

# FAIRNESS: DEFINITIONS AND MEASUREMENTS

Eunsuk Kang

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)
- Group fairness (independence)
- Separation (equalized odds)
- ...and numerous others!

# FAIRNESS: DEFINITIONS

- **Anti-classification (fairness through blindness)**
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# ANTI-CLASSIFICATION



- Also called *fairness through blindness*
- Ignore certain sensitive attributes when making a decision
- Example: Remove gender or race from a credit scoring model
- **Q. Easy to implement, but any limitations?**

# RECALL: PROXIES

*Features correlate with protected attributes*





# RECALL: NOT ALL DISCRIMINATION IS HARMFUL



FEDERAL TRADE COMMISSION

Mortgage discrimination is against the law.



- 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 certain sensitive attributes when making a decision
- 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 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)*

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.

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# 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 on-time loan payment)
- $Y'$ : Classifier output
  - $Y' = 1$  if and only if  $R > T$  for some threshold  $T$
  - e.g., Grant the loan ( $Y' = 1$ ) if the likelihood of paying back  $> 80\%$
- $Y$ : Target variable being predicted ( $Y = 1$  if the person actually pays back on time)

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,  $Y' \perp A$ 
  - 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.,  $P[\text{promote} = 1 | \text{gender} = M] = P[\text{promote} = 1 | \text{gender} = F]$

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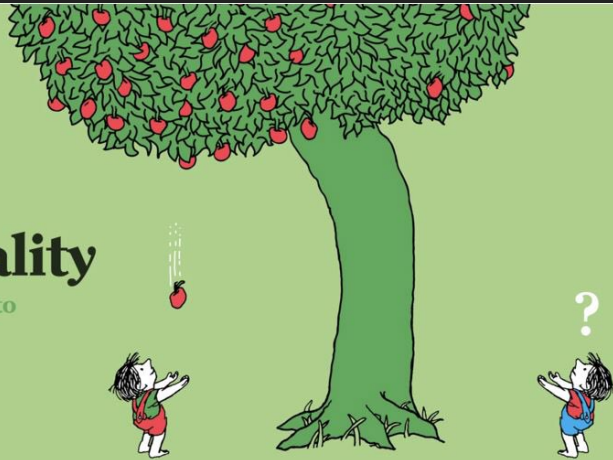
# GROUP FAIRNESS

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  - 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

## Inequality

Unequal access to opportunities

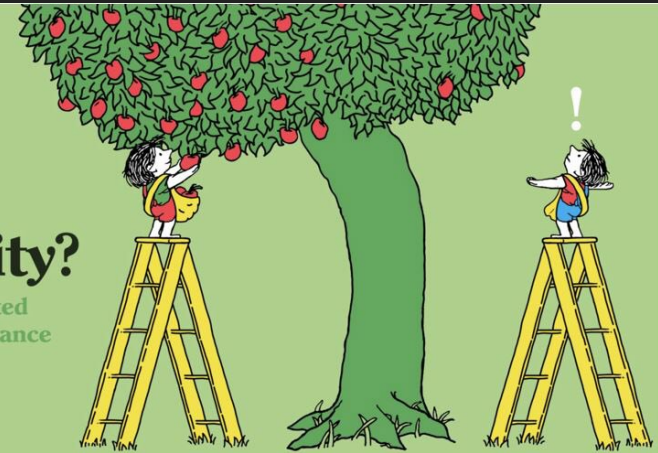


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## Equality?

