4th Summer School on Machine Learning
13 July, 2019. IIIT Hyderabad

Fairness in Machine Learning

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Object Detection

Method	data	mAP	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
Fast[6]	07++12	68.4	82.3	78.4	70.8	52.3	38.7	77.8	71.6	89.3	44.2	73.0	55.0	87.5	80.5	80.8	72.0	35.1	68.3	65.7	80.4	64.2
Faster[2]	07++12	70.4	84.9	79.8	74.3	53.9	49.8	77.5	75.9	88.5	45.6	77.1	55.3	86.9	81.7	80.9	79.6	40.1	72.6	60.9	81.2	61.5
Faster[2]	07++12+COCO	75.9	87.4	83.6	76.8	62.9	59.6	81.9	82.0	91.3	54.9	82.6	59.0	89.0	85.5	84.7	84.1	52.2	78.9	65.5	85.4	70.2
YOLO[5]	07++12	57.9	77.0	67.2	57.7	38.3	22.7	68.3	55.9	81.4	36.2	60.8	48.5	77.2	72.3	71.3	63.5	28.9	52.2	54.8	73.9	50.8
SSD300	07++12	72.4	85.6	80.1	70.5	57.6	46.2	79.4	76.1	89.2	53.0	77.0	60.8	87.0	83.1	82.3	79.4	45.9	75.9	69.5	81.9	67.5
SSD300	07++12+COCO	77.5	90.2	83.3	76.3	63.0	53.6	83.8	82.8	92.0	59.7	82.7	63.5	89.3	87.6	85.9	84.3	52.6	82.5	**74.1**	**88.4**	74.2
SSD512	07++12	74.9	87.4	82.3	75.8	59.0	52.6	81.7	81.5	90.0	55.4	79.0	59.8	88.4	84.3	84.7	83.3	50.2	78.0	66.3	86.3	72.0
SSD512	07++12+COCO	**80.0**	**90.7**	**86.8**	**80.5**	**67.8**	**60.8**	**86.3**	**85.5**	**93.5**	**63.2**	**85.7**	**64.4**	**90.9**	**89.0**	**88.9**	**86.8**	**57.2**	**85.1**	72.8	**88.4**	**75.9**

Table 4: **PASCAL VOC2012 `test` detection results.** Fast and Faster R-CNN use

SSD: Single Shot MultiBox Detector

W Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C. Fu, A. C. Berg


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Fairness in ML Systems

- Names that are associated with black people are found to be significantly more associated with unpleasant than with pleasant terms, compared to names associated with whites.

- The models learned on such text data for opinion or sentiment mining have a possibility of inheriting the prejudices reflected in the data.

A. Caliskan-Islam, J. J. Bryson, and A. Narayanan.
Semantics derived automatically from language corpora necessarily contain human biases.

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Fairness in ML Systems

- Strong ethnic bias in COMPAS score: a predictive model for the “risk of crime recidivism”

- According to the score:
  - A black who did not re-offend were classified as high risk twice as much as whites who did not re-offend, and
  - White repeat offenders were classified as low risk twice as much as black repeat offenders

http://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

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Fairness in ML Systems

- In 2016, the software used to determine the areas of the US to which Amazon would offer free same-day delivery, unintentionally restricted minority neighborhoods from participating in the program (often when every surrounding neighborhood was allowed)

http://www.techinsider.io/how-algorithms-can-be-racist-2016-4

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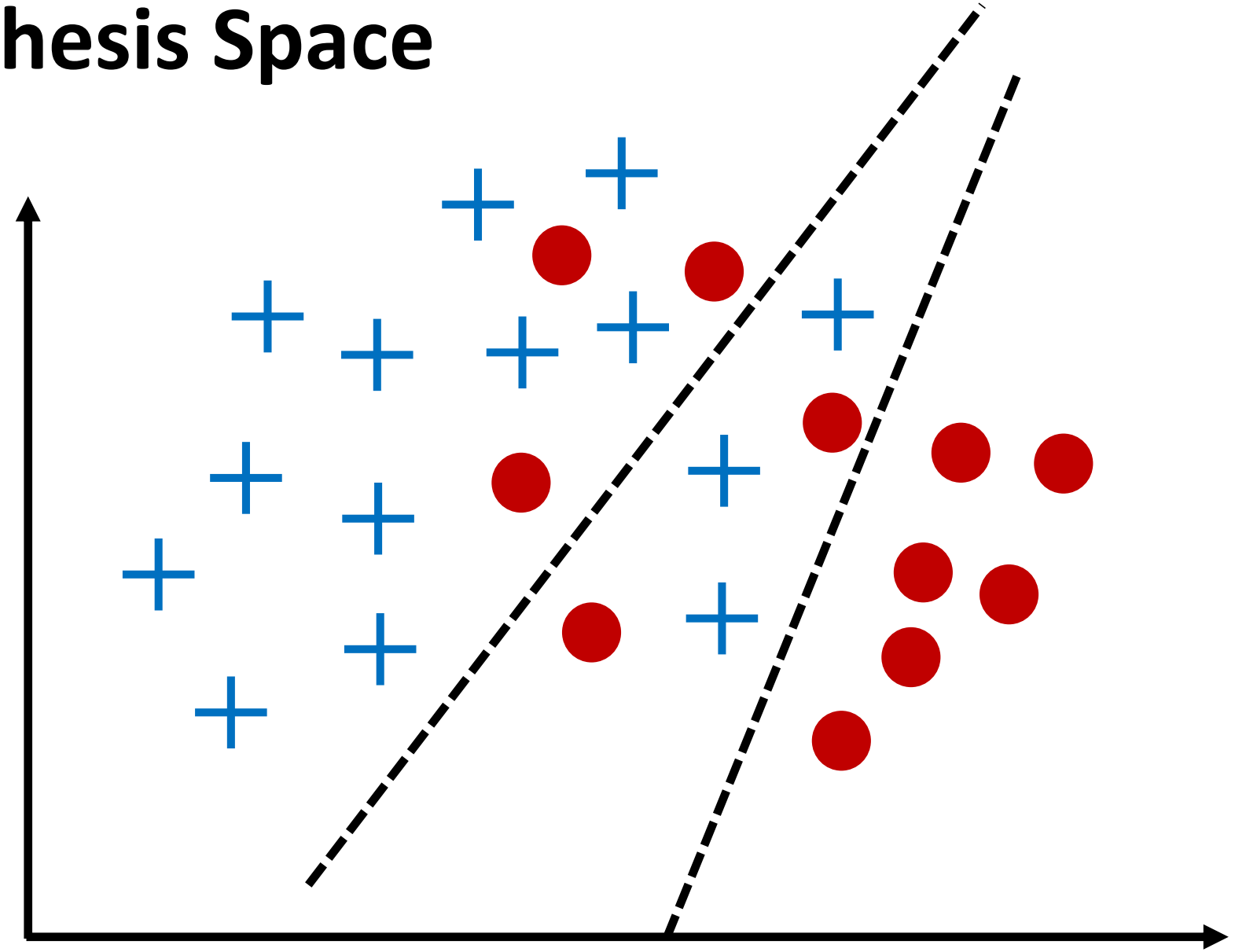
Hypothesis Space

