FAIRNESS: DEFINITIONS AND MEASUREMENTS

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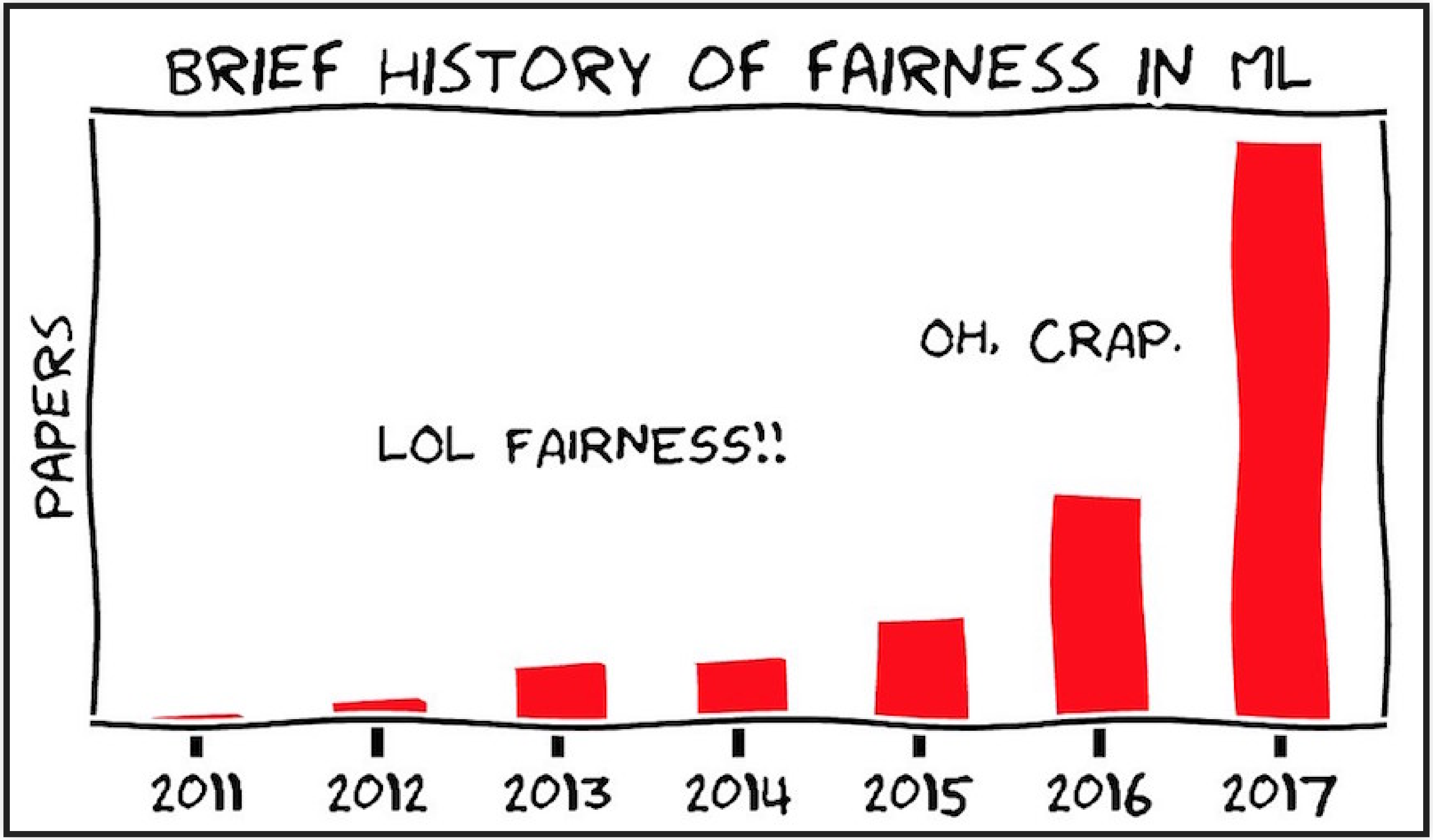
Required reading: Holstein, Kenneth, Jennifer Wortman Vaughan, Hal Daumé III, Miro Dudik, and Hanna Wallach. "Improving fairness in machine learning systems: What do industry practitioners need?" In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-16. 2019.

LEARNING GOALS

- Understand different definitions of fairness
- Discuss methods for measuring fairness
- Consider fairness throughout an ML lifecycle

FAIRNESS: DEFINITIONS

FAIRNESS IS STILL AN ACTIVELY STUDIED & DISPUTED CONCEPT!



