
Machine Learning in Production
Measuring Fairness

Diving into Fairness...

Fundamentals of Engineering AI-Enabled Systems

Holistic system view: AI and non-AI components, pipelines, stakeholders, environment interactions, feedback loops

Requirements:
System and model goals
User requirements
Environment assumptions
Quality beyond accuracy
Measurement
Risk analysis
Planning for mistakes

Architecture + design:
Modeling tradeoffs
Deployment architecture
Data science pipelines
Telemetry, monitoring
Anticipating evolution
Big data processing
Human-AI design

Quality assurance:
Model testing
Data quality
QA automation
Testing in production
Infrastructure quality
Debugging

Operations:
Continuous deployment
Contin. experimentation
Configuration mgmt.
Monitoring
Versioning
Big data
DevOps, MLOps

Teams and process: Data science vs software eng. workflows, interdisciplinary teams, collaboration points, technical debt

Responsible AI Engineering

Provenance, versioning, reproducibility

Safety

Security and privacy

Fairness

Interpretability and explainability

Transparency and trust

Ethics, governance, regulation, compliance, organizational culture

Reading

Required:

- Nina Grgic-Hlaca, Elissa M. Redmiles, Krishna P. Gummadi, and Adrian Weller. Human Perceptions of Fairness in Algorithmic Decision Making: A Case Study of Criminal Risk Prediction In WWW, 2018.

Recommended:

- Ian Foster, Rayid Ghani, Ron S. Jarmin, Frauke Kreuter and Julia Lane. Big Data and Social Science: Data Science Methods and Tools for Research and Practice. Chapter 11, 2nd ed, 2020
- Solon Barocas and Moritz Hardt and Arvind Narayanan. Fairness and Machine Learning. 2019 (incomplete book)
- Pessach, Dana, and Erez Shmueli. "A Review on Fairness in Machine Learning." ACM Computing Surveys (CSUR) 55, no. 3 (2022): 1-44.

Learning Goals

- Understand different definitions of fairness
- Discuss methods for measuring fairness
- Outline interventions to improve fairness at the model level

Real change, or lip service?

TikTok Claims It's Limiting Teen Screen Time. Teens Say It Isn't.

This month, the company announced a new 60-minute "daily screen time limit" for users under 18. But for most young users, staying on the app takes just a few taps.

