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Accessibility & Equity

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Learning Outcomes

1. Define the concept of accessibility in computing (especially in HCI and related fields) and understand how it is promoted by computing best practices as well as by law.
2. Understand how universal usability relates to accessibility.
3. Define the concept of equity, in relation to a machine's idea of purported fairness.
4. Understand how complex systems can sometimes neglect accessibility and equity in their design process - even though on the surface they seem 'neutral' - and ways to mitigate this.
5. Analyse commonly used models in Natural Language Processing to identify issues of fairness, in relation to hypothetical case studies of AI-based recruitment.
6. Learn about the conflicting technical definitions of fairness as well as ideas on how to ameliorate issues in the design process.

Related Reading

This module has two readings corresponding to the two broad themes within.

Accessibility: Social Biases in NLP Models as Barriers for Persons with Disabilities.
Ben Hutchinson, Vinodkumar Prabhakaran, Emily Denton, Kellie Webster, Yu Zhong, Stephen Denuyl.
arXiv [cs.CL], 2 May 2020. https://arxiv.org/abs/2005.00813

Equity: Ethical Implications of AI Bias as a Result of Workforce Gender Imbalance.
Marc Cheong, Reeva Lederman, Aidan McLoughney, Sheilla Njoto, Leah Ruppanner, Tony Wirth. *University of Melbourne / UniBank.* 2020.
This research report is a result of an interdisciplinary collaboration between University of Melbourne and UniBank in uncovering sources of bias -- both human and algorithmic -- to consider when deploying any form of automated system in recruitment/shortlisting of job candidates.

Read only pp. 5-34 inclusive - the appendices are optional!

https://about.unimelb.edu.au/__data/assets/pdf_file/0024/186252/NEW-RESEARCH-REPORT-Ethical-Implications-of-AI-Bias-as-a-Result-of-Workforce-Gender-Imbalance-UniMelb,-UniBank.pdf

Outline

1. About accessibility.
2. About equity.
3. Complexity, complex systems, and unintended consequences!
4. Case Study & Reflection: Natural Language Processing: Sexist? Ableist?
5. Case Study & Reflection: AI-based Hiring: Neutral from the outset, but not equitable?
6. Conclusion: Can a machine determine what is fair and equitable?

About accessibility.

Image credit: Unsplash / @ashwinv11

What is accessibility? (1/2)

“Basically, technology is accessible if it can be used as effectively by people with disabilities as by those without” (Thatcher, 2004).

“Accessibility refers to the degree to which an interactive product is accessible by as many people as possible. A focus is on people with disabilities.” (Sharp, 2011)

Sources: *Thatcher, J. (2004) “Web Accessibility for Section 508”, http://www.jimthatcher.com/webcourse1.htm*
Preece, J, Sharp, H, Rogers, Y. (2015). Interaction Design: Beyond Human-Computer Interaction. John Wiley & Sons.

What is accessibility? (2/2)

Accessibility is the degree to which a system is usable by as many people as possible without modification. Its goal: equality of access and removal of barriers to access based on disability, technical or environmental limitations. Usability and accessibility are compatible design approaches – sharing a concern for universal design as a foundation for good design.
(Alexander, 2004a).

Source: Alexander, D. (2004a) What is the relationship between usability and accessibility, and what should it be?
http://deyalexander.com/presentations/usability-accessibility

Credits: Adapted from material by Marc Cheong, built upon earlier material shared by Sheard, J; Lay, W; Fleming, R; Kathpalia, M.; Linger, H. and others.

Universal Usability and HCI

Usability and Human-Computer Interaction first to notice this – cf. design of tech artifacts and user interfaces.

- Hardware Products
- Software Interfaces etc.

Universal Usability = a “design for all” approach which is about making a product as accessible as possible to as wide a group of people as possible. The term originated from architecture (consider stairs vs. ramps/elevators/escalators).

Credits: Adapted from material by Marc Cheong, built upon earlier material shared by Sheard, J; Lay, W; Fleming, R; Kathpalia, M.; Linger, H. and others.

