Trusted AI

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Outline

- Pillars of Trust –IBM perspective
- Fairness
  - Motivation
  - Metrics
  - Mitigation Algorithms for Group Fairness
  - Individual Discrimination Testing

AI is now used in many high-stakes decision making applications

Credit

Employment

Admission

Sentencing

Pillars of Trust

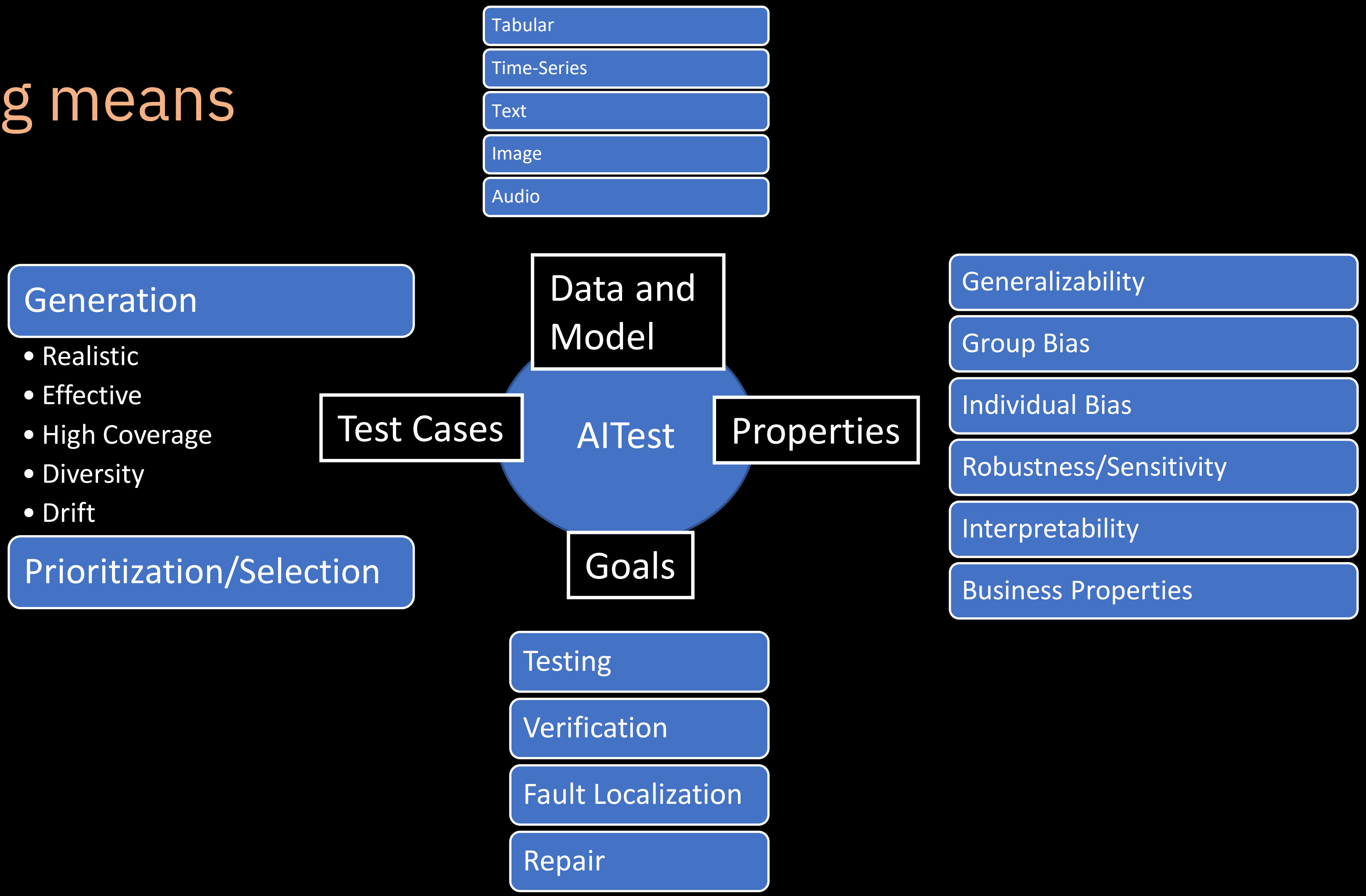
- Fairness
- Explainability
- Robustness
- Transparency
- Privacy

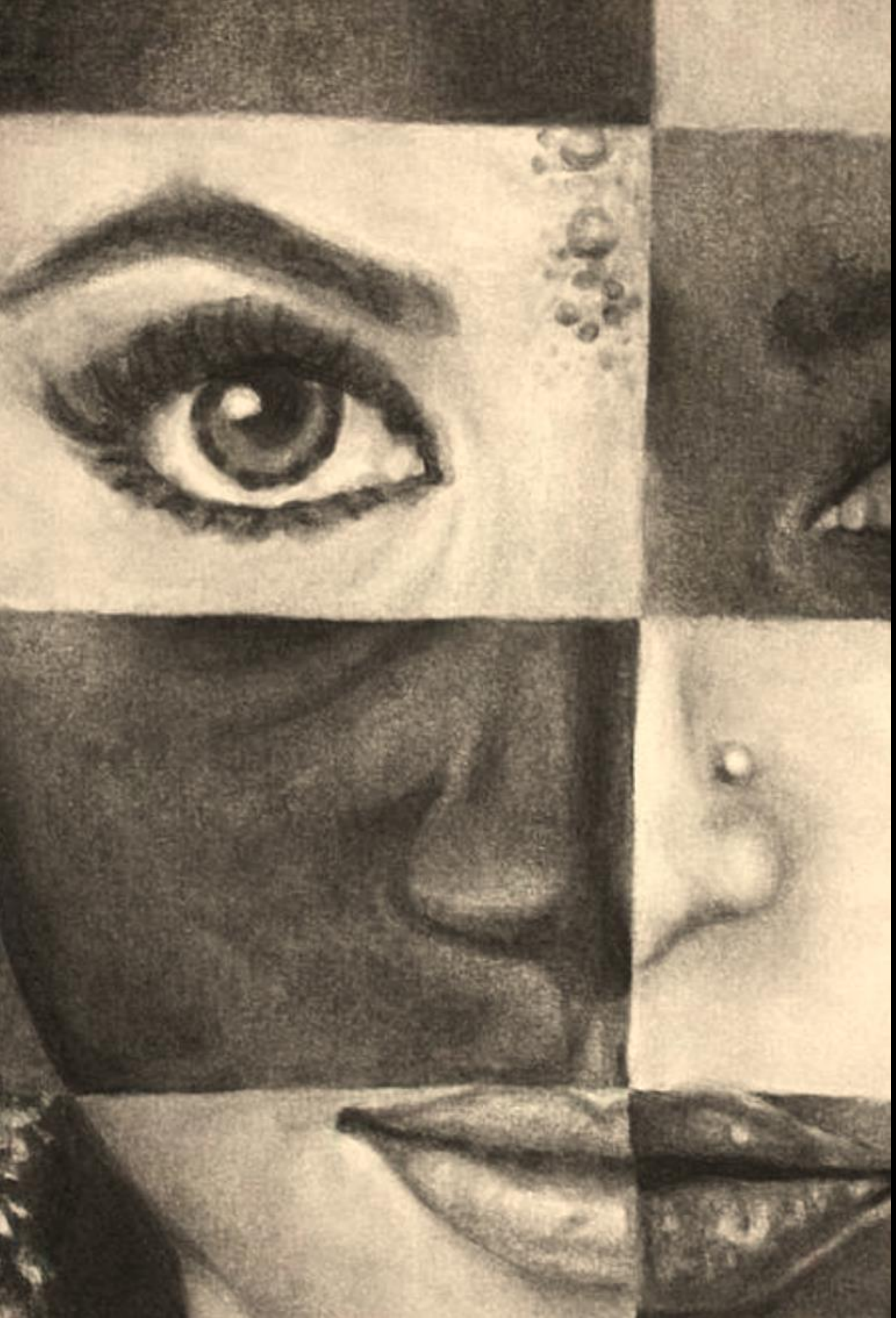
https://www.ibm.com/watson/trustworthy-ai

