

Fairness in Machine Learning

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Presentation based on

- Tutorial *Fairness in Machine Learning* by Patrick Loiseau
- Tutorial *Fairness-aware Machine Learning* [[link](#)]

OUTLINE

Automated Decision Making

- What is it?

- Examples

Machine Learning

Fairness in Machine Learning

- Algorithmic Biases

- Examples (Evidence)

- Different Types of Fairness

Possible Solutions

- Biased Data

- Processing

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DECISION MAKING

Automated decisions are everywhere

- Bank loans
- Insurance
- Justice
- Education
- Medicine
- Pricing
- Recommendation systems: music, movies, job offers, etc.
- Etc...

Interest: Making decisions optimally (under which criterion?)

J. Correa et al. (2019) School Choice in Chile. In Proceedings of the 2019 ACM Conference on Economics and Computation (EC'19)

- 2015 Change in the school inclusion law
- Elimination of profit regarding co-payment in subsidized private schools
- Prohibition of public schools choosing students based on social, religious, economic, or academic criteria
- Main reasons for segregation
- Centralized application system to public and subsidized schools
- Advantages at an informational level
- Eliminates the need for traveling to school
- Fair and transparent system

EDUCATION (2)

J. Correa et al. (2019) School Choice in Chile. In Proceedings of the 2019 ACM Conference on Economics and Computation (EC'19)

- Nationally with students from pre-kindergarten to last grade
- Siblings assigned to the same school
- Students assigned to schools where parents work
- Students can try to change schools
- If the change is not possible, the student must have their old position secured

	2016	2017	2018
Regions	1	5	15
Schools	63	2,174	6,421
Students	3,436	76,821	274,990
% assigned 1st preference	58.0	56.2	59.2
% assigned any preference	86.4	83.0	82.5
% unassigned	9.0	8.7	8.9

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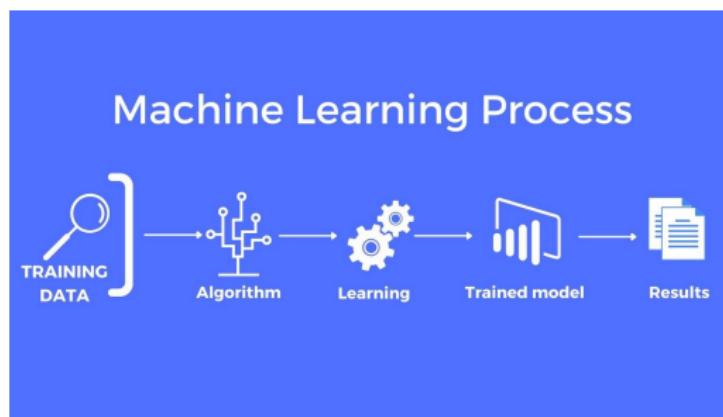
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MACHINE LEARNING

"In machine learning a computer observes **data**, builds a model based on that data and uses that model as [...] a piece of software that can **solve problems**".

Russell and Norvig (2021). Artificial Intelligence: A Modern Approach



But, how can we talk about fairness if a computer makes the decisions?

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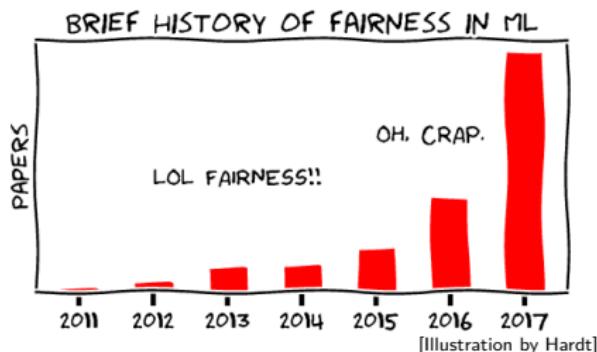
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FAIRNESS IN MACHINE LEARNING

Fairness in the field of machine learning seeks to correct and prevent possible biases in automated decision-making processes, when these decisions are based on machine learning models

Furthermore, these decisions can be considered illegal if they are based on sensitive variables such as gender, ethnicity, sexual orientation, disability, among others



ALGORITHMIC BIASES

- It studies algorithms that reflect "systematic and unfair **discrimination**"
- **Bank loans.** We say that the algorithm has biases if
 - it recommends loans to one group of users but denies loans to another almost identical group of users based on unrelated criteria
 - this behavior can be repeated on different occasions
- These biases can be **unintentional**

DISCRIMINATION IN ML-BASED HIRING PROCESSES

The New York Times

The Upshot

ROBO RECRUITING

Can an Algorithm Hire Better Than a Human?



By Claire Cain Miller

June 25, 2015

"hiring could become faster and less expensive, and [...] lead recruiters to more highly skilled people [...]. Another potential result: a more diverse workplace. The software relies on data to surface candidates from a wide variety of places and match their skills to the job requirements, free of human biases."