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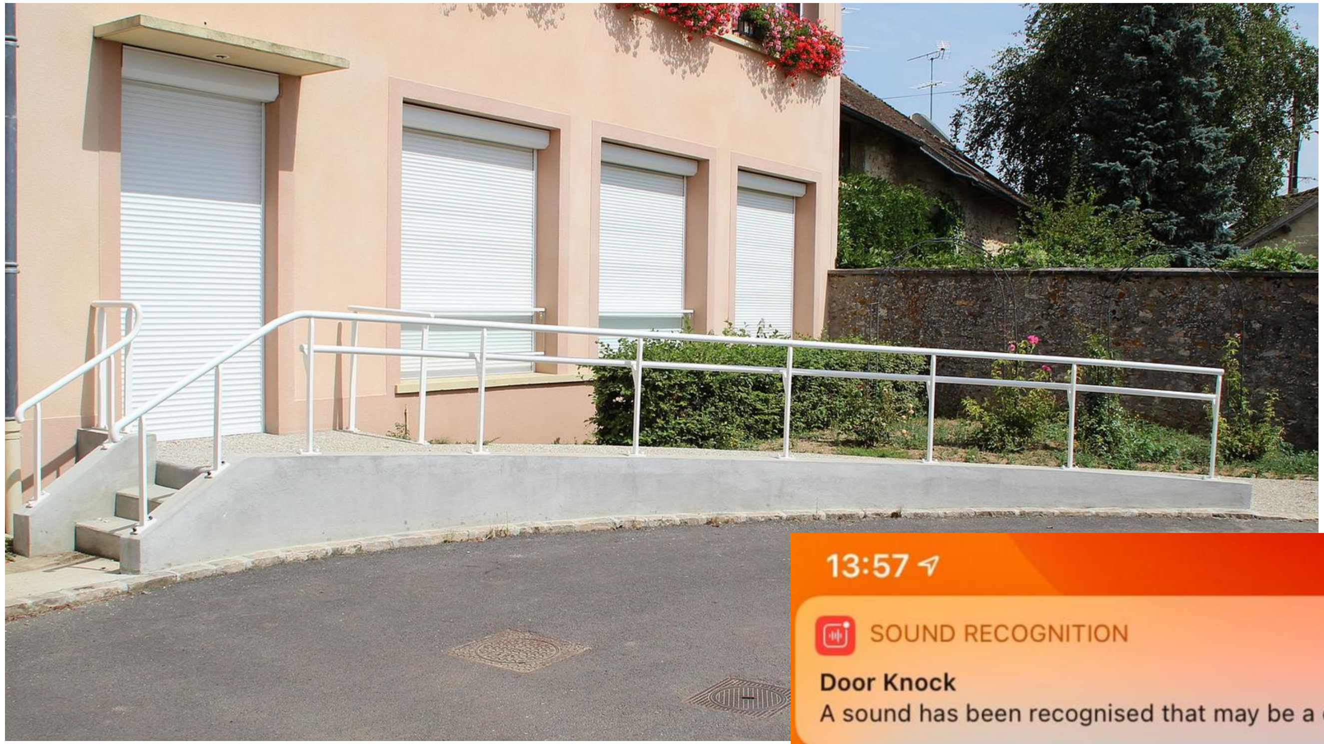
Examples



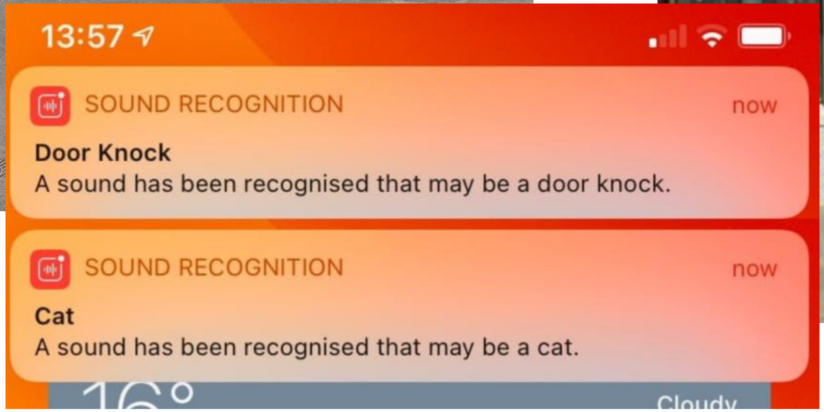


Image source: Wikipedia / The Verge (Owen, 2020).

Misconceptions

Accessibility goes beyond just ’catering for those with disabilities’.

- Situational impairments
  - Consider: a busy mother during the breakfast rush
  - Consider: defense personnel during deployments in a humanitarian crisis
  - Consider: remote learning/work during the Covid-19 pandemic
- Temporary disability/temporary impairment
  - Consider: a student who broke their arm after a bicycle accident
  - Consider: a lecturer who has a spinal injury

See: https://www.w3.org/WAI/EO/wiki/Situational_terminology

Credits thanks to Lay, W.

Accessibility and the Law

<u>Landmark case: Maguire versus SOCOG (Sydney Org. Committee for the Olympic Games)</u>

- "Maguire made a complaint to the human rights and equal opportunity commission (HREOC)… (SOCOG) had discriminated against him as a person disabled, in contravention of the Disability Discrimination Act 1992…"
- **Main point: "failure to provide a website which was accessible to Maguire…"**
- "SOCOG said that it did not discriminate unlawfully … cost and effort in retraining staff and redrawing entire development methods was an unjustifiable hardship in providing an accessible website…"
  - Basically: SOCOG gave excuses (too much time needed etc); refuted by expert witnesses!
  - "The Commissioner found that SOCOG had engaged in unlawful discrimination against Maguire in violation of Section 24 of the DDA 1992"
  - SOCOG was stubborn; "The Commissioner found that SOCOG only partially complied and as a result, by section 103(1)(b)(iv) of the DDA, the commissioner awarded Maguire $20,000.

Verbatim quotes taken from Wikipedia Contributors (2020)

https://en.wikipedia.org/wiki/Maguire_v_Sydney_Organising_Committee_for_the_Olympic_Games_(2000)

Reflection.

Human-Computer Interaction (HCI), specifically
Usability studies – subfields of CS to first notice issues with accessibility.

→ Designing tech artifacts (e.g. how to design the hardware); user interfaces (the software).

Reflection: But wait – where does this factor into AI/ML?

Image source: HowToGeek / Imagentle/Shutterstock

About equity.

Image credit: Unsplash / @ashwinv11

What is equity?

equity | ˈɛkwɪti | noun (plural **equities**) *[mass noun]*

1 the quality of being fair and impartial: *equity of treatment*.

• *Law* a branch of law that developed alongside common law and is concerned with fairness and justice, formerly administered in special courts: *if there is any conflict between the principles of common law and equity, equity prevails*.