Testing for Trustworthiness of AI Models

AI Testing   Tabular   Text   Conversation   Time-Series   Image   Speech2Text

- Forrester: No testing means no Trust in AI





Fairness

- **Protected attribute** – an attribute that partitions a population into groups whose outcomes should have parity; examples include race, gender, caste, and religion
- **Privileged / Unprivileged group** – a value of the protected attribute indicating a group that has historically been at systematic advantage
- **Bias** – a systematic error; in the context of fairness, we are concerned with **unwanted bias** that places privileged groups at systematic advantage and unprivileged groups at systematic disadvantage
- **Fairness metric** – a quantification of unwanted bias in training data or models
- **Favorable Outcome** – class label that is favorable to the user

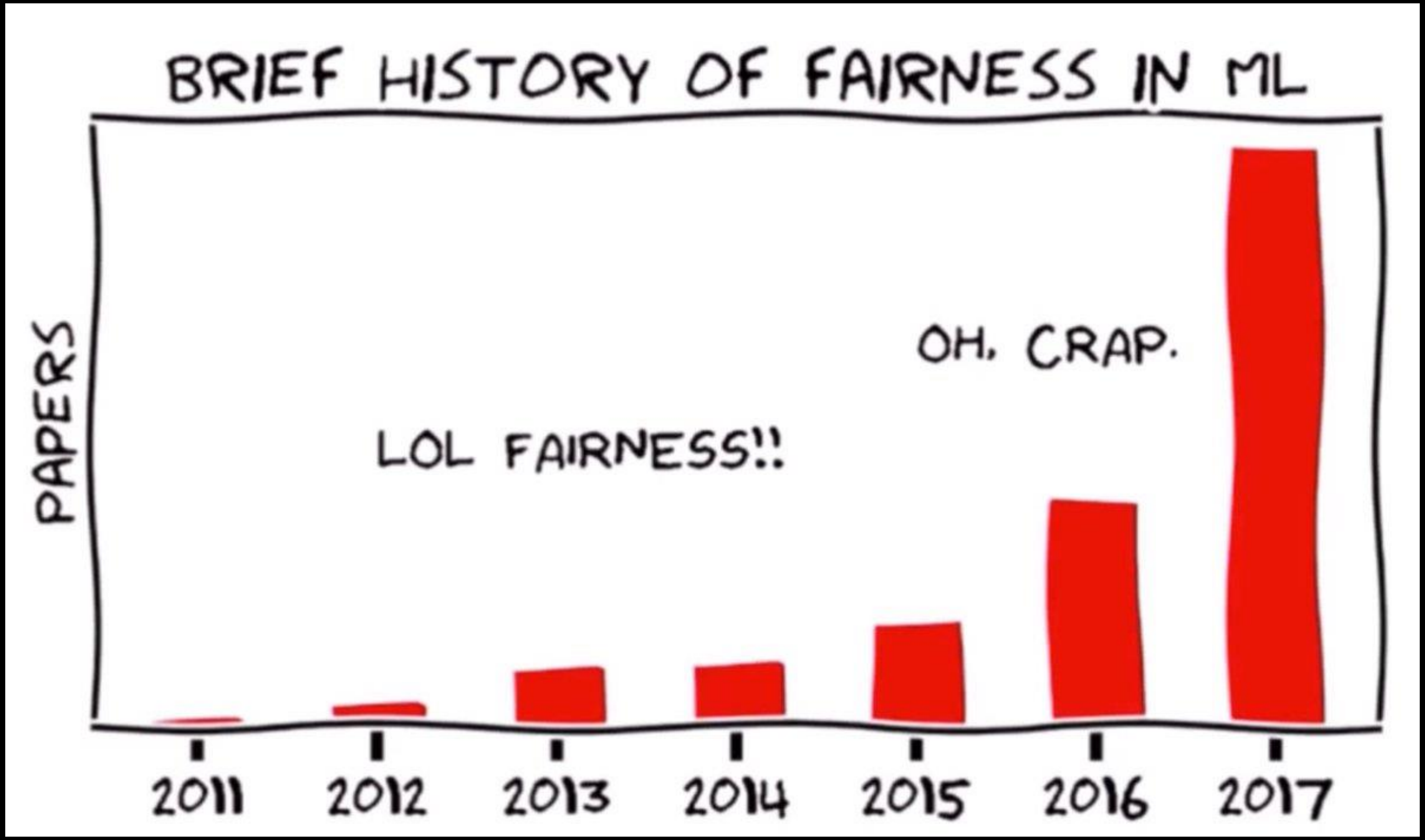
What is unwanted bias?

Discrimination becomes objectionable when it places certain **privileged** groups at systematic advantage and certain **unprivileged** groups at systematic disadvantage

Illegal in certain contexts

Unethical in general

(Barocas and Selbst, 2017)


BRIEF HISTORY OF FAIRNESS IN ML
PAPERS
LOL FAIRNESS!!
OH. CRAP.
2011
2012
2013
2014
2015
2016
2017

(Hardt, 2017)

Motivation – Instances of Bias

Company settles age-bias lawsuit

Google agreed to pay an undisclosed amount to settle the claims of job applicants who said the company discriminated against them on the basis of age. A lawyer for the applicants age 40 and older, said the parties agreed to a dollar amount during a conference on Friday. The lawsuit alleged that qualified older job workers were less likely than similarly qualified younger applicants to be hired by the search giant. BLOOMBERG

Amazon scraps secret AI recruiting tool that showed bias against women

Jeffrey Dastin 8 MIN READ

SAN FRANCISCO (Reuters) - Amazon.com Inc's (AMZN.O) machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

IBM's commercial facial recognition systems have been criticized in the past for displaying the very biases this dataset is intended to combat. A study from MIT Media Lab published in February found that IBM's error rate in identifying the gender of darker-skinned women was nearly 35 percent, while white men were misgendered only 1 percent of the time. Such mistakes will become increasingly important as facial recognition systems are used for tasks from hiring to the identification of criminal suspects.

Latinos in Iowa City faced worst U.S. bias in home loans, data show

www.press-citizen.com/story/news/2018/02/15/...bias-home-loans/340392002/

Feb 15, 2018 - Latinos seeking conventional **home loans** in the Iowa City area were nearly four times more likely to be denied than non-Hispanic whites in ...

