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- algorithms bias available information (search, recommendations, social media)
- algorithms can have big impacts (parole, credit)
- avoid unintended (and often unobservable) negative consequences
- legal requirements
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Important questions for algorithm designers:

- What is the harm of false positives? False negatives?
- How can errors change the data distribution in the future?
Examples

▶ Credit decisioning: HDMA https://www.consumerfinance.gov/data-research/hmda/explore, apple credit card
▶ Criminal justice: COMPAS https://github.com/propublica/compas-analysis/
▶ Advertising (eg, job openings)
▶ Hiring https://www.businessinsider.com/amazon-built-ai-to-hire-people-discriminated-against-
▶ Information feeds and recommender systems
▶ College admissions
▶ Medical diagnosis or treatment recommendation

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Fairness: definitions

Fairness vs discrimination

**Q:** What does it mean for a classifier to be unfair?

- What groups or individuals should be protected from discrimination?
- How can we tell if the algorithm is unfair or discriminatory?
- What information is it permissible for the algorithm to use?
Fairness: legal definitions

**Housing:** The Equal Housing Opportunity Act states that someone seeking to rent a home has the right to expect that housing will be available to them without discrimination or other limitations based on race, sex, color, religion, sex, disability, familial status, or nationality.
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**Credit and banking:** The Equal Credit Opportunity Act makes discrimination unlawful in credit applications based on race, color, religion, national origin, sex, marital status, age, or because all or part of the applicant’s income comes from a public assistance program.
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**Labor market:** The Equal Employment Opportunity Act prohibits employment discrimination in its programs based on race, color, national origin, sex, religion, age, disability, political beliefs, and marital or familial status.
Definitions and notation

Definition

A **protected attribute** is a feature on which discrimination is prohibited
(eg, race, color, national origin, sex, religion, age, disability, political beliefs, and marital or familial status)

Notation: (assume classification problem)

- **binary outcomes** $y \in \mathcal{Y} = \{0, 1\}$
- **covariates** $x \in \mathbb{R}^d$
- **binary protected attribute** $a \in \{0, 1\}$
- **prediction** $\hat{y}$
Unawareness

Definition
A classifier is **unaware** of the protected attribute if the prediction is independent of the protected attribute given other covariates:

\[ \hat{y} \perp a \mid x \iff P(\hat{y} \mid x, a = 0) = P(\hat{y} \mid x, a = 1). \]
## Fair Lending laws

<table>
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Two doctrines of discrimination

- Disparate Treatment
  - Treatment must not depend explicitly on group
  - Example: redlining – refusing to finance mortgages in minority neighborhoods – violates disparate treatment

- Disparate Impact
  - Outcomes must not differ (excessively) between groups
  - Example: four-fifths rule (of thumb) says hiring rates of majority and minority should be within 80% of each other

Other quantifications of fairness: [Kleinberg Mullainathan Raghavan 2016], [Hardt Price Srebro 2016], ...
Personal Information

FIRST NAME

MI

LAST NAME

DATE OF BIRTH

SOCIAL SECURITY NUMBER

ARE YOU A U.S. CITIZEN?

○ YES ○ NO

WHY ARE YOU ASKING ME THIS?
A graph showing the relationship between income and creditworthiness. The x-axis represents income, and the y-axis represents creditworthiness. The data points suggest a positive correlation, with higher income associated with higher creditworthiness.
income
creditworthiness

approve
income
creditworthiness

approve

income
creditworthiness

approve
Treatment disparity > disparate learning policies: [Chouldechova Lipton McAuley 2018]
What’s wrong with fairness through unawareness?

- **Reduced accuracy:** e.g., gender and violent crime.

- Proxies: Other covariates (called proxies) may correlate with the protected attribute. How much correlation is too much? e.g., zip code and race.

- Allowable proxies: e.g., credit score and race; Pinterest and gender.
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Fairness metrics

How can we define fairness? Active research area!

