AI: Strategy + Marketing (MGT 853)

Ethics in AI (Session 6)

Vineet Kumar

Yale School of Management
Spring 2024

Project

- Everyone has chosen projects now, right?
- Each group meets with me next week
- Choose a 10 minute slot that works for *ALL* group members
- Read the paper and have a preliminary plan before we meet
  - introduction and results fully, skim other parts
- In class: Each group gets 12 minutes to present + 3 minutes of Q&A and Discussion
- Asking questions of other groups also counts in participation

Beyond Transparency

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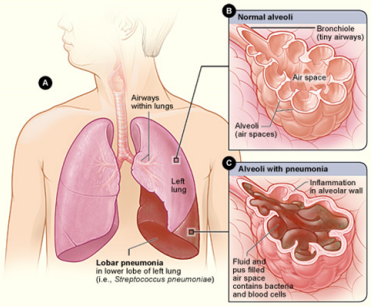

Gaming in Learning (Adversarial Learning)

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- Retailer observes a number of different behaviors X

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So, what's the problem?

Ethics in AI

Algorithmic Decisions

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Major Challenge:
Algorithmic Bias leads to differential performance across groups (think race, gender, age, income)

Humans may be able to override decisions, but...

- often have limited time / energy / attention
- power of defaults from marketing and psychology

Impact of Bias: Human Capital

RETAIL OCTOBER 10, 2018 / 7:04 PM / UPDATED 4 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

By Jeffrey Dastin 8 MIN READ

SAN FRANCISCO (Reuters) - Amazon.com Inc's AMZN.O machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

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ML Problem:

Prediction Problem: Predict quality or fit of applicant (one to five stars)
Input to algorithm: Resume
Decision: Interview or Not
Bias: Women-related words decreased stars

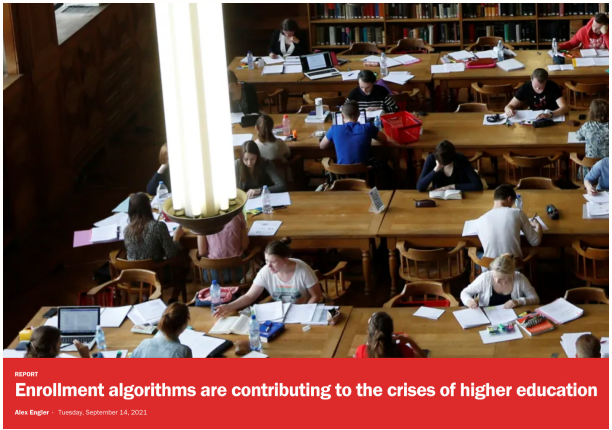
Impact of Bias: Human Capital

REPORT

Enrollment algorithms are contributing to the crises of higher education

Alex Engler · Tuesday, September 14, 2021

Impact of Bias: Human Capital



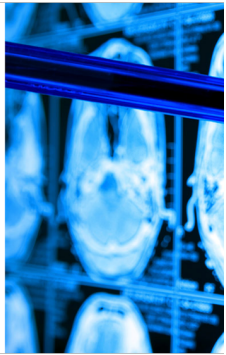
ML Problem:

Prediction problem (Y): Likelihood of accepting
Input to algorithm (X): Student information
Decision: How much financial aid to offer
Bias: More accurate for higher income

Impact of Bias: Medical Care

Algorithms Are Making Decisions About Health Care, Which May Only Worsen Medical Racism

Unclear regulation and a lack of transparency increase the risk that AI and algorithmic tools that exacerbate racial biases will be used in medical settings.



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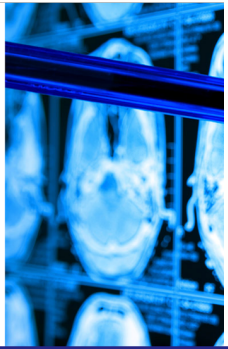
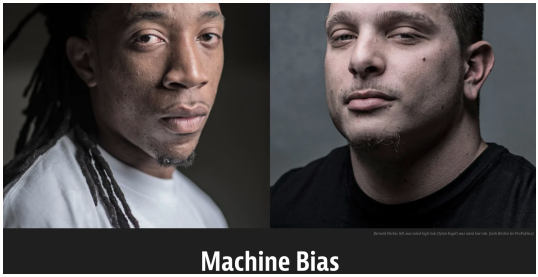


ML Problem:

Prediction problem (Y): who is likely to have a serious condition
Input to algorithm (X): insurance claims, diagnosis codes, etc.
Decision: extra medical attention and care
Bias: For same risk assessment, Black patients sicker than White patients

Impact of Bias: Criminal Justice



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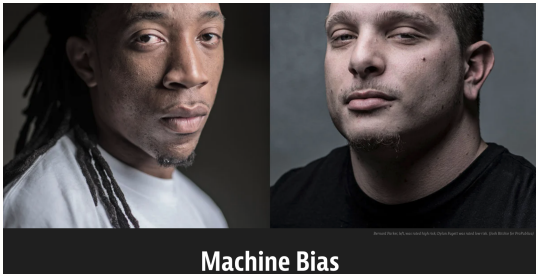


ML Problem:

Prediction problem (Y): likelihood of re-offending
Input to algorithm (X): 137 question survey
Decision: Offer Bail or Not
Bias: Higher FPR among Blacks

- Is Prediction Accuracy a good metric?
- Accuracy cannot distinguish between FP and FN (Type 1 and Type 2)

Where does Algorithmic Bias come in?