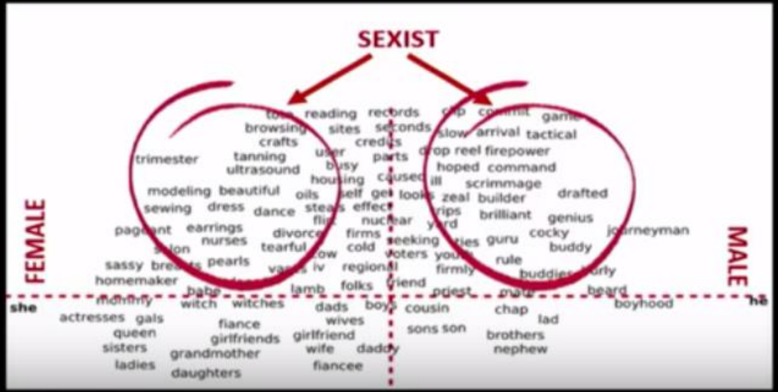
Investigation reveals discriminatory home loan practices for minorities in San Antonio

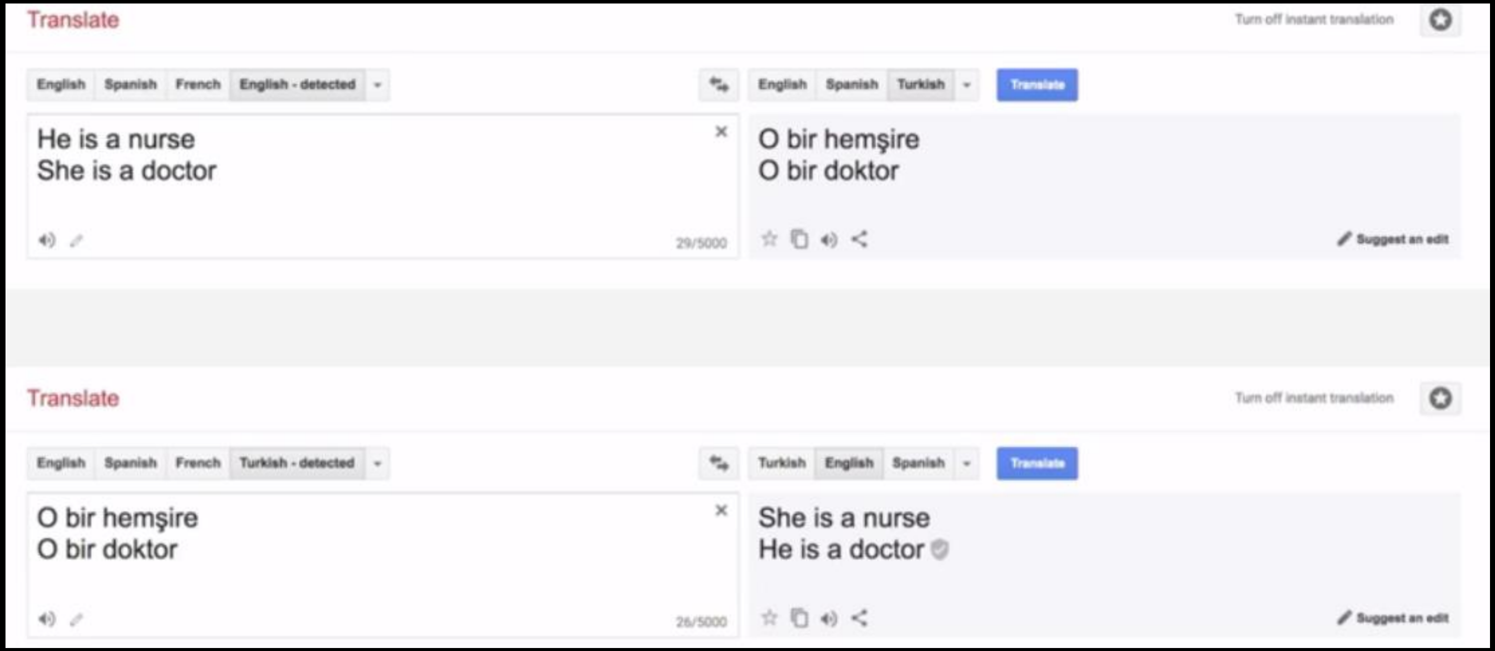
Juan A. Lozano, Associated Press Updated 11:39 am CST, Thursday, February 15, 2018

Google engineer apologizes after Photos app tags two black people as gorillas

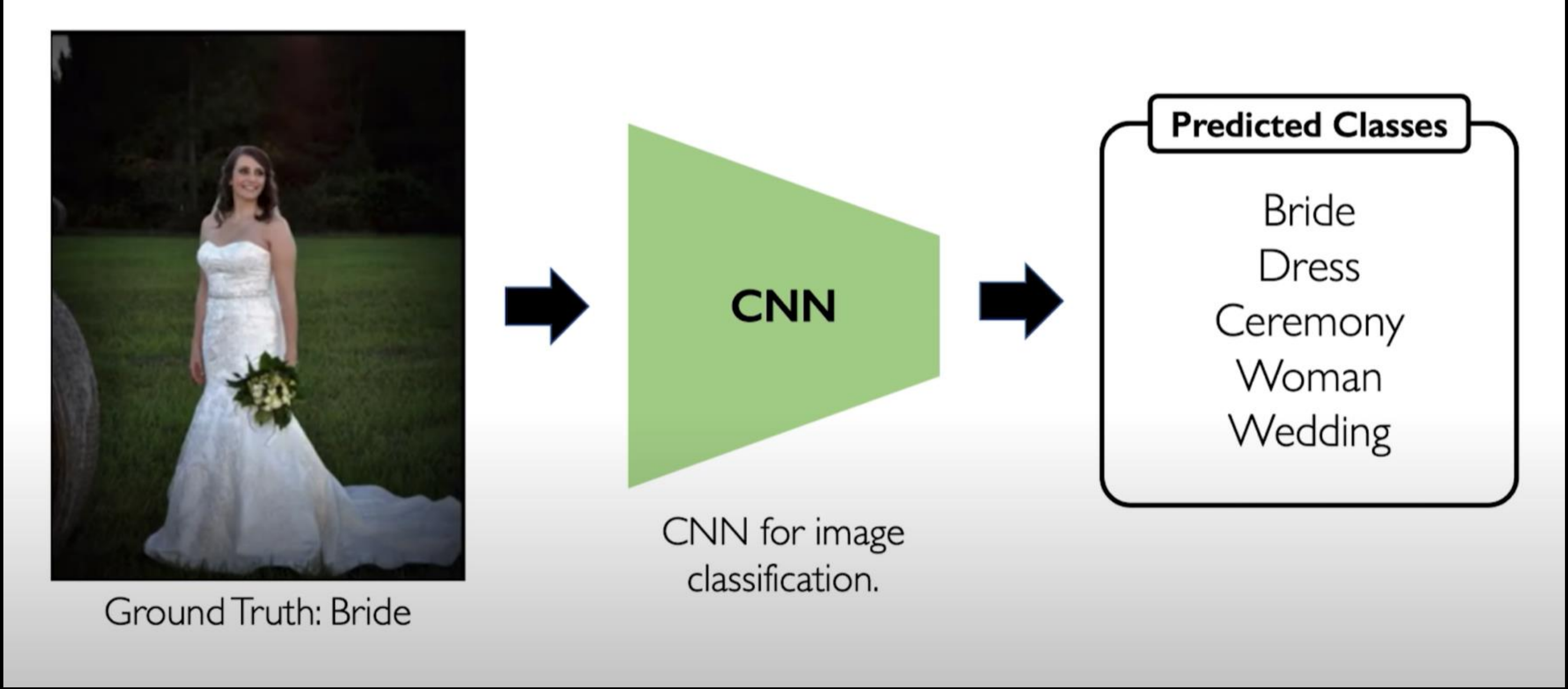
1. Timesofindia.com
2 https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G
3 https://www.theverge.com/2018/6/27/17509400/facial-recognition-bias-ibm-data-training
4 https://www.theverge.com/2015/7/1/8880363/google-apologizes-photos-app-tags-two-black-people-gorillas
6 https://www.mysanantonio.com/news/local/article/Review-Home-loan-bias-for-minorities-in-5-Texas-12616677.php

