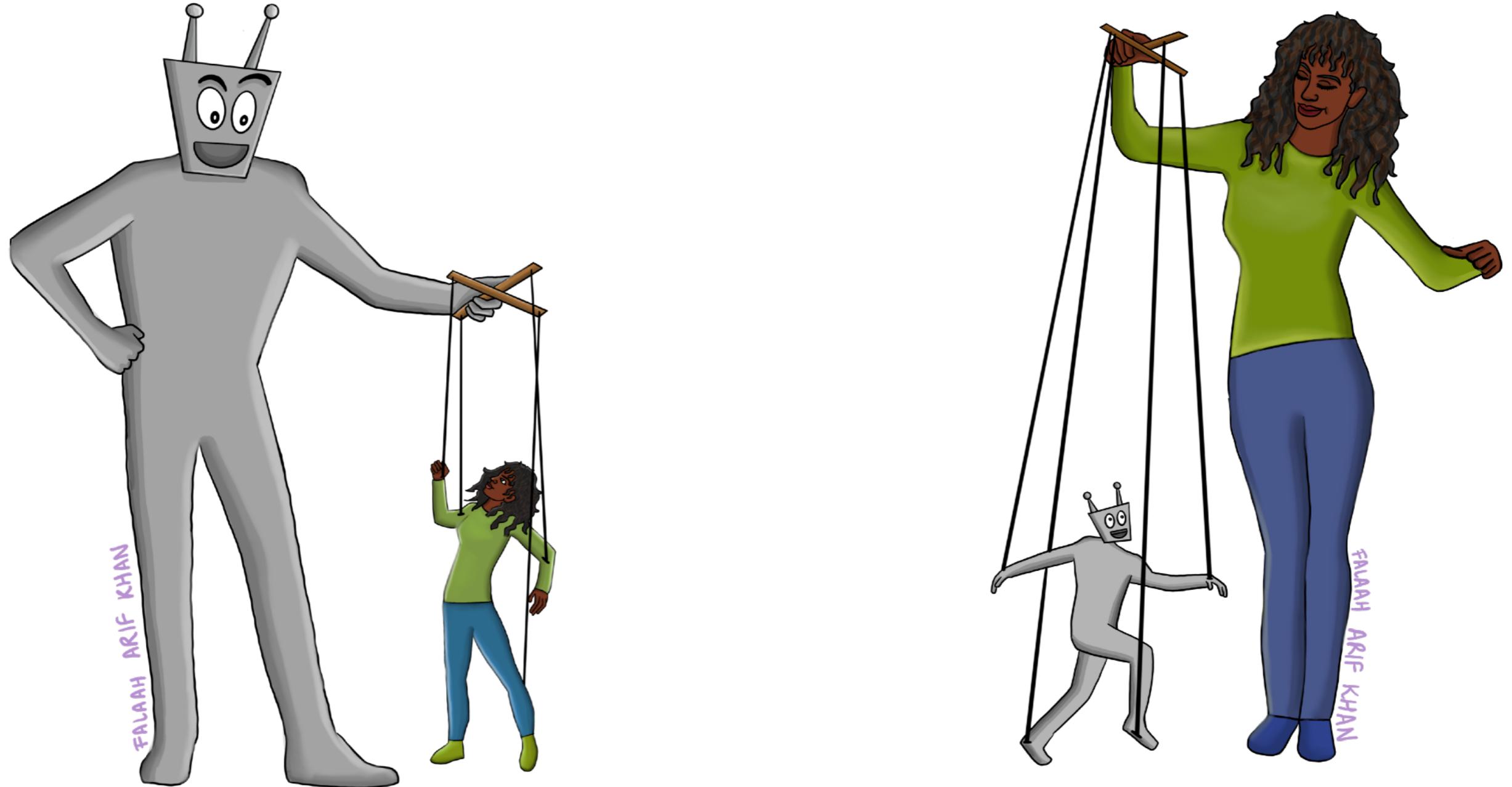
# Algorithmic morality?

## Algorithmic morality

is the act of attributing moral reasoning to algorithmic systems



# Algorithmic morality?



# Tech rooted in people



**examples: racial  
bias in risk  
assessment**

# Racial bias in criminal sentencing

## Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016



### May 2016

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.**

**Black people are almost twice as likely as white people to be labeled a higher risk but not actually re-offend.**

The tool makes **the opposite mistake among whites:** They are much more likely than black people to be labeled lower risk but go on to commit other crimes.

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

# Racial bias in criminal sentencing

## Machine Bias

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by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016

May 2016

### 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%

*Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)*

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

# Racial bias in healthcare

## Dissecting racial bias in an algorithm used to manage the health of populations

October 2019

Ziad Obermeyer<sup>1,2,\*</sup>, Brian Powers<sup>3</sup>, Christine Vogeli<sup>4</sup>, Sendhil Mullainathan<sup>5,\*†</sup>

\* See all authors and affiliations

Science 25 Oct 2019:  
Vol. 366, Issue 6464, pp. 447-453  
DOI: 10.1126/science.aax2342

Science

Health systems rely on commercial prediction algorithms to identify and help patients with complex health needs. We show that a widely used algorithm, typical of this industry-wide approach and **affecting millions of patients**, exhibits significant **racial bias: At a given risk score, Black patients are considerably sicker than White patients, as evidenced by signs of uncontrolled illnesses**. Remedyng this disparity would increase the percentage of Black patients receiving additional help from 17.7 to 46.5%. The bias arises because the algorithm **predicts health care costs rather than illness**, but unequal access to care means that we spend less money caring for Black patients than for White patients. Thus, **despite health care cost appearing to be an effective proxy for health by some measures of predictive accuracy, large racial biases arise**. We suggest that the choice of convenient, seemingly effective proxies for ground truth can be an important source of algorithmic bias in many contexts.