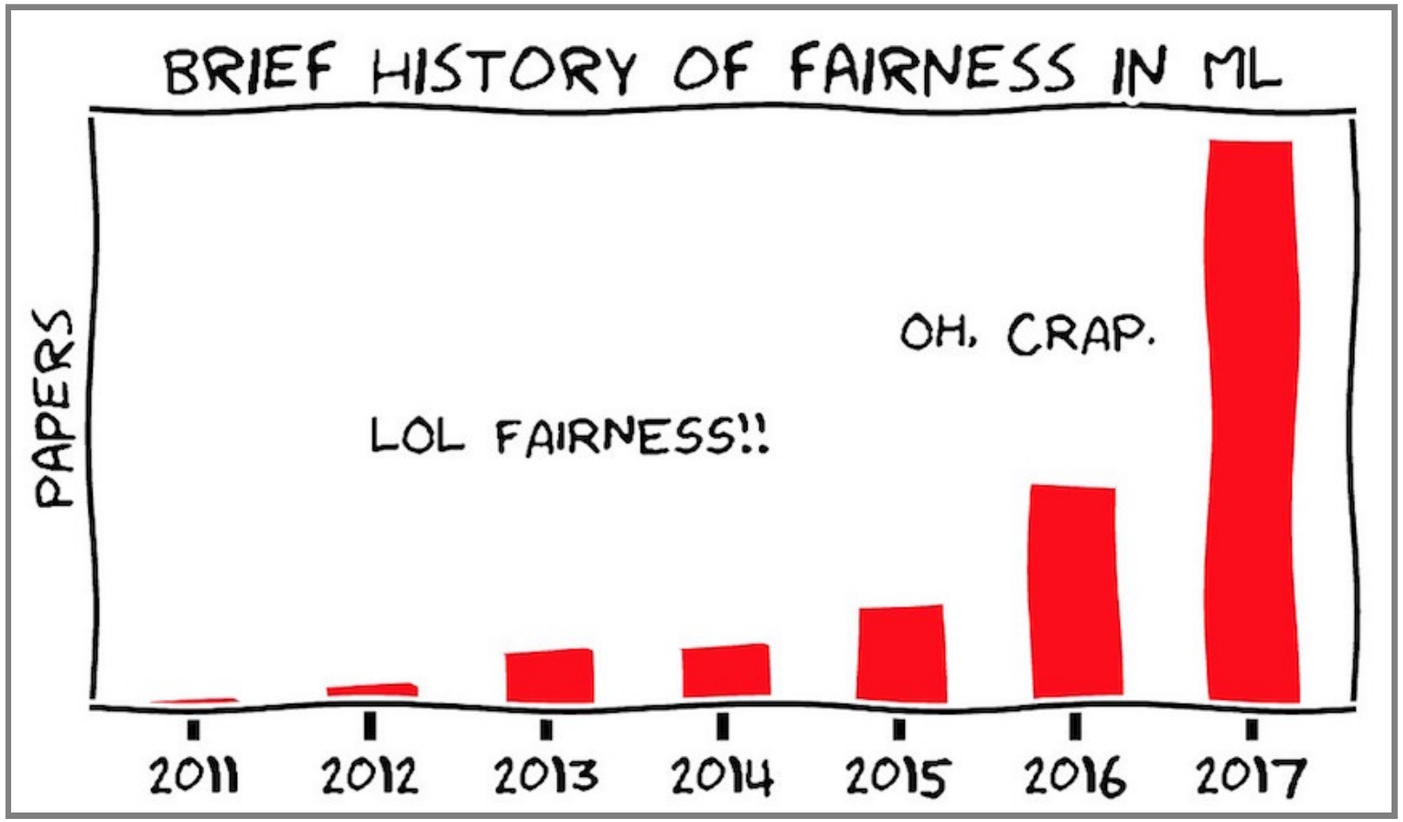
March 23, 2023, 3:00 a.m. ET

https://www.nytimes.com/2023/03/23/business/tiktok-screen-time.html

Fairness: Definitions

How do we measure the fairness of an ML model?

Fairness is still an actively studied & disputed concept!



Fairness: Definitions

- Anti-classification (fairness through blindness)
- Group fairness (independence)
- Equalized odds (separation)
- ...and numerous others and variations!