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Inductive Bias

Set of assumptions that the learner uses to predict outputs given inputs that it has not encountered

- **Minimum cross-validation error:** When trying to choose among hypotheses, select the hypothesis with the lowest cross-validation error.

- **Maximum margin:** when drawing a boundary between two classes, attempt to maximize the width of the boundary.


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Inductive Bias

Set of assumptions that the learner uses to predict outputs given inputs that it has not encountered

- **Minimum features:** Delete a feature unless there is good evidence that it is useful. This is the assumption behind feature selection algorithms.

- **Nearest neighbors:** Assume that most of the cases in a small neighborhood in feature space belong to the same class. Used in the k-nearest neighbors and many manifold learning algorithms.


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Undesirable Biases in ML Systems

- **Selection Bias**
  - Bias introduced by the selection of data for analysis in such a way that proper randomization is not achieved, thereby ensuring that the sample obtained is not representative of the population
  - **Sampling Bias:** Bias in which a sample is collected in such a way that some members of the intended population have a lower sampling probability than others

- **Reporting Bias**
  - Selective revealing or suppression of information. Authors under-reporting unexpected or undesirable experimental results


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Differentiation Vs Discrimination

- Differentiation is the basis of prediction in any ML system.

- Unjustified basis for differentiation is Discrimination

  - **Practical irrelevance**
    - Gender, Religion, Caste, Financial Status etc.

  - **Moral irrelevance**
    - Caste, Disability etc.

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Legal Regulations Against Discrimination

- Credit
- Education
- Employment
- Housing
- Public Accommodation

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Doctrines of Discrimination

1. Disparate Treatment

- **Formal**
  - Using protected attributes explicitly
- **Intentional**
  - Using proxies for the protected attributes

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Doctrines of Discrimination

2. Disparate Impact

- **Unjustified**
  - Predicted outcome is significantly different for two groups
- **Avoidable**
  - There is way to achieve the same score with lesser disparate impact

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Targets of Discrimination Doctrines

- **Disparate Treatment**
  - Procedural fairness
  - Equality of opportunity

- **Disparate Impact**
  - Distributive justice
  - Minimized inequality of outcome

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Discrimination Vs Affirmative Action

- **Equality of opportunity**
  - Ensure that decision-making treats similar people similarly on the basis of relevant features, given their current degree of similarity
  - Organize society in such a way that people of equal talents and ambition can achieve equal outcomes over the course of their lives

- **Affirmative Action**
  - Equality of opportunity should be balanced with the need to treat seemingly dissimilar people similarly, on the belief that their current dissimilarity is the result of past injustice

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Tradeoff: Disparate Treatment and Impact

- Bias in the data may imply that there will be inherent contradiction or tradeoff between need to treat each group similarly or need to have similar outcome for each group.

- Visible regularly in the case of affirmative action

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Does ML Prevent Disparate Treatment?

- Automated decision leaves no scope of human discretion.
- Model learns what the data supports
- Protected attributes can be withheld

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How Machines Learn to Discriminate

- **Skewed sample**
  - School A produces good students
  - Feedback Loop
- **Tainted examples**
  - Unreliable labels
  - Group A are tax evaders.
- **Proxies**
  - Considering features that are correlated with protected attribute

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How Machines Learn to Discriminate

- **Limited features**
  - Features may be less informative or less reliably collected for certain parts of the population
  - A feature set that supports accurate predictions for the majority group may not for a minority group
  - Different models with the same reported accuracy can have a very different distribution of error across population

- **Sample size disparity**
  - Objective functions are biased against the minority classes

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Handling Discrimination in ML Systems

- **Discovering unobserved differences in performance**
  - Skewed samples
  - Tainted examples

- **Coping with observed differences in performance**
  - Limited features
  - Sample size disparity

- **Understanding the causes of disparities in predicted outcome**
  - Proxies

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Problem Formulation

Example: A company wants to hire a software engineer (SWE) and is going to advertise for the same. An ML system needs to predict which persons to show the advertisement based upon if he/she is currently a SWE.

- X: features of an individual (browsing history etc.)
- A: sensitive or protected attributes (gender etc.)
- $C = c(X, A)$: predicted score/class (show ad or not). Also denoted as $\hat{Y}$
- Y: target variable (whether the person is a SWE)

Notation: $\mathbb{P}_a\{E\} = \mathbb{P}\{E|A = a\}$

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Problem Formulation

- Score function is any random variable $R = r(X, A) \in [0,1]$
- Can be turned into (binary) predictor by thresholding
- Example: Bayes optimal score given by $r(x, a) = \mathbb{E}[Y|X = x, A = a]$

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Fundamental Criterion for Fairness

- **Independence:** C independent of A
- **Separation:** C independent of A conditional on Y
- **Sufficiency:** Y independent of A conditional on C

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First criterion: Independence

- Require C and A to be independent. Denoted as $C \perp A$

- That is, for all groups g_1, g_2 and all predictions c:

$$\mathbb{P}_{g_1}\{C = c\} = \mathbb{P}_{g_2}\{C = c\}$$

- When C is a binary 0/1-variable:

$$\mathbb{P}_{g_1}\{C = 1\} = \mathbb{P}_{g_2}\{C = 1\}, \forall a, b$$

- Also called **demographic parity**, or **statistical parity**

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First criterion: Independence