# Fixing bias in algorithms?

The New York Times

By Sendhil Mullainathan

Dec. 6, 2019

ECONOMIC VIEW

## *Biased Algorithms Are Easier to Fix Than Biased People*

Racial discrimination by algorithms or by people is harmful — but that's where the similarities end.



Tim Cook

<https://www.nytimes.com/2019/12/06/business/algorithm-bias-fix.html>

December 2019

In one study published 15 years ago, **two people applied for a job**. Their résumés were about as similar as two résumés can be. One person was named Jamal, the other Brendan.

In a study published this year, **two patients sought medical care**. Both were grappling with diabetes and high blood pressure. One patient was black, the other was white.

Both studies documented **racial injustice**: In the first, the applicant with a black-sounding name got fewer job interviews. In the second, the black patient received worse care.

**But they differed in one crucial respect. In the first, hiring managers made biased decisions. In the second, the culprit was a computer program.**

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<https://www.nytimes.com/2019/12/06/business/algorithm-bias-fix.html>

December 2019

Changing algorithms is easier than changing people: software on computers can be updated; the “wetware” in our brains has so far proven much less pliable.

[...] In a 2018 [paper](#) [...], I took a cautiously optimistic perspective and argued that **with proper regulation, algorithms can help to reduce discrimination.**

But the key phrase here is **“proper regulation,”** which we do not currently have.

We must ensure all the necessary inputs to the algorithm, including the data used to test and create it, are carefully stored. \* [...] **We will need a well-funded regulatory agency with highly trained auditors to process this data.**



course overview

# **module 1:**

## **algorithmic**

## **fairness**

# Bias in computer systems

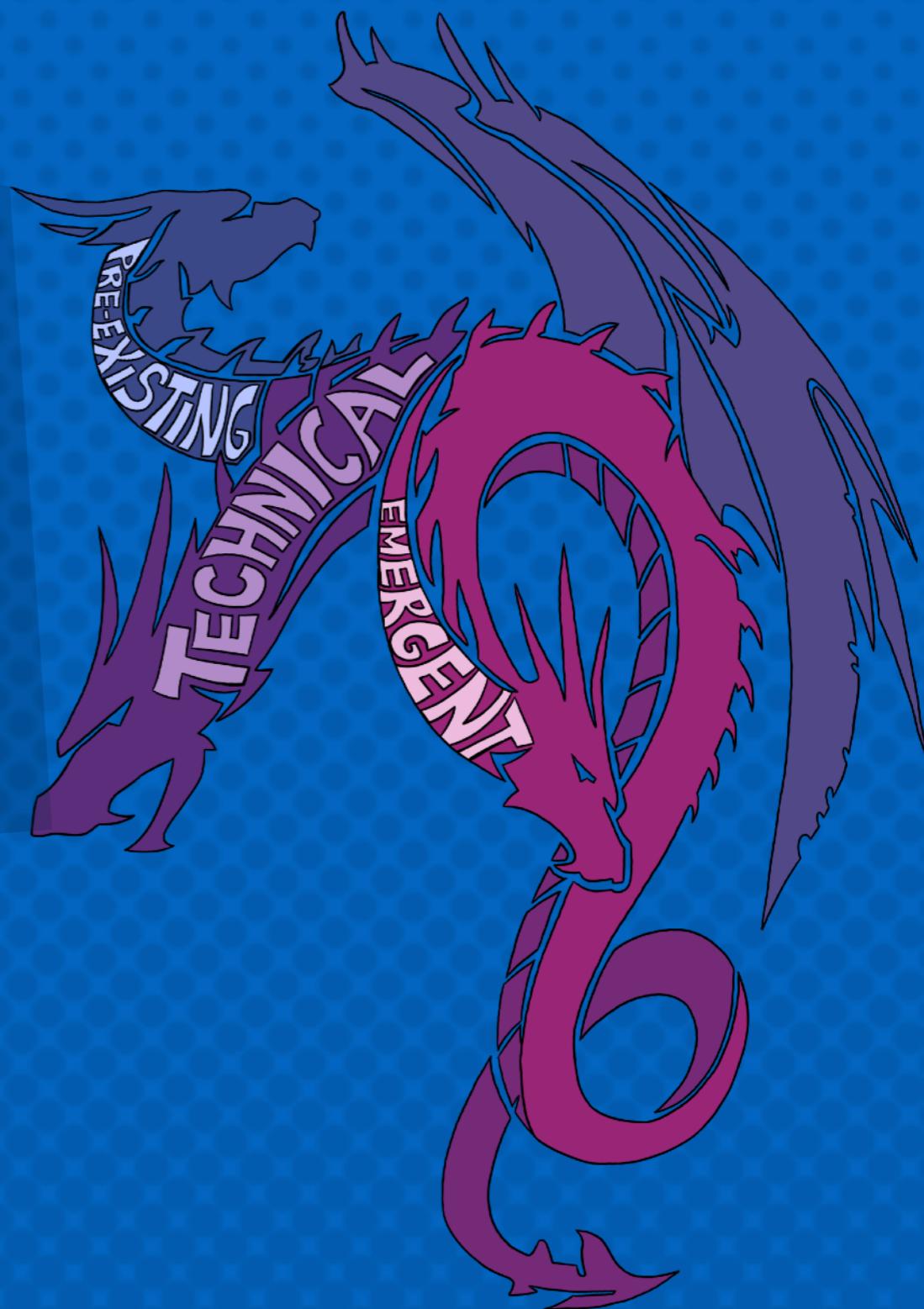
**Pre-existing:** exists independently of algorithm, has origins in society