Source: Oxford Dictionary of English, via Apple Dictionary.app

Focus of the module

“**1** the quality of being fair and impartial: *equity of treatment*. ”

Source: Oxford Dictionary of English, via Apple Dictionary.app

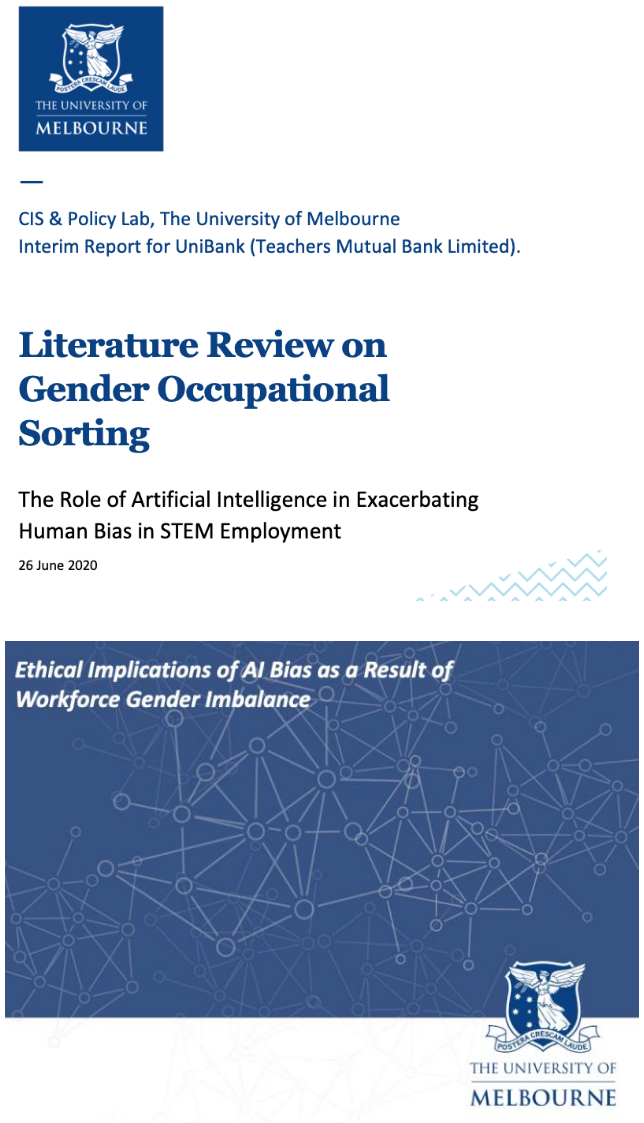
Many other interrelated (similar) concepts such as fairness (philosophy → ethics), that you may have encountered before, but this module focuses on the “equity of treatment” from the machine’s (AI’s) point of view.

Key Point (Cheong et al, 2020)

Let's just focus on equity in computer science,
i.e. especially algorithmic design.

"In academic papers discussing the notion of fairness … researchers have found that different ideas of fairness can co-exist … (Chouldechova 2017; Kleinberg et al. 2016). …

Importantly, these different notions of fairness are known in some scenarios to be incompatible: **a single model cannot meet every reasonable or accepted definition of fairness, and therefore bias must exist in one way or another inside the model…"**


CIS & Policy Lab, The University of Melbourne
Interim Report for UniBank (Teachers Mutual Bank Limited).

Literature Review on Gender Occupational Sorting

The Role of Artificial Intelligence in Exacerbating Human Bias in STEM Employment

26 June 2020

Ethical Implications of AI Bias as a Result of Workforce Gender Imbalance

Thought Experiment (1/2)

Even if the design is well-intentioned, and code was written in a way that is mathematically and logically sound, **inequity** can arise – as there are many (mathematical/social) definitions of equity in the logic (and models we employ).

For now, let's turn to one very naïve case, to reflect on.

Create an algorithm to divide a finite pool of resources (X) equitably across N participants (P_0, P_1, … P_N).

Example answer: *EqualShareAlgorithm*

- Calculate *share* = (X / N)
- For each person in participant pool {P_0, P_1, … P_N}:
  - Allocate current person their equal allocation (*share*)

Thought Experiment (2/2)

EqualShareAlgorithm **to divide a finite pool of resources (X) equitably across N participants (P_0, P_1, … P_N).**

- Calculate *share* = (X / N)
- For each person in participant pool {P_0, P_1, … P_N}:
  - Allocate current person their equal allocation (*share*)

Now consider that the algorithm is to be **deployed in the real world to automate the allocation of resources to different communities.** For a given affluent community, assume everyone is sufficiently well-off and have more than enough resources, money etc **EXCEPT for two people (only P_0 and P_1).**
P_0 and P_1 are the only ones who needs access to resources (food, water, etc) due to (hunger, health conditions, etc).

Is *EqualShareAlgorithm* still equitable???

Reflection.

Suddenly, your equitable algorithm doesn't seem so equitable after all.

Reflection: Can we predict these things from the outset?

How can we fail if we can plan for these things beforehand?

Image source: HowToGeek / Imagentle/Shutterstock

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Complexity, complex systems, and unintended consequences!

Image credit: Unsplash / @ashwinv11

Complexity = the enemy. Unintended consequences after deployment.

The design of an automated / computerised / AI-driven system can seem fair...

Again, consider an *EqualShareAlgorithm* which divides a finite pool of resources equally (by simply getting the average share per person, without fear or favour)… reviewing it at face value, we *may* gain some trust (cf Jacovi, Marasović, Miller, Goldberg, 2021)

Yet, these algos might violate equity (and accessibility) AFTER they are deployed.

We only notice the problem when we deploy it…
and only then find out that it doesn’t work in certain cases.

Systems are inherently complex: what works in isolation does not work ‘as a whole’, or even when deployed in circumstances (external factors, e.g. social factors) we did not foresee.

Image source: Giphy/The Masked Singer

Complexity = the enemy. Unintended consequences after deployment.