Approximate versions

- $\frac{\mathbb{P}_a\{C=1\}}{\mathbb{P}_b\{C=1\}} \geq 1-\epsilon$

- Also known in the legal context as “80% Rule”. Declare unfair if the impact differs by more than 20%

- Additive version: $|\mathbb{P}_a\{C=1\} - \mathbb{P}_b\{C=1\}| \leq \epsilon$

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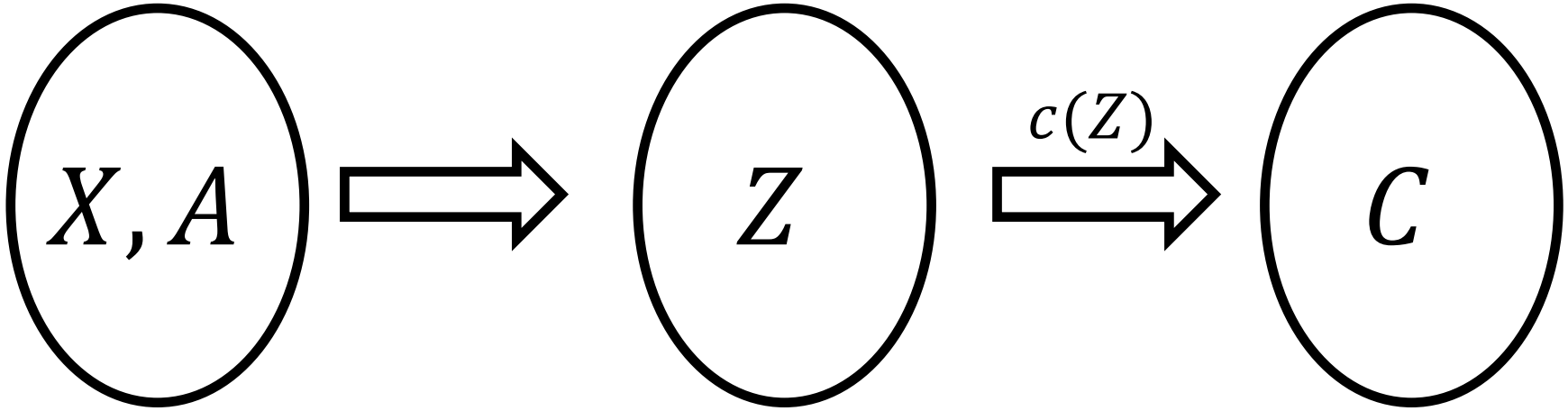
Achieving Fairness by Independence

Representation Learning Approach

- Maximize *Mutual Information* between X and latent representation Z while minimizing the same between A and Z



$$I(X,Y) = \sum_{x \in X} \sum_{y \in Y} \mathbb{P}(x,y) \log \frac{\mathbb{P}(x,y)}{\mathbb{P}(x)\mathbb{P}(y)}$$

R. Zemel, Y. Wu, K. Swersky T. Pitassi, and C. Dwork
Learning Fair Representations. ICML 2013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Problems with Independence based Fairness

- Ignores possible correlation between Y and A.
  - There could be less woman software engineers.
- Rules out perfect predictor $C = Y$.
- Permits laziness: Accept the qualified in one group, random people in other
- Allows to trade false negatives for false positives.
- Conflates desirable long-term goal with algorithmic constraint

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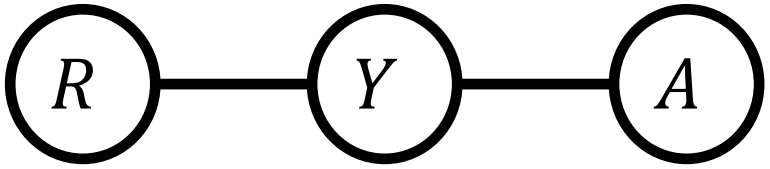
Second criterion: Separation

- Require R and A to be independent, conditional on target variable Y
- Denoted as $R \perp A \mid Y$
- For all groups a, b and all values r and y:

$$\mathbb{P}_a\{R = r \mid Y = y\} = \mathbb{P}_b\{R = r \mid Y = y\}$$

- PGMs: Random variable R **separated** from A if $R \perp A \mid Y$



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Desirable Properties of Separation

$$\mathbb{P}_a\{R = r \mid Y = y\} = \mathbb{P}_b\{R = r \mid Y = y\}$$

- Optimality compatibility: $R = Y$ is allowed
- Penalizes laziness: Incentive to reduce errors uniformly in all groups
- Recall, none of the above is achieved by Independence.
- Assume Y is unbiased: Problematic with tainted and skewed samples