Representational Harms - Stereotyping



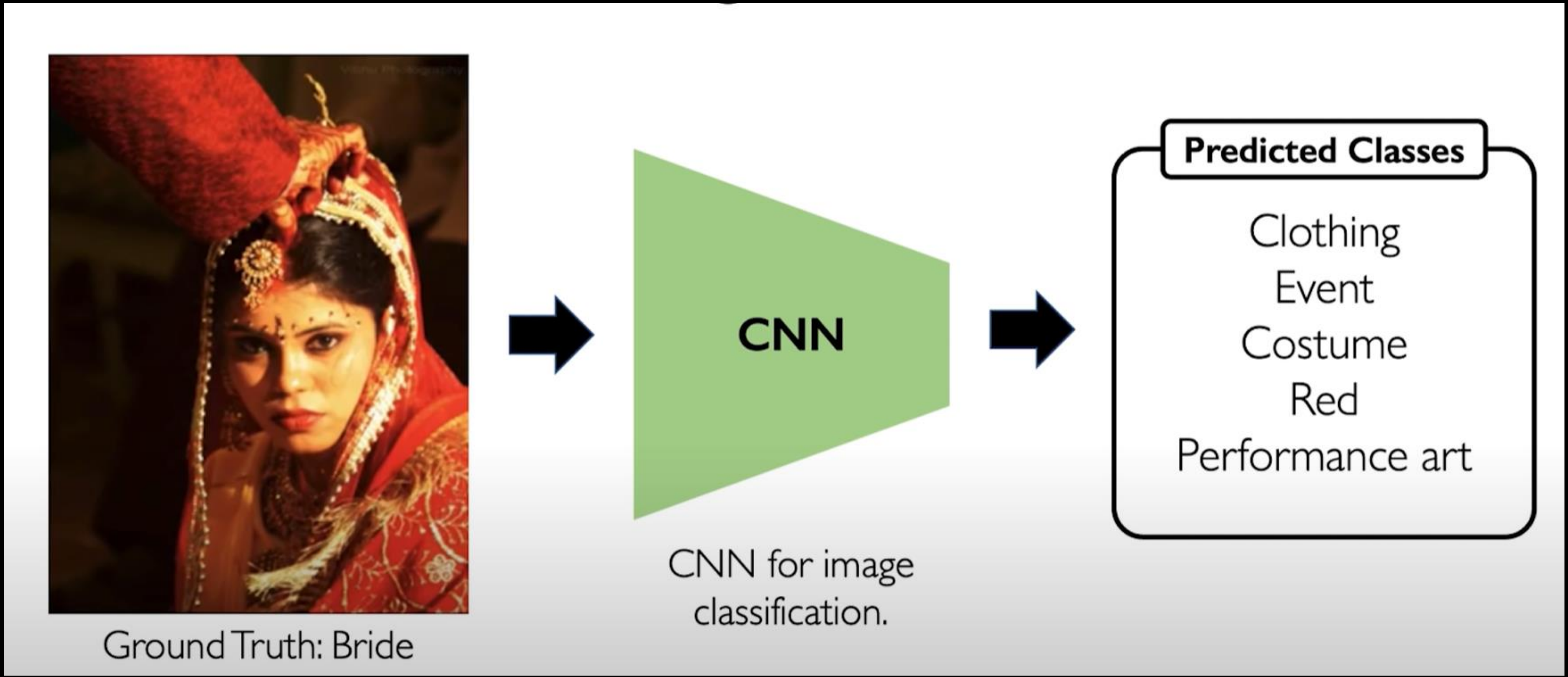


Bias in Image Classification



Source: MIT 6.S191

Bias in Image Classification

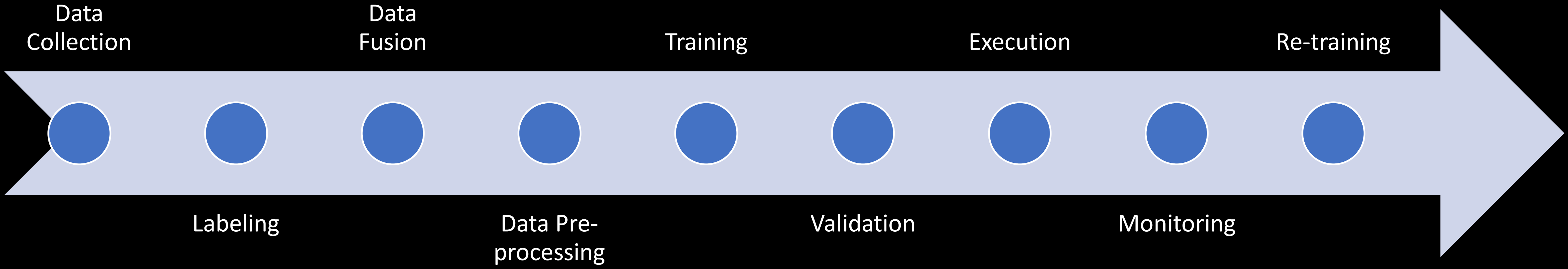


Recognition

Under-representation

Allocative harms are immediate, easily quantifiable, discrete while representational harms are long term, difficult to formalize and diffuse

Source of Bias in AI Lifecycle



Source of Data

Human Labeling

Source Prioritization

Human controlled feature

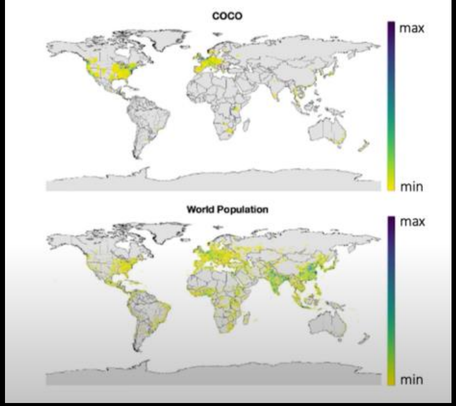
Human controlled parameters

Testing procedure
Test Data Selection

Human Interpretation

Metric Selection

Data Selection



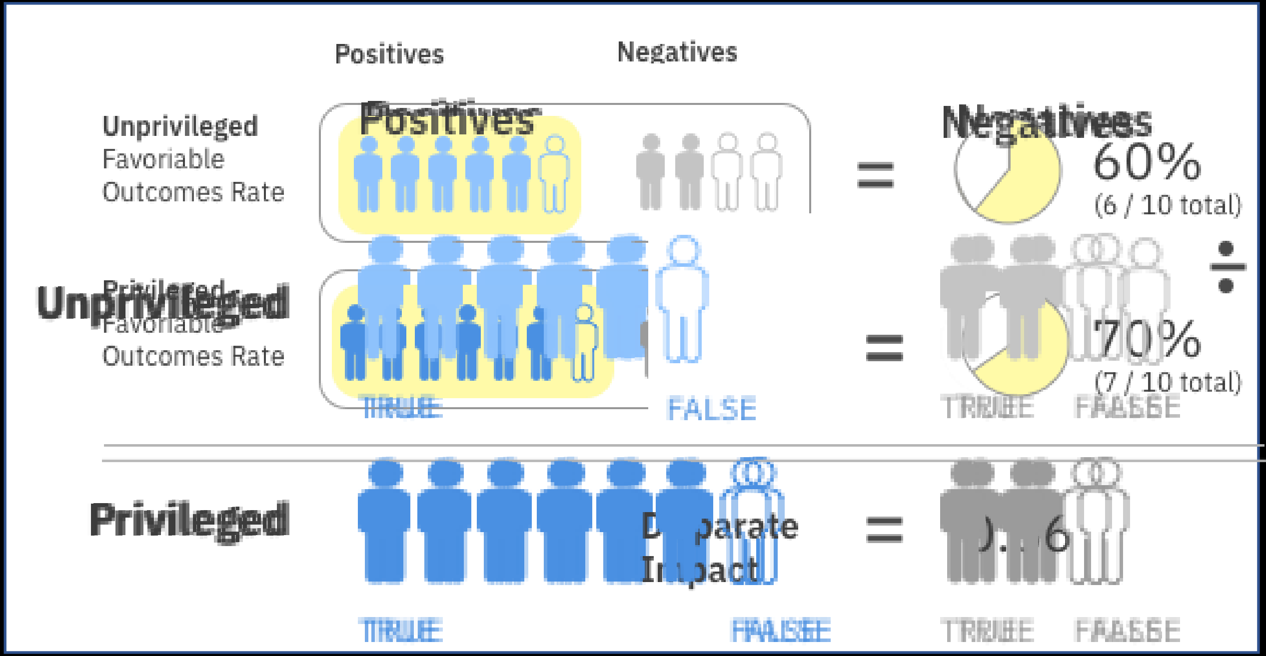
Fairness – Types

Group Fairness

- Groups defined by protected attributes receiving similar treatments or outcomes

