FAIRNESS: DEFINITIONS AND MEASUREMENTS

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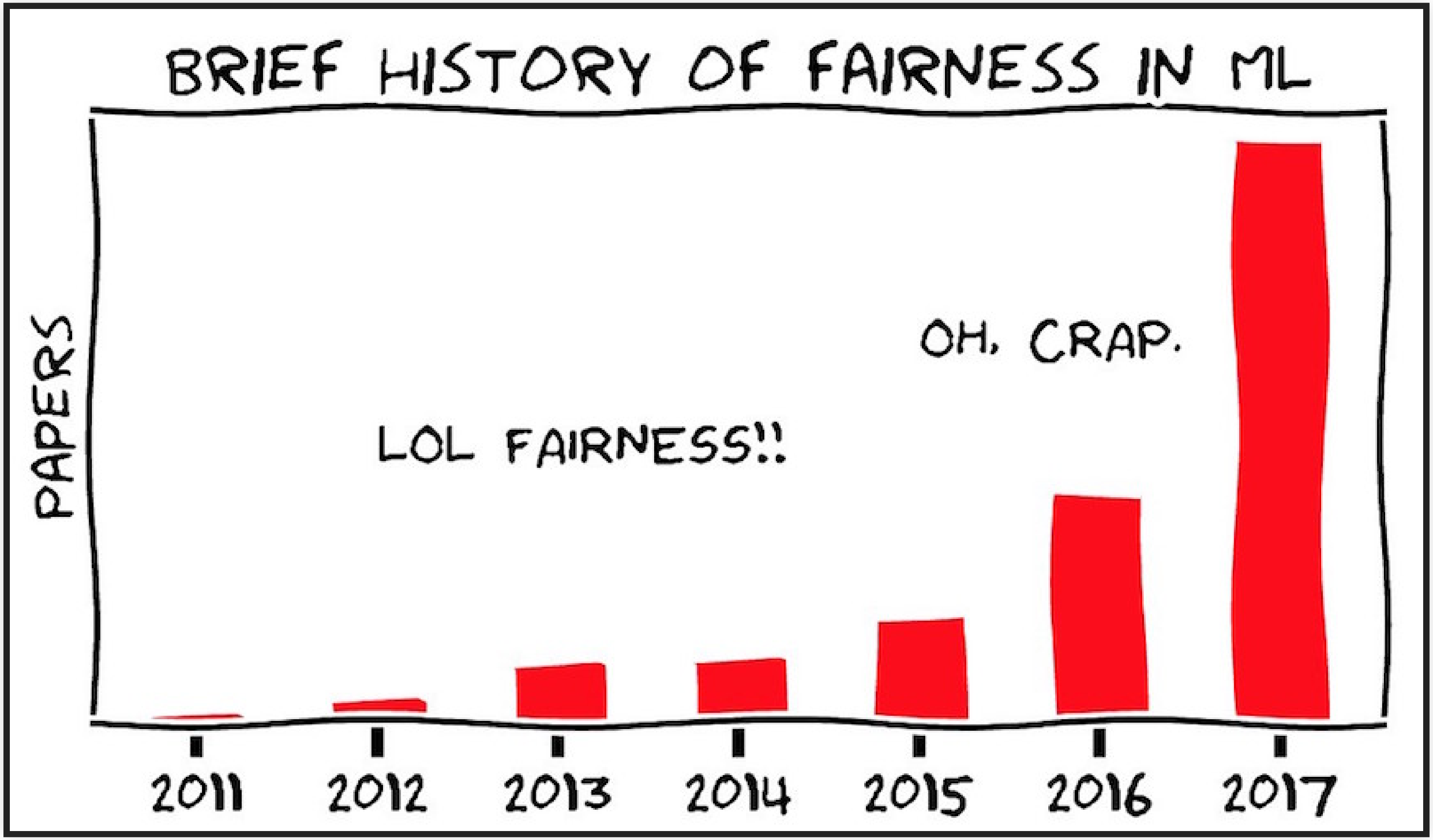
Required reading: Holstein, Kenneth, Jennifer Wortman Vaughan, Hal Daumé III, Miro Dudik, and Hanna Wallach. "Improving fairness in machine learning systems: What do industry practitioners need?" In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-16. 2019.