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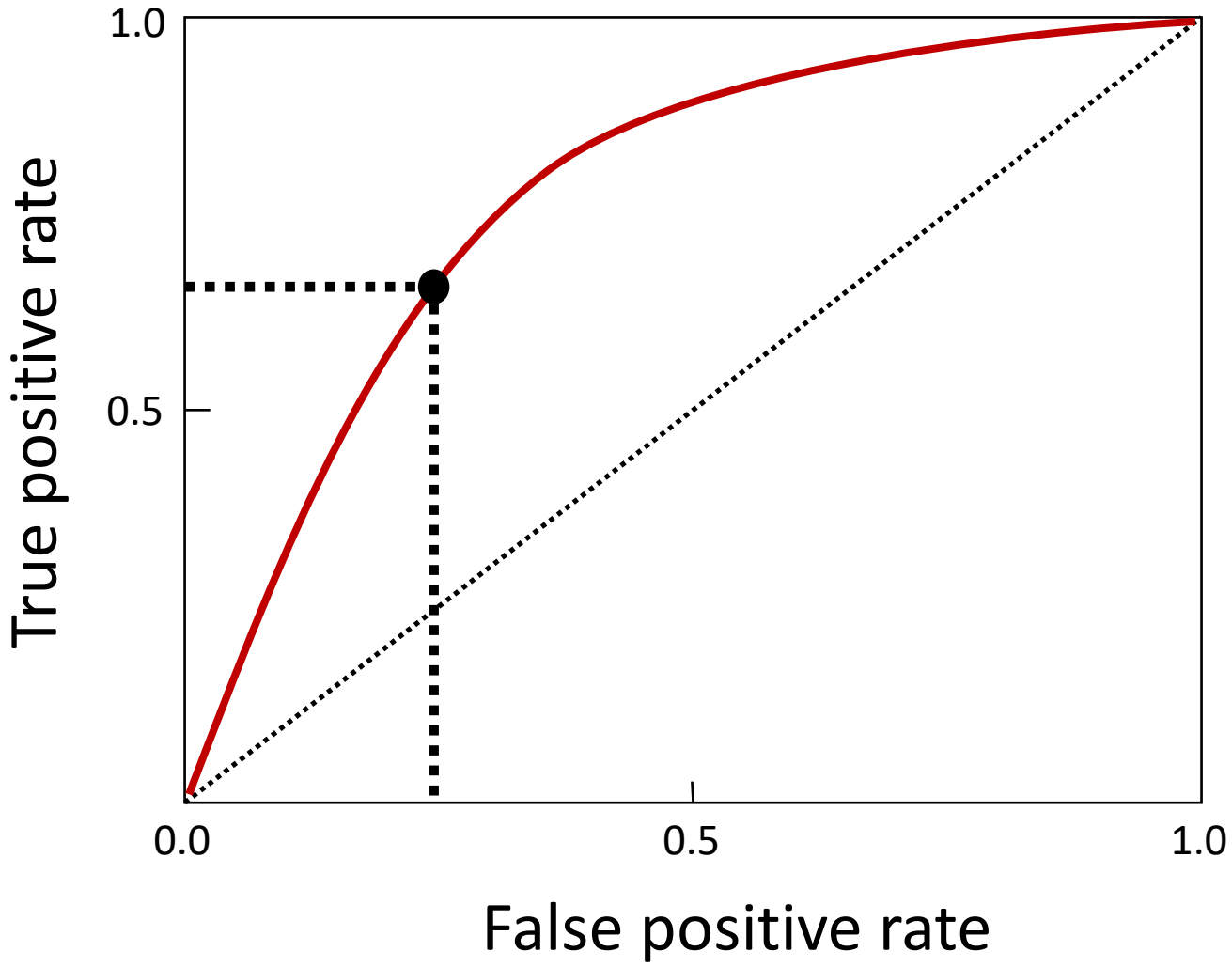
Achieving Fairness by Separation



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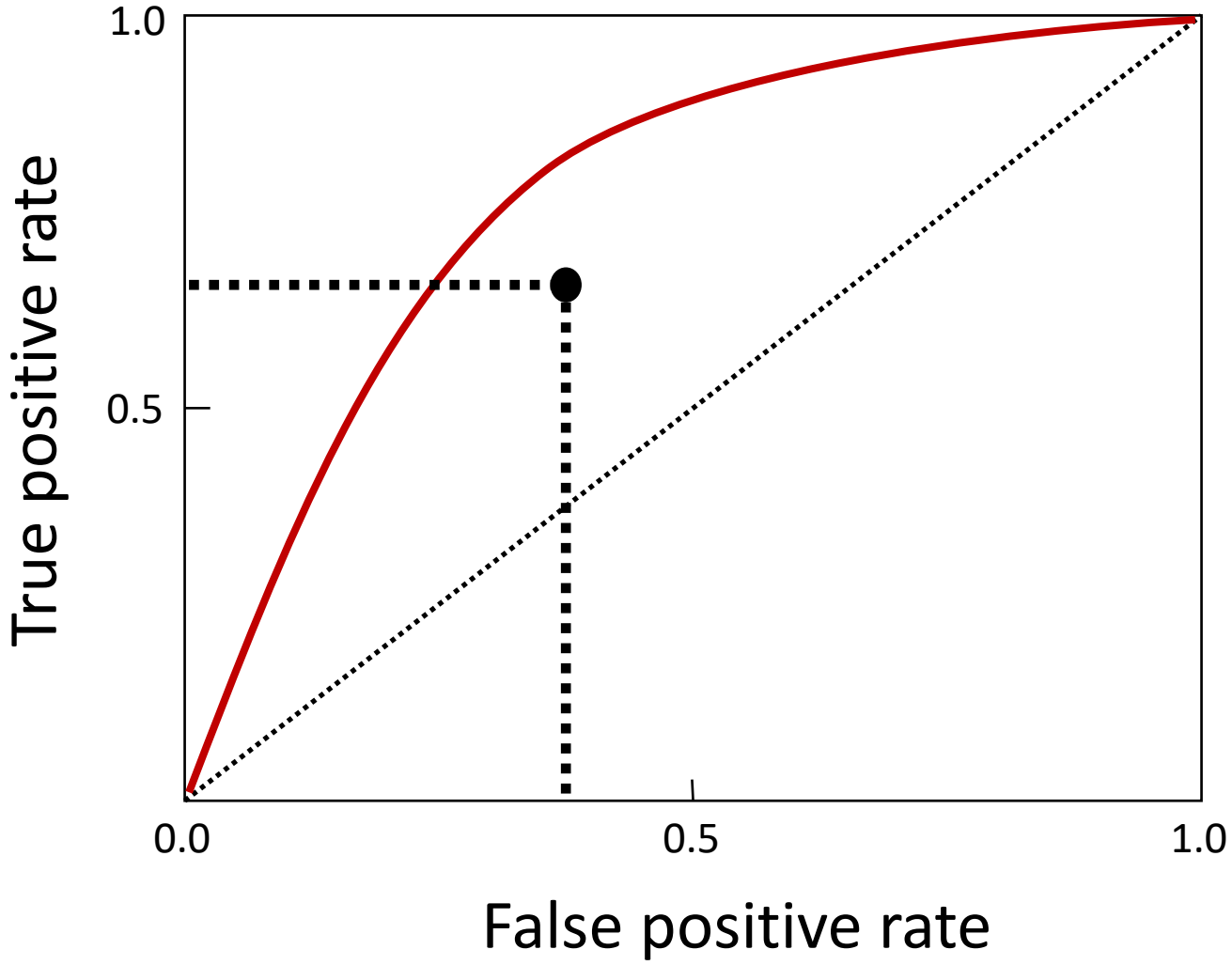
Achieving Fairness by Separation