Concepts of Fairness in ML

Fairness through Unawareness – 1

Orchestrating Impartiality: The Impact of "Blind" Auditions on Female Musicians

By Claudia Goldin and Cecilia Rouse*

A change in the audition procedures of symphony orchestras—adoption of "blind" auditions with a "screen" to conceal the candidate's identity from the jury—provides a test for sex-biased hiring. Using data from actual auditions, in an individual fixed-effects framework, we find that the screen increases the probability a woman will be advanced and hired. Although some of our estimates have large standard errors and there is one persistent effect in the opposite direction, the weight of the evidence suggests that the blind audition procedure fostered impartiality in hiring and increased the proportion women in symphony orchestras. (*JEL* J7, J16)

Sex-biased hiring has been alleged for many occupations but is extremely difficult to prove. The empirical literature on discrimination, deriving from the seminal contributions of Gary Becker (1971) and Kenneth Arrow (1973), has focused mainly on disparities in earnings between groups (e.g., males and females), given differences in observable productivity-altering characteristics. With the exception of various audit studies (e.g., Genevieve Kenney and Douglas A. Wissoker, 1994; David Neumark et al., 1996) and others, few researchers have been

* Goldin: Department of Economics, Harvard University, Cambridge, MA 02183; Rouse: Woodrow Wilson School, Princeton University, Princeton, NJ 08544. Rouse acknowledges The National Academy of Education, the NAE Spencer

Fairness through Unawareness – 2

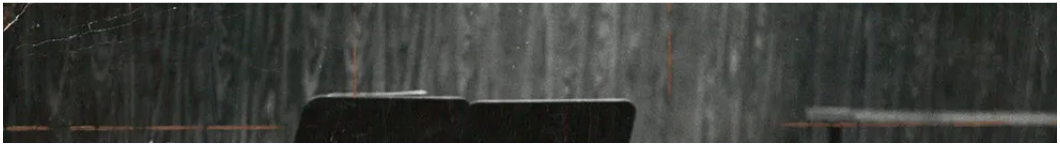
The New York Times

CRITIC'S NOTEBOOK

To Make Orchestras More Diverse, End Blind Auditions

If ensembles are to reflect the communities they serve, the audition process should take into account race, gender and other factors.

Share full article



Can we satisfy all concepts of fairness?

The (Im)possibility of Fairness: Different Value Systems Require Different Mechanisms For Fair Decision Making

By Sorelle A. Friedler, Carlos Scheidegger, Suresh Venkatasubramanian
Communications of the ACM, April 2021, Vol. 64 No. 4, Pages 136-143
10.1145/3433949
Comments

VIEW AS: SHARE:

Automated decision-making systems (often machine learning-based) now commonly determine criminal sentences, hiring choices, and loan applications. This widespread deployment is concerning, since these systems have the potential to discriminate against people based on their demographic characteristics. Current sentencing risk assessments are racially biased,[4] and job advertisements discriminate on gender.[8] These concerns have led to an explosive growth in fairness-aware machine learning, a field that aims to enable algorithmic systems that are fair by design.

Back to Top

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ARTICLE CONTENTS:

Introduction

Key Insights

An Example

Spaces: Construct vs. Observed and Features vs. Decisions

Fairness and Non-Discrimination

Worldviews and Assumptions

It is impossible to simultaneously satisfy all the notions of fairness

How can fairness impact profitability?

- You're a bank making loans to 2 groups of people: (O)range and (B)lue

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How to trade-off profitability with fairness?

Simulation

See how different notions of fairness lead to different levels of profitability in this simulation:

`http:`

Confusion Matrix for Bank Loans

Pareto Frontier

Intersectionality of Race and Gender

Proceedings of Machine Learning Research 81:1–15, 2018 Conference on Fairness, Accountability, and Transparency

Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*

Joy Buolamwini JOYAB@MIT.EDU
MIT Media Lab 75 Amherst St. Cambridge, MA 02139

Timnit Gebru TIMNIT.GEBRU@MICROSOFT.COM
Microsoft Research 641 Avenue of the Americas, New York, NY 10011

Editors: Sorelle A. Friedler and Christo Wilson

Abstract

Recent studies demonstrate that machine learning algorithms can discriminate based on classes like race and gender. In this work, we present an approach to evaluate bias present in automated facial analysis algorithms and datasets with respect to phenotypic subgroups. Using the dermatologist approved Fitzpatrick Skin Type classification system, we characterize the gender and skin type distribution of two facial analysis benchmarks, IJB-A and Adience. We find that these datasets are overwhelmingly composed of lighter-skinned subjects

who is hired, fired, granted a loan, or how long an individual spends in prison, decisions that have traditionally been performed by humans are rapidly made by algorithms (O'Neil, 2017; Citron and Pasquale, 2014). Even AI-based technologies that are not specifically trained to perform high-stakes tasks (such as determining how long someone spends in prison) can be used in a pipeline that performs such tasks. For example, while face recognition software by itself should not be trained to determine the fate of an individual in the criminal justice system, it is very likely that such software is used to identify suspects. Thus,