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

FAIRNESS: DEFINITIONS

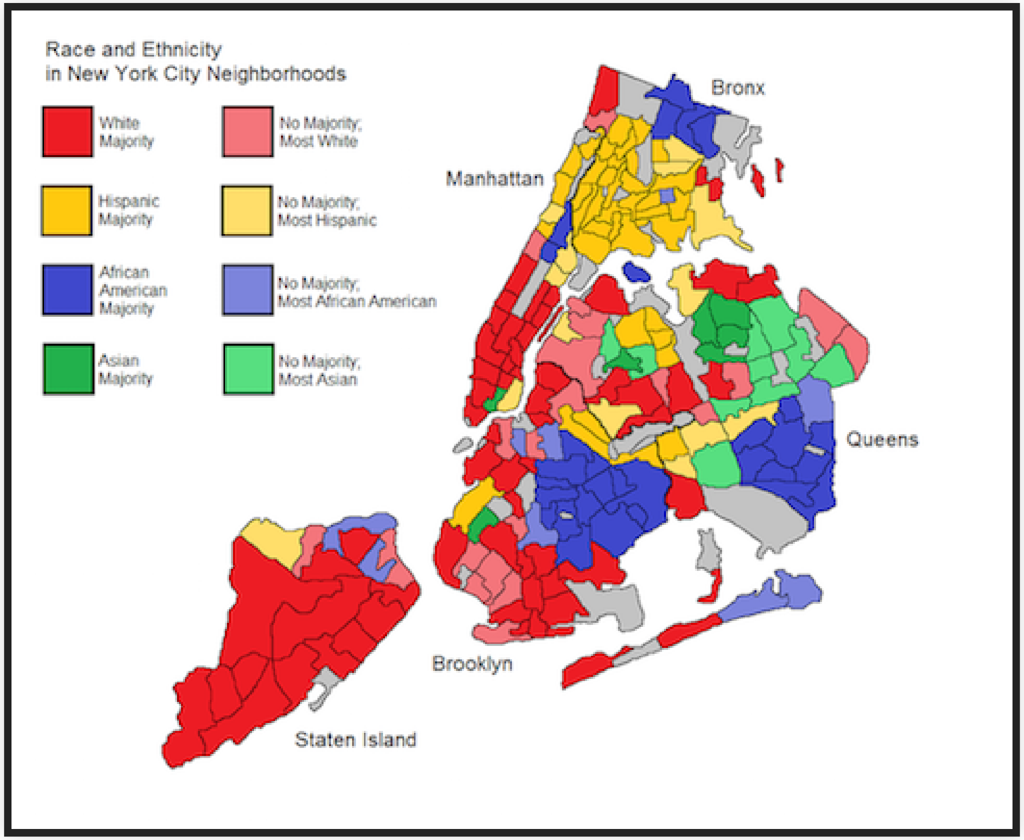
- Anti-classification (fairness through blindness)
- Independence (group fairness)
- Separation (equalized odds)
- ...and numerous others!

ANTI-CLASSIFICATION

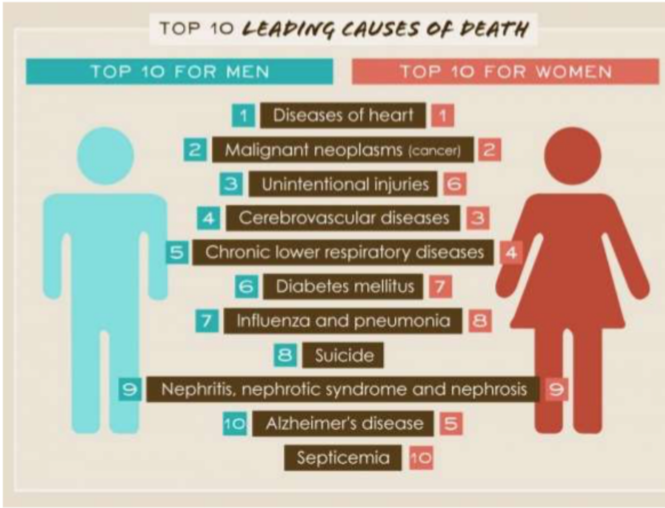
- Also called *fairness through blindness*
- Ignore/eliminate sensitive attributes from dataset
- Example: Remove gender or race from a credit card scoring system
- **Q. Advantages and limitations**?

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)