**Technical:** introduced or exacerbated by the technical properties of an ADS

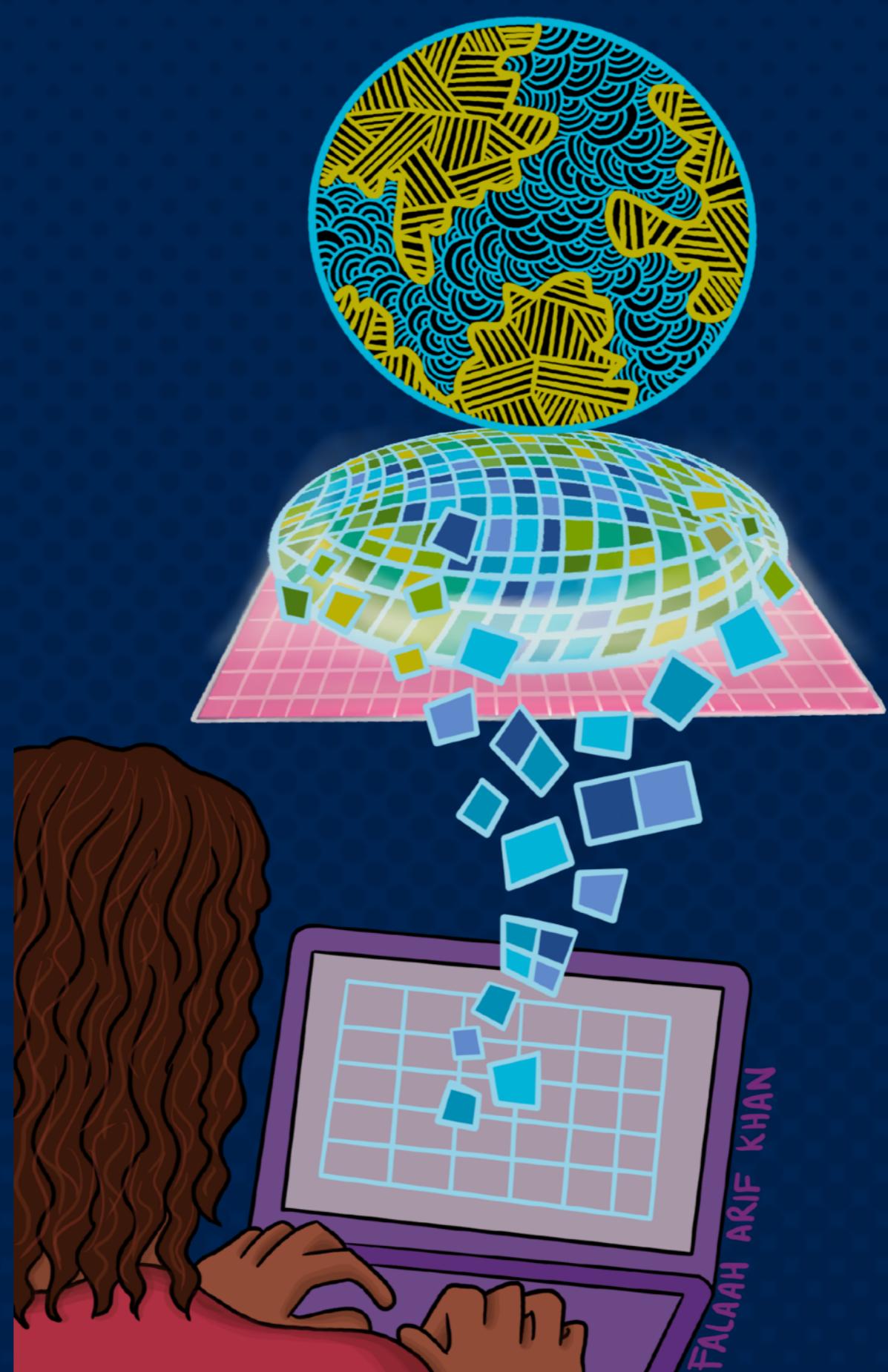
**Emergent:** arises due to context of use



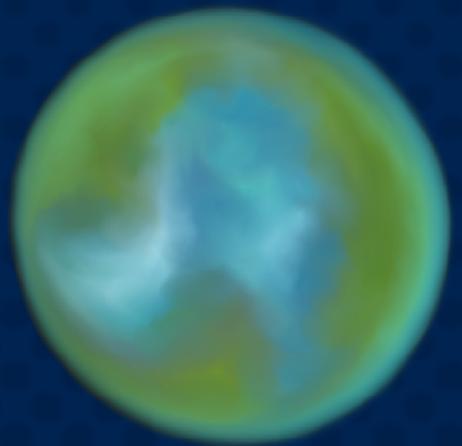
[Friedman & Nissenbaum (1996)]







