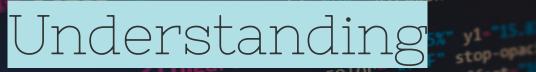
Icebreaker

Please share in the chat: What algorithms have you interacted with today?

Breaking the Code:



Algorithmic Bias

Science Research Workshop Series



Slides derived & inspired by: <u>https://libguides.lmu.edu/digcitizen/algobias</u>; https://sandbox.acrl.org/library-collection/foryou-algorithms-attention-economy

Welcome!

Shelby Hallman

O Physical Sciences & Engineering Librarian

Ashley Peterson

Research & Instruction Librarian, Media & Data Literacy

Alexandra Solodkaya

Rothman Family Food Studies Librarian



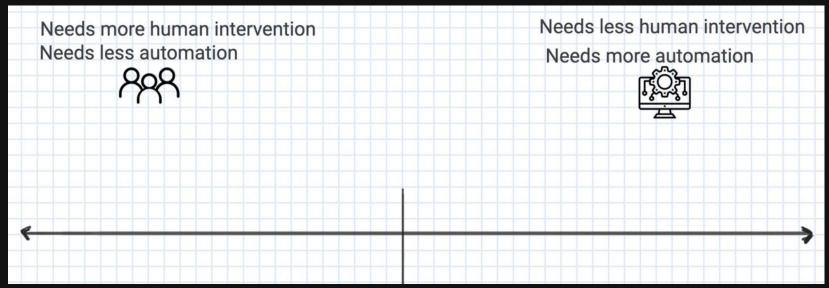
What are we <mark>doing</mark> today?

- O Define algorithms
- Reflect on the role of algorithms in daily life
- Identify the potential causes of algorithmic bias and some preventive strategies

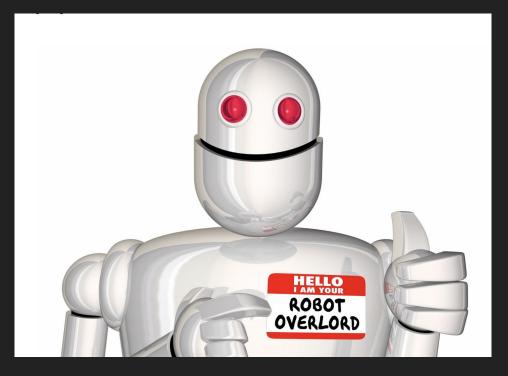
Algorithm Spectrum Activity

Assigning algorithms to a spectrum of human intervention versus automated

bit.ly/algo_spectrum







What is an <mark>algorithm</mark>?

"[Algorithms]...are mathematical objects. They take a sequence of mathematical operations...and translate them into computer code. They are fed with data from the real world, given an objective and set to work crunching through the calculations to achieve their aim." Fry, H. (2018). Hello world: Being human in the age of algorithms. W. W. Norton & Company

See also: (Golbeck, 2016)

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promise():this
[2][2].lock),ei
[].d|a&&n.isFunction
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[].function K(){(d)

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Types of algorithms

Rule-based algorithms

A set of human-coded rules that result in pre-defined outcomes (e.g., if X performs Y, then Z is the result).

Machine–learning algorithms

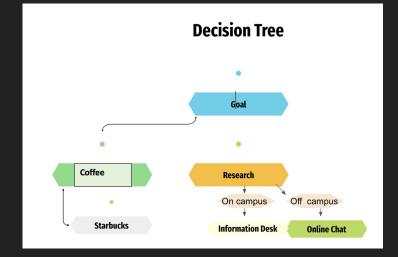
Programmed to define its own set of rules, without human intervention. Output based on statistical analysis of large data sets.

Example: Rule-based algorithm

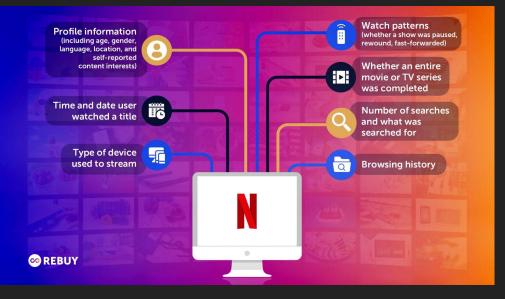
in this program, we are encoding a person's options navigating the library