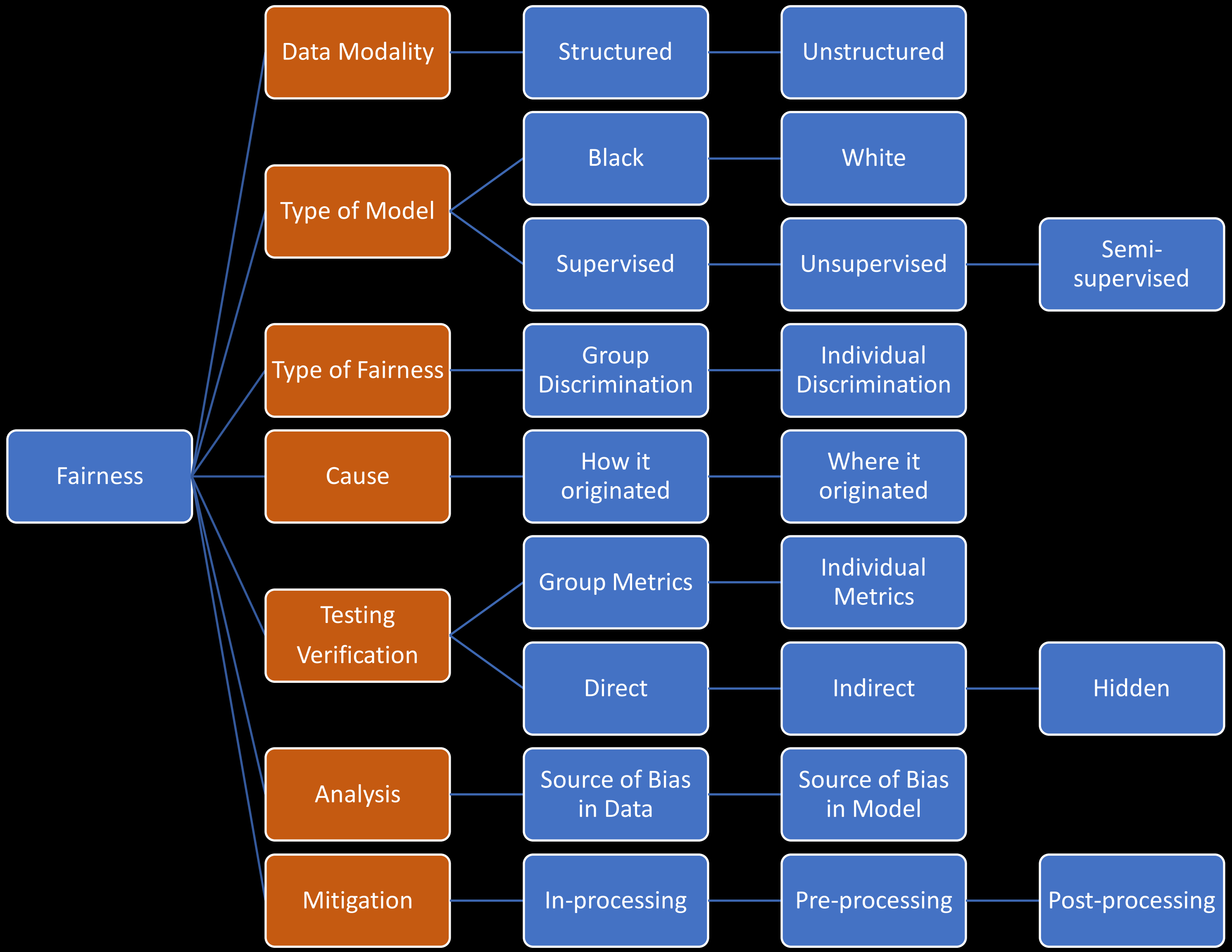
Individual Fairness

- Similar individuals receive similar treatments or outcomes



	Gender			Creditability
1	Male	10	100	Y
1	Female	10	100.2	N

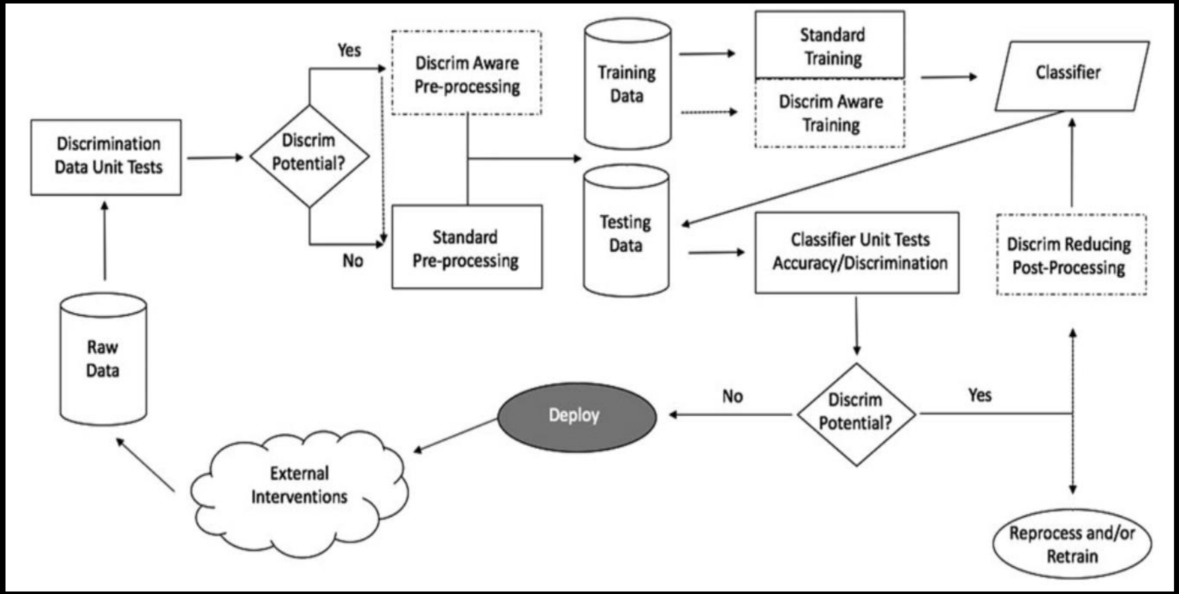
Fairness Dimensions

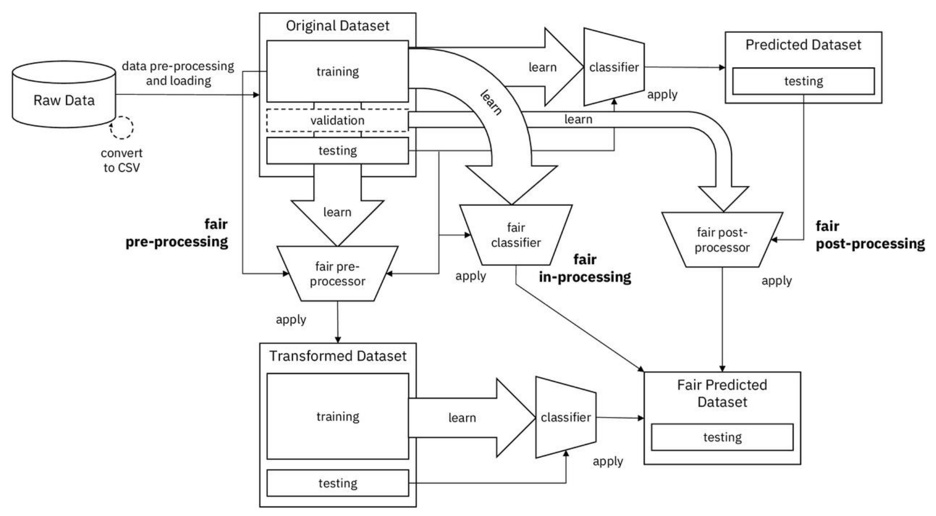


IBM in Fairness

IBM Watson OpenScale

Group Discrimination Detection
Source of Bias
Individual Discrimination Detection
Post-Processing based Mitigation
Hidden and Indirect Bias