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# **module 2:**

## **the data science lifecycle**

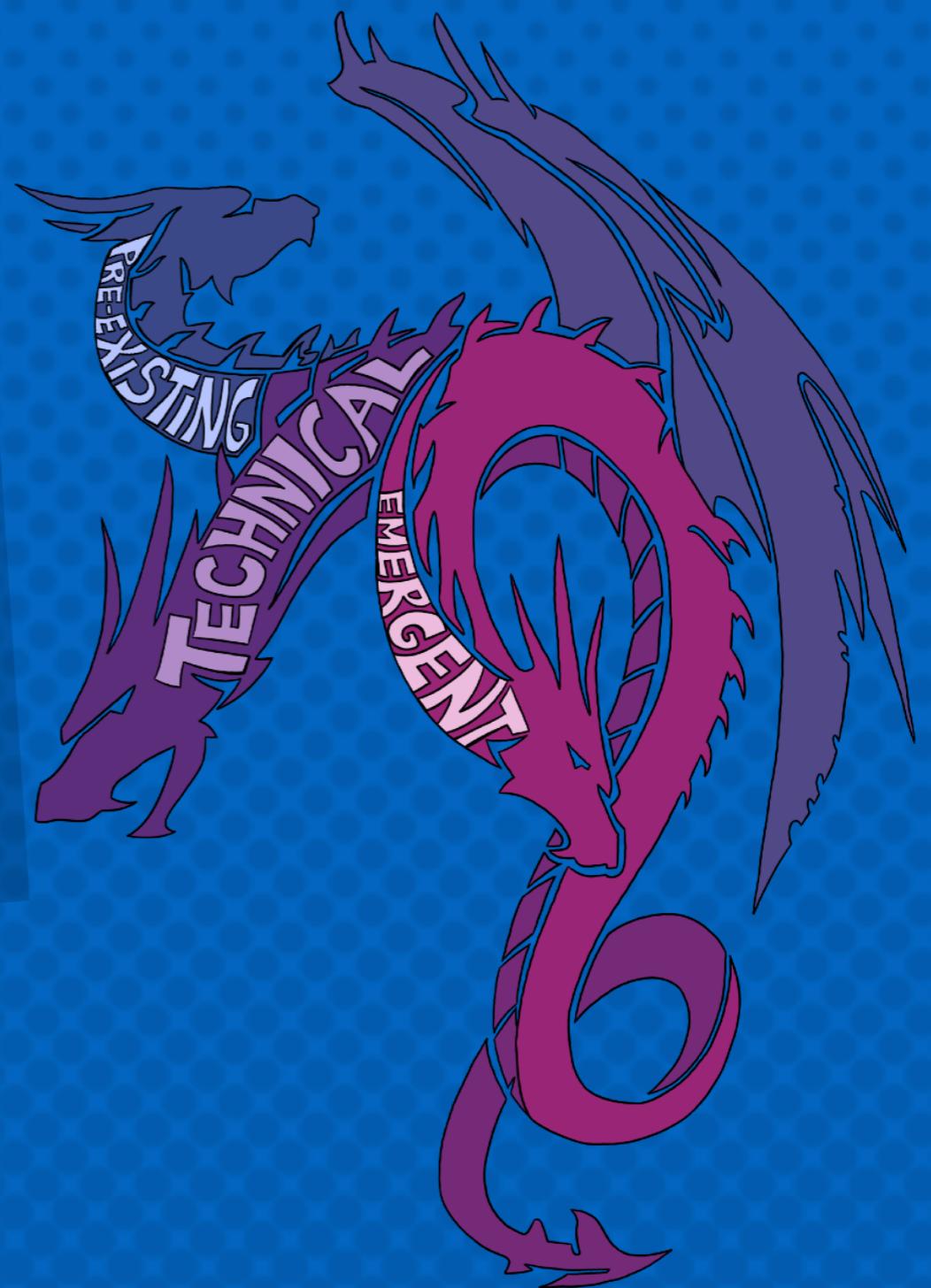
# Bias in computer systems

**Pre-existing:** exists independently of algorithm, has origins in society

**Technical:** introduced or exacerbated by the technical properties of an ADS

**Emergent:** arises due to context of use

to fight bias, state  
beliefs and  
assumptions  
explicitly



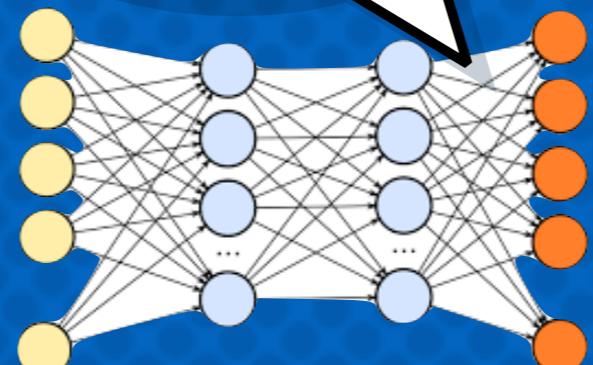
# Fair-ML view

where did the data come from?

1	A	B	C	D	E	F	G	H	
1	UID	sex	race	MarriageSta	DateOfBirth	age	cour	decile	score
2	1	0	1	1	4/18/47	69	0	1	
3	2	0	2	1	1/22/82	34	0	3	
4	3	0	2	1	5/14/91	24	0	4	
5	4	0	2	1	1/21/93	23	0	8	
6	5	0	1	2	1/22/73	43	0	1	
7	6	0	1	3	8/22/71	44	0	1	
8	7	0	3	1	7/23/74	41	0	6	
9	8	0	1	2	2/25/73	43	0	4	
10	9	0	3	1	6/10/94	21	0	3	
11	10	0	3	1	6/1/88	27	0	4	
12	11	1	3	2	8/22/78	37	0	1	
13	12	0	2	1	12/2/74	41	0	4	
14	13	1	3	1	6/14/68	47	0	1	
15	14	0	2	1	3/25/85	31	0	3	
16	15	0	4	4	1/25/79	37	0	1	
17	16	0	2	1	6/22/90	25	0	10	
18	17	0	3	1	12/24/84	31	0	5	
19	18	0	3	1	1/8/85	31	0	3	
20	19	0	2	3	6/28/51	64	0	6	
21	20	0	2	1	11/29/94	21	0	9	
22	21	0	3	1	8/6/88	27	0	2	
23	22	1	3	1	3/22/95	21	0	4	
24	23	0	4	1	1/23/92	24	0	4	
25	24	0	3	3	1/10/73	43	0	1	
26	25	0	1	1	8/24/83	32	0	3	
27	26	0	2	1	2/8/89	27	0	3	
28	27	1	3	1	9/3/79	36	0	3	
29	28	0	2	1	6/22/80	36	0	7	