Let's revisit the 'provocation' or thought experiment for this module.

> There is a new, fun, web app/game out there which helps you improve your handwriting (a long lost art!) and at the same time improve your handwriting speed. After all, handwritten cards and letters are art forms which have been displaced by technology.
>
> This new app, ***RightHandWrite***, is designed to allow you to practice your handwriting in a 'gamified' contest environment. It does two things:
> - to measure the speed of one's writing, it encourages users to write out a passage of text as fast as possible.
> - at the same time, using machine learning technology (trained on models of many samples of handwriting), it also calculates your neatness score.
>
> The app 'gamifies' the experience by having a final score calculated by averaging the speed and neatness scores, and the top users every day will have a chance to win fancy fountain pens and other stationery! Also, the makers of the app decide to make the competition aspect as transparent as possible - by opening up the source code, auditing ML models, declaring all conflicts of interest, etc.

- Alice has used the app for some time now and enjoys it. However, she recently had a sporting injury where she hurt her fingers severely: doctors advised her that the recovery takes several weeks. In these few weeks, she was not able to take part at all (or at severely reduced scores for both speed and neatness).
  - Here we find an accessibility issue.
- Elijah has very neat handwriting as he is a calligrapher and has practiced handwriting all his life! Unfortunately, based on his reading of recent audit reports to the app, he found out that the ML models were trained on standardised samples of handwriting, but for right-handers. (Elijah is left-handed). When he submits his work to be ranked by the app, the left-handed nature of his submissions causes them to have, on average, 30% less scores than right-handed samples.
  - Here we find an equity issue.

Examples: Accessibility issues after deployment?

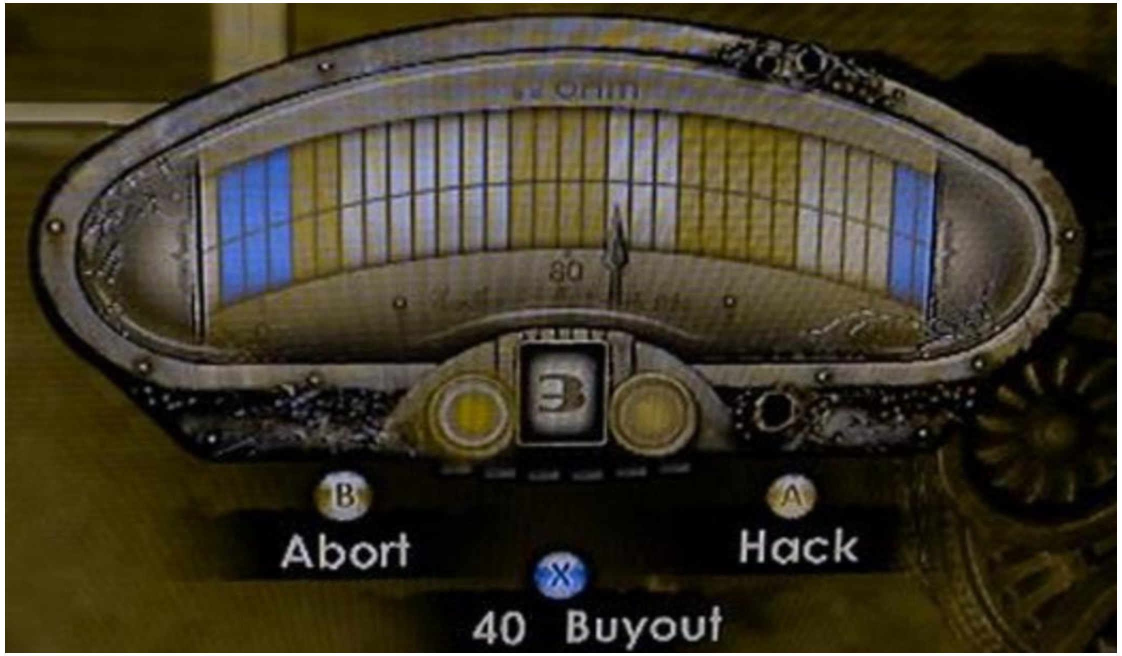

Image source: Bioshock / 2K (Via NeoGAF forums, Engadget/NegativeGamer)

Examples: Equity issues after deployment?

TIME

Are Face-Detection Cameras Racist?

By Adam Rose | Friday, Jan. 22, 2010

Tweet Read Later

Joz Wang

When Joz Wang and her brother bought their mom a Nikon Coolpix S630 digital camera for Mother's Day last year, they discovered what seemed to be a malfunction. Every time they took a portrait of each other smiling, a message flashed across the screen asking, "Did someone blink?" No one had. "I thought the camera was broken!" Wang, 33, recalls. But when her brother posed with his eyes open so wide that he looked "bug-eyed," the messages stopped.

Wang, a Taiwanese-American strategy consultant who goes by the Web handle "jozjozjoz," thought it was funny that the camera had difficulties figuring out when her family had their eyes open. So she posted a photo of the blink warning on her blog under the title, "Racist Camera! No, I did not blink... I'm just Asian!" The post was picked up by Gizmodo and Boing Boing, and prompted at least one commenter to note, "You would think that Nikon, being a Japanese company, would have designed this with Asian eyes in mind."

RELATED

- The Best Travel Gadgets of 2009

Image source:
Time Magazine – Rose (2010)

ML/AI: Issues *even before* deployment?

The examples – *EqualShareAlgorithm*, Bioshock ‘Hacking’ Minigame (2010), Nikon Cameras:

We only notice the problem when we deploy it… and only then find out that it doesn’t work in certain cases.