- Unawareness / anti-classification
- Demographic parity
- Equalized odds, Equality of opportunity
- Predictive Rate Parity
- Individual Fairness
- Counterfactual fairness
Demographic parity

Definition

The algorithmic classifier satisfies **demographic parity** if the prediction is independent of the protected attribute:

\[ P(\hat{y}|a = 1) = P(\hat{y}|a = 0) = P(\hat{y}) \]

In other words, acceptance rates of applicants from both groups are the same.
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**Q:** Problems with demographic parity?
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► **Accuracy.** What if base rates are different? e.g., gender and violent crime. Demographic parity rules out the perfect predictor when base rates are different.
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**Q:** Problems with demographic parity?

- **Accuracy.** What if base rates are different? e.g., gender and violent crime. Demographic parity rules out the perfect predictor when base rates are different.

- **Unjust and misleading.** To achieve demographic parity, could admit qualified (e.g., college) applicants from group \( a = 0 \) and random applicants from group \( a = 1 \). (And then complain: “Students from group 1 just aren’t prepared!”)


Equalized odds

**Definition**

The algorithmic classifier satisfies **equalized odds** if the prediction \( \hat{y} \) is independent of the protected attribute \( a \) conditional on the outcome \( y \).

\[
\hat{y} \perp a \mid y \iff \mathbb{P}(\hat{y} \mid y, a = 1) = \mathbb{P}(\hat{y} \mid y, a = 0)
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As a consequence, the true positive, true negative, false positive, and false negative rates are the same for both groups.
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**Variant:** weaker condition, **equality of opportunity**, holds if

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\textbf{Variant:} weaker condition, \textit{equality of opportunity}, holds if $P(\hat{y}|y = 1, a = 1) = P(\hat{y}|y = 1, a = 0)$.

$\blacktriangleright$ +: optimality compatibility (perfect prediction) is allowed.

$\blacktriangleright$ +: provides an incentive to reduce errors uniformly in all groups.

$\blacktriangleright$ -: it may not help to close the gap between different groups if true positive rates are quite different.
Predictive rate parity

**Definition**

The algorithmic classifier satisfies **predictive rate parity** if the outcome $y$ is independent of the protected attribute $a$ conditional on the prediction $\hat{y}$.

$$y \perp a | \hat{y} \iff \mathbb{P}(y | \hat{y}, a = 1) = \mathbb{P}(y | \hat{y}, a = 0)$$

In hiring, this would mean that the score returned from a prediction algorithm should reflect the candidate’s real capability of doing this job. It is consistent with the employer’s benefit.
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- **+**: optimality compatibility (perfect prediction) is allowed.
- **+**: encourages (equal) error reduction in all groups.
- **-**: may not close the gap between different groups if true positive rates are quite different.
Impossibility theorem for fairness metrics


Recent discussion in the public sphere about algorithmic classification has involved tension between competing notions of what it means for a probabilistic classification to be fair to different groups. We formalize three fairness conditions that lie at the heart of these debates, and we prove that except in highly constrained special cases, there is no method that can satisfy these three conditions simultaneously.

- calibration within groups (strengthens predictive rate parity)
- equalized odds for $y = 1$ (equality of opportunity)
- equalized odds for $y = 0$
Individual fairness

Previous, statistical, notions of fairness judge fairness wrt group.

Definition
The algorithmic classifier satisfies individual fairness if similar individuals receive similar (distribution of) predictions.

- can assess fairness without defining groups
- how to define similarity?
- only makes sense for randomized predictions

Definition
The algorithmic classifier satisfies counterfactual fairness if flipping the group $a \rightarrow 1 - a$ doesn’t change the prediction $\hat{y}$.

- agrees with intuitive notion of fairness
- how to assess? need randomized experiments?
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Best practice for assessing fairness?

- Choose fairness metrics that make sense for your problem.
- See how accuracy and fairness metrics change as you tweak your model.
- Report fairness (just like you’d report test set accuracy).
Exercise: fairness metrics

Pick an application (e.g., parole, credit, admissions, hiring, your project). Which notion of fairness makes sense? Which have problems?

- Unawareness / anti-classification
- Demographic parity
- Equalized odds, Equality of opportunity
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References

- Impossibility for fairness:

- Fairness under unawareness:
  https://arxiv.org/abs/1811.11154