LEARNING GOALS

- Understand different definitions of fairness
- Discuss methods for measuring fairness

FAIRNESS: DEFINITIONS

FAIRNESS IS STILL AN ACTIVELY STUDIED & DISPUTED CONCEPT!



Source: Mortiz Hardt, https://fairmlclass.github.io/

FAIRNESS: DEFINITIONS

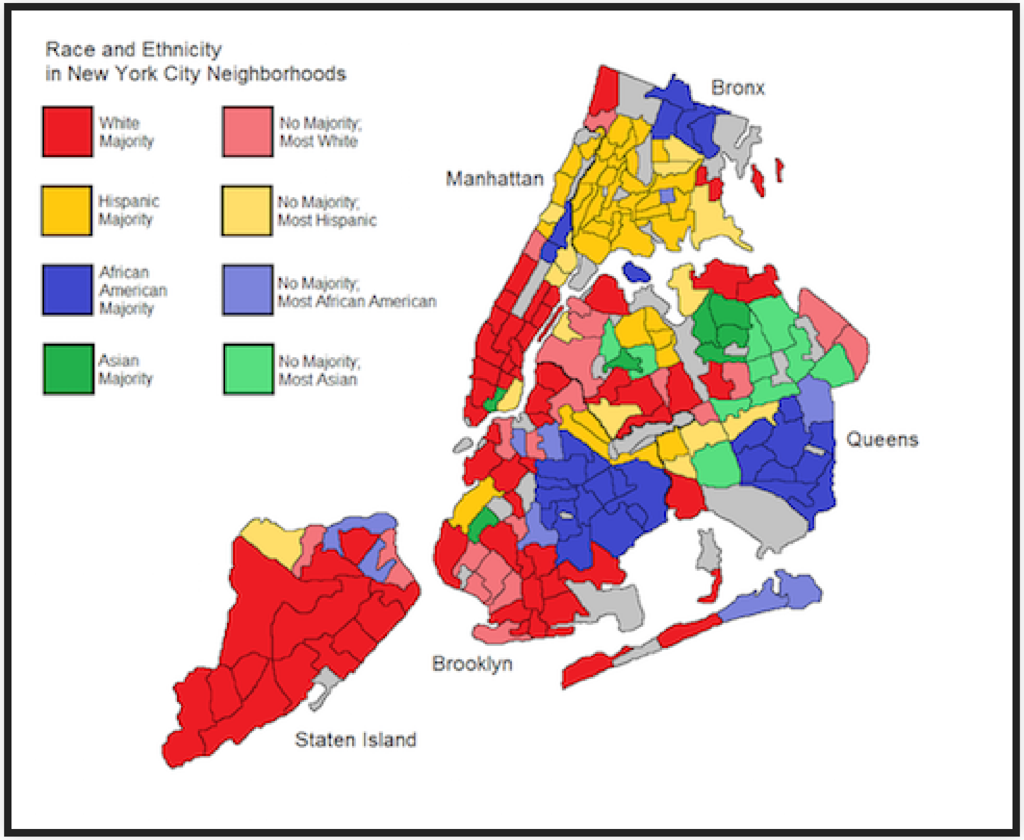
- Anti-classification (fairness through blindness)
- Independence (group fairness)
- Separation (equalized odds)
- ...and numerous others!