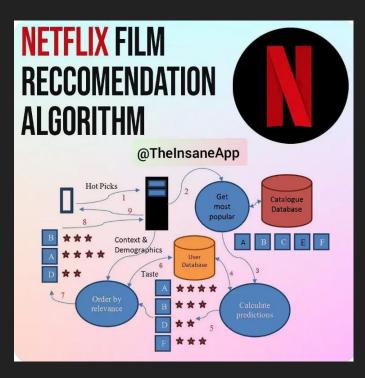
```
goals = ['coffee', 'research']
locations = ['on campus', 'off campus']
```

```
def navigate_library(goals, locations=0):
    if goals == 'coffee' and actions == 0:
        location = 'Starbucks'
            message = "Have some Starbucks coffee!"
    elif goals == 'research':
        if locations == 'on campus':
            message = "Visit us at the Information Desk!"
        elif locations == 'off campus':
        message = "Use our ask-a-librarian chat service."
```



Example: Machine learning algorithm





A note on algorithmic infrastructure



Source: https://www.invisibly.com/learn-blog/netflix-recommendation-algorithm/

Algorithmic Bias

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-sm-6 col-xs-12

permalink();



Algorithmic

Bias

Decision-making by computer systems that delivers outcomes that are systematically less favorable to individuals within a particular group and where there is no relevant difference between groups that justified such harms. (www.unwomen.org)

Poll

What causes bias in algorithms?
a) Historical human biases in training datasets
b) Incomplete or unrepresentative training data
Proxies for sensitive attributes become feedback loops
d) Algorithmic objectives



Causes of Bias

Historical Biases

Human biases included in training datasets

Unrepresentative Training Data

Incomplete or unrepresentative data

Proxies & Feedback Loops

Proxies for sensitive attributes become loops

Algorithmic Objectives

Minimize prediction errors and benefit majority groups

Example– Historical Bias

Microsoft's Tay Twitter Chatbot

- Trained on anonymized \bigcirc public data from Internet
- After 1 day, Tay had to be \bigcirc shut down for a series of lewd and racist tweets



@geraldmellor

"Tay" went from "humans are super cool" to full nazi in <24 hrs and I'm not at all concerned about the future of Al

...

16



Data Labelers Remove <mark>Toxic Content</mark> in ChatGPT

Exclusive: OpenAI Used Kenyan Workers on Less Than \$2 Per Hour to Make ChatGPT Less Toxic



This image was generated by OpenAl's image-generation software, Dall-E 2. The prompt was: "A seemingly endless view of African workers at desks in front of computer screens in a printmaking style." TIME does not typically use Al-generated art to illustrate its stories, but chose to in this instance in order to draw attention to the power of OpenAl's technology and shed light on the labor that makes it possible. Image generated by Dall-E 2/OpenAl Image Credit: Perrigo, B. (2023, January 18). OpenAl used Kenyan workers on less than \$2 per hour to make ChatGPT less toxic. *Time. https://time. com/6247678/openai-c hatgpt-kenya-workers/*

Example-<mark>Unrepresentative</mark> Training Data

Facial Recognition Software

- Training set mostly lighter-skinned faces
- Darker-skinned females were the most misclassified group (error rates of up to 34.7%)
- Maximum error rate for lighter-skinned males at 0.8%.



Buolamwini, J., & Gebru, T. (2018). Gender shades: intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research*, 81, 77-91.

Image credit: Buolamwini, J. (2016, Dec. 14). *The Algorithmic Justice League*. MIT Media Lab. https://medium.com/mit-media-lab/the-algorithmic-justice-league-3cc4131c5148.

Example–Proxies and Feedback Loops

COMPAS Recidivism Algorithm

- O Brisha, a black teenager with a previous misdemeanor who stole a kid's bike, was assigned a "high" risk
- \bigcirc

Vernon, a white man who shoplifted goods equivalent to the value of the bike but had a previous criminal record, was a "low" risk

Two Petty Theft Arrests

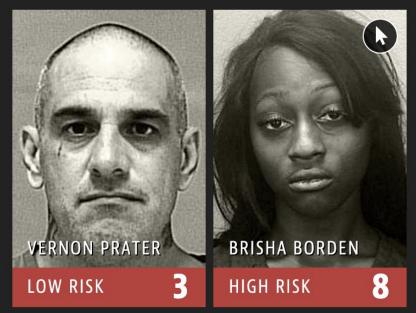


Image Credit: Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016, May 23). Machine bias. *ProPublica*.