Evenly distributed tools and assistance

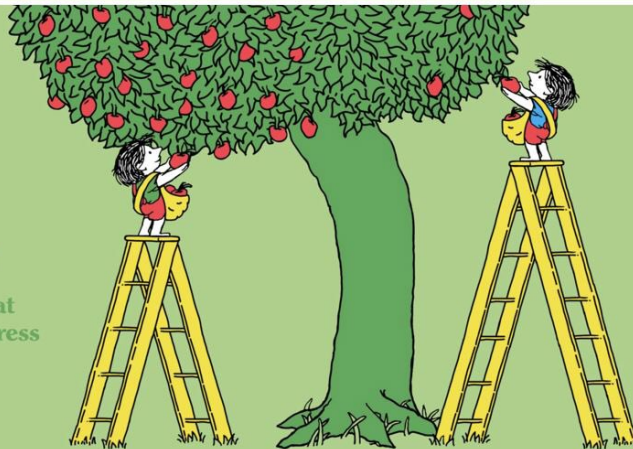


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## Equity

Custom tools that identify and address inequality

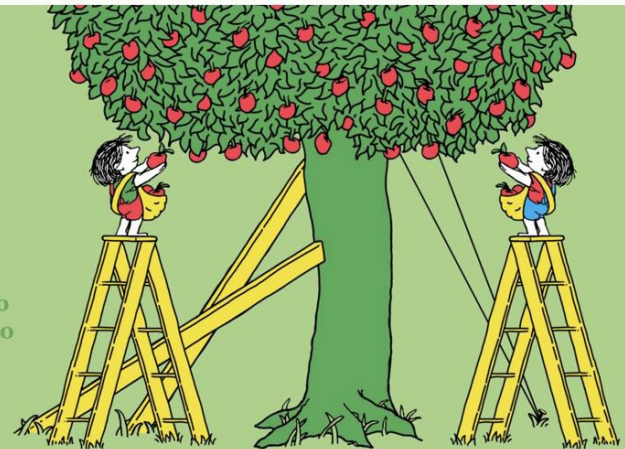


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## Justice

Fixing the system to offer equal access to both tools and opportunities



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- Example: Loan lending
  - 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
    - $P[R > 0.6 | A = 0] = P[R > 0.8 | A = 1]$

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  - Adjust thresholds to achieve group fairness
    - $P[R > 0.6 | A = 0] = P[R > 0.8 | A = 1]$
- But this also seems unfair to some of the groups! (i.e.,  $A = 1$ )
  - Q. When does this type of adjustment make sense?



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  - e.g.,  $P[\text{promoted} = 1 \mid \text{gender} = \text{M}]$ ,  $P[\text{promoted} = 1 \mid \text{gender} = \text{F}] = ?$
- Report issue if the rates differ beyond some threshold  $\epsilon$  across groups

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# SEPARATION

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

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- Also called *equalized odds*
- $Y' \perp A \mid Y$ 
  - 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?