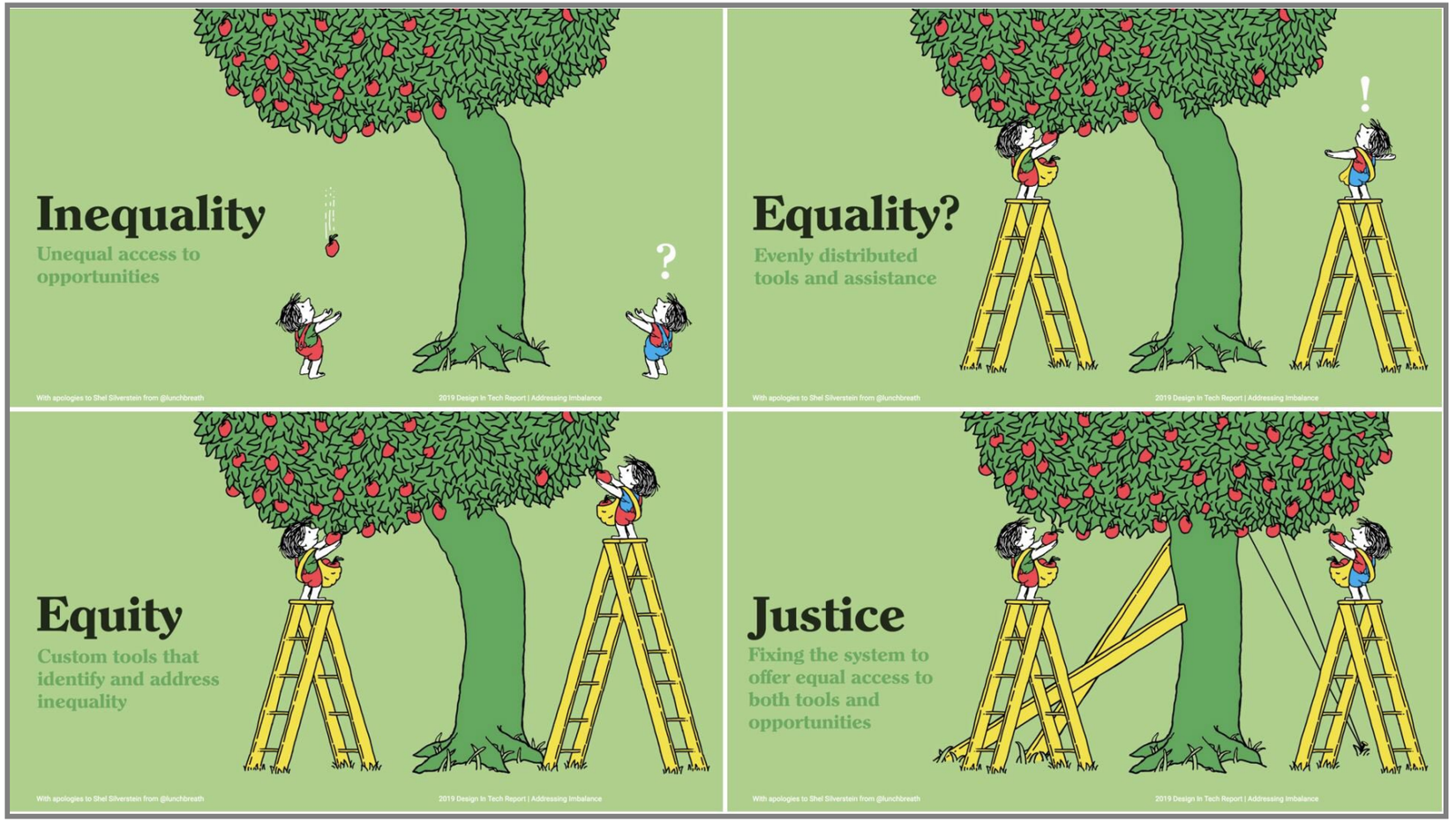
Running Example: Mortgage Applications

- Large loans repayed over long periods, large loss on default
- Home ownership is key path to build generational wealth
- Past decisions often discriminatory (redlining)
- Replace biased human decisions by objective and more accurate ML model
  - income, other debt, home value
  - past debt and payment behavior (credit score)

Recall: What is fair?

Fairness discourse asks questions about how to treat people and whether treating different groups of people differently is ethical. If two groups of people are systematically treated differently, this is often considered unfair.

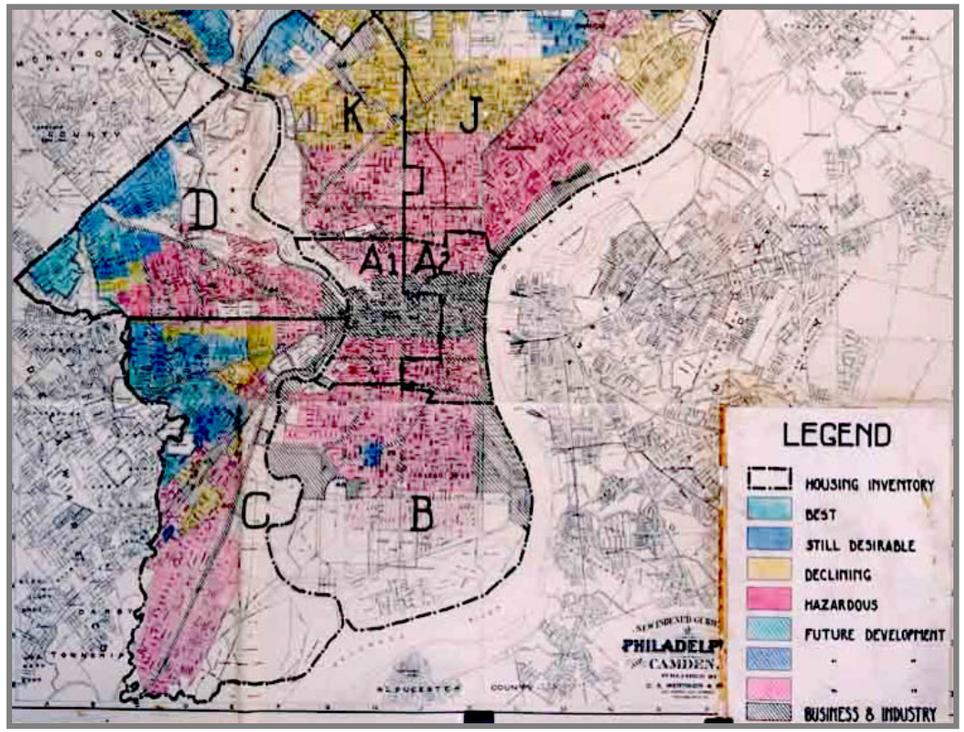
Recall: What is fair?



