Bias in AI Systems

Module 7 of a course on *Ethical Issues in AI*

Prepared by

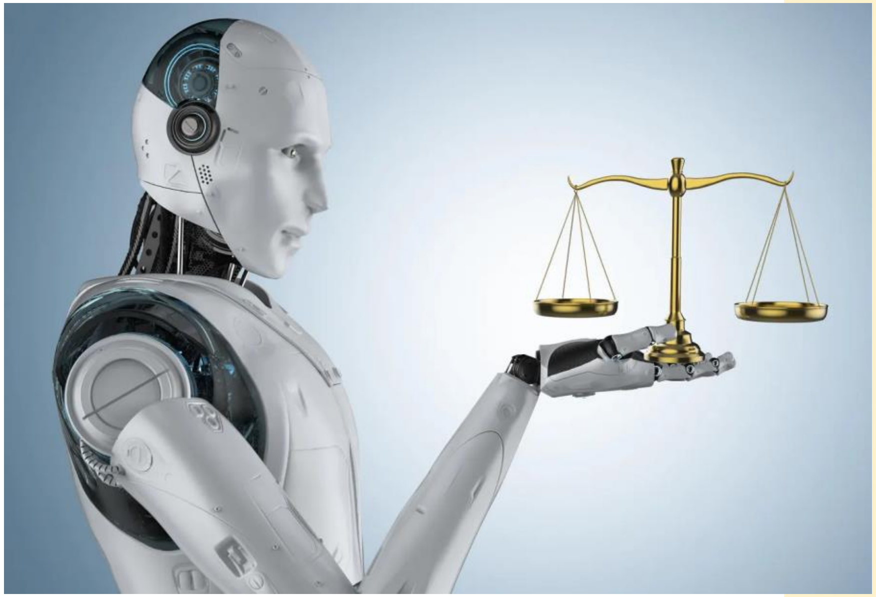
John Hooker

Emeritus Professor, Carnegie Mellon University

CMU Osher, February 2025

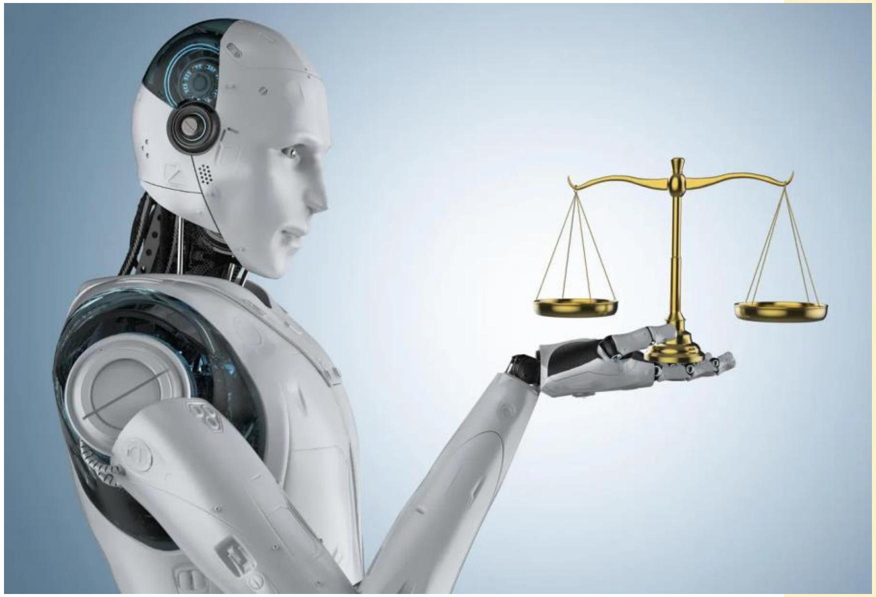
The ethical problem

- Do AI-based decisions **treat groups equally** in a morally relevant sense?
  - *Groups may be based on race, ethnic background, gender, economic status, etc.*



The ethical problem

- How should we **measure** group parity for purposes of ethics?
  - What kind of inequality is unethical?
  - Should we use preferential treatment, DEI hiring, affirmative action, etc.?