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

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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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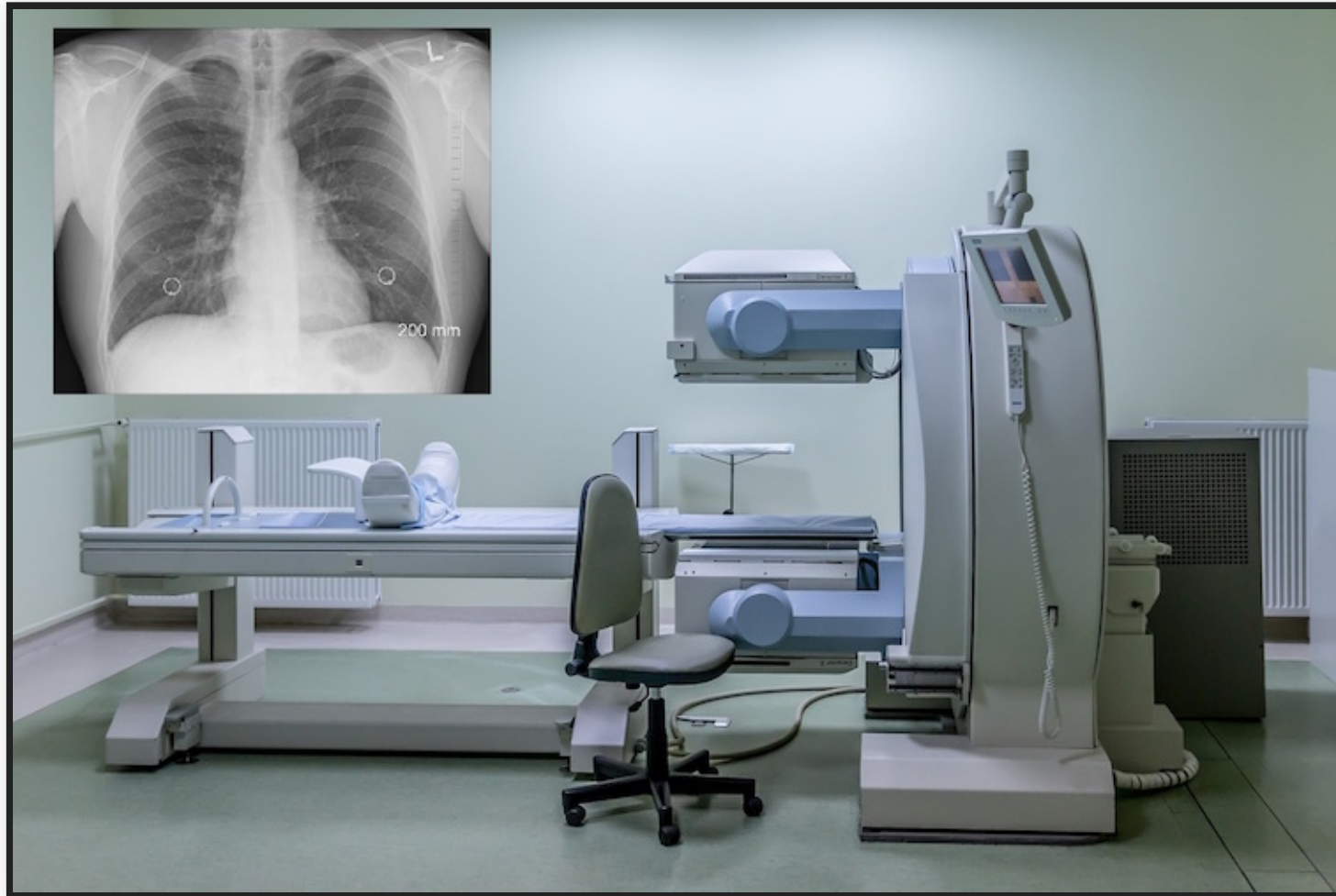
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- $Y' \perp A \mid Y$ 
  - Prediction must be independent of the sensitive attribute *conditional* on the target variable
- i.e., All groups are susceptible to the same false positive/negative rates
- Example: Promotion
  - Y': Promotion decision, 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
  - e..g, for FNR, compare  $P[\text{promoted} = 0 \mid \text{female, good employee}]$  vs  $P[\text{promoted} = 0 \mid \text{male, good employee}]$
- Q. How is this different from testing group fairness?

# 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 group fairness? 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: ?
- Group fairness: ?
- 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
- Group fairness: 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

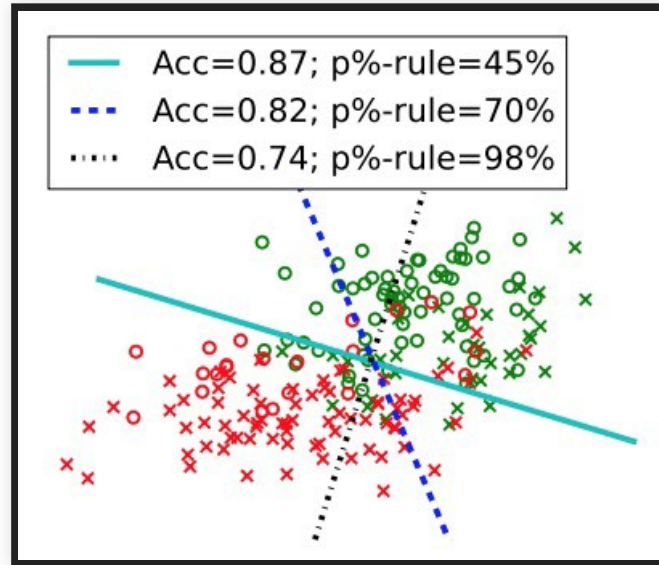
# ACHIEVING FAIRNESS CRITERIA

# 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 constraints
  - 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 IN FAIRNESS VS ACCURACY