What is fair in mortgage applications?

1. Distribute loans equally across all groups of protected attribute(s) (e.g., ethnicity)
2. Prioritize those who are more likely to pay back (e.g., higher income, good credit history)

Redlining

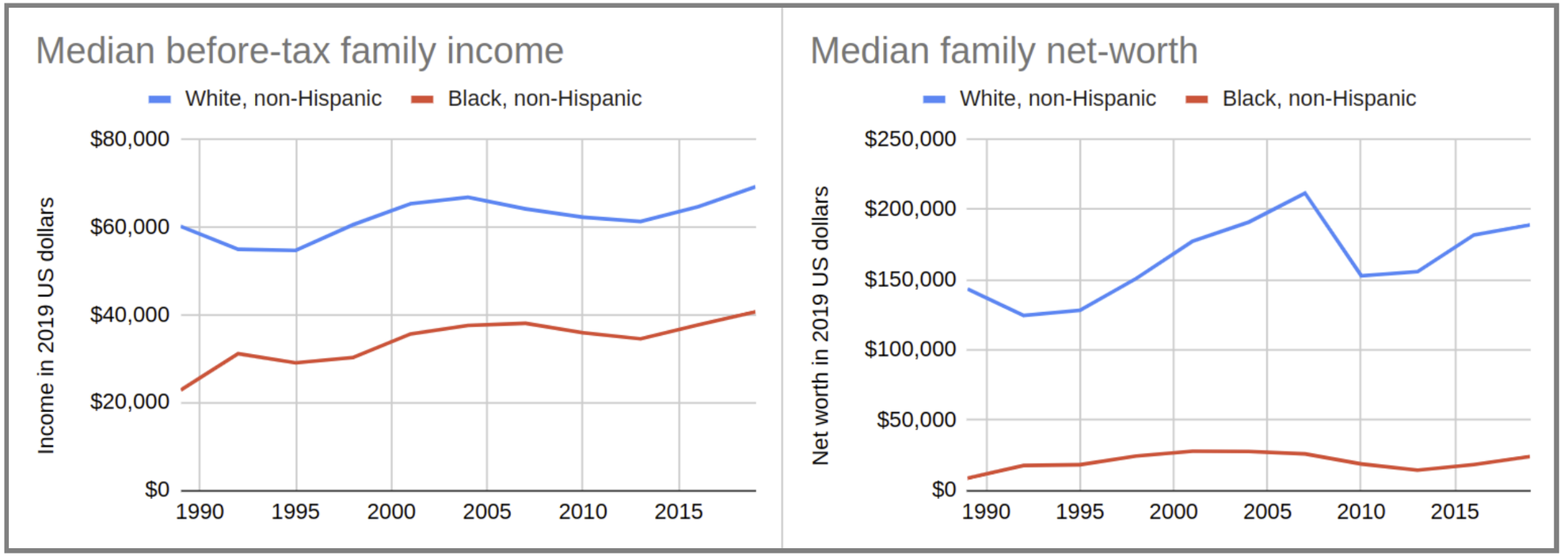


Withold services (e.g., mortgage, education, retail) from people in neighborhoods deemed "risky"

Map of Philadelphia, 1936, Home Owners' Loan Corps. (HOLC)

- Classification based on estimated "riskiness" of loans

Past bias, different starting positions



Source: Federal Reserve's Survey of Consumer Finances

Anti-classification

- **Anti-classification (fairness through blindness)**
- Group fairness (independence)
- Equalized odds (separation)
- ...and numerous others and variations!

Anti-Classification

- Also called *fairness through blindness* or *fairness through unawareness*
- Ignore certain sensitive attributes when making a decision
- Example: Remove gender and race from mortgage model

Anti-Classification: Example

Remote Appraisals of Homes Could Reduce Racial Bias

Desktop appraisals, in which an appraiser never meets a homeowner, could reduce discriminatory practices, such as undervaluing homes owned by Black people.

"After Ms. Horton removed all signs of Blackness, a second appraisal valued a Jacksonville home owned by her and her husband, Alex Horton, at 40 percent higher."