Create Random False Positives

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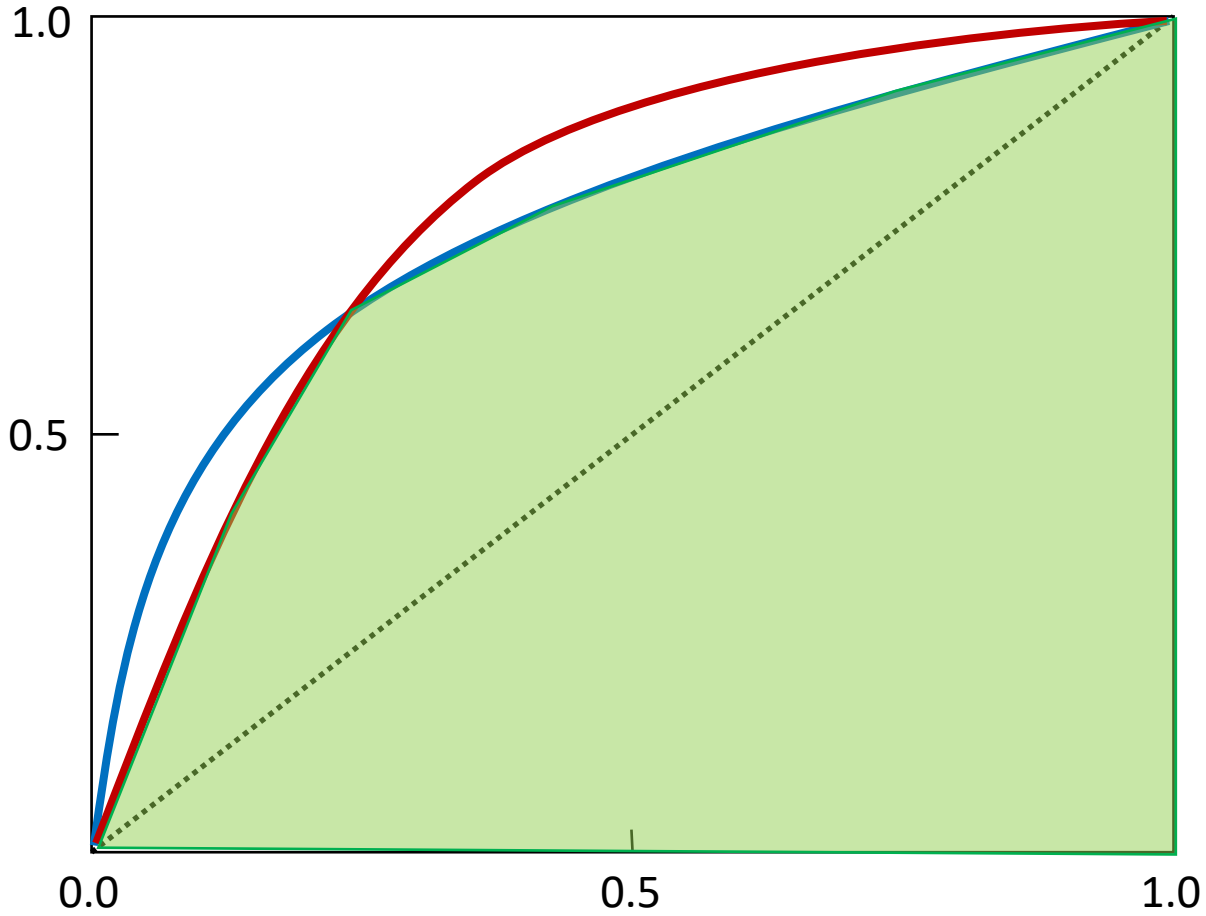
Achieving Fairness by Separation



Moritz Hardt, Eric Price, Nathan Srebro
Equality of Opportunity in Supervised Learning. NIPS 2016

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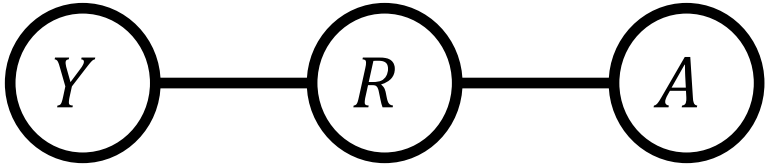
Third criterion: Sufficiency

- Random variable R is sufficient for A if $Y \perp A \mid R$



- For the purpose of predicting Y, we don't need to see A when we have R

- For the purpose of showing the SWE advertisement, I don't need to know gender, if I already know the programming score.

- For the purpose of approving loan, I don't need to the know the race, when I know the credit rating

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Achieving Fairness by Sufficiency

$$Y \perp A \mid R$$

- Sufficiency satisfied by Bayes optimal score:

$$r(X, A) = \mathbb{E}[Y \mid X = x, A = a]$$

- Can be achieved using **calibration by group**: $\mathbb{P}\{Y = 1 \mid R = r, A = a\} = r$

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Achieving Fairness by Sufficiency

$$\mathbb{P}\{Y = 1 \mid R = r, A = a\} = r$$

Plat Scaling:

- Given uncalibrated score R, fit a sigmoid function: $S = \frac{1}{1+\exp(\alpha R+\beta)}$

- Minimize log loss: $-\mathbb{E}[Y \log S + (1 - Y)\log(1 - S)]$
  - Objective function nudges S to take similar value as Y
  - $\frac{Y}{S} - \frac{1-Y}{1-S} = 0. \quad \Rightarrow \frac{Y}{S} = \frac{1-Y}{1-S} \quad \Rightarrow Y(1 - S) = S(1 - Y). \quad \Rightarrow Y = S$

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Fairness Tradeoffs

Any two of the three criteria we saw are mutually exclusive except in degenerate cases.

For example:

- If $A \not\perp Y$ and $R \not\perp Y$, then either independence or separation holds, not both.