Example: Hiring and recruiting

- Google and Amazon AI hiring tools
  - *Intended to diversify work force.*
  - *Had the opposite effect: Gender, race, and age bias*

THE WALL STREET JOURNAL.

Google Settles Gender Discrimination Lawsuit for $118 Million

Company doesn't admit wrongdoing in agreement to resolve class-action suit that covers some 15,500 women

By Patrick Thomas Follow

June 12, 2022 8:10 pm ET

Example: Mortgage decisions

- An application may be rejected, despite sound finances, because…
  - *The applicant belongs to a **minority group**.*
  - *The **default rate** is higher for the minority group.*

Example: Mortgage decisions

- An application may be rejected, despite sound finances, because…
  - *The applicant belongs to a **minority group**.*
  - *The **default rate** is higher for the minority group.*
- **Remove** race/ethnic group from data?

Example: Mortgage decisions

- An application may be rejected, despite sound finances, because…
  - *The applicant belongs to a **minority group**.*
  - *The **default rate** is higher for the minority group.*
- **Remove** race/ethnic group from data?
  - *That may not work.*
  - *There may be **latent bias** even in sanitized data.*

Example: Mortgage decisions

- Why latent bias?
  - *The applicant may be* ***rejected*** *due to having an address in a* ***low-income neighborhood****, where people have a higher default rate (redlining)*
  - *Members of minority group are more likely to live in a low-income neighborhood due to* ***historical discrimination****.*
  - *Their address nonetheless* ***correlates*** *a higher default rate.*

Other examples

- Parole (minimize recidivism risk)
- College admissions
- Fraud detection
- Credit scoring

What to do about it?

- **Option 1**: Get rid of AI.
  - *Even though this* ***reduces prediction accuracy***
    - We assume AI is more biased than humans
  - *Fails* ***utilitarian*** *principle, unless using AI is* ***not generalizable****.*
    - There is arguably an **implicit agreement** with applicant to use only financial criteria.
    - Violating this agreement is **not generalizable** (for loans).
    - There be **no such agreement** for college admissions**.**

What to do about it?

- **Option 2**: Improve AI to satisfy the implicit agreement.
  - *Apply **statistical bias** metrics.*
  - ***Adjust** AI predictions to **get rid** of bias. This requires **explicitly considering** minority status in the decision.*
  - *A popular approach, incentivized by equal opportunity laws.*
    - Scheduled classes (India)
    - Bumiputera quotas (Malaysia)
    - Fair Housing Act (US), e.g.

Bias metrics

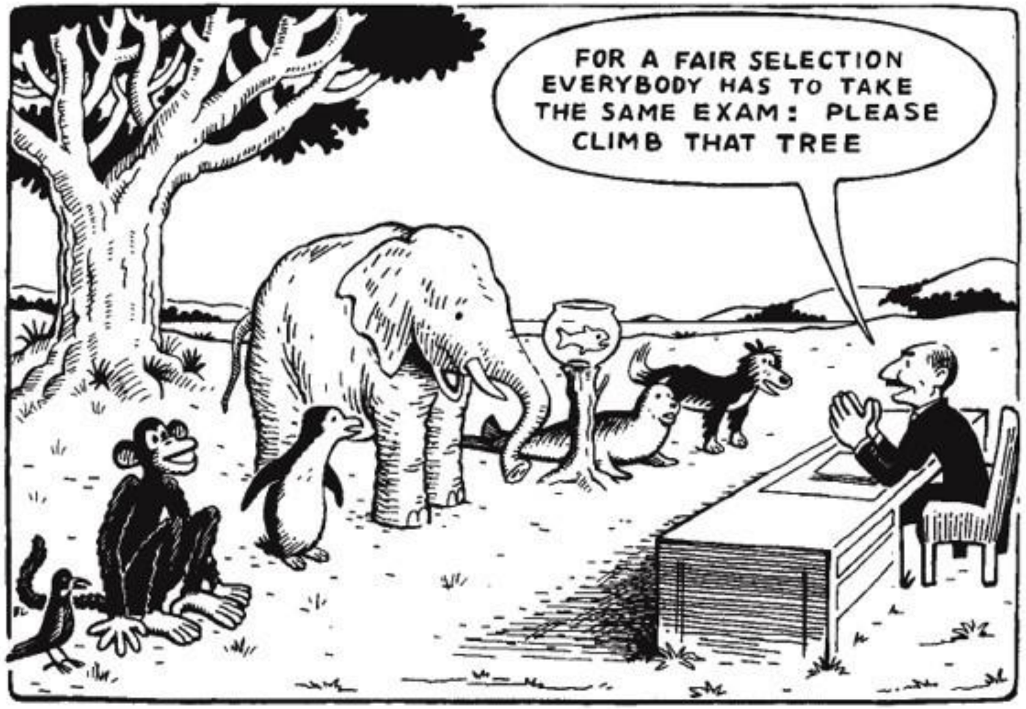
- **Bias metrics** are ways of measuring whether two groups are treated "equally."
  - *For short, we refer to these groups as the **majority** and **minority** (= protected group).*
- Most popular metrics:
  - ***Demographic parity***
  - ***Equalized odds***
    - We focus on equality of opportunity
  - ***Predictive rate parity***