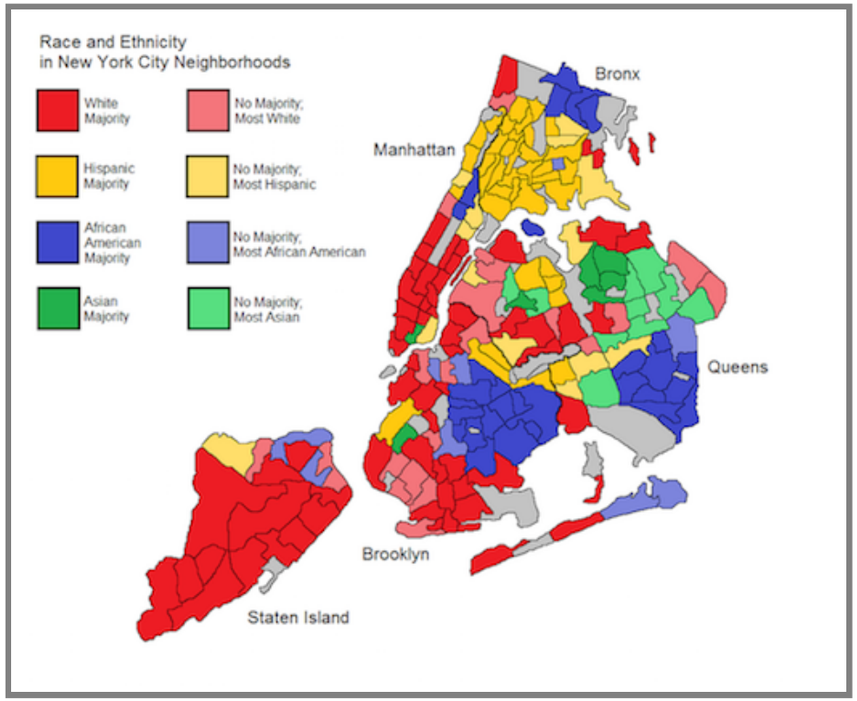
https://www.nytimes.com/2022/03/21/realestate/remote-home-appraisals-racial-bias.html

Anti-Classification

Easy to implement, but any limitations?

Recall: Proxies

Features correlate with protected attributes



Recall: Not all discrimination is harmful

- Loan lending: Gender and racial discrimination is illegal.
- Medical diagnosis: Gender/race-specific diagnosis may be desirable.
- Discrimination is a **domain-specific** concept!

Anti-Classification

- Ignore certain sensitive attributes when making a decision
- Advantage: Easy to implement and test
- Limitations
  - Sensitive attributes may be correlated with other features
  - Some ML tasks need sensitive attributes (e.g., medical diagnosis)

Ensuring Anti-Classification

How to train models that are fair w.r.t. anti-classification?

Ensuring Anti-Classification

How to train models that are fair w.r.t. anti-classification?

--> Simply remove features for protected attributes from training and inference data

--> Null/randomize protected attribute during inference

(does not account for correlated attributes, is not required to)

Testing Anti-Classification

How do we test that a classifier achieves anti-classification?

Testing Anti-Classification

Straightforward invariant for classifier f and protected attribute p:

$$\forall x.\ f(x[p \leftarrow 0]) = f(x[p \leftarrow 1])$$

(does not account for correlated attributes, is not required to)

Test with *any* test data, e.g., purely random data or existing test data

Any single inconsistency shows that the protected attribute was used.
Can also report percentage of inconsistencies.

See for example: Galhotra, Sainyam, Yuriy Brun, and Alexandra Meliou. "Fairness testing: testing software for discrimination." In Proceedings of the 2017 11th Joint Meeting on Foundations of Software Engineering, pp. 498-510. 2017.

Anti-Classification Discussion

Testing of anti-classification barely needed, because easy to ensure by constructing during training or inference!

Anti-classification is a good starting point to think about protected attributes

Useful baseline for comparison

Easy to implement, but only effective if (1) no proxies among features and (2) protected attributes add no predictive power

Group fairness

- Anti-classification (fairness through blindness)
- **Group fairness (independence)**
- Equalized odds (separation)
- ...and numerous others and variations!

Group fairness

Key idea: Compare outcomes across two groups

- Similar rates of accepted loans across racial/gender groups?
- Similar chance of being hired/promoted between gender groups?
- Similar rates of (predicted) recidivism across racial groups?

Outcomes matter, not accuracy!