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TheUpshot

HIDDEN BIAS

When Algorithms Discriminate



By Claire Cain Miller

July 9, 2015

"But software is not free of human influence. Algorithms are written and maintained by people, and machine learning algorithms adjust what they do based on people's behavior. As a result, [...] algorithms can reinforce human prejudices.

DISCRIMINATION IN AUTOMATIC TRANSLATION

Google Translate January 15, 2021

The screenshot shows the Google Translate interface. At the top, there are language selection bars for the left and right sides. The left side has "DETECT LANGUAGE", "GERMAN", "ENGLISH" (which is underlined in blue), and "SPANISH". The right side has "FRENCH" (underlined in blue), "ENGLISH", "SPANISH", and a dropdown arrow. Below these are two text boxes separated by a double-headed arrow icon. The left text box contains the English sentence "the nurse is tall". The right text box contains the French translation "l'infirmière est grande". Each text box has a microphone icon for audio, a character count indicator (17 / 5000), and a settings icon. There are also edit and share icons at the bottom right of each text box.

DISCRIMINATION IN AUTOMATIC TRANSLATION

Google Translate January 15, 2021

DETECT LANGUAGE	GERMAN	ENGLISH	SPANISH	X	FRENCH	ENGLISH	SPANISH	v
the nurse is tall				X		l'infirmière est grande		☆
					17 / 5000			

DETECT LANGUAGE	GERMAN	ENGLISH	SPANISH	v	FRENCH	ENGLISH	SPANISH	v
the male nurse is tall				X		l'infirmier est grand		☆
					22 / 5000			

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					26 / 5000				

COMPAS SOFTWARE¹



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

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

- Software to predict the likelihood of criminal recidivism
- Useful for measuring the need for rehabilitation of the person

¹ [Angwin et al., Propublica 2016]

DISCRIMINATION IN ONLINE ADVERTISING

- Advertisements are calculated/optimized for each user
- Job opportunities, financial services, rentals, etc.
- The goal is to maximize the probability of click
- The law prohibits discrimination at every stage of the process (i.e., not just at the final decision)

DIGITAL

Online Ads for High-Paying Jobs Are Targeting Men More Than Women

New study uncovers gender bias

By Garrett Slosane | July 7, 2015 

Facebook, Amazon, and hundreds of companies post targeted job ads that screen out older workers

Facebook users are suing them for age discrimination.
By Aleixa Fernández Campbell | @AleixaCampbell | aleixa@vox.com | May 21, 2018, 8:50am EDT

Facebook still runs discriminatory ads, new report finds

Over a year after it pledged to stop
By Makenna Kelly | @makennakelly | Aug 26, 2020, 4:00pm EDT

- Removing sensitive attributes is not enough • Correlation among features
- The artificial intelligence matching algorithm discriminates²

²[Ali et al., 2019]

FAIRNESS IN MACHINE LEARNING IS A COMPLEX ISSUE

- There are various **sources of discrimination**
 - Biased observations
 - Feedback loop
 - Low dimensionality of our data
 - High variance
 - etc...
- Highly **interdisciplinary**
- Different fairness doctrines (disparate impact vs treatment)
- Definitions are generally domain- or task-specific (laws)
- This is **not** necessarily **negative**

DIFFERENT TYPES OF FAIRNESS

- Individual fairness

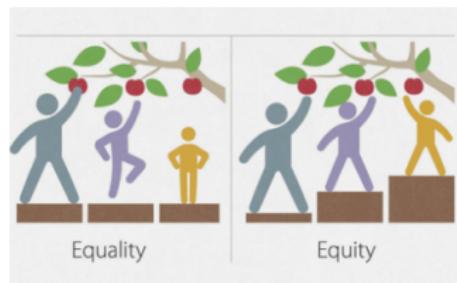
- Similar individuals should receive similar outcomes
- Requires a measure of similarity

- Utility-based fairness (economics)

- Seeks Pareto optimality
- Uses inequality measures like the Gini index
- Example: Allocation of teachers to public schools in France

- Group fairness

- Groups based on sensitive attributes
- Groups should be treated similarly
- Groups should have similar outcomes



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- Biased data: Systematic distortion that compromises its use
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- **Biased data:** Systematic distortion that **compromises** its use
- Bias must be considered **contextualized** to the task

Gender in loan application

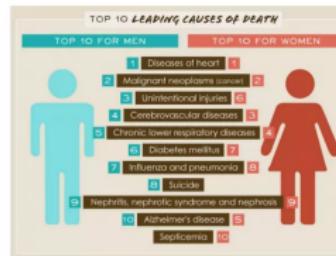


FEDERAL TRADE COMMISSION

Mortgage discrimination is against the law.