- Recall that Separation $\Rightarrow R \perp A \mid Y$, and Independence $\Rightarrow R \perp A$

- $\frac{\mathbb{P}\{R,A\}}{\mathbb{P}\{Y\}} = \frac{\mathbb{P}\{R\}}{\mathbb{P}\{Y\}} \times \frac{\mathbb{P}\{A\}}{\mathbb{P}\{Y\}}$. $A \not\perp Y$ and $R \not\perp Y \Rightarrow \mathbb{P}(Y)$ can not be removed in R.H.S.

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The COMPAS Debate

Bernard Parker, left, was rated high risk; Dylan Fugett, right, was rated low risk. (Josh Ritchie for ProPublica)

Machine Bias

- There's software used across the country to predict future criminals. And it's biased against blacks.

Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica May 23, 2016


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Essence of COMPAS debate

ProPublica's main charge: Black defendants face higher false positive rate.

Northpointe's main defence: Scores are calibrated by group.

- Recall that sufficiency $\Rightarrow Y \perp A \mid R$, and can be achieved using **calibration by group**: $\mathbb{P}\{Y = 1 \mid R = r, A = a\} = r$ implemented by Platt Scaling

Neither calibration nor equality of false positive rates rule out blatantly unfair practices

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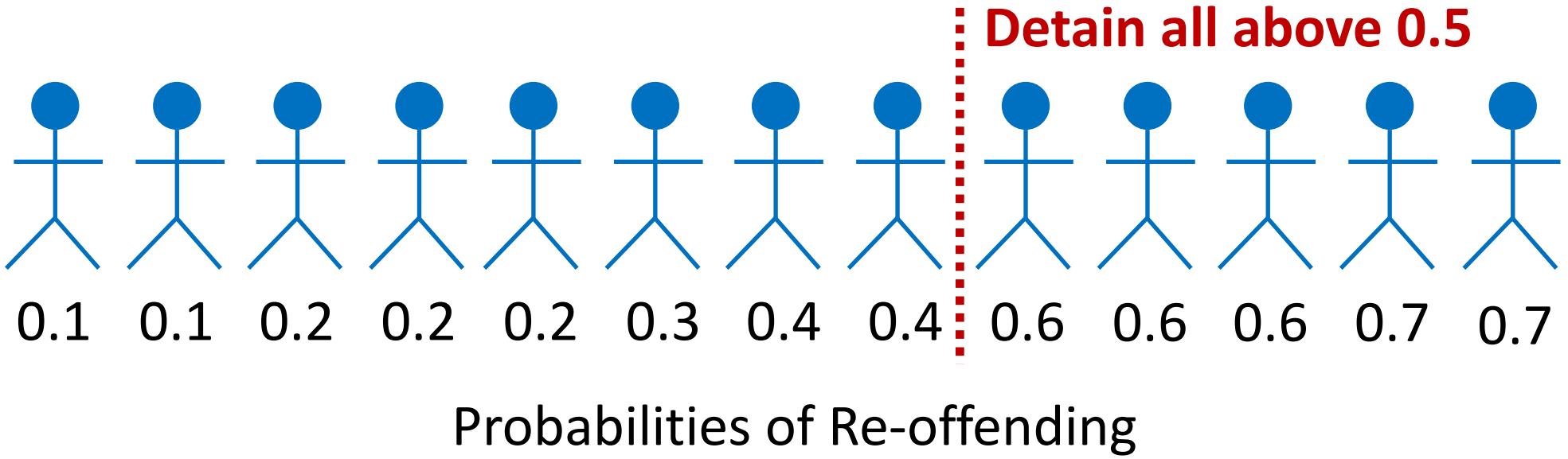
Calibration in Insufficient



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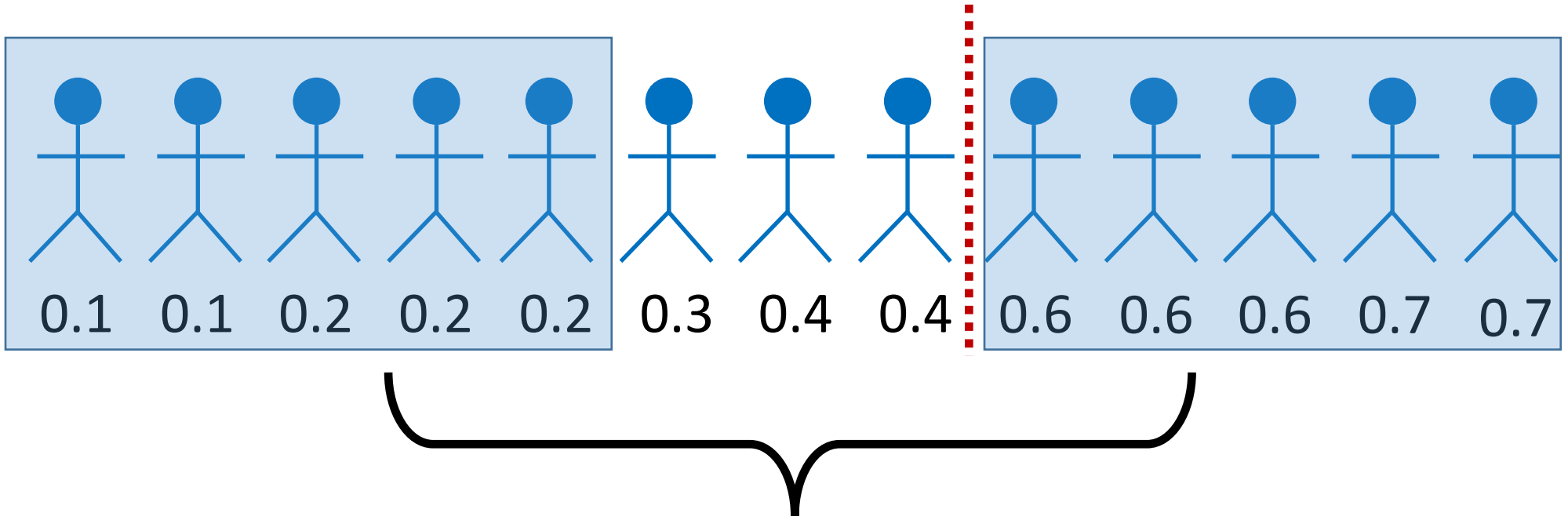
Calibration is Insufficient