Bias metrics

- **Bias metrics** are ways of measuring whether two groups are treated "equally."
  - *For short, we refer to these groups as the **majority** and **minority** (= protected group).*
- Most popular metrics:
  - ***Demographic parity***
  - ***Equalized odds***
    - We focus on equality of opportunity
  - ***Predictive rate parity***
- These are usually **incompatible**.
  - *Must choose one or none!*

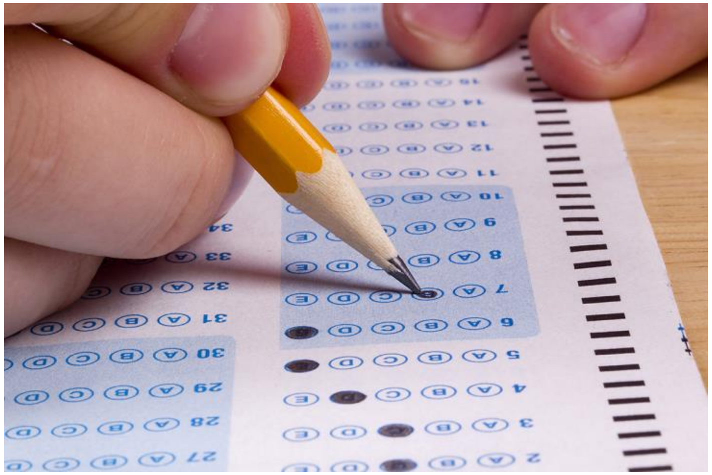
Assessing bias metrics

- **"Fairness"** seems an intuitively compelling idea.
  - *But it is a **notoriously vague** concept.*
    - What seems **fair** to me seems **unfair** to you.
  - *"Group parity" has **dozens** of mathematical definitions.*



Assessing bias metrics

- Shouldn't decisions be based on **merit?**
  - *"Merit" is in the eye of the beholder.*
- Consider college admissions.
  - *Minority applicants with lower test scores:*
    - "We had to over come **greater obstacles**."
  - *Majority applicants with higher test scores:*
    - "Merit is based on **competence**, not how one **acquired** competence."



Assessing bias metrics

- Shouldn’t a positive decision be based on whether one has **earned** it?
  - *If so, why do we reward people with* ***innate talent?***
  - *Talent is a* ***gift****, not something earned.*
    - We even refer to such people as “gifted.”

Assessing bias metrics

- We can argue all day about this.
    - *…and accomplish nothing.*
- So, let's assess parity metrics directly with **ethical principles**.
    - *Rather than trying to guess which one measures "fairness" or "merit".*

Assessing bias metrics

- **Demographic parity**.
  - *Definition:*

    $$\boxed{\text{\% of majority group \textbf{accepted}}} = \boxed{\text{\% of minority group \textbf{accepted}}}$$

    - Probability of **accepting** a given person (e.g., for loan) is the same for the two groups**.**
  - *Characteristics:*
    - May give preference to **less qualified** minority individuals.
    - Compensates for **historical discrimination**.
    - May discriminate against **more qualified** minority groups (as in Malaysia).