Gender discrimination is illegal

Gender in medical diagnosis



Gender-specific medical diagnosis is desirable

ORIGIN OF BIAS

- Bias in data can come from various sources
 - Population-related bias
 - Behavior-related bias
 - Content production bias
 - Connection bias
 - Temporality bias

POPULATION

- Demographic differences

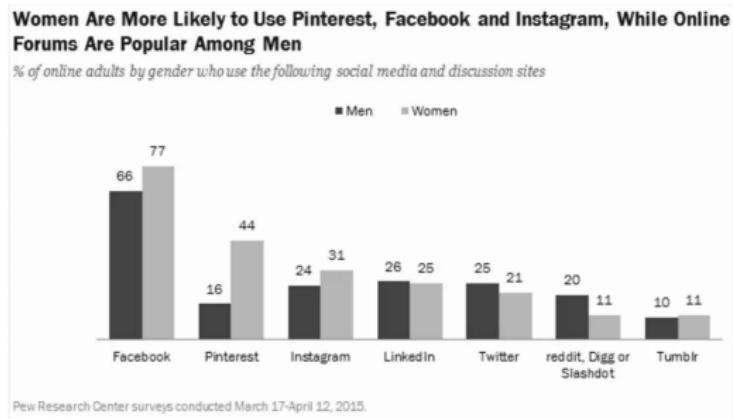
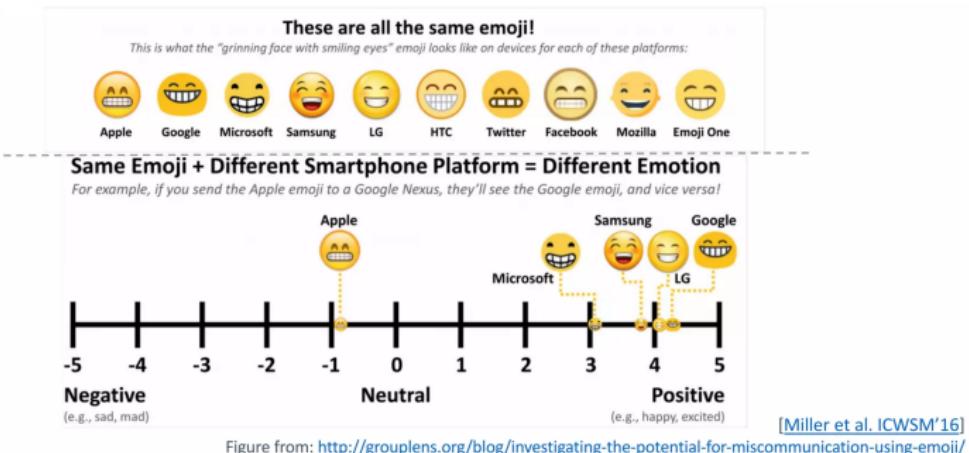


Figure from <http://www.pewinternet.org/2016/11/11/social-media-update-2016/>

BEHAVIOR

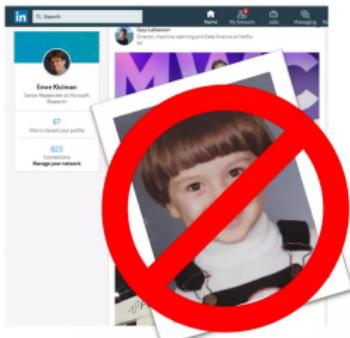
- Differences in behavior on different platforms or contexts



CONTENT PRODUCTION

Lexical, syntactic, semantic bias or structural differences in user-generated content

The kind of photos we use on
Instagram vs LinkedIn



The same mechanism can have different meanings depending on the context

Likes on a social network can mean

- affirmation
- denunciation
- approval
- displeasure
- etc.

CONNECTIONS AND TEMPORALITY

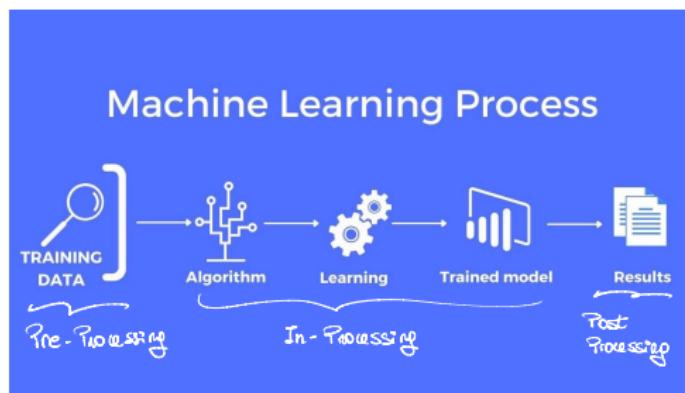
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 - Clusters tend to enhance polarization
 - For example, results in political elections