ANTI-CLASSIFICATION

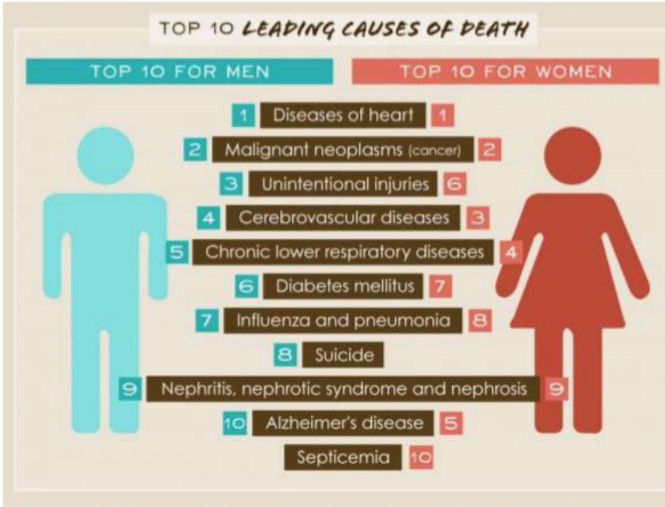
- Also called *fairness through blindness*
- Ignore/eliminate sensitive attributes from dataset
- Example: Remove gender or race from a credit card scoring system
- **Q. Advantages and limitations**?

RECALL: PROXIES

Features correlate with protected attributes



RECALL: NOT ALL DISCRIMINATION IS HARMFUL



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

Other examples?

ANTI-CLASSIFICATION

- Ignore/eliminate sensitive attributes from dataset
- Limitations
  - Sensitive attributes may be correlated with other features
  - Some ML tasks need sensitive attributes (e.g., medical diagnosis)

TESTING ANTI-CLASSIFICATION

How do we test that an ML model 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)

Test with random input data or on any 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.

NOTATIONS

- X: Feature set (e.g., age, race, education, region, income, etc.,)
- $A \in X$: Sensitive attribute (e.g., gender)
- R: Regression score (e.g., predicted likelihood of loan default)
- $Y^{'}$: Classifier output
  - $Y^{'} = 1$ if and only if $R > T$ for some threshold T
  - e.g., Deny the loan ($Y^{'} = 1$) if the likelihood of default > 30%
- Y: Target variable being predicted ($Y = 1$ if the person actually defaults on loan)

INDEPENDENCE

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

- Also called *group fairness* or *demographic parity*
- Mathematically, $Y' \perp A$
    - 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]