Setting classification thresholds: Loan lending example

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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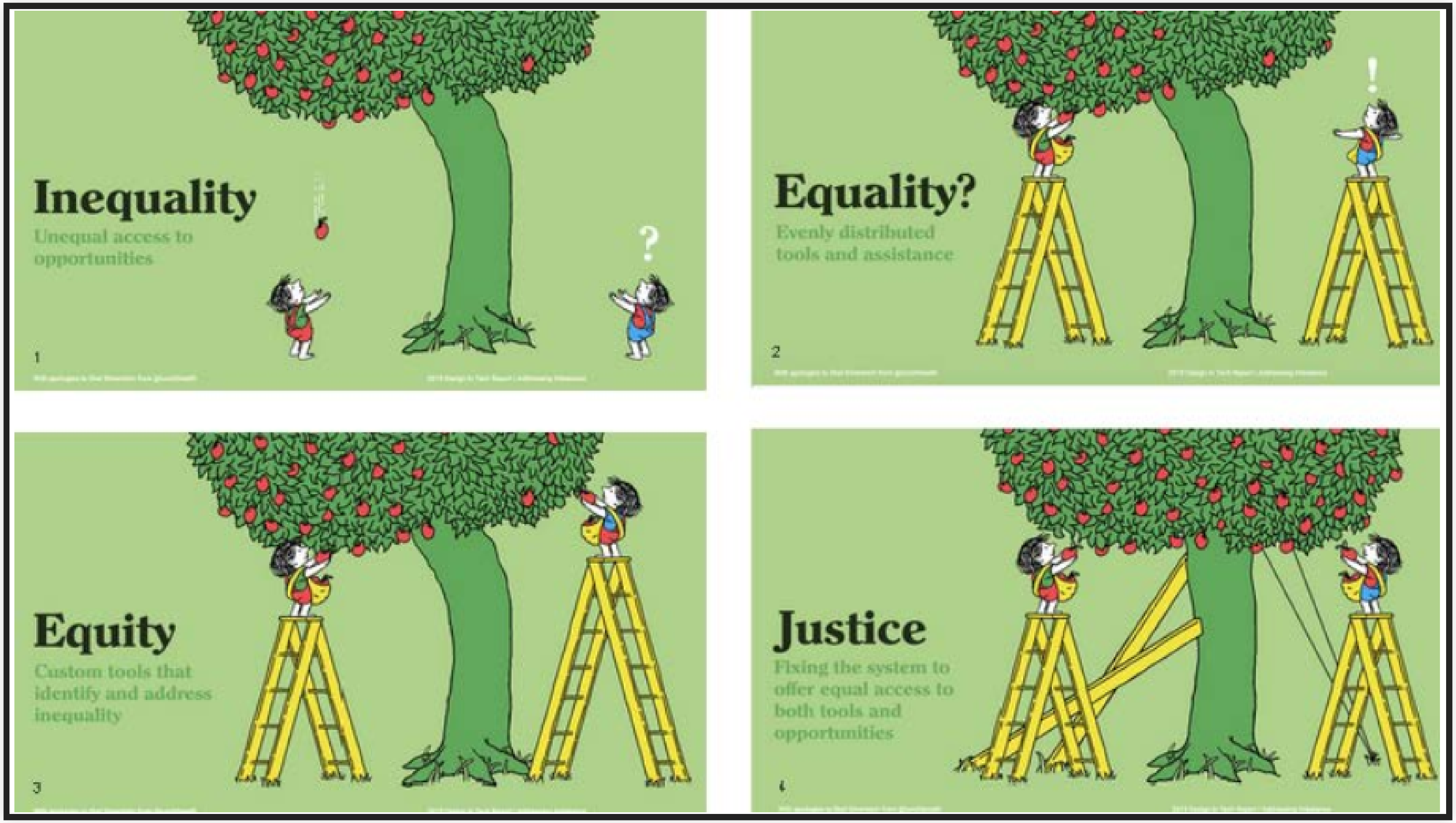
- Q. What are limitations of independence?
  - Ignores possible correlation between Y and A
    - Rules out perfect predictor $Y' = Y$ when Y & A are correlated
  - Permits abuse and laziness: Can be satisfied by randomly assigning a positive outcome ($Y' = 1$) to protected groups
    - e.g., Randomly 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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- Separate validation/telemetry data by protected attribute
  - 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 $P[Y' = 1 \mid Y = 1]$	False Positive Rate $P[Y' = 1 \mid Y = 0]$