Disparate impact vs. disparate treatment

Disparate treatment: Practices or rules that treat a certain protected group(s) differently from others

- e.g., Apply different mortgage rules for people from different backgrounds

Disparate impact: Neutral rules, but outcome is worse for one or more protected groups

- Same rules are applied, but certain groups have a harder time obtaining mortgage in a particular neighborhood

Group fairness in discrimination law

Relates to *disparate impact* and the four-fifth rule

Can sue organizations for discrimination if they

- mostly reject job applications from one minority group (identified by protected classes) and hire mostly from another
- reject most loans from one minority group and more frequently accept applicants from another

Notations

- : Feature set (e.g., age, race, education, region, income, etc.,) X
- : Sensitive attribute (e.g., gender) $A \subset X$
- : Regression score (e.g., predicted likelihood of on-time loan payment) R
- : Classifier output
  - if and only if for some threshold $Y' = 1$ $R \geq T$ T
  - e.g., Grant the loan () if the likelihood of paying back > 80% $Y' = 1$
- : Target variable being predicted (if the person actually pays back on time) Y $Y = 1$

Setting classification thresholds: Loan lending example

Group Fairness

$$P[Y' = 1 | A = a] = P[Y' = 1 | A = b]$$

- Also called *independence* or *demographic parity*
- Mathematically,
  - Prediction (Y') must be independent of the sensitive attribute (A)
- Examples:
  - The predicted rate of recidivism is the same across all races
  - Both women and men have the equal probability of being promoted
    - i.e., P[promote = 1 | gender = M] = P[promote = 1 | gender = F]

Group Fairness Limitations

What are limitations of group fairness?

Group Fairness Limitations

- Ignores possible correlation between Y and A
  - Rules out perfect predictor $Y' = Y$ when Y & A are correlated!
- Permits abuse and laziness: Can be satisfied by randomly assigning a positive outcome ($Y' = 1$) to protected groups
  - e.g., Randomly promote people (regardless of their job performance) to match the rate across all groups

Adjusting Thresholds for Group Fairness

Select different classification thresholds (,) for different groups (A = 0, A = 1) to achieve group fairness, such that t_0 t_1

$$P[R > t_0 | A = 0] = P[R >$$

Example: Mortgage application

- R: Likelihood of paying back the loan on time
- Suppose: With a uniform threshold used (i.e., R = 80%), group fairness is not achieved
  - P[R > 0.8 | A = 0] = 0.4, P[R > 0.8 | A = 1] = 0.7
- Adjust thresholds to achieve group fairness
  - P[R > 0.6 | A = 0] = P[R > 0.8 | A = 1]
- Wouldn't group A = 1 argue it's unfair? When does this type of adjustment make sense?

Testing Group Fairness

How would you test whether a classifier achieves group fairness?

Testing Group Fairness

Collect realistic, representative data (not randomly generated!)

- Use existing validation/test data
- Monitor production data
- (Somehow) generate realistic test data, e.g. from probability distribution of population

Separately measure the rate of positive predictions

- e.g., P[promoted = 1 | gender = M], P[promoted = 1 | gender = F] = ?

Report issue if the rates differ beyond some threshold ϵ across groups

Equalized odds

- Anti-classification (fairness through blindness)
- Group fairness (independence)
- **Equalized odds (separation)**
- ...and numerous others and variations!

Equalized odds

Key idea: Focus on accuracy (not outcomes) across two groups

- Similar default rates on accepted loans across racial/gender groups?
- Similar rate of "bad hires" and "missed stars" between gender groups?
- Similar accuracy of predicted recidivism vs actual recidivism across racial groups?

Accuracy matters, not outcomes!

Equalized odds in discrimination law

Relates to *disparate treatment*

Typically, lawsuits claim that protected attributes (e.g., race, gender) were used in decisions even though they were irrelevant

- e.g., fired over complaint because of being Latino, whereas other White employees were not fired with similar complaints

Must prove that the defendant had *intention* to discriminate

- Often difficult: Relying on shifting justifications, inconsistent application of rules, or explicit remarks overheard or documented