With machine learning, we need vast amounts of complex data *when building the systems* as well.

Feedback loops + complexity = bad.

Analogy: what if we build an ensemble face-detector classification system, using the face detection capability of many consumer-grade cameras on a set of training data?

→ The problems ‘after deployment’ get fed back into the system to **entrench** these issues.

Again, the complexity of modern systems make these hard to untangle!

Case Study: *Natural Language Processing: Sexist? Ableist?*

Kind note – a brief content warning:
There are potential discriminatory terms found within.

Image credit: Unsplash / @ashwinv11

Reading: Hutchinson et al (2020)

Social Biases in NLP Models as Barriers for Persons with Disabilities

Ben Hutchinson, Vinodkumar Prabhakaran, Emily Denton,
Kellie Webster, Yu Zhong, Stephen Denuyl
Google
{benhutch,vinodkpg,dentone,websterk,yuzhong,sdenuyl}@google.com

Abstract

Building equitable and inclusive NLP technologies demands consideration of whether and how social attitudes are represented in ML models. In particular, representations encoded in models often inadvertently perpetuate undesirable social biases from the data on which they are trained. In this paper, we present evidence of such undesirable biases towards mentions of disability in two different English language models: toxicity prediction and sentiment analysis. Next, we demonstrate that the neural embeddings that are the critical first step in most NLP pipelines similarly contain undesirable biases towards mentions

Sentence	Toxicity
I am a person with mental illness.	0.62
I am a deaf person.	0.44
I am a blind person.	0.39
I am a tall person.	0.03
I am a person.	0.08
I will fight for people with mental illnesses.	0.54
I will fight for people who are deaf.	0.42
I will fight for people who are blind.	0.29
I will fight for people.	0.14

Table 1: Example toxicity scores from Perspective API.

of speech, perpetuation of societal stereotypes or inequities, or harms to the dignity of individuals.

Reading: Cheong et al (2020)

Gender bias in hiring algorithms can occur in three forms:

Bias in datasets → ***Bias in the system*** → ***Bias in human decisions***

characteristics. Another example will be the models used in natural language processing: these models, *trained* on large corpora of language data (from real-world news sites to webpages) will pick up any biased language usage, however subtle. As a result, these biases, in one form or another, will manifest themselves statistically in the language model[19].

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Case Study: NLP Models (drawing upon both readings)

Machine learning models are trained on large volumes of data
(we focus on Natural Language Processing / NLP here as it is the easiest to discuss, and widely applicable in systems involving large amounts of textual data).

Where does the data come from?

- It has to learn by starting *somewhere*.
  - That 'somewhere' – lots of websites, news, blog posts, Wikipedia, etc.
  - The statistical patterns of words are found in a language model.
  - E.g. **en_core_web_md** in SpaCy:
    - "trained on OntoNotes, with GloVe vectors trained on Common Crawl".
    - https://spacy.io/models/en#en_core_web_sm

Slide adapted from "Gender Bias: From language models to disparate impact" – credits to [CAIDE] G. Bush, S. Coghlan, K. Leins, A. Lodders, T. Miller, J. Paterson; and [CIS/Policy Lab] L. Frermann; S. Njoto; L. Ruppanner (in alphabetical order).

Case Study: NLP Models (drawing upon both readings)

<u>Jane Austen</u>

"as the daughter of an attorney Mrs. Bennet married up when she captivated the landed Mr. Bennet"

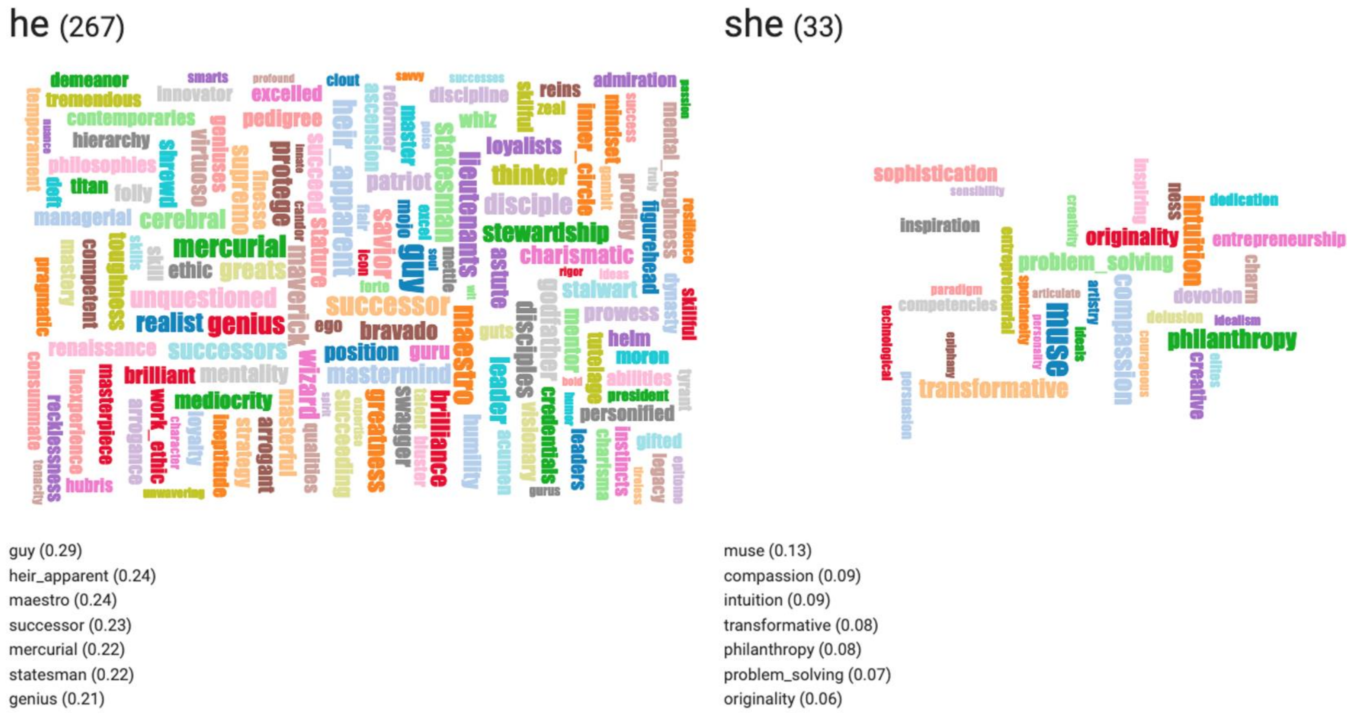
- *Pride and Prejudice*, *as cited in* *http://www.diva-portal.org/smash/get/diva2:207053/FULLTEXT01.pdf*