AI Fairness 360

http://aif360.mybluemix.net

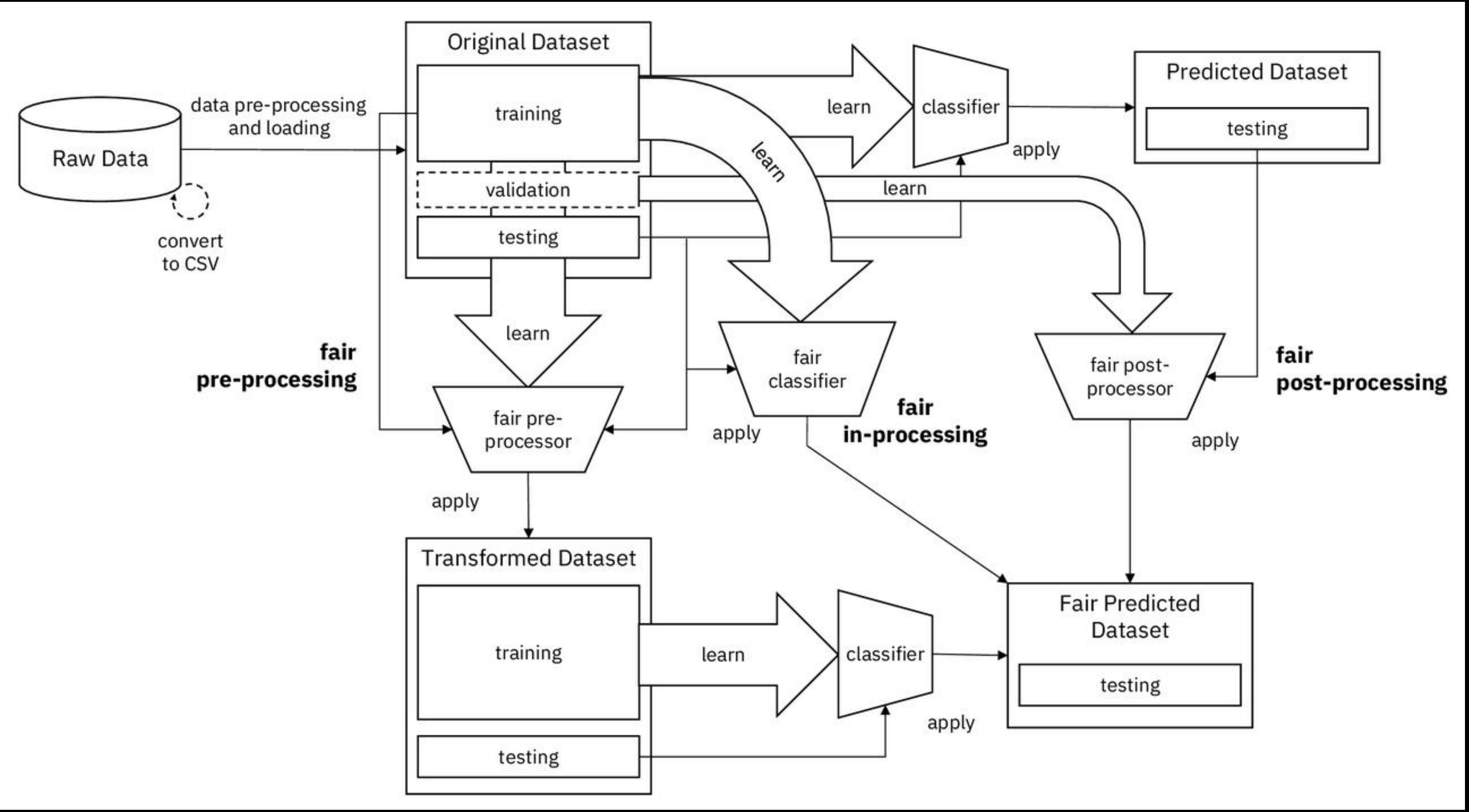
https://github.com/ibm/aif360

https://pypi.org/project/aif360

AIF360

https://github.com/Trusted-AI/AIF360

https://aif360.mybluemix.net/



Metrics and Algorithms in AIF360

Group and Individual Fairness Metrics

- Group
  - WAE
    - Disparate Impact
    - Statistical Parity Difference
  - WYSWYG
    - Equality of Odds
      - Average odds difference
      - Average absolute odds difference
  - In-between
    - false_negative_rate_ratio
    - false_positive_rate_ratio
    - error_rate_ratio
    - and error_rate_difference
- Individual
  - Distortion metrics
- Both
  - Theil Index: Measures the inequality of benefit allocation

Mitigation Algorithms

- Pre-Processing
  - Re-weighing (Kamiran and Calders, KIS'12)
  - Disparate impact remover (Feldman et al. KDD'15)
  - Optimized pre-processing (Calmon et al. NIPS'17)
  - LFR (Zemel et al. ICML'13)
- In-Processing
  - Prejudice remover (Kamishima et al. ECML-PKDD'12)
  - Adversarial debiasing (Zhang et al. AIES'18)
  - Meta algorithm for Fair Classification (Celis et al. FAT*19)
- Post-Processing
  - Equalized Odds Postprocessing (Hardt et al. NIPS'16)
  - Calibrated Equalized Odds PostProecssing (Pleiss et al. NIPS'17)
  - Reject Option Classification (Kamiran et al. ICDM'12)

Notations

Term	Explanation
P(A|B)	Conditional probability of A given B
X	All attributes which is used for prediction
Y	Ground truth (Y=1: favorable outcome; Y=0: unfavorable outcome)
Z	Binary protected attribute (Z=1: privileged; Z=0: unprivileged)
$\hat{Y}$	Predicated outcome; $\hat{Y} = 1 \leftrightarrow h(X) > \sigma$
$P(\hat{Y} = 1 \mid Z = 1)$	Probability of favorable outcome for the privileged group
$Z \notin X$	Fairness thru Unawareness