Assessing bias metrics

- **Demographic parity**.
  - *Definition:*

    $\boxed{\text{\% of majority group \textbf{accepted}}} = \boxed{\text{\% of minority group \textbf{accepted}}}$

    - Probability of **accepting** a given person (e.g., for loan) is the same for the two groups**.**
  - *Ethical assessment:*
    - May violate **generalizability** by overriding evident qualifications (applies to loans, perhaps not college?)
    - May maximize long-term **utility** by providing equal opportunity to marginalized groups.
    - May reduce long-term **utility** if there is backlash from the majority.

Assessing bias metrics

- **Equalized odds**.
  - *Definition:*

    % of **qualified** majority accepted = % of **qualified** minority accepted

    - Probability of accepting a **qualified** person (e.g., for loan) is the same for the two groups**.**
  - *Characteristics:*
    - Can allow **few** minority persons to be accepted if **relatively few are qualified** due to social and historical factors.
    - But allows selecting a greater fraction of minority persons when they are **more qualified** than average.

Assessing bias metrics

- **Equalized odds.**
  - *Definition:*

% of **qualified** majority accepted	=	% of **qualified** minority accepted

    - Probability of accepting a **qualified** person (e.g., for loan) is the same for the two groups.
  - *Ethical assessment:*
    - Consistent with any implied **agreement** to consider only evident qualifications.
    - May maximize long-term **utility** by avoiding backlash.
    - May reduce long-term **utility** by failing to address chronic discrimination.

Assessing bias metrics

- **Predictive rate parity**.
  - *Definition:*

% of **accepted** majority persons who are **qualified**	=	% of **accepted** minority persons who are **qualified**

    - Probability that an **accepted** person is **qualified** (e.g., for loan) is the same for the two groups**.**
  - *Characteristics:*
    - Avoids appearance that **acceptance standards** are different for the two groups.
    - Can allow **few** minority persons to be selected, by ensuring they are as **qualified as accepted majority persons**.

Assessing bias metrics

- **Predictive rate parity**.
  - *Definition:*

% of **accepted** majority persons who are **qualified**	=	% of **accepted** minority persons who are **qualified**

    - Probability that an **accepted** person is **qualified** (e.g., for loan) is the same for the two groups**.**
  - *Ethical assessment:*
    - May violate **generalizability** by overriding evident qualifications.
    - May maximize long-term **utility** by avoiding backlash.
    - May reduce long-term **utility** by failing to address chronic discrimination.

Assessing bias metrics

- **Highly publicized example: Parole**
  - *COMPAS predictions achieve **predictive rate parity**.*
    - Minority parolees have **same recidivism rate** as majority parolees.
  - *But they **do not equalize odds**.*
    - Apparently qualified minority candidates are about **40% less likely to be paroled** than qualified majority candidates.

From: *Pro Publica*, 23 May 2016

Assessing bias metrics

- **Highly publicized example: Parole**
  - *COMPAS predictions achieve **predictive rate parity**.*
    - Minority parolees have **same recidivism rate** as majority parolees.
  - *But they **do not equalize odds**.*
    - Apparently qualified minority candidates are about **40% less likely to be paroled** than qualified majority candidates.
  - Debate **still unresolved.**

From: *Pro Publica*, 23 May 2016

Assessing bias metrics

Factual issues to resolve

Is there an **implied agreement** that decisions will reflect only evident (measurable) qualifications?

- **yes** → *Aim for* ***equalized odds***
- **no** → Does demographic parity create greater long-run **social benefit** than equalized odds, taking backlash into account?
  - **yes** → *Aim for* ***demographic parity***
  - **no** → Perform **utilitarian evaluation** of other metrics

Assessing bias metrics

- **Counterfactual fairness**.
  - *Definition:*

% of minority persons accepted in the **actual world**	=	% of minority persons accepted in an **alternate world** where they belong to the **majority**