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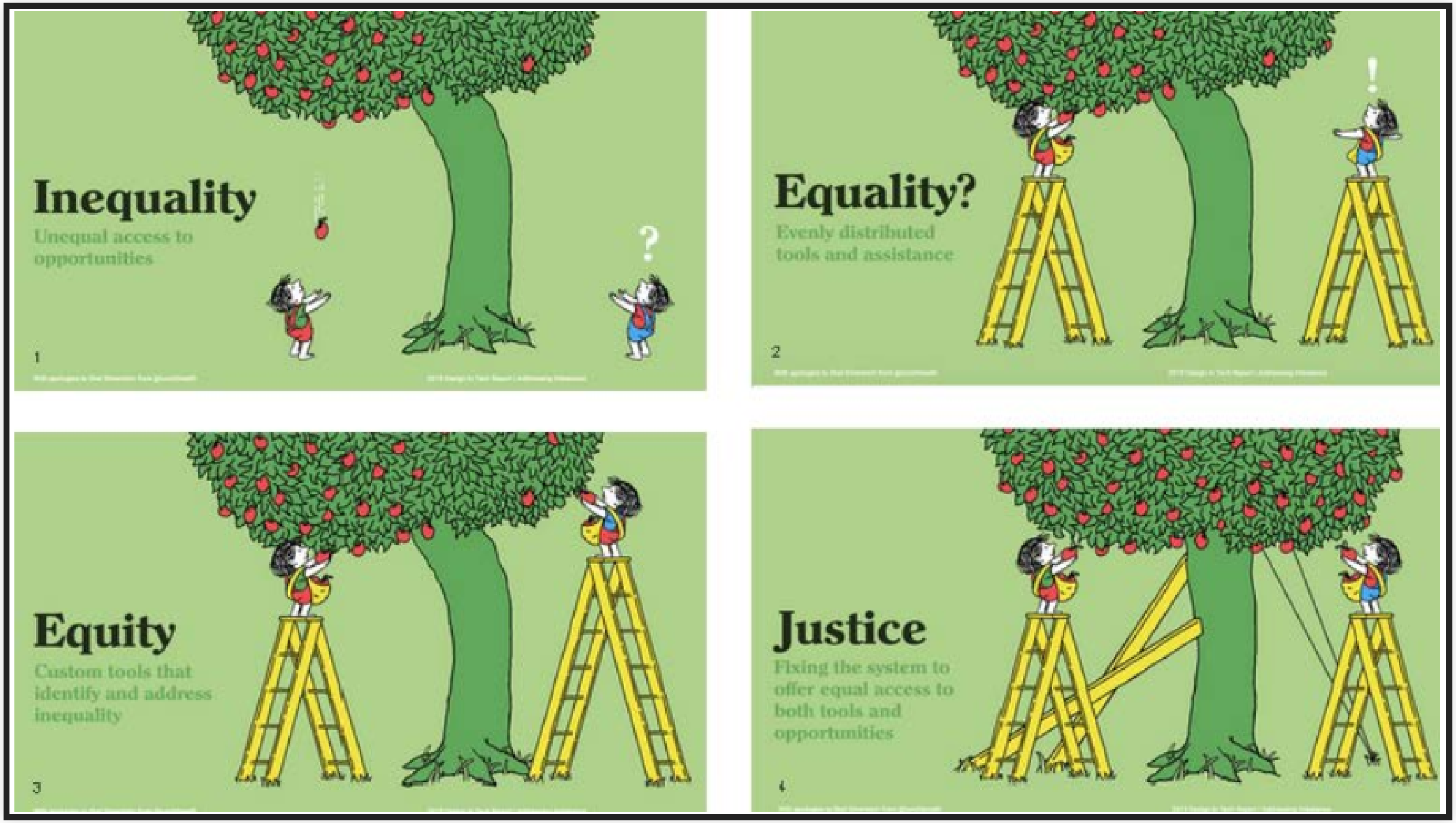
- Q. What are limitations of independence?
    - Ignores possible correlation between Y and A
        - Rules out perfect predictor $Y' = Y$ when Y & A are correlated
    - Permits abuse and laziness: Can be satisfied by randomly assigning a positive outcome ($Y' = 1$) to protected groups
        - e.g.,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

RECALL: EQUALITY VS EQUITY



CALIBRATION TO ACHIEVE INDEPENDENCE

Select different thresholds for different groups to achieve prediction parity:

$$P[R > t_0 | A = 0] = P[R > t_1 | A = 1]$$

Lowers bar for some groups -- equity, not equality

TESTING INDEPENDENCE

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  - Or generate realistic test data, e.g. from probability distribution of population
- Separately measure rate of positive predictions
- Report issue if rate differs beyond ϵ across groups

SEPARATION

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

- Also called *equalized odds*
- $Y' \perp A | Y$
  - Prediction must be independent of the sensitive attribute *conditional* on the target variable

REVIEW: CONFUSION MATRIX

		Actual value	
		Y = 1	Y = 0
Predicted value	Y' = 1	True Positive Rate P[Y' = 1 | Y = 1]	False Positive Rate P[Y' = 1 | Y = 0]
	Y' = 0	False Negative Rate P[Y' = 0 | Y = 1]	True Negative Rate P[Y' = 0 | Y = 0]

Can we explain separation in terms of model errors?