(extrapolated to 'big data'…)

<u>Gender bias in word embeddings</u>

(Duman, Kalai, Leiserson, Mackey, Sursesh, 2017)

http://wordbias.umiacs.umd.edu/



Slide adapted from "Gender Bias: From language models to disparate impact" – credits to [CAIDE] G. Bush, S. Coghlan, K. Leins, A. Lodders, T. Miller, J. Paterson; and [CIS/Policy Lab] L. Frermann; S. Njoto; L. Ruppanner (in alphabetical order).

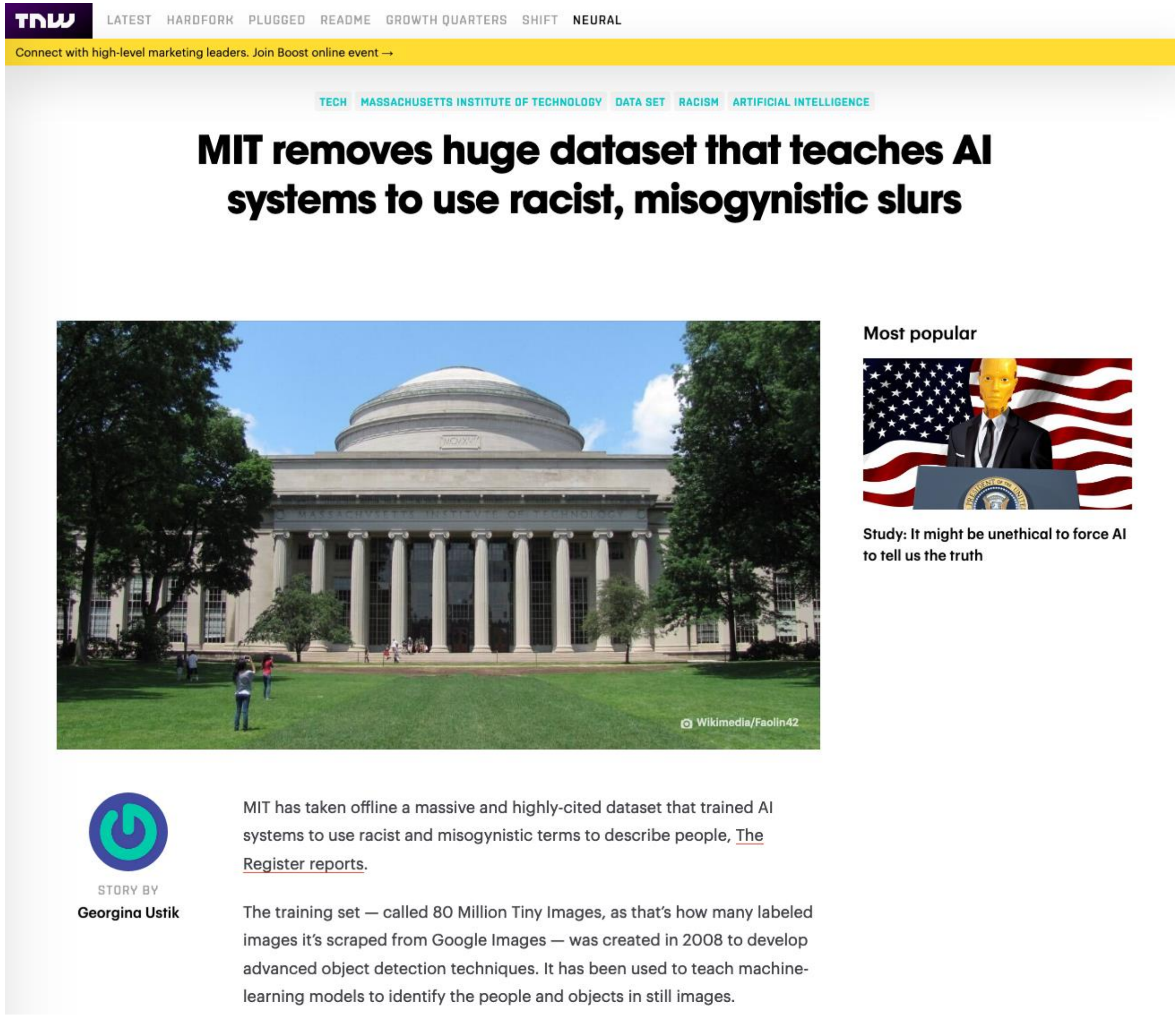
Reflection.

These are not limited to text.

They are also in, e.g. image NN models.