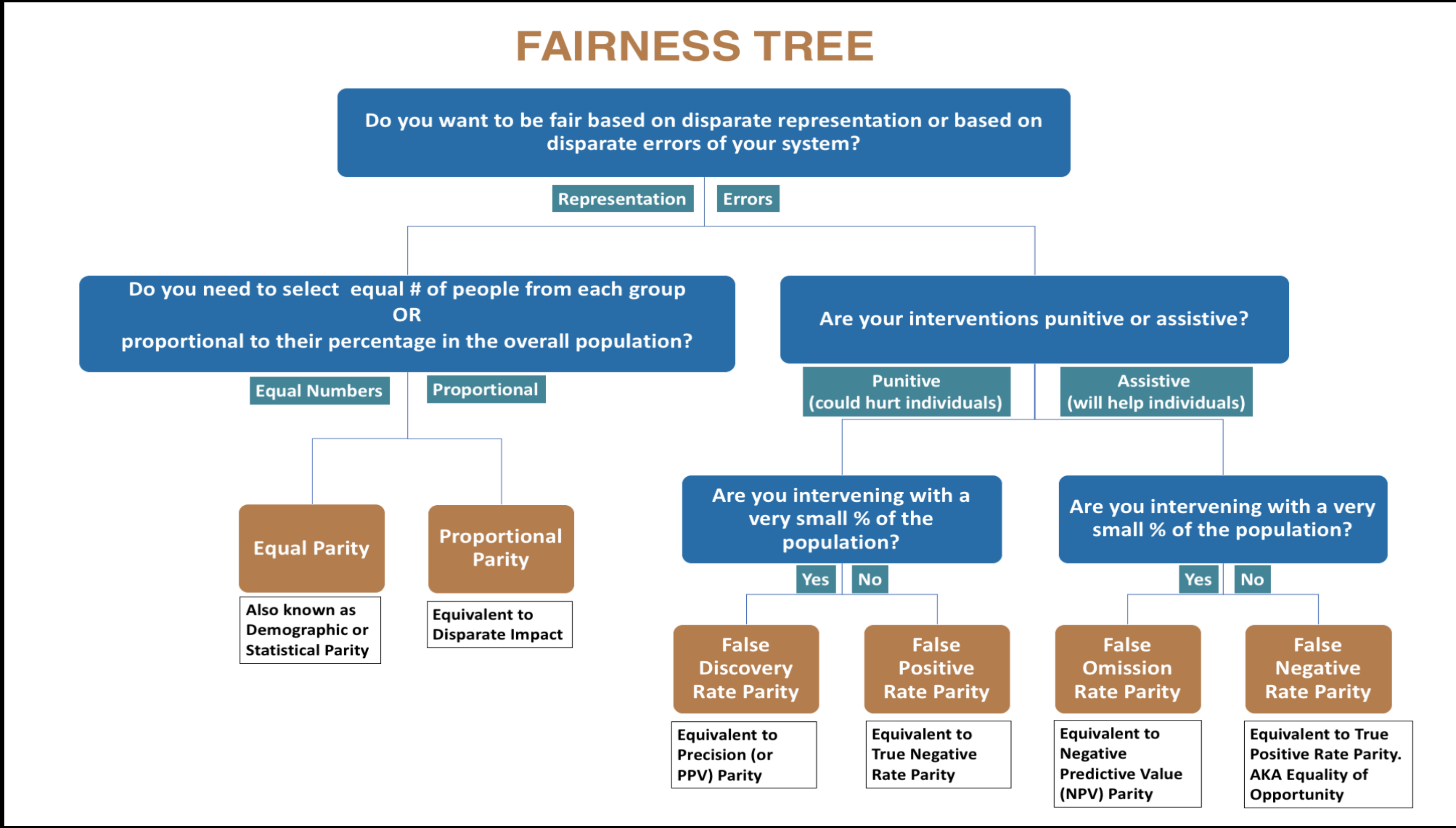
Metrics - Recap

Fairness Metric	Equality	Expression
Disparate Impact	AR	$P(\hat{Y} = 1 \mid Z = 1) / P(\hat{Y} = 1 \mid Z = 0)$
Statistical parity difference	AR	$P(\hat{Y} = 1 \mid Z = 1) - P(\hat{Y} = 1 \mid Z = 0)$
Predictive Parity	PREC	$P(Y = 1 \mid \hat{Y} = 1, Z = 1) = P(Y = 1 \mid \hat{Y} = 1, Z = 0)$
Equality of Opportunity	TPR	$P(\hat{Y} = 1 \mid Y=1, Z = 1) = P(\hat{Y} = 1 \mid Y=1, Z = 0)$
Equalized Odds	TPR, FPR	$P(\hat{Y} = 1 \mid Y=i, Z = 1) = P(\hat{Y} = 1 \mid Y=i, Z = 0) \quad i:\{0,1\}$
Accuracy Equality	AC	$P(\hat{Y} = Y \mid Z = 1) = P(\hat{Y} = Y \mid Z = 0)$
Treatment Equality	FPR/FNR	$FPR/FNR \mid z = 0 = FPR/FNR \mid z = 1$

Why do we need so many metrics?

- Problem with Disparate Impact/Demographic Parity
  - We can accept qualified applicants in the demographic $Z = 0$, but unqualified individuals in $Z = 1$, so long as the percentages of acceptance match

Metric Selection (Aequitas)



https://textbook.coleridgeinitiative.org/chap-bias.html

Pre-Processing Mitigation Algorithm

- Training data change
  - What can you change
    - Sample distribution
    - Weights
    - Feature values
    - Class labels
  - Mitigation Effect
    - Group Fairness
    - Individual Fairness

- Algorithms
  - Re-weighing (Kamiran and Calders, KIS’12)
    - Modifies the weights of different training examples
  - Disparate impact remover (Feldman et al. KDD’15)
    - Edit feature values to improve group fairness
  - Optimized pre-processing (Calmon et al. NIPS’17)
    - Modifies features and labels to address both group and individual fairness
  - LFR (Zemel et al. ICML’13)
    - Learns fair representation by obfuscating information about protected attribute

Re-weighing

DI = $\frac{P(Y = 1 \mid Z = 0)}{P(Y = 1 \mid Z = 1)} > 0.8$

|{X | Y = 1, Z = 0}| = a
|{X | Y = 0, Z = 0}| = b
|{X | Y = 1, Z = 1}| = c
|{X | Y = 0, Z = 1}| = d

W = $\frac{|\{X \mid Z = z\}| \times |\{X \mid Y = y\}|}{|D| \; |\{X \mid Z = z \wedge Y = y\}|}$

|{X | Y = 1, Z = 0}| = (a + b) (a + c)
|{X | Y = 0, Z = 0}| = (a + b) (b + d)
|{X | Y = 1, Z = 1}| = (c + d) (a + c)
|{X | Y = 0, Z = 1}| = (c + d) (b + d)

DI = 1

Optimized Pre-Processing (Calmon et al. NIPS'17)

Learns a probabilistic transformation that can modify the features and the labels in the training data

$$
\begin{aligned}
\min_{p_{\tilde{X},\tilde{Y}|X,Y,Z}} \quad & \Delta\left(p_{\tilde{X},\tilde{Y}}, p_{X,Y}\right) \\
\text{s.t.} \quad & D\left(p_{\tilde{Y}|Z}(y \mid z), p_{Y_T}(y)\right) \leq \epsilon_{y,z} \text{ and} \\
& E\left(\delta((x,y),(\tilde{X},\tilde{Y})) \mid Z=z, X=x, Y=y\right) \leq c_{z,x,y} \forall (x,y,z) \in \mathcal{D}, \\
& p_{\tilde{X},\tilde{Y}|X,Y,Z} \text{ is a valid distribution}
\end{aligned}
$$

Utility Preservation

Limit the dependence of the transformed outcome $\tilde{Y}$ on the protected variable Z.