Average Re-offending Rate = 0.4

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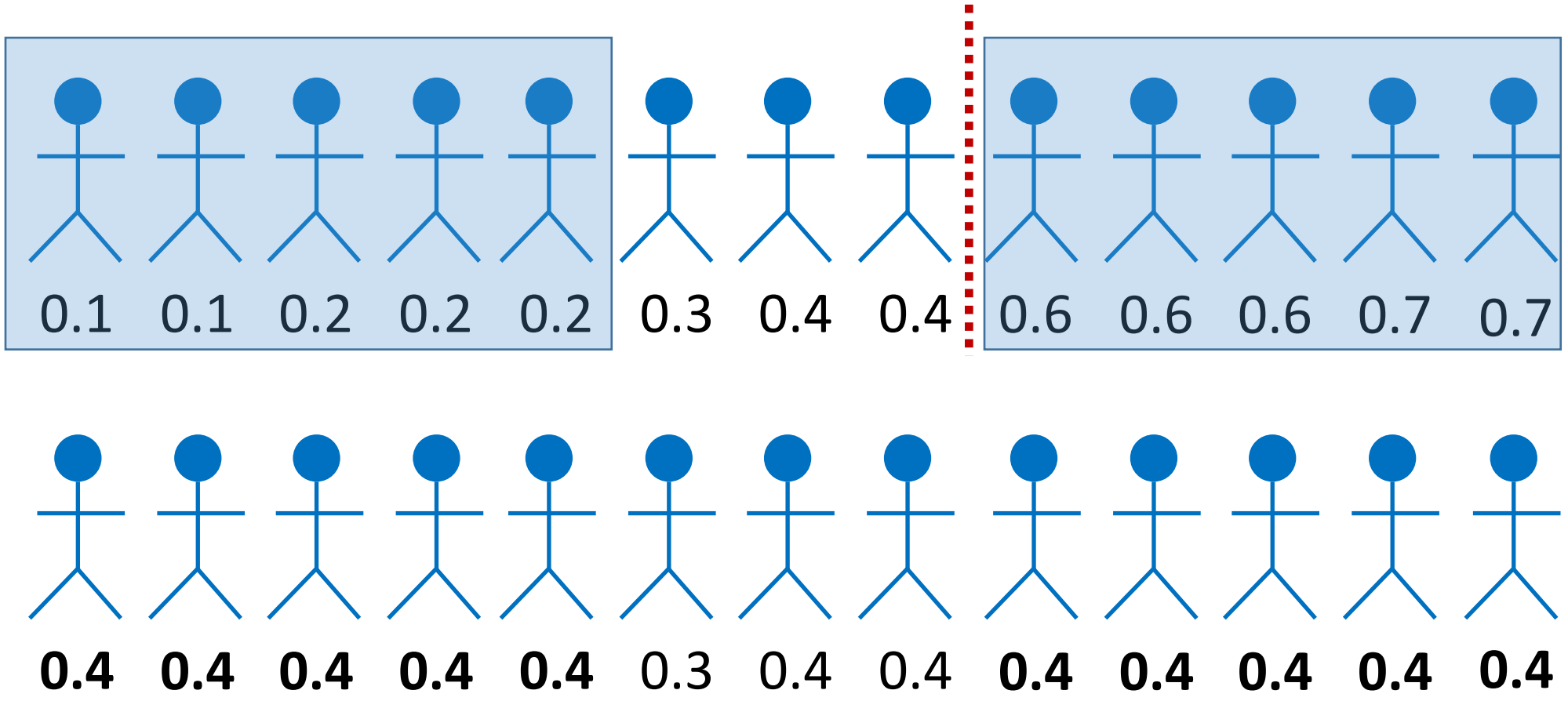
Calibration is Insufficient



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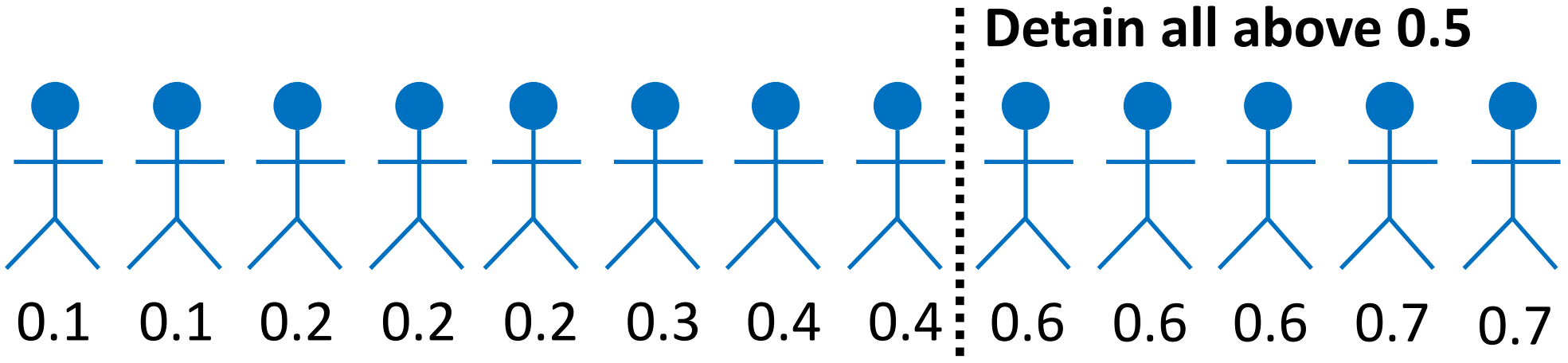
False Positive Rate