Equalized odds

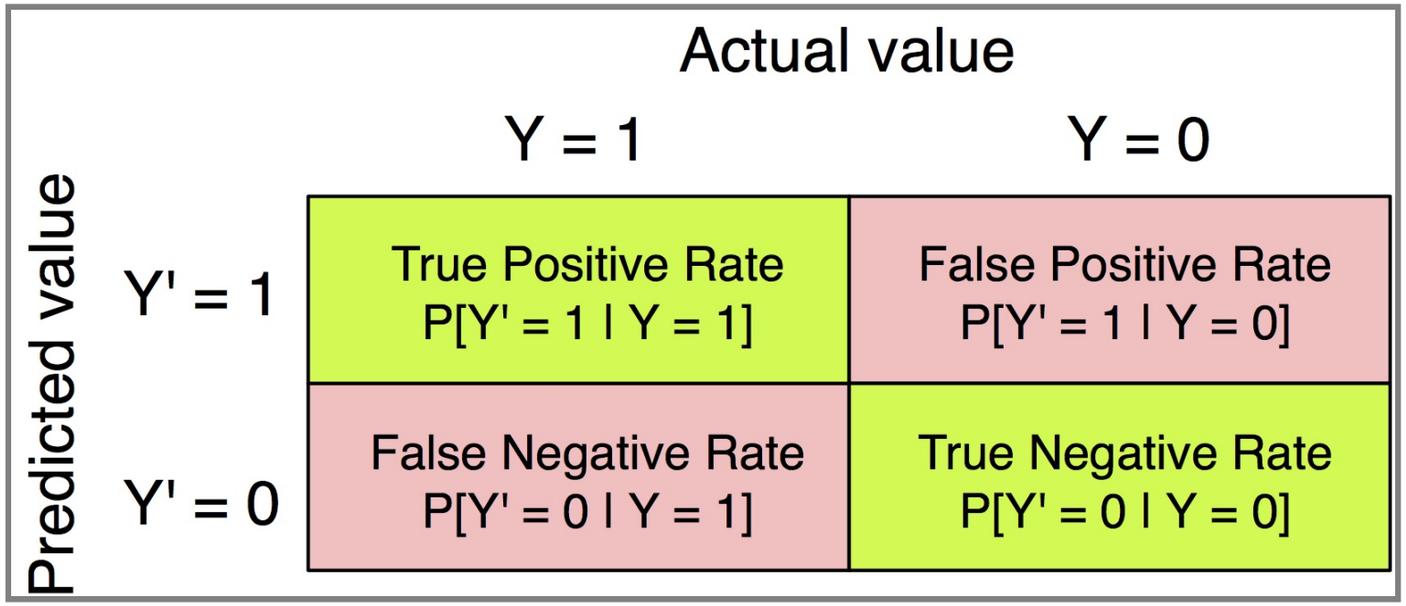
$$P[Y' = 1 \mid Y = 0, A = a] = P[Y' = 1 \mid Y = 0, A = b]$$

Statistical property of *separation*:

- Prediction must be independent of the sensitive attribute *conditional* on the target variable

$$Y' \perp A | Y$$

Review: Confusion Matrix



Can we explain separation in terms of model errors?

- $P[Y' = 1 \mid Y = 0, A = a] = P[Y' = 1 \mid Y = 0, A = b]$
  $P[Y' = 0 \mid Y = 1, A = a] = P[Y' = 0 \mid Y = 1, A = b]$

Separation

(FPR parity)
$$P[Y' = 1 \mid Y = 0, A = a] = P[Y' = 1 \mid Y = 0, A = b]$$
(FNR parity)
$$P[Y' = 0 \mid Y = 1, A = a] = P[Y' = 0 \mid Y = 1, A = b]$$

- : Prediction must be independent of the sensitive attribute *conditional* on the target variable $Y' \perp A|Y$
- i.e., All groups are susceptible to the same false positive/negative rates
- Example: Y': Promotion decision, A: Gender of applicant: Y: Actual job performance

Testing Separation

Requires realistic representative test data (telemetry or representative test data, not random)

Separately measure false positive and false negative rates

- e..g, for FNR, compare P[promoted = 0 | female, good employee] vs P[promoted = 0 | male, good employee]

How is this different from testing group fairness?

Breakout: Cancer Prognosis

	Male Patient Results	
	Actual cancer	Actually no cancer
Predicted cancer	23	11
Predicted no cancer	41	925