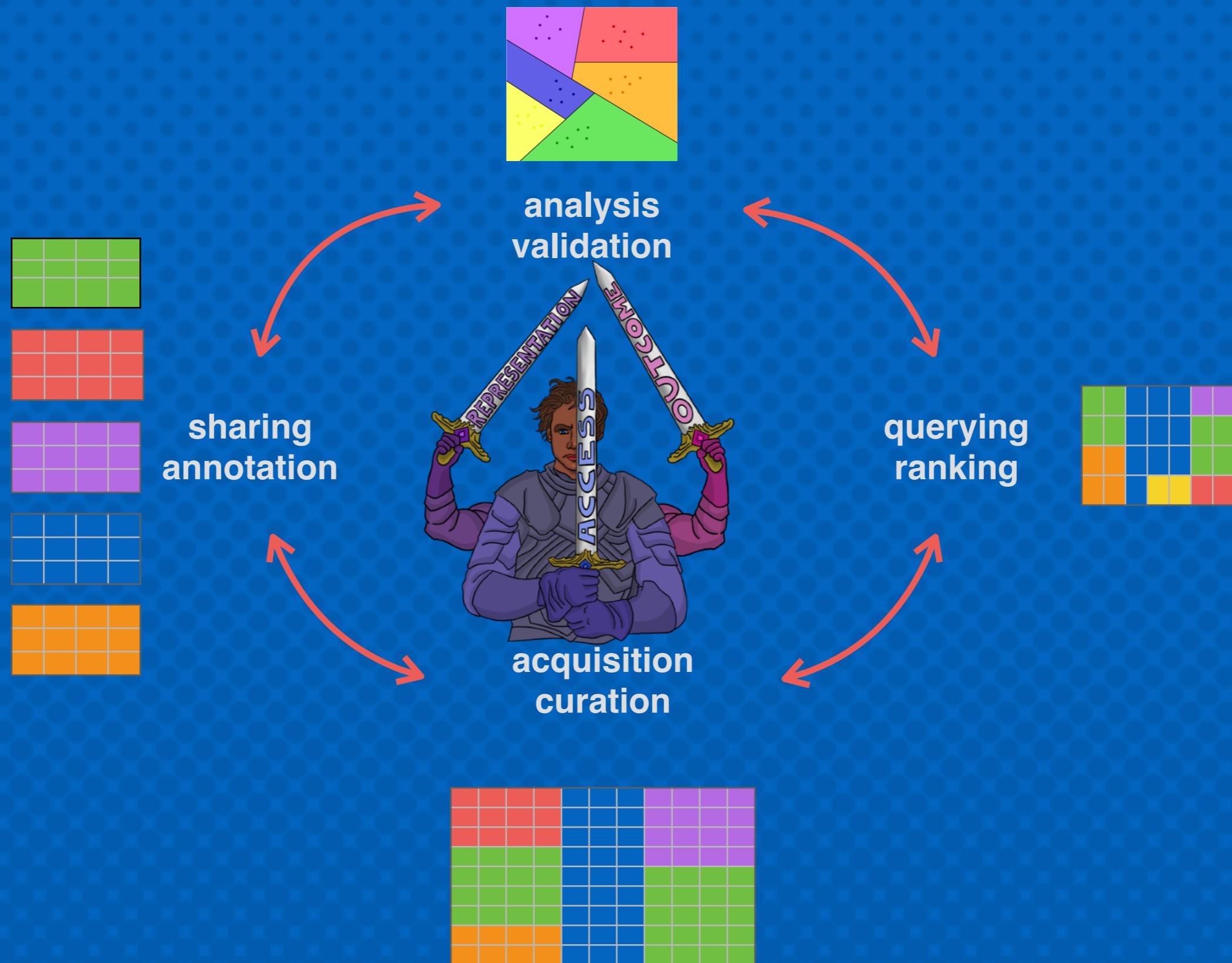
what happens inside the box?



how are results used?



# Lifecycle view



# Models and assumptions



# **module 3:**

## **data protection & privacy**

# Privacy: two sides of the same coin

**Did you go out drinking over the weekend?**

protecting an individual

---

plausible deniability



learning about the population

---

noisy estimates

# Truth or dare

Did you go out drinking over the weekend?

let's call this property **P** (Truth=Yes) and estimate **p**, the fraction of the group for whom **P** holds

thus, we estimate **p** as:

$$\tilde{p} = 2A - \frac{1}{2}$$

1. flip a coin **C1**

1. if **C1** is tails, then **respond truthfully**
2. if **C1** is heads, then flip another coin **C2**
  1. if **C2** is heads then **Yes**
  2. else **C2** is tails then respond **No**



randomization - adding noise - is what gives plausible deniability a process privacy method



the expected number of **Yes** answers is:

$$A = \frac{3}{4}p + \frac{1}{4}(1-p) = \frac{1}{4} + \frac{p}{2}$$

privacy comes from plausible deniability



# Differential privacy

## review articles

DOI:10.1145/1866739.1866758

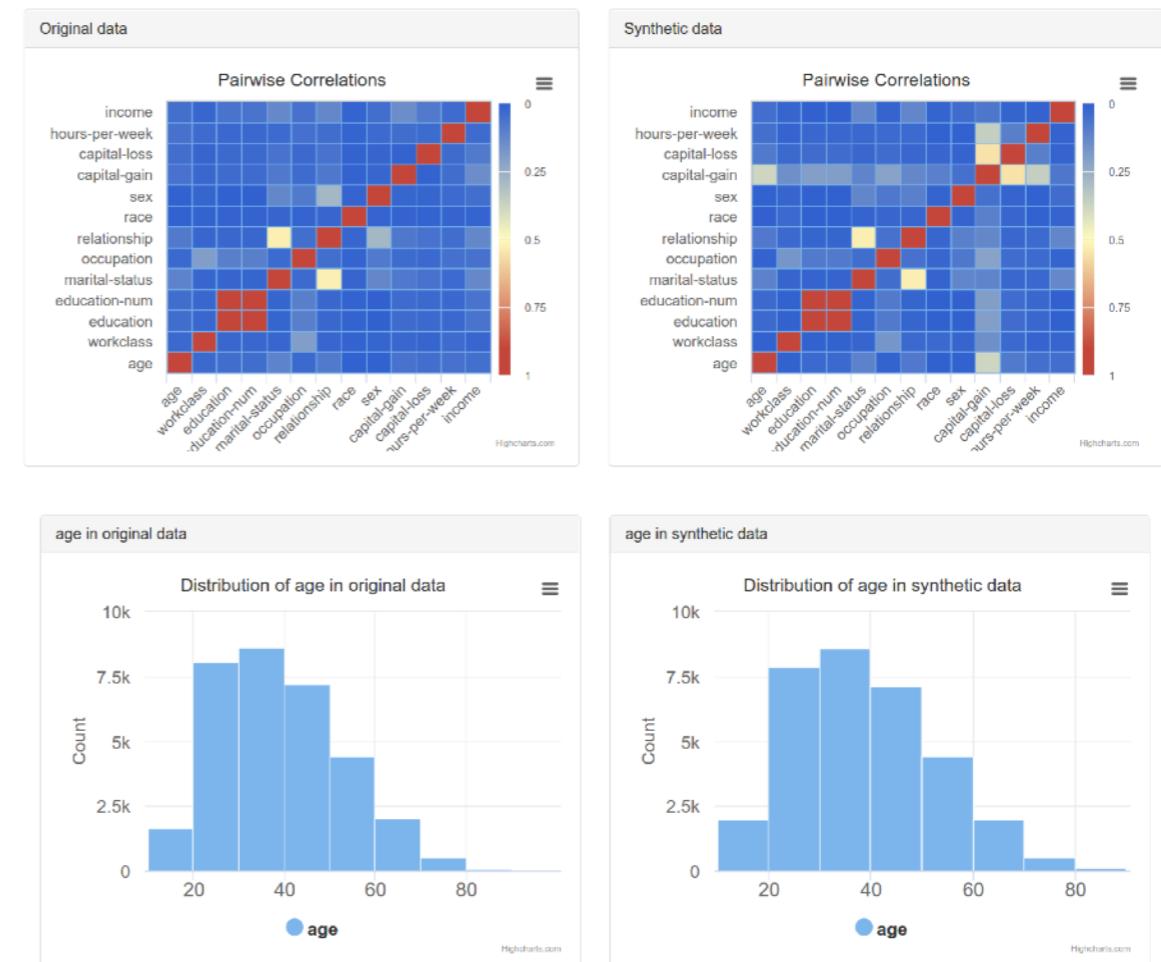
### What does it mean to preserve privacy?

BY CYNTHIA DWORK

# A Firm Foundation for Private Data Analysis

Communications of the ACM [CACM Homepage archive](#)

Volume 54 Issue 1, January 2011  
Pages 86-95



# Regulating ADS?

Precautionary

Nah! I'm fine!



The Anti-Elon ✅  
@antiElon

Regulation rocks!

2.3K 9.2K 126K

Risk-based



r/ai

# Legal frameworks

GENERAL DATA PROTECTION REGULATION (GDPR)    RECITALS    KEY ISSUES    Deutsch

**GDPR**

- Chapter 1 (Art. 1 – 4)
- General provisions
- Chapter 2 (Art. 5 – 11)
- Principles
- Chapter 3 (Art. 12 – 23)
- Rights of the data subject
- Chapter 4 (Art. 24 – 43)
- Controller and processor
- Chapter 5 (Art. 44 – 50)
- Transfers of personal data to third countries or international organisations
- Chapter 6 (Art. 51 – 59)
- Independent supervisory authorities
- Chapter 7 (Art. 60 – 76)
- Cooperation and consistency
- Chapter 8 (Art. 77 – 84)
- Remedies, liability and penalties
- Chapter 9 (Art. 85 – 91)
- Provisions relating to specific processing situations
- Chapter 10 (Art. 92 – 93)
- Delegated acts and implementing acts
- Chapter 11 (Art. 94 – 99)
- Final provisions

**General Data Protection Regulation  
GDPR**

Welcome to gdpr-info.eu. Here you can find the official [PDF](#) of the Regulation (EU) 2016/679 (General Data Protection Regulation) in the current version of the OJ L 119, 04.05.2016; cor. OJ L 127, 23.5.2018 as a neatly arranged website. All Articles of the GDPR are linked with suitable recitals. The European Data Protection Regulation is applicable as of May 25th, 2018 in all member states to harmonize data privacy laws across Europe. If you find the page useful, feel free to support us by sharing the project.

**Quick Access**

Chapter 1 – 1 2 3 4  
Chapter 2 – 5 6 7 8 9 10 11  
Chapter 3 – 12 13 1  
Chapter 4 – 24 25 2  
Chapter 5 – 44 45 4  
Chapter 6 – 51 52 5  
Chapter 7 – 60 61 6  
Chapter 8 – 77 78 7  
Chapter 9 – 85 86 8

 **Government of Canada**    **Gouvernement du Canada**



[Home](#) → [How government works](#) → [Policies, directives, standards and guidelines](#)

## Directive on Automated Decision-Making

The Government of Canada is increasingly looking to utilize artificial intelligence to make, or assist in making, administrative decisions to improve service delivery. The Government is committed to doing so in a manner that is compatible with core administrative law principles such as transparency, accountability, legality, and procedural fairness. Understanding that this technology is changing rapidly, this Directive will continue to evolve to ensure that it remains relevant.