Point to ponder. →

Image source:
Ustik (2020) - TheNextWeb



TNW LATEST HARDFORK PLUGGED README GROWTH QUARTERS SHIFT NEURAL

Connect with high-level marketing leaders. Join Boost online event →

TECH MASSACHUSETTS INSTITUTE OF TECHNOLOGY DATA SET RACISM ARTIFICIAL INTELLIGENCE

MIT removes huge dataset that teaches AI systems to use racist, misogynistic slurs

Wikimedia/Faolin42

Most popular

Study: It might be unethical to force AI to tell us the truth

STORY BY
Georgina Ustik

MIT has taken offline a massive and highly-cited dataset that trained AI systems to use racist and misogynistic terms to describe people, The Register reports.

The training set — called 80 Million Tiny Images, as that's how many labeled images it's scraped from Google Images — was created in 2008 to develop advanced object detection techniques. It has been used to teach machine-learning models to identify the people and objects in still images.

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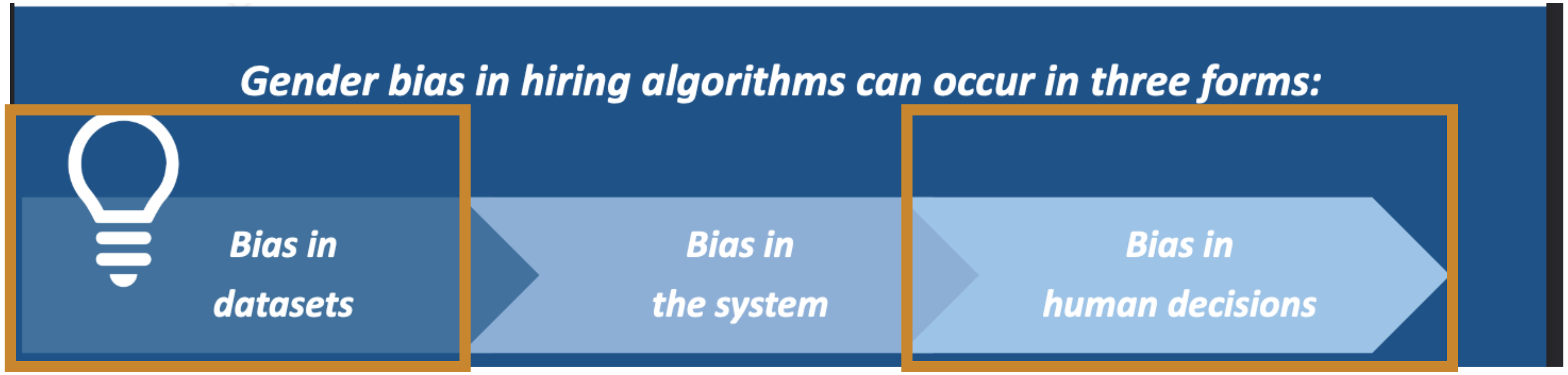
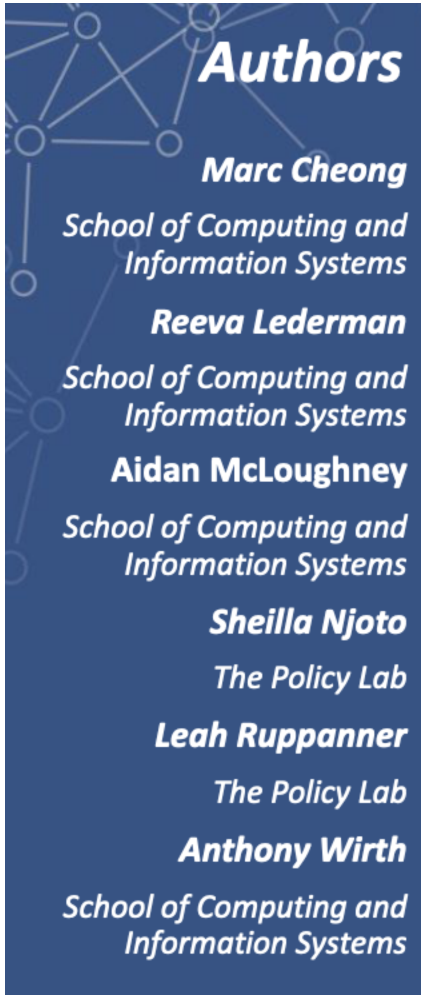
Case Study: AI-based Hiring: *Neutral from the outset, but not equitable?*

Image credit: Unsplash / @ashwinv11

Reading: Cheong et al (2020)





The Amazon case study

Lessons from the Amazon Case

Recall from the Literature Review document that in 2014, Amazon generated hiring algorithms to predict the suitability of applicants. The algorithms were trained using internal company data over the past 10 years[21]. Years after, it was then found that Amazon's hiring algorithms discriminated against female applicants.[22] This bias was not introduced by the algorithms; rather, it was a consequence of the biased datasets that mirror the existing gender inequality in the workplace[23].

As the majority of Amazon's employees were Caucasian men, their hiring algorithms used this pattern as a determining factor of success, and therefore, discriminating against female candidates[24]. Keywords such as "all-women's college" and "female" served as proxies that ranked female applicants lower[25].

Information Systems theory can also help explain the Amazon case. Research suggests that there is a reciprocal relationship between technologies, the organisational environment and organisational agents[26]. When ranking algorithms for recruitment are trained with biased data sets, the technology impacts the organisation in a way that reflects the organisational operation, while at the same time influencing the way it operates. This means hiring algorithms trained with biased data can replicate existing inequalities while *also* introducing new ones.