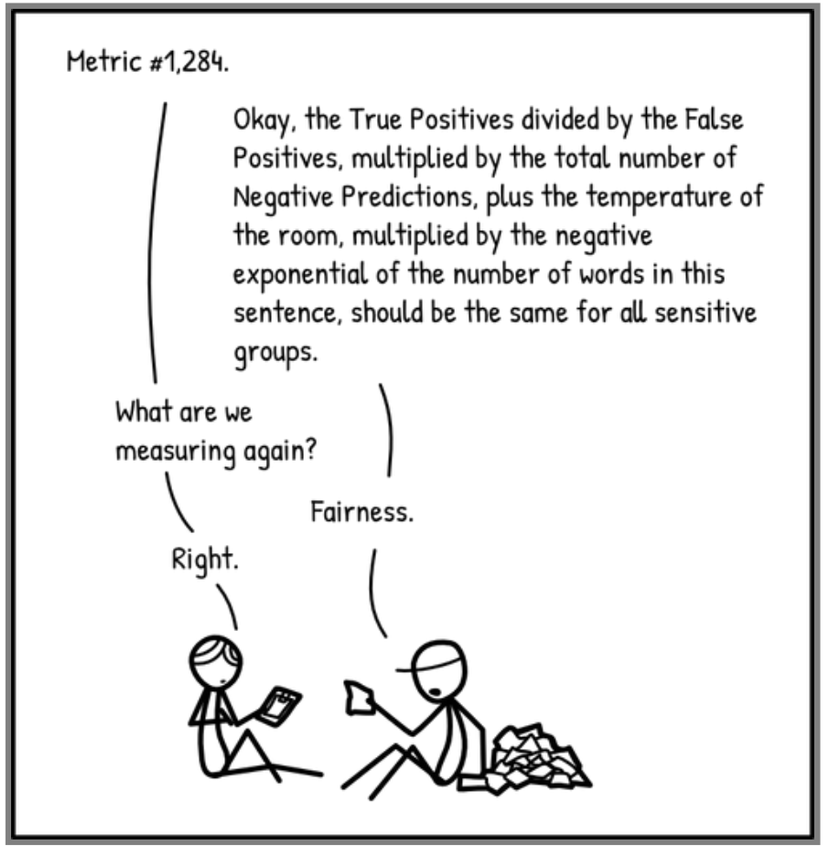
	Female Patient Results	
	Actual cancer	Actually no cancer
Predicted cancer	13	5
Predicted no cancer	2	480

In groups, post to `#lecture` tagging members:

- Does the model meet anti-classification fairness w.r.t. gender?
- Does the model meet group fairness?
- Does the model meet equalized odds?
- Is the model fair enough to use?

Other fairness measures

- Anti-classification (fairness through blindness)
- Group fairness (independence)
- Equalized odds (separation)**
- **...and numerous others and variations!**


Metric #1,284.
Okay, the True Positives divided by the False Positives, multiplied by the total number of Negative Predictions, plus the temperature of the room, multiplied by the negative exponential of the number of words in this sentence, should be the same for all sensitive groups.
What are we measuring again?
Fairness.
Right.

Many measures

Many measures proposed

Some specialized for tasks (e.g., ranking, NLP)

Some consider downstream utility of various outcomes

Most are similar to the three discussed

- Comparing different measures in the error matrix (e.g., false positive rate, lift)

Outlook: Building Fair ML-Based Products

Next lecture: Fairness is a *system-wide* concern

- Identifying and negotiating fairness requirements
- Fairness beyond model predictions (product design, mitigations, data collection)
- Fairness in process and teamwork, barriers and responsibilities
- Documenting fairness at the interface
- Monitoring
- Promoting best practices

Summary

- Three definitions of fairness: Anti-classification, group fairness, equalized odds
- Tradeoffs between fairness criteria
  - What is the goal?
  - Key: how to deal with unequal starting positions
- Improving fairness of a model
  - In all *pipeline stages*: data collection, data cleaning, training, inference, evaluation

Further Readings

- Ian Foster, Rayid Ghani, Ron S. Jarmin, Frauke Kreuter and Julia Lane. Big Data and Social Science: Data Science Methods and Tools for Research and Practice. Chapter 11, 2nd ed, 2020
- Solon Barocas and Moritz Hardt and Arvind Narayanan. Fairness and Machine Learning. 2019 (incomplete book)
- Pessach, Dana, and Erez Shmueli. "A Review on Fairness in Machine Learning." ACM Computing Surveys (CSUR) 55, no. 3 (2022): 1-44.

Practitioner Challenges

- Fairness is a system-level property
  - Consider goals, user interaction design, data collection, monitoring, model interaction (properties of a single model may not matter much)
- Fairness-aware data collection, fairness testing for training data
- Identifying blind spots
  - Proactive vs reactive
  - Team bias and (domain-specific) checklists
- Fairness auditing processes and tools
- Diagnosis and debugging (outlier or systemic problem? causes?)
- Guiding interventions (adjust goals? more data? side effects? chasing mistakes? redesign?)