Date modified: 2019-02-05

# **module 4:**

## **transparency & interpretability**

# The evils of discrimination

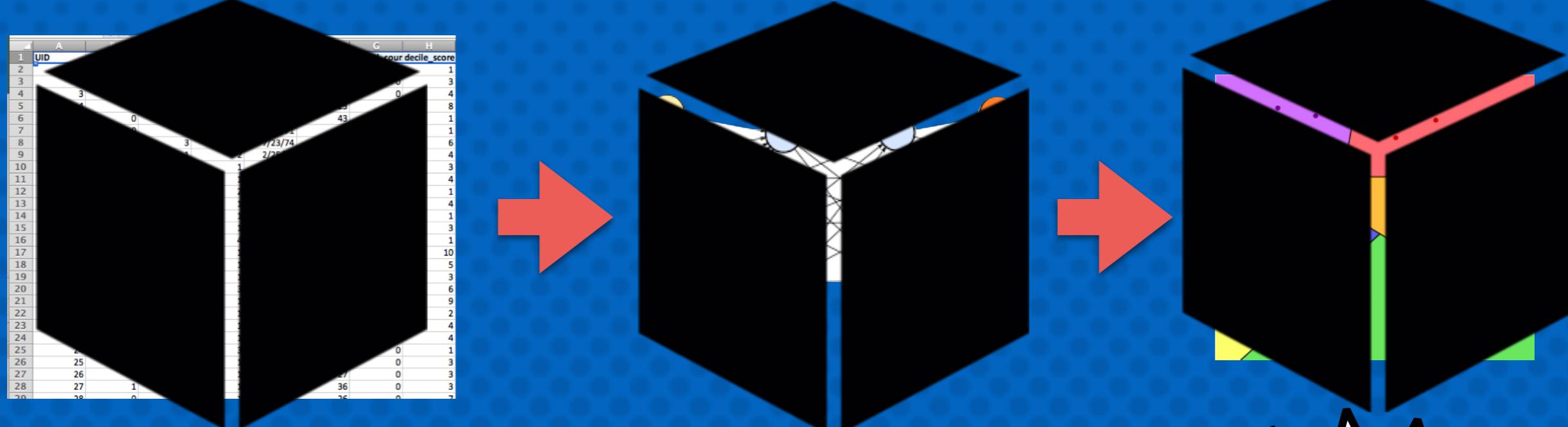
## Disparate treatment

is the illegal practice of treating an entity, such as a job applicant or an 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**.

# Regulating automated decisions

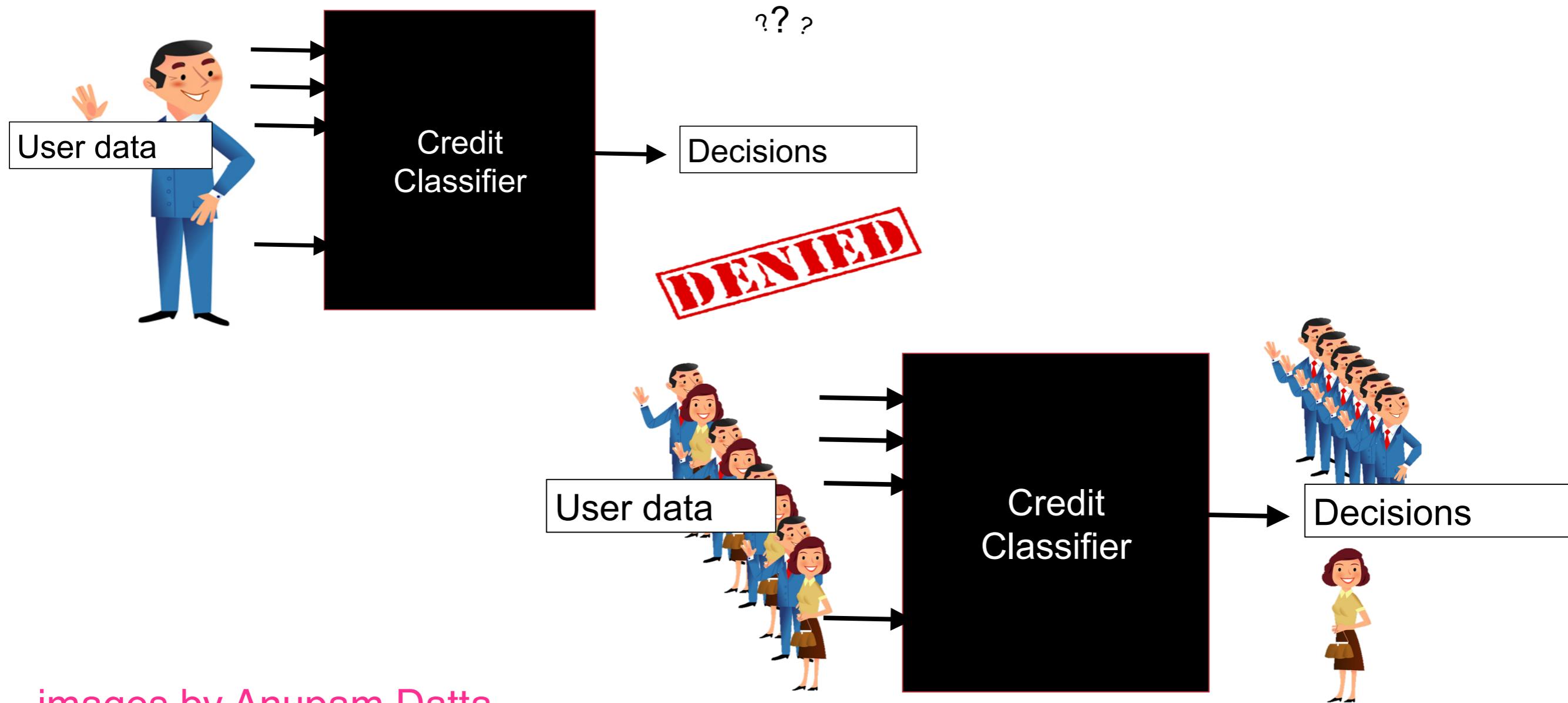


Fair Housing  
Act

Equal Credit  
Opportunity  
Act, 1964

Civil Rights  
Act, 1964

# Auditing black-box models



images by Anupam Datta

# Nutritional labels

**Ranking Facts**

**Ingredients** →

Attribute	Importance
PubCount	1.0
CSRakingAllArea	0.24
Faculty	0.12

Importance of an attribute in a ranking is quantified by the correlation coefficient between attribute values and items scores, computed by a linear regression model. Importance is high if the absolute value of the correlation coefficient is over 0.75, medium if this value falls between 0.25 and 0.75, and low otherwise.