	Y' = 0	False Negative Rate $P[Y' = 0 \mid Y = 1]$	True Negative Rate $P[Y' = 0 \mid Y = 0]$

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

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

- $Y^{'} \perp A | Y$
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- $Y' \perp A \mid Y$
  - 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

SEPARATION

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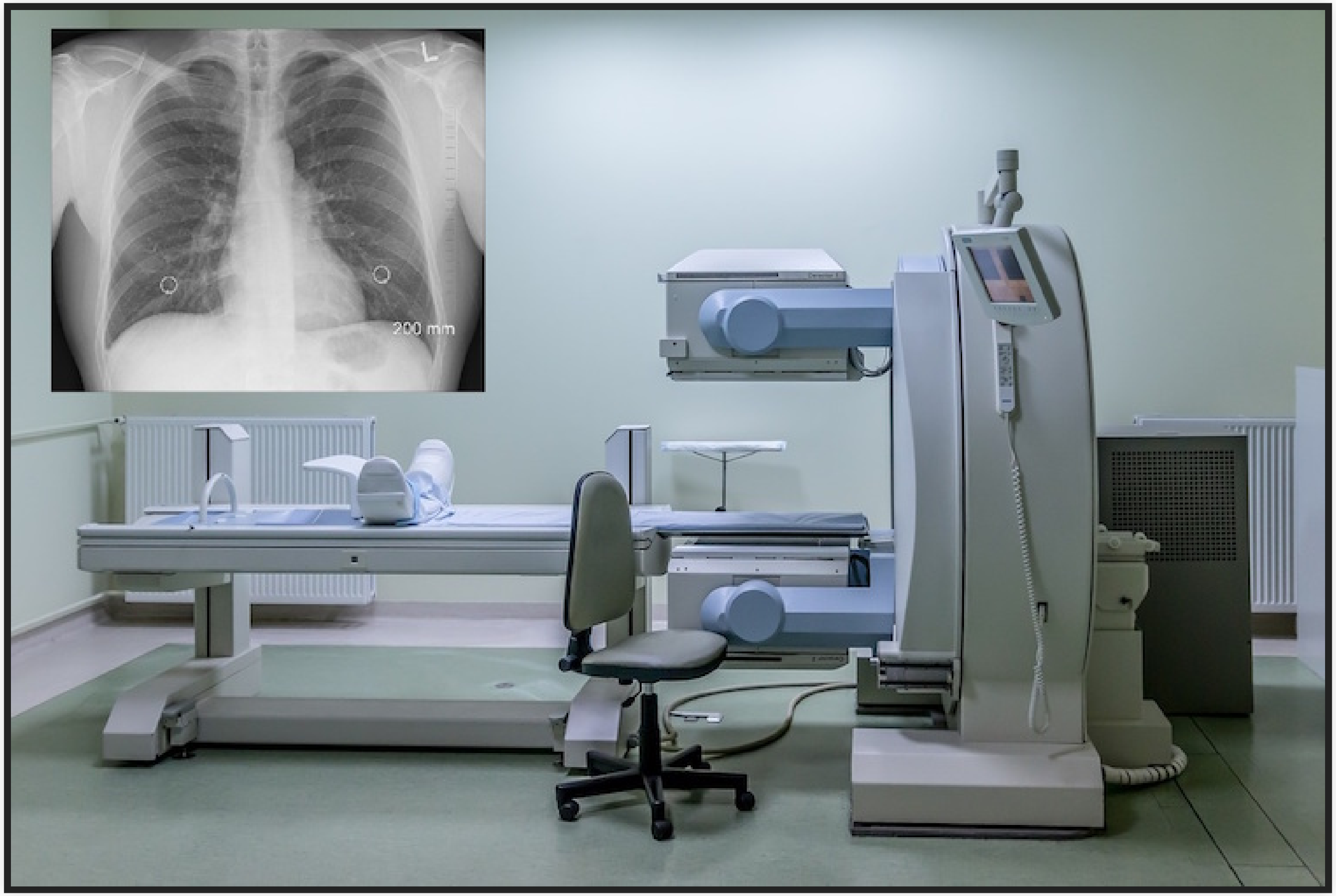
- $Y' \perp A | Y$
  - Prediction must be independent of the sensitive attribute *conditional* on the target variable
- i.e., All groups are susceptible to the same false positive/negative rates
- Example: Promotion
  - Y': Promotion decision, A: Gender of applicant: Y: Actual job performance
  - Separation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