Intersectionality of Race and Gender

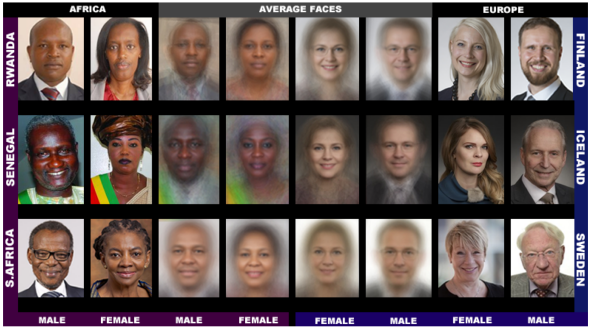

Figure 1: Example images and average faces from the new Pilot Parliaments Benchmark (PPB). As the examples show, the images are constrained with relatively little variation in pose. The subjects are composed of male and female parliamentarians from 6 countries. On average, Senegalese subjects are the darkest skinned while those from Finland and Iceland are the lightest skinned.

Intersectionality in ML

Classifier	Metric	All	F	M	Darker	Lighter	DF	DM	LF	LM
MSFT	PPV(%)	93.7	89.3	97.4	87.1	99.3	79.2	94.0	98.3	**100**
	Error Rate(%)	6.3	10.7	2.6	12.9	0.7	**20.8**	6.0	1.7	0.0
	TPR (%)	93.7	96.5	91.7	87.1	99.3	92.1	83.7	**100**	98.7
	FPR (%)	6.3	8.3	3.5	12.9	0.7	**16.3**	7.9	1.3	0.0
Face++	PPV(%)	90.0	78.7	99.3	83.5	95.3	65.5	**99.3**	94.0	99.2
	Error Rate(%)	10.0	21.3	0.7	16.5	4.7	**34.5**	0.7	6.0	0.8
	TPR (%)	90.0	98.9	85.1	83.5	95.3	98.8	76.6	**98.9**	92.9
	FPR (%)	10.0	14.9	1.1	16.5	4.7	**23.4**	1.2	7.1	1.1
IBM	PPV(%)	87.9	79.7	94.4	77.6	96.8	65.3	88.0	92.9	**99.7**
	Error Rate(%)	12.1	20.3	5.6	22.4	3.2	**34.7**	12.0	7.1	0.3
	TPR (%)	87.9	92.1	85.2	77.6	96.8	82.3	74.8	**99.6**	94.8
	FPR (%)	12.1	14.8	7.9	22.4	3.2	**25.2**	17.7	5.20	0.4

Fairness & Bias in ML – Takeaways 1

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   - Pre-processing
   - In-processing
   - Post-processing
3. Fairness is not the only issue wrt AI and society $\Longrightarrow$ Responsible AI

Pop Quiz (0 Points)

Multiple choice: More than one option may be true

Q1

- You're working with an online retailer who has browsing and purchase data for users. They would like you to identify which consumers have been most responsive to their messaging promotions over the past year. Which of the following approaches could be helpful here?
  1. Unsupervised
  2. Supervised
  3. Reinforcement

Q2

- Which of these is an example of reducing model complexity?
  1. Deciding not to use certain features X in a prediction problem
  2. Including interaction terms $\boxed{y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2}$
  3. Dropping out neurons in a neural network
  4. Penalizing models that have too many parameters

Q3

- Which of the following weather related problems would Unsupervised Learning *not* be suitable for?
  1. Identify features for inclusion in prediction problems
  2. Predict tomorrow's weather
  3. Determine which cities have similar weather patterns
  4. Discover a rule like "If it has rained today, and it is sunny now, we're likely to see a rainbow"

Q4

- Suppose we're predicting prices for cars based on visual features using images, in addition to characteristics like mpg, hp etc. You have annual data from 2010-2014. You split the data into training and test samples to predict prices and use Deep Learning to predict sales prices. Which options below are correct?
  1. Data splitting is not helpful because we are not leveraging all the data
  2. Data splitting is a good practice because of model complexity
  3. Data splitting is helpful because prediction on test data provides the best estimate
  4. There is data leakage when we split the data by years

Q5

- Observe the following reinforcement learning example. Can you specify the following?
  - State s
  - Action a
  - Rewards R

Q5

- Observe the following reinforcement learning example. Can you specify the following?
  - State s
  - Action a
  - Rewards R

- States s could include the type of chess piece at each square and whom it belongs to (white or black)
- Action a involves the set of all possible moves that can be played by a particular player
- Rewards R: This could either be defined as being based on every move (dense rewards) or only for eventually winning the game (sparse rewards)