CONNECTIONS AND TEMPORALITY

- **Connections:** How the structure of the social network conditions our actions
 - Clusters tend to enhance polarization
 - For example, results in political elections
- **Temporality** refers to how the social network changes over time
 - The increase in the number of people in the social network can be conditioned
 - Changes in platform characteristics impact user behavior

PRE, IN, AND POST-PROCESSING

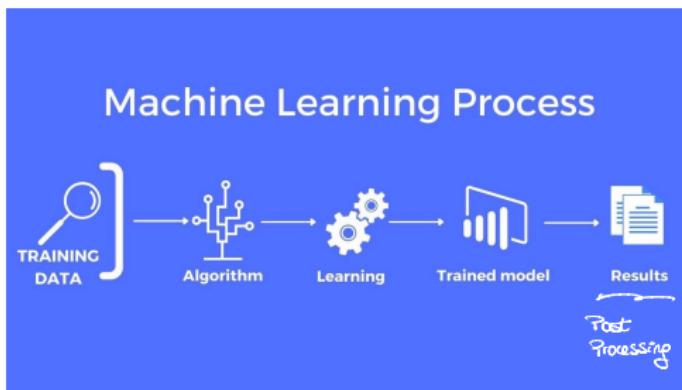
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PRE, IN, AND POST-PROCESSING

There are three main ways to achieve fair methods

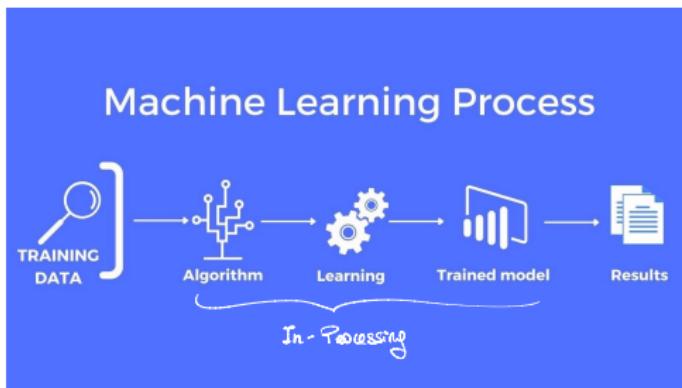
- Post-processing: take a classifier without changes and massage the output to satisfy fairness metrics
 - Good for black-box methods
 - High risk of utility loss



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There are three main ways to achieve fair methods

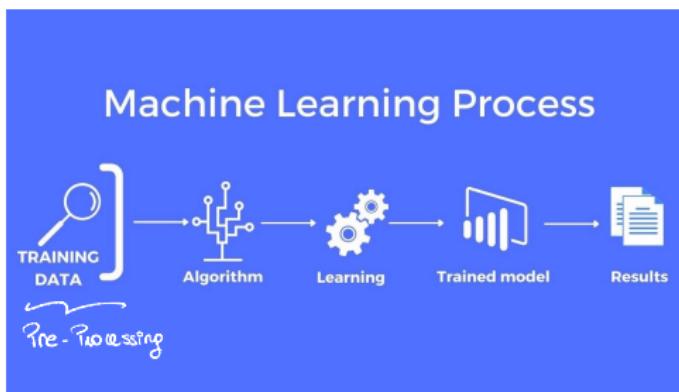
- **In-processing:** Modify the training by including fairness constraints
 - Better utility
 - Specific to each method
 - Requires access to the database
 - May involve high mathematical complexity (optimization)



PRE, IN, AND POST-PROCESSING

There are three main ways to achieve fair methods

- Pre-processing: Transform the database before training the model to be fair
 - Converts data obtained from various sources into a single clean database
 - Independent of the task
 - Specific to the fairness measure used



OPEN PROBLEMS

- Many nascent or **open problems**
- A lot of done in **classification** but not much in
 - Regression, recommendation, ranking, matching
 - Reinforcement learning, dynamic aspects
- **Multi-sided** and multi-stakeholders scenarios
- **Multi-dimensional** sensitive attributes
 - Intersectionality
- **Multi-agent** systems (e.g., ad auctions)
- Link fairness and **privacy** or fairness and **stability**
- Others...

KEY REFERENCES

- Book “fairness and ML” [Barocas et al, 2020]
- Tutorials on fairness
 - Fairness-Aware Machine Learning in Practice [Bird et al., 2019]
 - Fairness in ML [Barocas & Hardt, 2017] [video](#)
 - 21 fairness definitions and their politics [Narayanan, 2018]
 - Fairness and representation learning tutorial [Cisse, Koyejo, 2019]
- Book “Pattern recognition and ML” [Bishop, 2006]
- Tutorial on Variational Autoencoders [Doersch, 2016]

Thank You :)