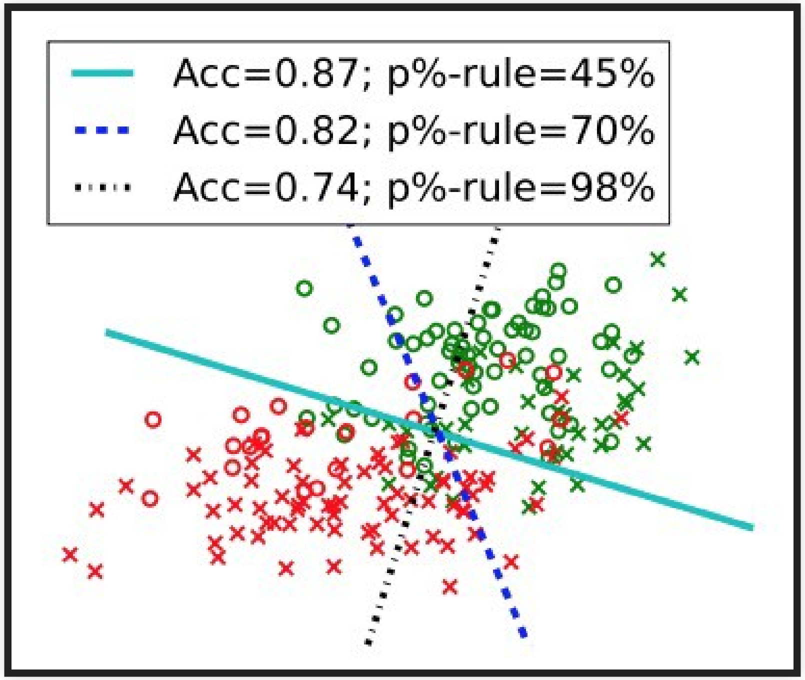
ACHIEVING FAIRNESS CRITERIA

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

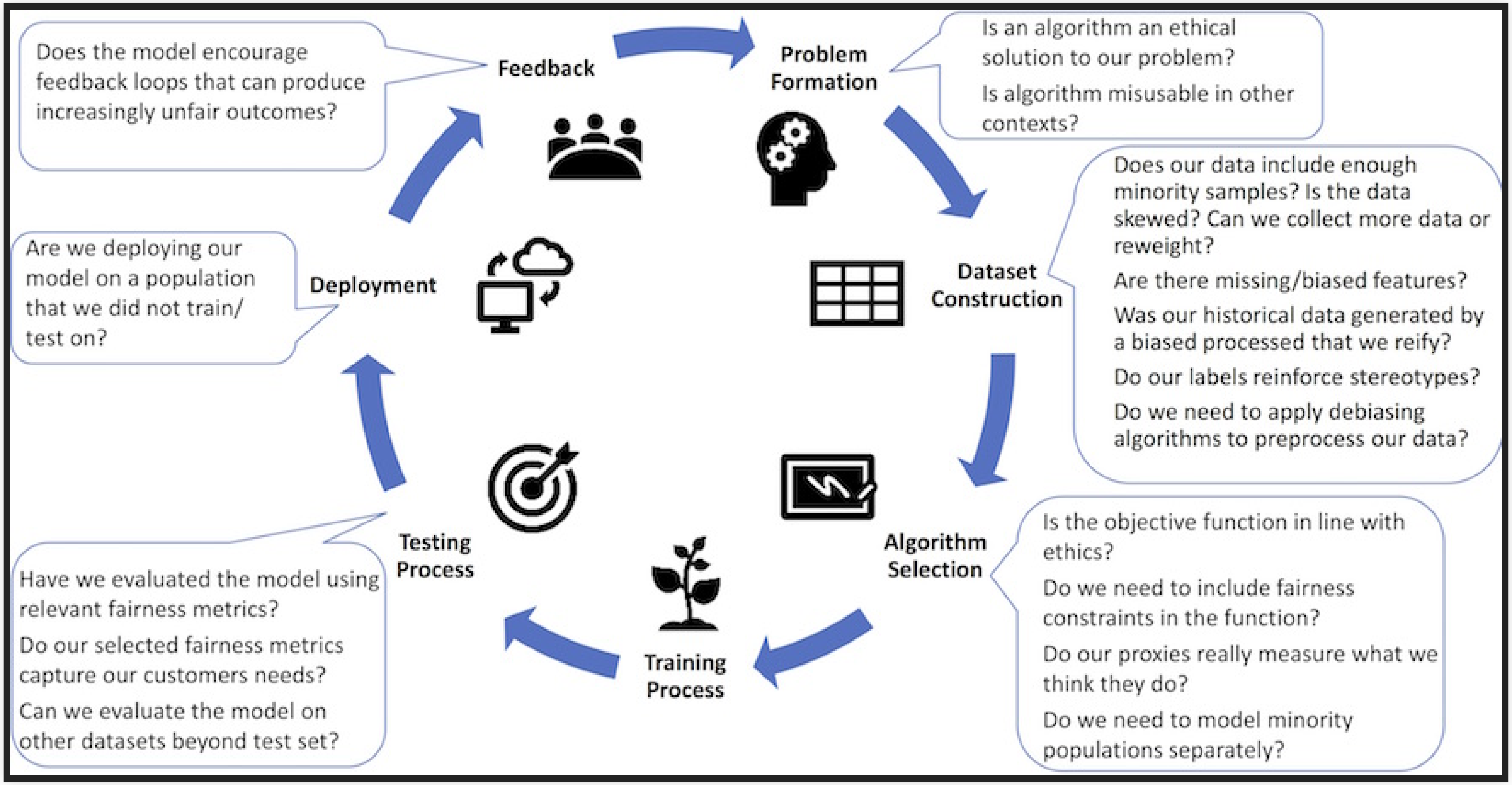


- In general, accuracy is at odds with fairness
  - e.g., Impossible to achieve perfect accuracy ($R = Y$) while ensuring independence
- Determine how much compromise in accuracy or fairness is acceptable to your stakeholders

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

BUILDING FAIR ML SYSTEMS

FAIRNESS MUST BE CONSIDERED THROUGHOUT THE ML LIFECYCLE!



Fairness-aware Machine Learning, Bennett et al., WSDM Tutorial (2019).