**Diversity overall** ?

DeptSizeBin = Regional Code =

Large Small  
NE W MW SA SC

**Fairness** ? →

DeptSizeBin	FA*IR	Pairwise	Proportion
Large	Fair	Fair	Fair
Small	Unfair	Unfair	Unfair

A ranking is considered unfair when the p-value of the corresponding statistical test falls below 0.05.

← **Stability**

Top-K	Stability
Top-10	Stable
Overall	Stable

**comprehensible:** short, simple, clear

**consultative:** provide actionable info

**comparable:** implying a standard



**in summary**

# So what is RDS?

**As advertised:** ethics, legal compliance, personal responsibility.  
But also: **data quality!**

A technical course, with content drawn from:

1. fairness, accountability and transparency
2. data engineering
3. security and privacy



We will learn **algorithmic techniques** for data analysis.

We will also learn about recent **laws / regulatory frameworks**.

Bottom line: we will learn that many of the problems are **socio-technical**, and so cannot be “solved” with technology alone.

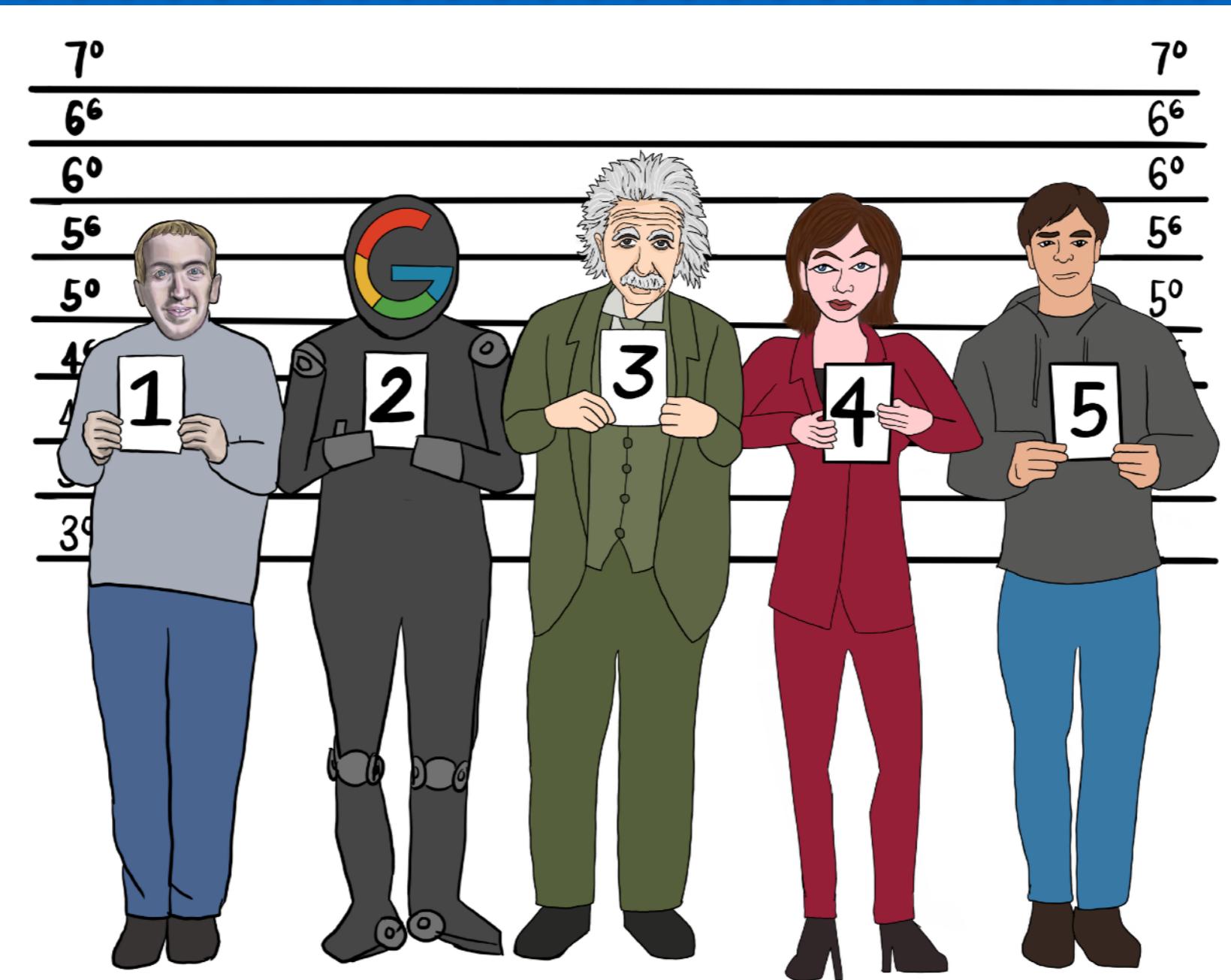
My perspective: a pragmatic engineer, **not** a technology skeptic.

# Nuance, please!



r/ai

# We all are responsible



@FalaahArifKhan

# Responsible Data Science

Introduction and Overview

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Thank you!