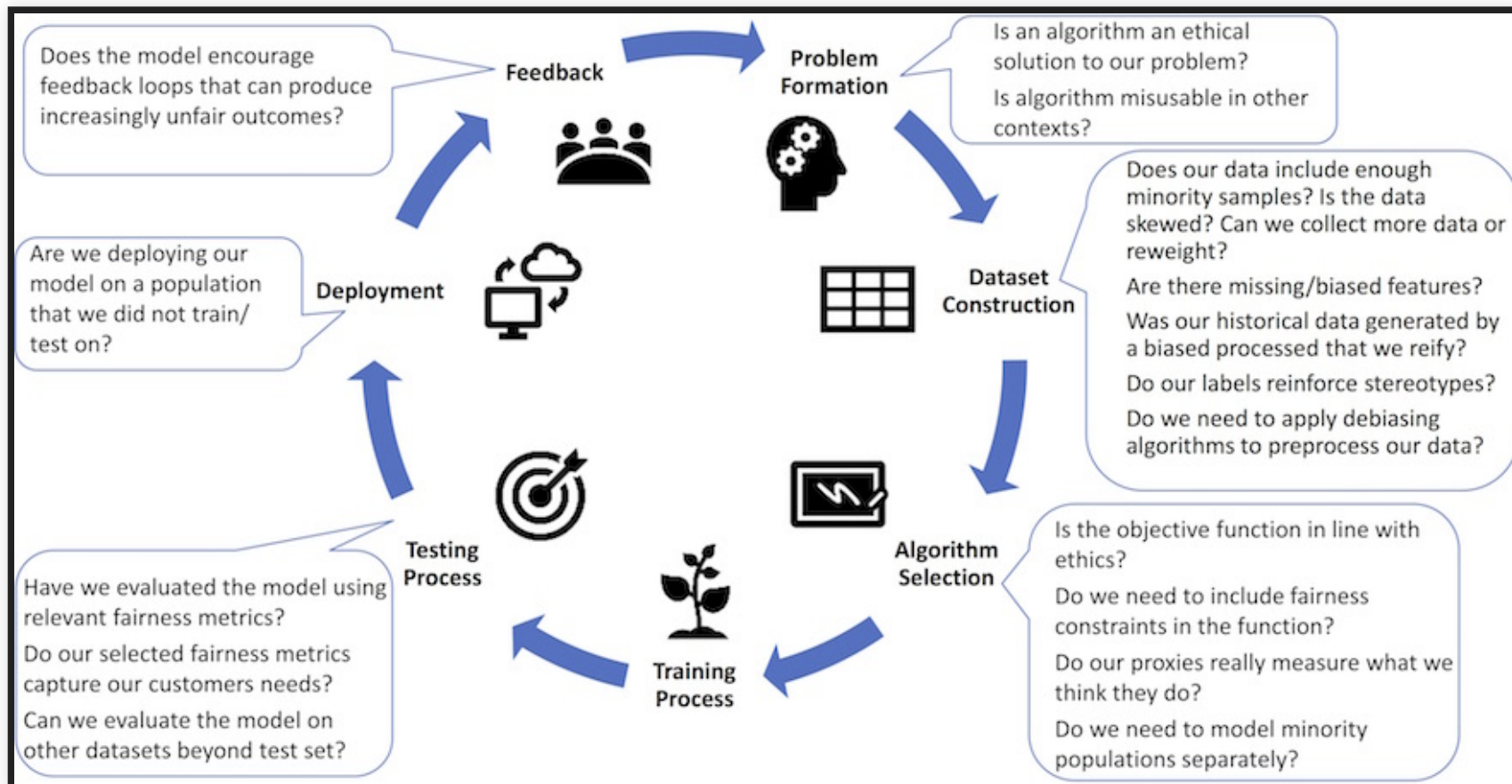


- In general, accuracy is at odds with fairness
  - e.g., Impossible to achieve perfect accuracy ( $R = Y$ ) while ensuring group fairness
- Determine how much compromise in accuracy or fairness is acceptable to your stakeholders

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

# BUILDING FAIR ML SYSTEMS

# FAIRNESS MUST BE CONSIDERED THROUGHOUT THE ML LIFECYCLE!







# 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

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# 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