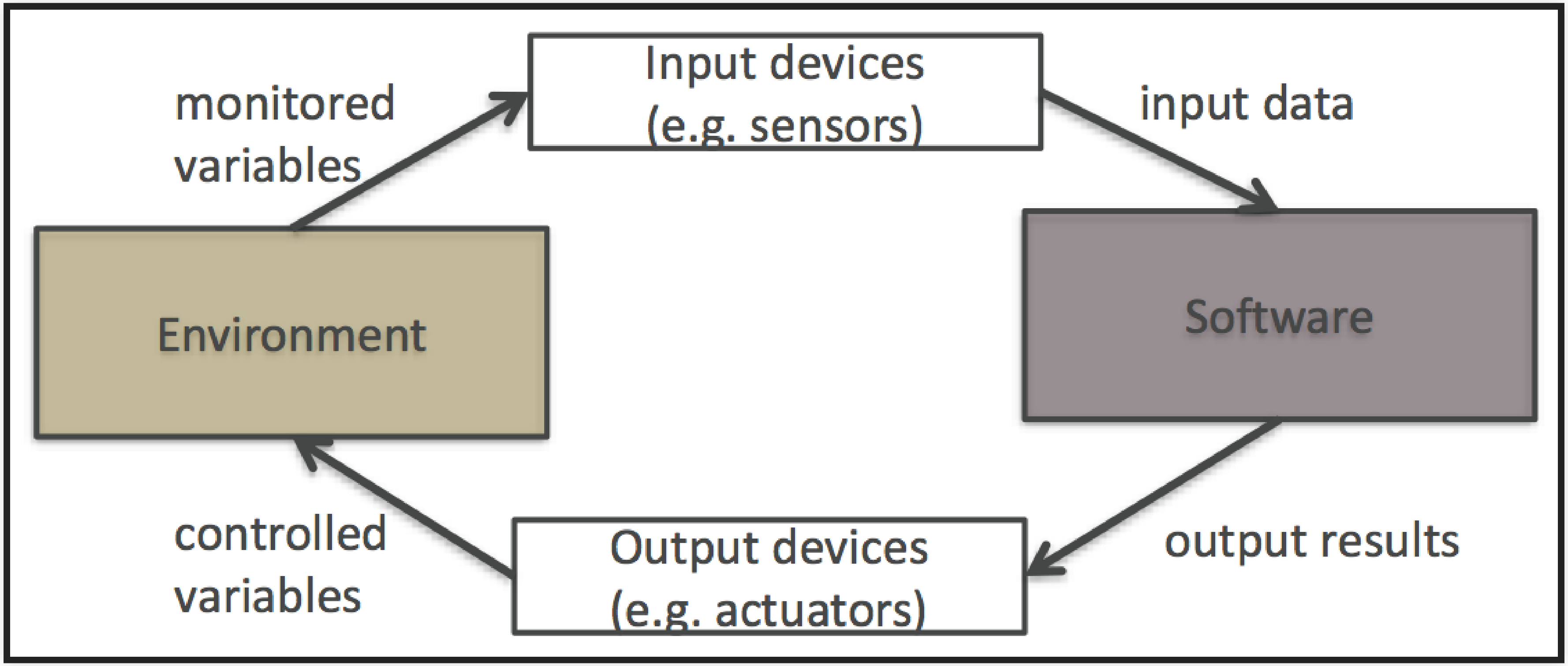
PRACTITIONER CHALLENGES

- 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?)
- Assessing human bias of humans in the loop

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.

REQUIREMENTS ENGINEERING FOR FAIRNESS

RECALL: MACHINE VS WORLD



- No ML/AI lives in vacuum; every system is deployed as part of the world
- A requirement describes a desired state of the world (i.e., environment)
- Machine (software) is *created* to manipulate the environment into this state

REQUIREMENTS FOR FAIR ML SYSTEMS

- Identify requirements (REQ) over the environment
  - What types of harm can be caused by biased decisions?
  - Who are stakeholders? Which population groups can be harmed?
  - Are we trying to achieve equality vs. equity?
  - What are legal requirements to consider?
- Define the interface between the environment & machine (ML)
  - What data will be sensed/measured by AI? Potential biases?
  - What types of decisions will the system make? Punitive or assistive?
- Identify the environmental assumptions (ENV)
  - Adversarial? Misuse? Unfair (dis-)advantages?
  - Population distributions?
- Devise machine specifications (SPEC) that are sufficient to establish REQ
  - What type of fairness definition is appropriate?

"FOUR-FIFTH RULE" (OR "80% RULE")

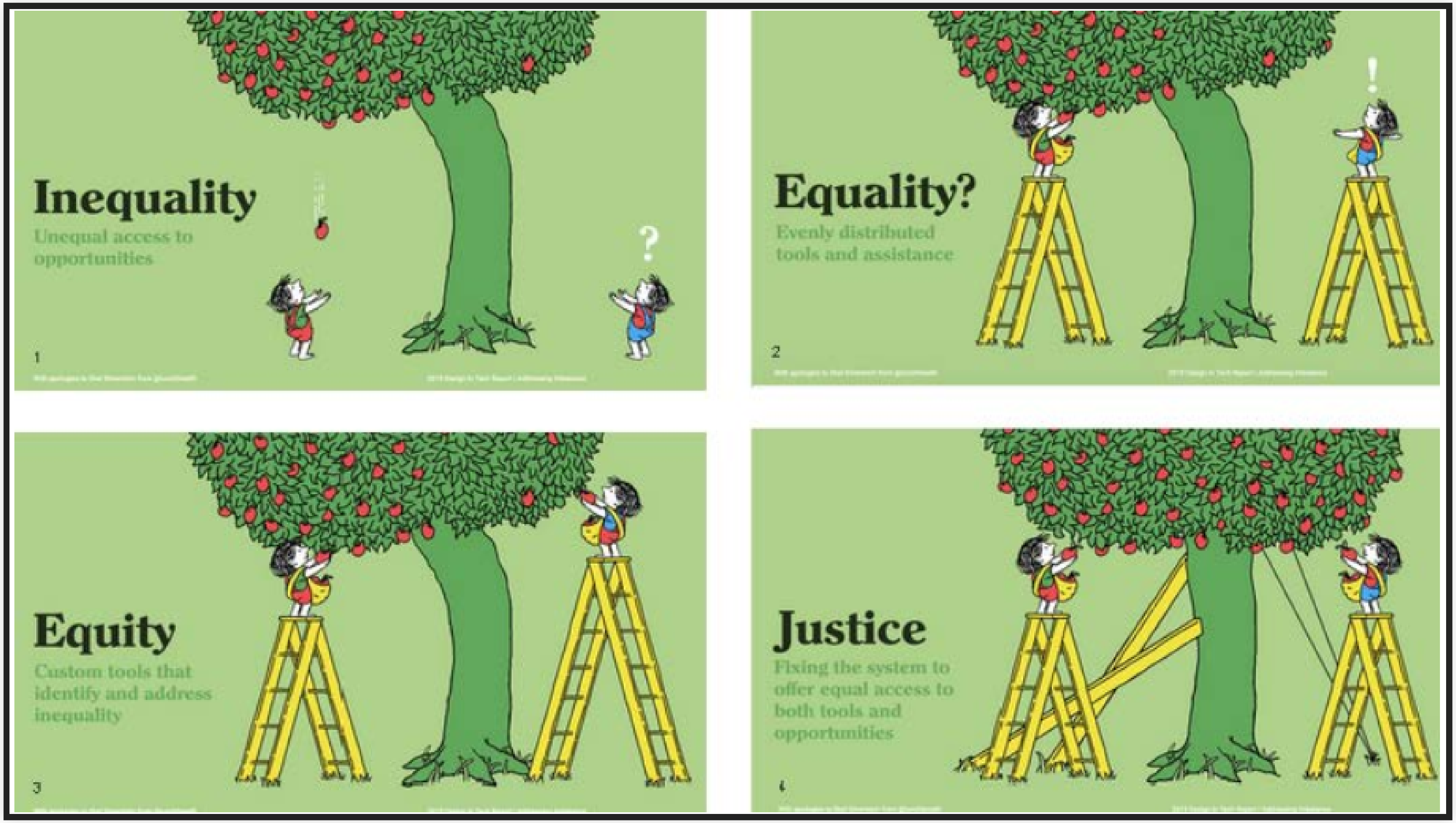
$$(P[R = 1 | A = a])/(P[R = 1 | A = b]) \geq 0.8$$