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SEPARATION

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

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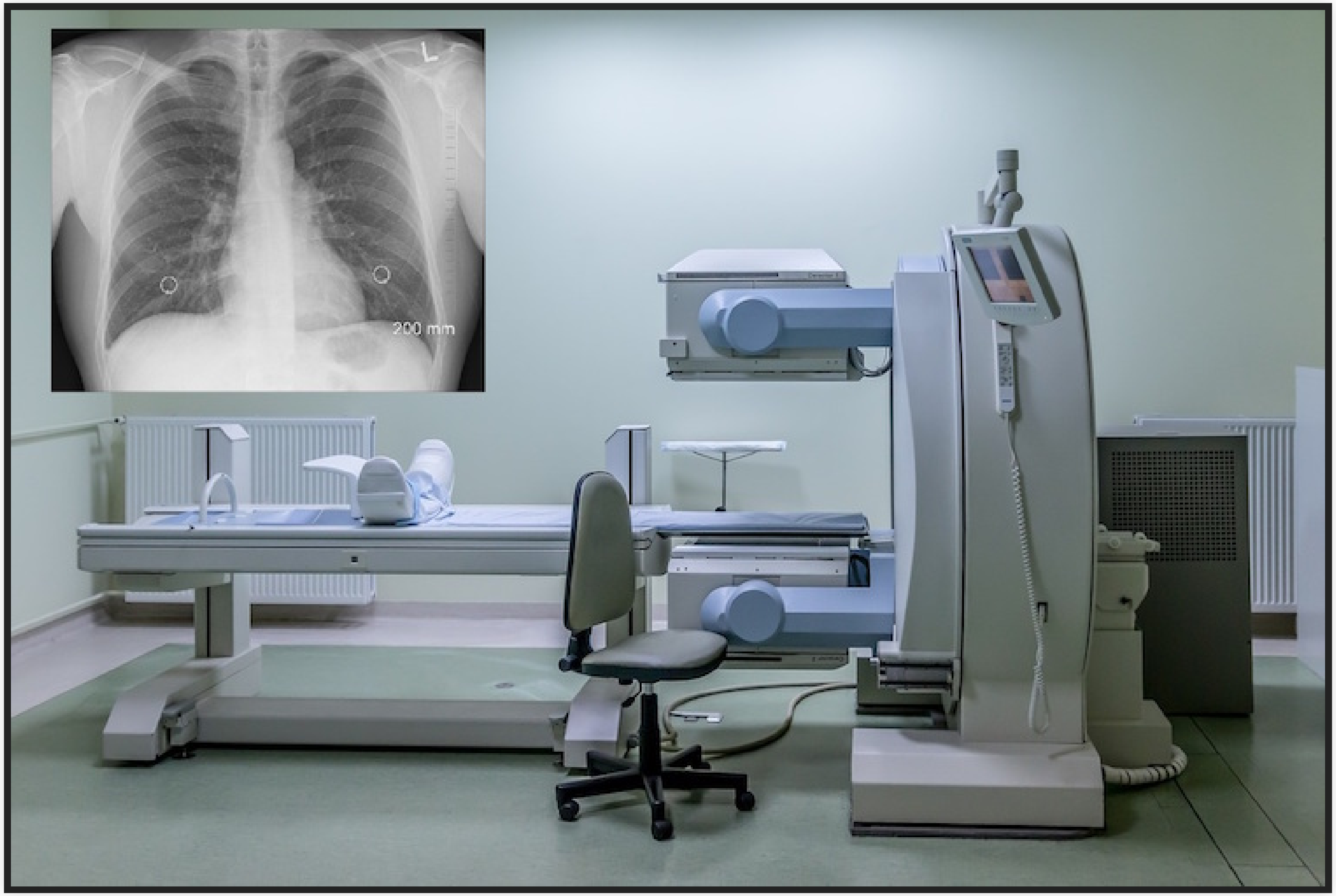
- $Y' \perp A | Y$
    - Prediction must be independent of the sensitive attribute *conditional* on the target variable
- i.e., All groups are susceptible to the same false positive/negative rates
- Example: Promotion
    - Y': Promotion decision, A: Gender of applicant: Y: Actual job performance
    - Separation w/ FNR: Probability of being incorrectly denied promotion is equal across both male & female employees

TESTING SEPARATION

- Generate separate validation sets for each group
- Separate validation/telemetry data by protected attribute
    - Or generate *realistic* test data, e.g. from probability distribution of population
- Separately measure false positive and false negative rates

CASE STUDY: CANCER DIAGNOSIS



EXERCISE: CANCER DIAGNOSIS

Overall Results

True positives (TPs): 16	False positives (FPs): 21
False negatives (FNs): 9	True negatives (TNs): 954

Male Patient Results

True positives (TPs): 3	False positives (FPs): 16
False negatives (FNs): 7	True negatives (TNs): 474

Female Patient Results

True positives (TPs): 13	False positives (FPs): 5
False negatives (FNs): 2	True negatives (TNs): 480

- 1000 data samples (500 male & 500 female patients)
- Does the model achieve independence? Separation w/ FPR or FNR?
- What can we conclude about the model & its usage?