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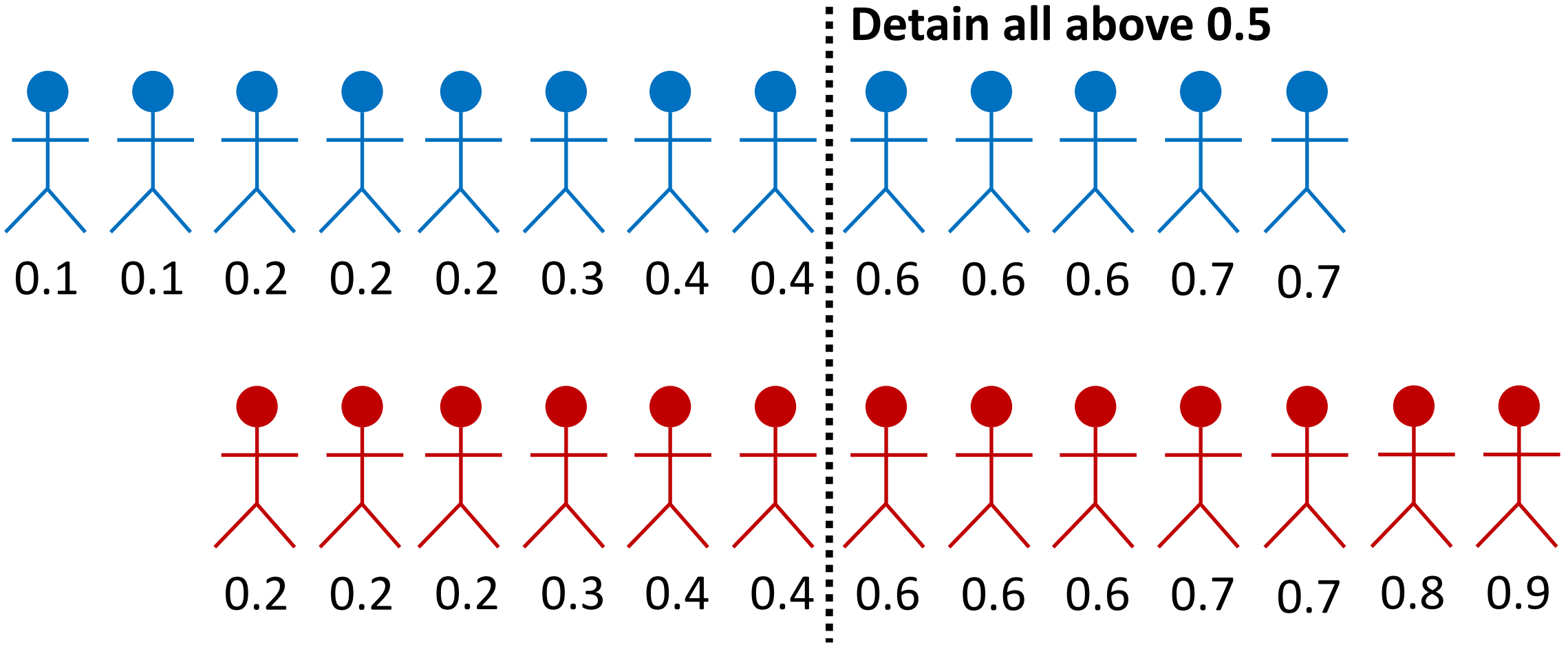

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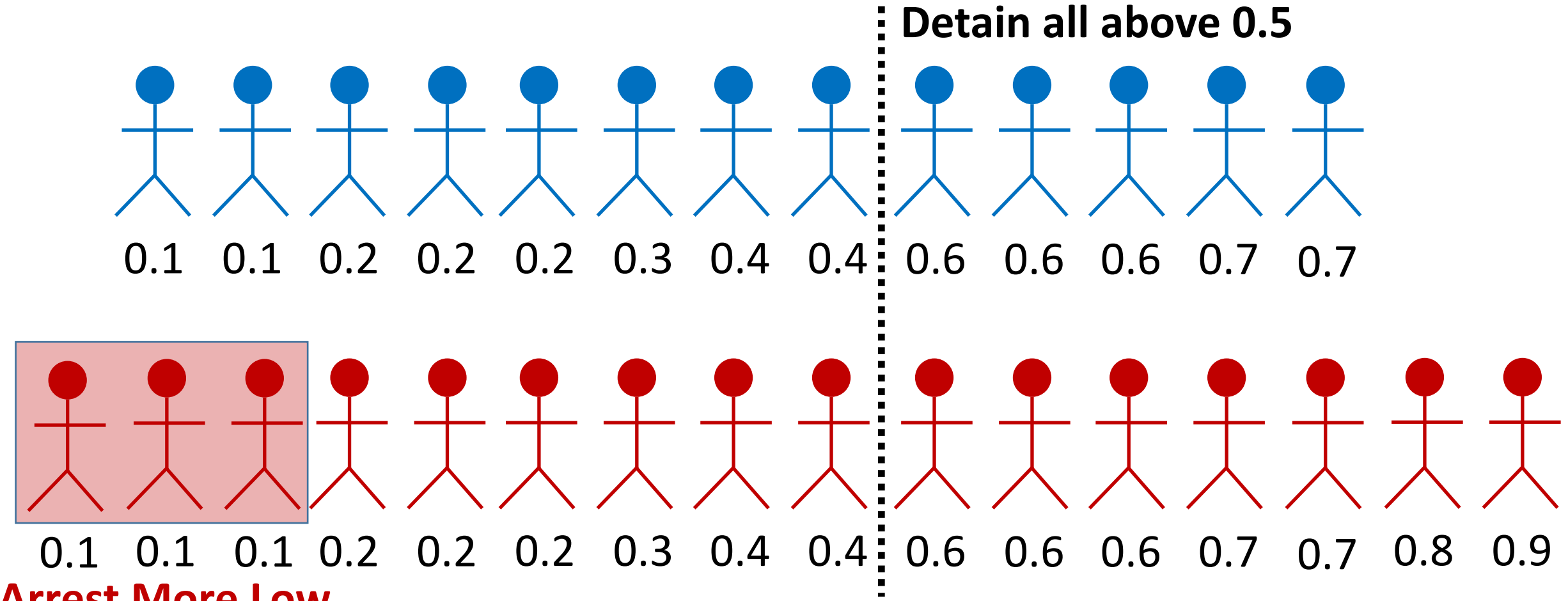
False Positive Rate



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