

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](#)]

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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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

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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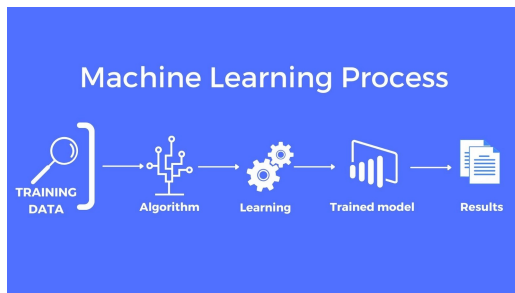
Possible Solutions

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"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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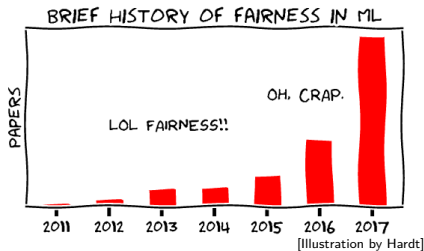
Biased Data

Processing

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



- 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**

The New York Times

 **TheUpshot**

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



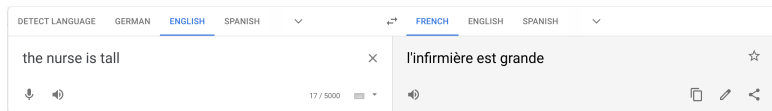
By Claire Cain Miller

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



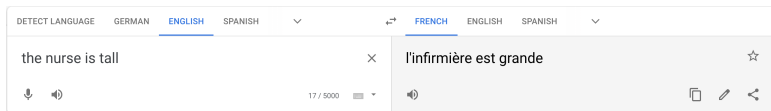
DISCRIMINATION IN AUTOMATIC TRANSLATION

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DETECT LANGUAGE GERMAN **ENGLISH** SPANISH ▾ ↕ **FRENCH** ENGLISH SPANISH ▾

the nurse is tall × l'infirmière est grande ☆

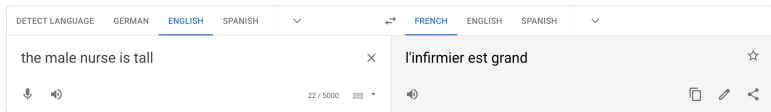
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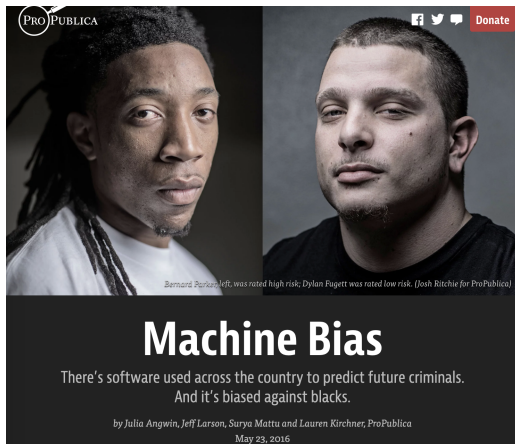
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- Software to predict the likelihood of criminal recidivism
- Useful for measuring the need for rehabilitation of the person

¹[Angwin et al., ProPublica 2016]

- 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 Sloane | 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 Alesia Ferninder Campbell | @AlesiaCampbell | alesia@vox.com | May 31, 2018, 8:50am EDT

Facebook still runs discriminatory ads, new report finds

Over a year after it pledged to stop

By Makana Kelly | @kellymakana | Aug 26, 2020, 4:00pm EDT

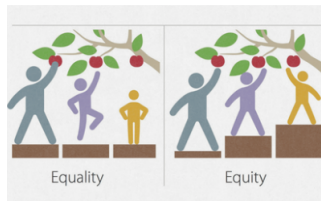
- Removing sensitive attributes is not enough
- Correlation among features
- The artificial intelligence matching algorithm discriminates²

²[Ali et al., 2019]

- 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
- Bias must be considered **contextualized** to the task

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Gender in loan application



FEDERAL TRADE COMMISSION

Mortgage discrimination is against the law.