- Selection rate for a protected group (e.g., $A = a$) < 80% of highest rate => selection procedure considered as having "adverse impact"
- Guideline adopted by Federal agencies (Department of Justice, Equal Employment Opportunity Commission, etc.,) in 1978
- If violated, must justify business necessity (i.e., the selection procedure is essential to the safe & efficient operation)
- Example: Hiring
    - 50% of male applicants vs 20% female applicants hired (0.2/0.5 = 0.4)
    - Is there a business justification for hiring men at a higher rate?

EXAMPLE: LOAN APPLICATION

- Who are the stakeholders?
- Types of harm?
- Legal & policy considerations?

RECALL: EQUALITY VS EQUITY



TYPE OF DECISION & POSSIBLE HARM

- If decision is *punitive* in nature:
  - e.g. decide whom to deny bail based on risk of recidivism
  - Harm is caused when a protected group is given an unwarranted penalty
  - Heuristic: Use a fairness metric (separation) based on **false positive rate**
- If decision is *assistive* in nature:
  - e.g., decide who should receive a loan or a food subsidy
  - Harm is caused when a group in need is incorrectly denied assistance
  - Heuristic: Use a fairness metric based on **false negative rate**

WHICH FAIRNESS CRITERIA?

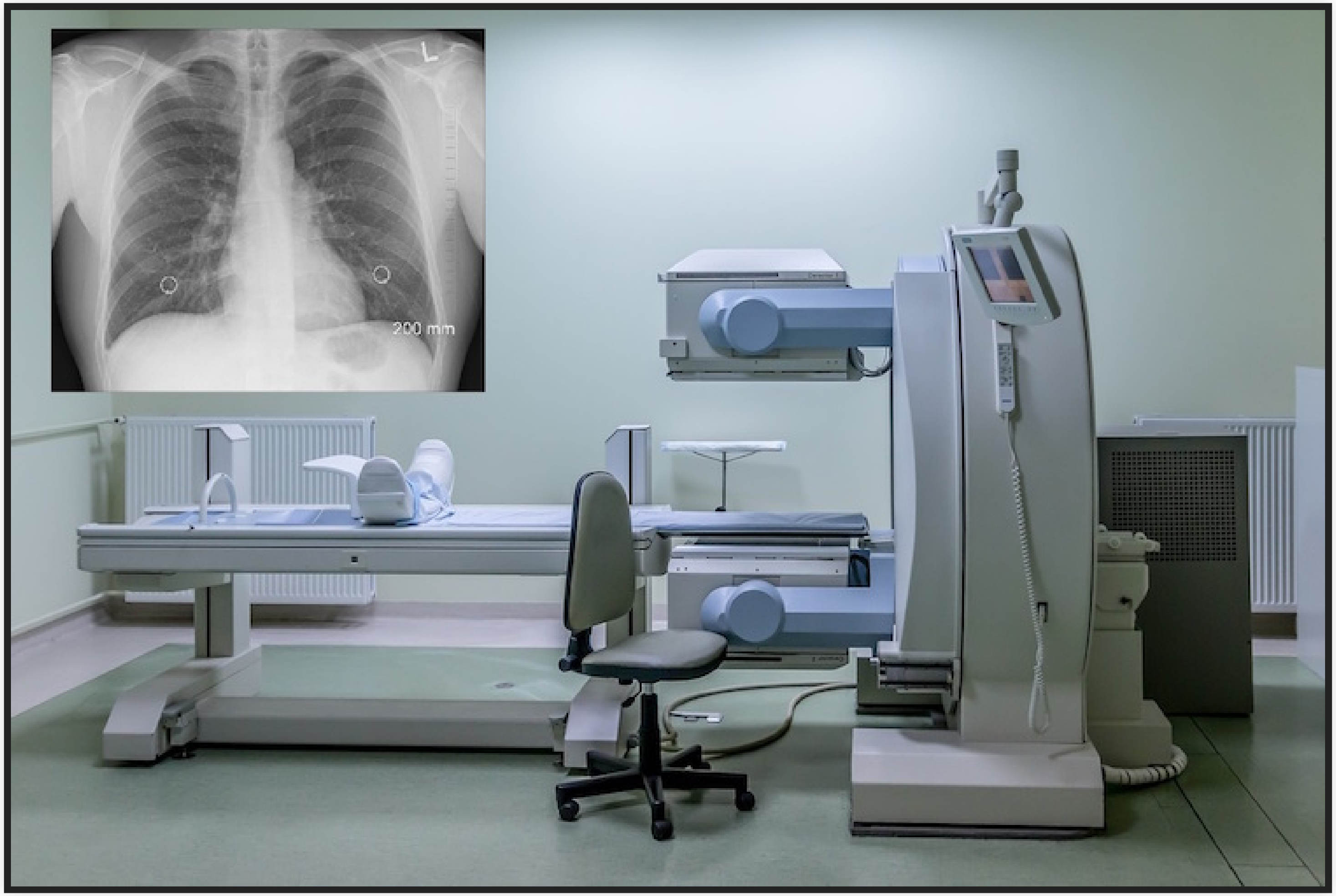
- Decision: Classify whether a defendant should be detained
- Criteria: Anti-classification,

independence, or seperation w/ FPR or FNR?