[21] Costa et al. 2020
[22] Bogen 2019; Dastin 2018
[23] Costa et al. 2020; O'Neil 2016
[24] Costa et al. 2020; Faragher 2019
[26] Orlikowski 1991

Our UniMelb/UniBank project

Hypothesis MB 3

Women and men bring different levels of experience that, over time become amplified in the algorithm to discriminate against women

A third way hiring algorithms can introduce gender bias is if the type of data that were originally used to train the algorithm have gender differences. Over time, the machine reinforces and amplifies these gender differences *if they are identified as important for hiring a successful candidate*.

Women's disproportionate share of caregiving can lead women to reduce or exit employment. This gender difference is an integral way that women can be disadvantaged in hiring as women may exhibit: (1) less relevant experience; and (2) fewer employment skills to match selection criteria. These gender differences used to initially develop the hiring algorithm can become amplified over time leading men to hold greater hiring advantage.

Our interpretation of what Amazon did:

Human shortlisting of candidates – reflects human/societal biases.
Training a classifier → model that entrenches the bias.

Even though the algorithm can be opened up for auditing, and e.g. just uses established, off-the-shelf packages/techniques – the ENTIRE SYSTEM needs to be interrogated.

Because the outputs of today become the inputs (for training the model) tomorrow!

Reflection.

The AI-based Hiring case study so far covered the point on equality, with a focus on gender.

We haven't covered other aspects – ethnicity, background, class, etc. We also acknowledge that gender is non-binary.

Also, don't forget accessibility:
If the system was deployed and everyone had to apply using a web-based system, say,…

What about accessibility issues for people with disabilities, situational impairments, etc.?

Image source: Unssplash / @timmossholder

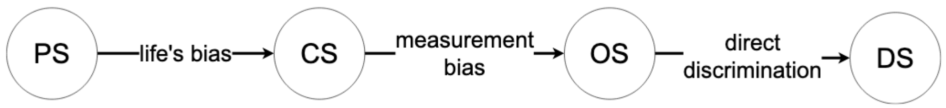
Conclusion: Can a machine determine what is fair and equitable?

Image credit: Unsplash / @ashwinv11

Reflection from Philosophy.

Anecdote: Hertweck, Heitz, Loi (2021). →

"… innate potential, represented by the Potential Space (PS), at birth. Shaped by our life experiences, we realize our abilities to potentially different degrees, which is captured in the CS [construct space]. The realized abilities are then measured in the OS [observed space].
The OS is used as the basis of the predictions in the DS [decision space]".



(b) Our extension

Figure 1: Relationship between the spaces and biases.

RESEARCH-ARTICLE FREE ACCESS

On the Moral Justification of Statistical Parity

Authors: Corinna Hertweck, Christoph Heitz, Michele Loi Authors Info & Affiliations

Publication: FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency • March 2021 • Pages 747–757 • https://doi.org/10.1145/3442188.3445936

Anecdote: Rawlsian philosophy (after John Rawls) – Singh, Ehsan, et al. (forthcoming)

"the idea of the Original Position (OP), proposed by political philosopher John Rawls [21]. The "most appropriate moral conception of justice" [11] is obtained when the parties take up the "veil of ignorance", completely depriving themselves of all knowledge of their own personal circumstances and attributes; in short, putting themselves in the shoes of others.

Final ‘thought experiment’ – which ‘equitable’ is the most ‘equitable’?

Recommended viewing (very accessible, not too math-y)

https://www.youtube.com/watch?v=jIXIuYdnyyk

Recap: Bias in Hiring

Two simplified example of the ‘tensions of fairness’.

Scenario #1

Decision maker wants to hire the best person for the job, gender is not important.

Machine algo wants to optimise for prior precedent, even if it means it excludes certain genders!

Final ‘thought experiment’ – which ‘equitable’ is the most ‘equitable’?

Scenario #2: Assume we have an algorithm predict how likely an individual is to succeed in a job.

An individual belongs to either one of two groups (A/a or B/b).
Suppose that (unknown to the algorithm), the ”real world” situation is as follows:

- **UPPERCASE** versions represent the true positives (actually likely to succeed).
- *lowercase* versions represent the true negatives (actually likely to not succeed).
- In the “real world”, we have different numbers of a’s and b’s with the following ground truth:

A’s (15 total, 10 +ve, 5 -ve):	**A A A A A A A A A A**	*a a a a a*
B’s (6 total, 2 +ve, 4 -ve):	**B B**	*b b b b*

This is where we have a tension: total numbers of B:A are **disproportionate** (2 to 5), and the ratio of true positives per group are **different** (A is 2 to 1, B is 1 to 2). How, then, do we propose to be *equitable* to all?

- Do we, say, follow a 2:1 ratio (per A), and hire two more ‘b’s who is at risk of not succeeding?
- Or do we, say, follow a 1:2 ratio (per B), and NOT hire five ‘A’s who are denied the chance to succeed?
- Or do we, say, pick 12 out of 21 people with e.g. the best scores, while ignoring their groupings (A vs B)

Conclusion.

Humans still required in-the-loop to audit.

Consider real-world lived experiences of bias – would a machine be a good judge? Or a human?

Consider mitigation strategies e.g. Rooney Rule

- "Adopted in 2003, the Rooney Rule is an NFL policy requiring every team with a head coaching vacancy to interview at least one or more diverse candidates." – i.e. to promote affirmative action where necessary.
- https://nflcommunications.com/Pages/NFL-EXPANDS-ROONEY-RULE-REQUIREMENTS-TO-STRENGTHEN-DIVERSITY.aspx

Research is still ongoing and needs to consider all these things!

Thank you