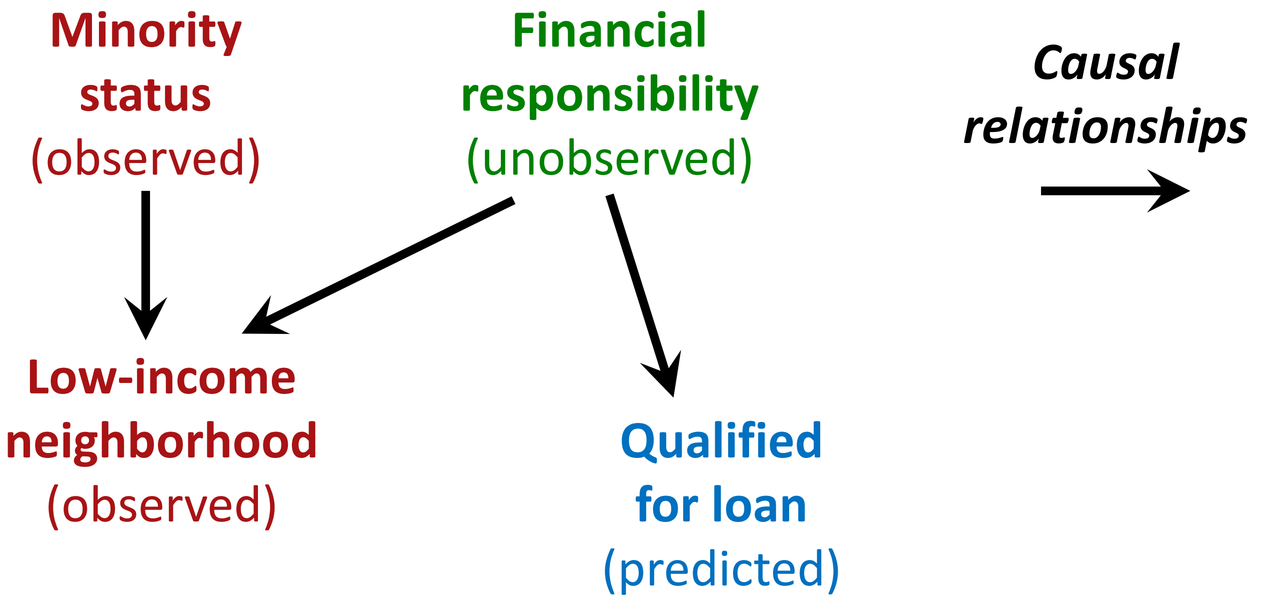
    - Acceptance probability of a given minority person **would have been the same** if that person belonged to the majority**.**
  - *Characteristics:*
    - Sounds **great**.
    - But how to **assess** this?

Assessing bias metrics

- **Counterfactual fairness**.
  - In the case of mortgage loans:
    - *Relevant factor is **financial responsibility**, but only minority status and address can be **observed**.*
    - *Acceptance decision must be the same if it were based **only on financial responsibility**.*
  - Represent this situation with a **causal network:**