REVIEW OF CRITERIA SO FAR:

Recidivism scenario: Should a person be detained?

- Anti-classification: ?
- Independence: ?
- Separation: ?

REVIEW OF CRITERIA SO FAR:

Recidivism scenario: Should a defendant be detained?

- Anti-classification: Race and gender should not be considered for the decision at all
- Independence: Detention rates should be equal across gender and race groups
- Separation: Among defendants who would not have gone on to commit a violent crime if released, detention rates are equal across gender and race groups

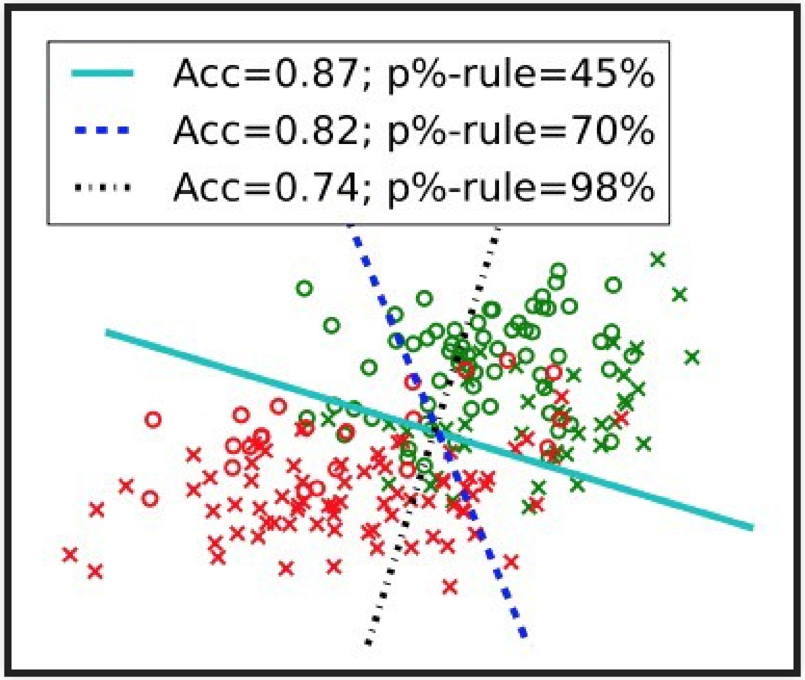
ACHIEVING FAIRNESS CRITERIA

CAN WE ACHIEVE FAIRNESS DURING THE LEARNING PROCESS?

- Data acquisition:
  - Collect additional data if performance is poor on some groups
- Pre-processing:
  - Clean the dataset to reduce correlation between the feature set and sensitive attributes
- Training time constraint
  - ML is a constraint optimization problem (i.e., minimize errors)
  - Impose additional parity constraint into ML optimization process (as part of the loss function)
- Post-processing
  - Adjust thresholds to achieve a desired fairness metric
- (Still active area of research! Many new techniques published each year)

Training Well-Generalizing Classifiers for Fairness Metrics and Other Data-Dependent Constraints, Cotter et al., (2018).

TRADE-OFFS: ACCURACY VS FAIRNESS



- In general, accuracy is at odds with fairness
    - e.g., Impossible to achieve perfect accuracy ($R = Y$) while ensuring independence
- Determine how much compromise in accuracy or fairness is acceptable to your stakeholders

Fairness Constraints: Mechanisms for Fair Classification, Zafar et al., AISTATS (2017).

SUMMARY

- Definitions of fairness
  - Anti-classification, independence, separation
- Achieving fairness
  - Trade-offs between accuracy & fairness