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing?token=aGnocAzF1vcRrdeLoElVR2hgvgtEPpJo

Example–Algorithmic Objectives

Healthcare Algorithm

- O Used to diagnose patients with bipolar disorder
- O Uses strict DSM-5 criteria
- Prioritizes accuracy over context
- Would not intentionally misdiagnose, even if better for the patient

DSM-5 Diagnosis

- Diagnostic Classifications
 - Bipolar I Disorder
 - One or more Manic Episode or Mixed Manic Episode
 - Minor or Major Depressive Episodes often present
 - May have psychotic symptoms
 - Specifiers: anxious distress, mixed features, rapid cycling, melancholic features, atypical features, mood-congruent psychotic features, mood incongruent psychotic features, catatonia, peripartium onset, seasonal pattem
 - Severity Ratings: Mild, Moderate, Severe (DSM-5, p. 154)

Image credit: American Psychiatric Association (Ed.). (2013). *Diagnostic and statistical manual of mental disorders: DSM-5* (5th ed). American Psychiatric Association Pub.

Sneak peek: **Bias in generative AI tools**

Save the

date!

2/15/24

How to build a Large Language Model (LLM)

- 1. Set a goal
- 2. Collect data (lots!), tokenize it
- 3. Build a neural network
- 4. Train the neural network
- 5. Fine-tune the model
- 6. Build a user interface & laun

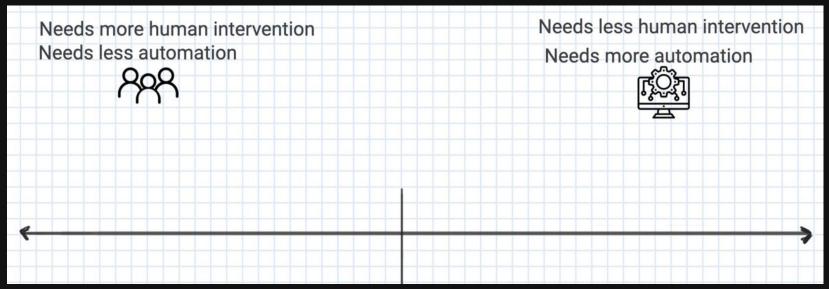
Adapted from How to Become an Expert on A.I., by Kevin Roose and Cade Metz for the New York Times

How might bias manifest in any of these steps?

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Assigning algorithms to a spectrum of human intervention versus automated

bit.ly/algo_spectrum



Our Takeaways

Think Twice Before downloading free apps you are paying with your data!

Provide Feedback /

Biased or inappropriate search results? Provide search feedback Request Transparency Q From corporations

Opt-out A From data collection whenever possible

Get Involved Advocacy and educational groups

Get Involved!

- Our Data Bodies
 - https://www.odbproject.org/
- © Electronic Frontier Foundation
 - <u>https://www.eff.org/</u>
- © Carceral Tech Resistance Network
 - <u>https://www.carceral.tech/</u>
- O Detroit Community Technology Project
 - https://detroitcommunitytech.org/
- O Data & Society
 - <u>https://datasociety.net/</u>
- O Al Now Institute
 - <u>https://ainowinstitute.org/</u>

Further Reading

- O The Supremacy of Bias in Al
- O The AI takeover of Google Starts Now
- O <u>The Problem With Biased Als (and How To</u> <u>Make Al Better)</u>
- O <u>"Do We Need Librarians Now that We Have ChatGPT?"</u>
- Al and the future of information literacy and information ethics
- O The dilemma of the direct answer
- O How to Become an Expert on A.I.
- Chatbots could one day replace search engines. Here's why that's a terrible idea.
- OpenAl Used Kenyan Workers on Less Than \$2 Per Hour to Make ChatGPT Less Toxic

- Al Fairness 360
 Al Fairness
 Al Fairnes
 Al Fairnes
- Noble, Safiya Umoja. 2018. <u>Algorithms of</u> <u>Oppression : How Search Engines Reinforce</u> <u>Racism</u>
- O'Neil, Cathy. 2016. <u>Weapons of Math Destruction:</u> <u>How Big Data Increases Inequality and Threatens</u> <u>Democracy</u>
- Broussard, Meredith. 2018. <u>Artificial Unintelligence:</u> <u>How Computers Misunderstand the World</u>
- Srinivasan, Ramesh. 2017. <u>Whose Global Village?:</u> <u>Rethinking How Technology Shapes Our World</u>
- Nemer, David. 2022. <u>Technology of the Oppressed:</u> <u>Inequity and the Digital Mundane in Favelas of</u> <u>Brazil</u>
- O Roberts, Sarah T. 2019. <u>Behind the Screen :</u> <u>Content Moderation in the Shadows of Social</u> <u>Media</u>

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Science Research Workshop Series UCLA Library





https://sandbox.acrl.org/library-collection/foryou-algorithms-attention-economy

'l'hanks!