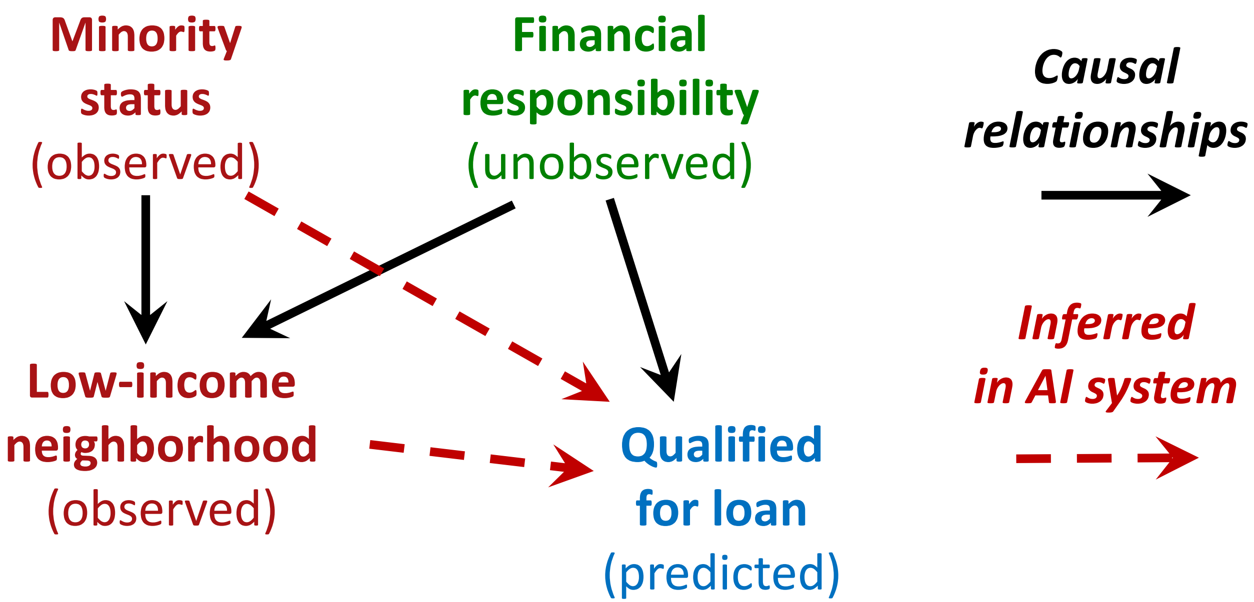
Assessing bias metrics

- **Counterfactual fairness**



Assessing bias metrics

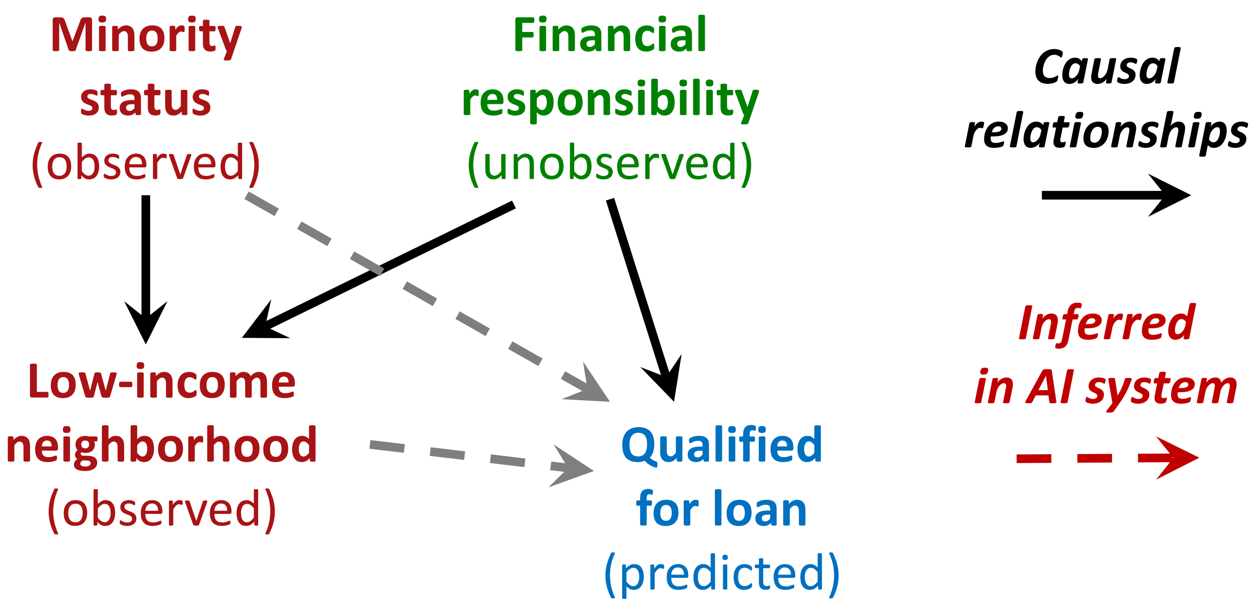
- **Counterfactual fairness**



Bias metrics

- **Counterfactual fairness**

Must use **Bayesian inference** to deduce financial responsibility



Assessing bias metrics

- **Counterfactual fairness.**
  - *Technical problems:*
    - There may be **many** confounding factors in the network.
    - Bayesian inference requires a **rich data set**, usually unavailable.
    - The desired Bayesian calculations are possible only in networks with a **certain kind of structure**.
    - Still a **research area**.

Assessing bias metrics

- **Counterfactual fairness.**
  - *Possible ethical problem:*
    - It is **counterfactual** – decisions are not based on actual qualifications.
    - Ethical arguments are similar to those surrounding **demographic parity**.