WHICH FAIRNESS CRITERIA?

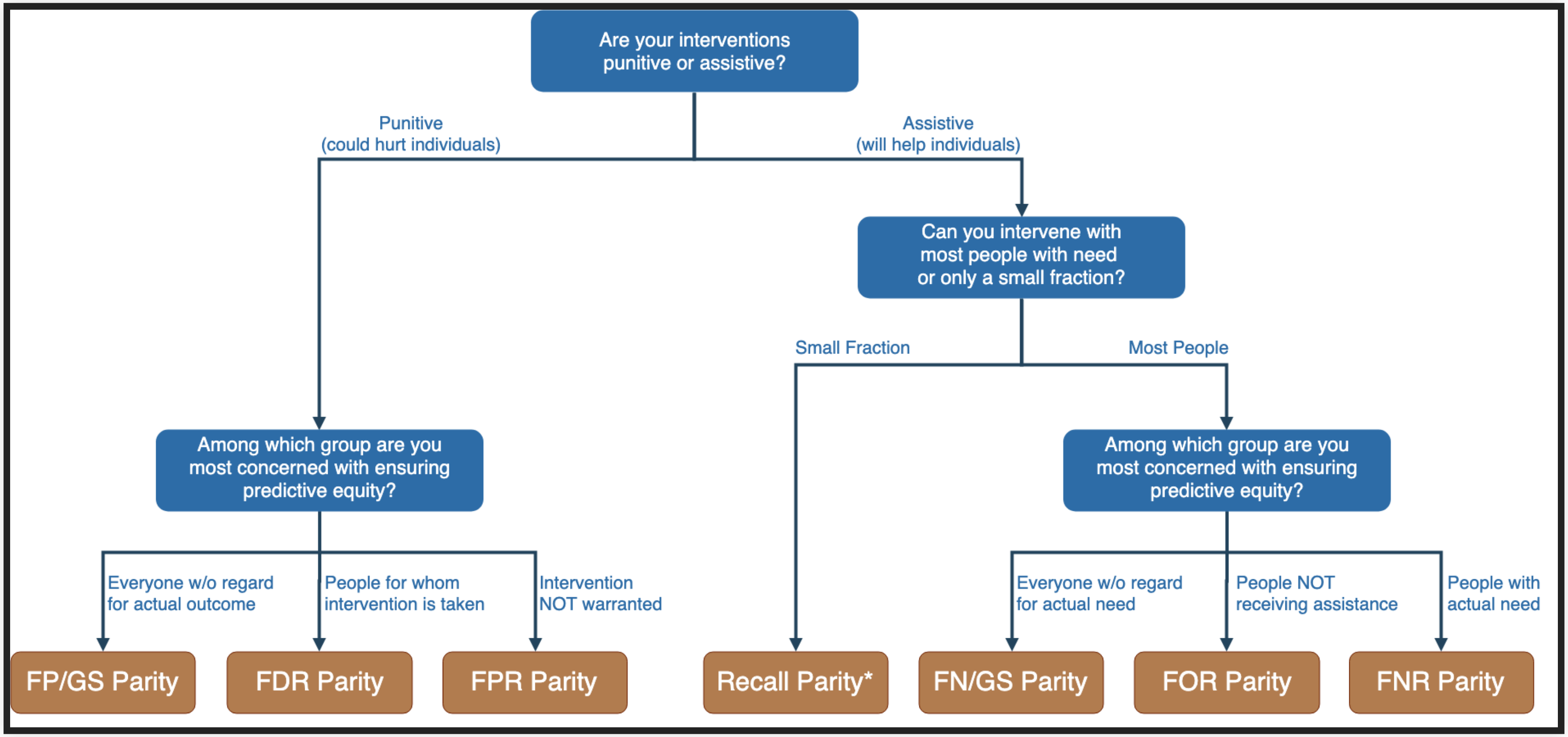
- Decision: Classify whether an applicant should be granted a loan.
- Criteria: Anti-classification, independence, or seperation w/ FPR or FNR?

WHICH FAIRNESS CRITERIA?



- Decision: Classify whether a patient has a high risk of cancer
- Criteria: Anti-classification, independence, or seperation w/ FPR or FNR?

FAIRNESS TREE



For details on other types of fairness metrics, see:
https://textbook.coleridgeinitiative.org/chap-bias.html

SUMMARY

- Definitions of fairness
  - Anti-classification, independence, separation
- Achieving fairness
  - Trade-offs between accuracy & fairness
- Achieving fairness as an activity throughout the entire development cycle
- Requirements engineering for fair ML systems
  - Stakeholders, sub-populations & unfair (dis-)advantages
  - Types of harms
  - Legal requirements