Gender discrimination is illegal

Gender in medical diagnosis



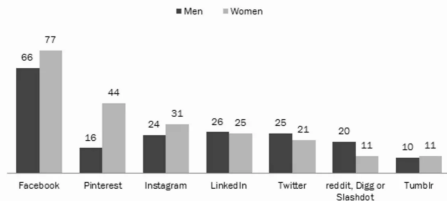
Gender-specific medical diagnosis is desirable

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

- Demographic differences

Women Are More Likely to Use Pinterest, Facebook and Instagram, While Online Forums Are Popular Among Men

% of online adults by gender who use the following social media and discussion sites

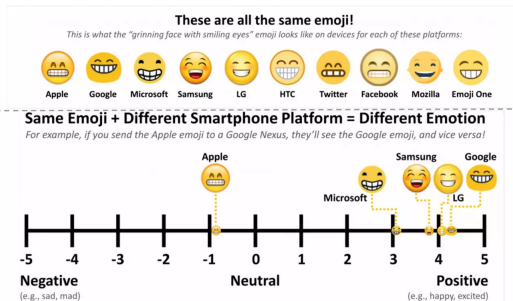


Pew Research Center surveys conducted March 17-April 12, 2015.

PEW RESEARCH CENTER

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

- Differences in behavior on different platforms or contexts

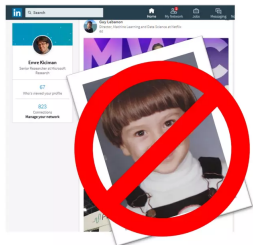


[Miller et al. ICWSM'16]

Figure from: <http://grouplens.org/blog/investigating-the-potential-for-miscommunication-using-emoji/>

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

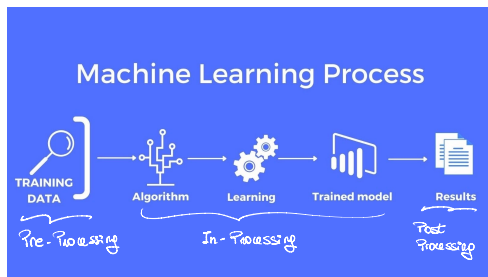
Likes on a social network can mean

- affirmation
- denunciation
- approval
- displeasure
- etc.

- **Connections:** How the structure of the social network conditions our actions
 - Clusters tend to enhance polarization
 - For example, results in political elections

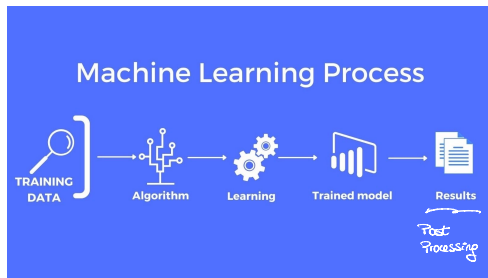
- **Connections:** How the structure of the social network conditions our actions
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- **Temporality** refers to how the social network changes over time
 - The increase in the number of people in the social network can be conditioned
 - Changes in platform characteristics impact user behavior

There are three main ways to achieve fair methods



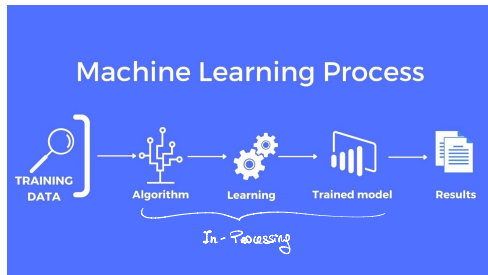
There are three main ways to achieve fair methods

- **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



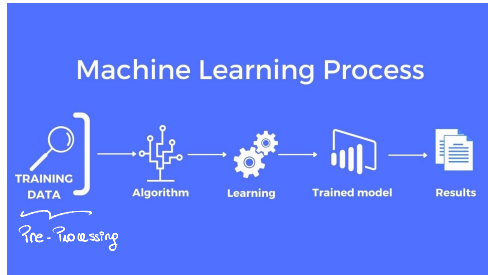
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- **In-processing:** Modify the training by including fairness constraints
 - Better utility
 - Specific to each method
 - Requires access to the database
 - May involve high mathematical complexity (optimization)



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



- 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...

- 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 :)