Individual distortion control

D = Distance metric
δ = distortion metric
Δ = dissimilarity measure between probability distribution

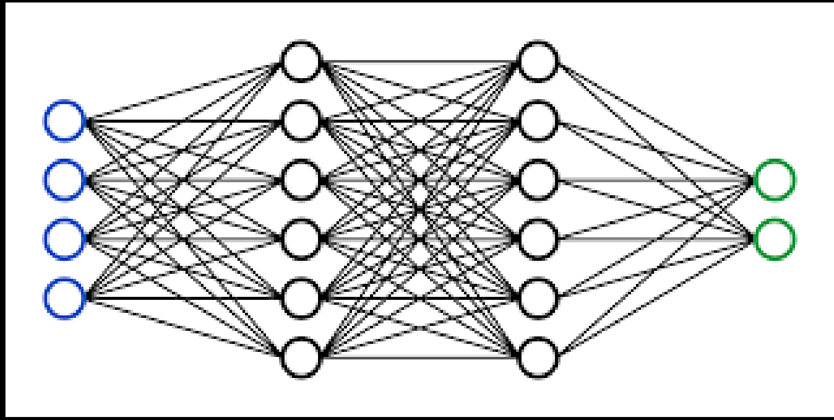
German-credit	Sex	Age
Acc – before	0.65	0.65
Acc - after	0.56	0.60
DI - before	.99	0.38
DI - after	1.06	0.82

In-Processing Mitigation Algorithm

- Prejudice remover (Kamishima et al. ECML-PKDD’12)
  - Include a regularization term to reduce bias
- Adversarial debiasing (Zhang et al. AIES’18)
  - Two network (Similar to GAN)
- Meta algorithm for Fair Classification (Celis et al. FAT*19)
  - A meta-algorithm for classification that takes as input a large class of fairness constraints

Adversarial De-biasing (zhang et al. AIES 2018)

X



$\hat{Y}$

$\hat{Z}$

Task: language model to complete analogies
He is to **she**, as **doctor** is to ?

biased		debiased	
neighbor	similarity	neighbor	similarity
nurse	1.0121	nurse	0.7056
nanny	0.9035	obstetrician	0.6861
fiancée	0.8700	pediatrician	0.6447
maid	0.8674	dentist	0.6367
fiancé	0.8617	surgeon	0.6303
mother	0.8612	physician	0.6254
fiance	0.8611	cardiologist	0.6088
dentist	0.8569	pharmacist	0.6081
woman	0.8564	hospital	0.5969

Sensitive attribute: Gender

Target Class label Y
Protected Output Z

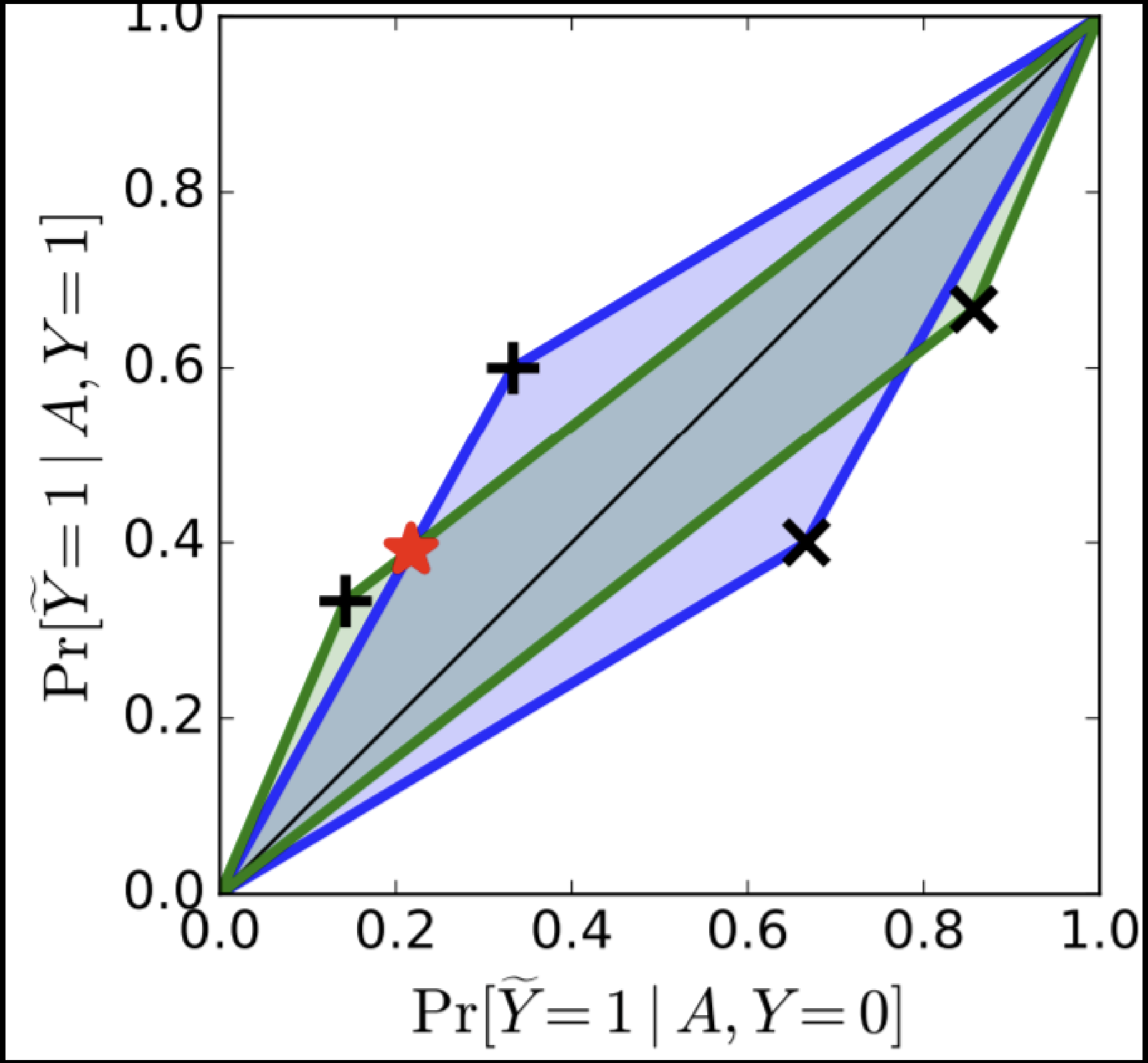
If $\hat{Z}$ can determine $\hat{Y}$ then protected attribute has affect on $\hat{Y}$

Post-Processing Mitigation Algorithms

- Equalized Odds Post-processing (Hardt et al. NIPS’16)
  - Solves a linear program to find probabilities with which to change output labels to optimize equalized odds
- Calibrated Equalized Odds Post-processing (Pleiss et al. NIPS’17)
  - Optimizes over calibrated classifier score outputs to find probabilities with which to change output labels with an equalized odds objective
- Reject Option Classification (Kamiran et al. ICDM’12)
  - Gives favorable outcomes to unprivileged groups and unfavorable outcomes to privileged groups in a confidence band around the decision boundary with the highest uncertainty

Equalized Odds Post-processing

- Equalized Odds [Recap]
  - True positive Rate and False Positive Rate should be same for protected and unprotected groups
- Goal: Unfair predictor $\hat{Y}$ to fair predictor $\tilde{Y}$ based on Y, Z, $\hat{Y}$
- $\gamma_z(\hat{Y}) = (P(\hat{Y} = 1 \mid Z=z, Y = 0), P(\hat{Y} = 1 \mid Z=z, Y = 1))$
- Eq. Odds: $\gamma_0(\hat{Y}) = \gamma_1(\hat{Y})$



Individual Discrimination Definition

Dwork's Definition

- Two similar individuals should get same decision

$D(h(x_i),h(x_j)) \leq d(x_i,x_j)$

forall x_i,x_j

Counterfactual Fairness:

- A decision is fair towards an individual if it is the same in (a) the actual world and in a (b) a counterfactual world where the individual belonged to a different demographic group

Individual Discrimination Testing of Black Box Models

	Gender			Creditability
1	**Male**	**10**	**100**	**Y**
1	Female	10	100	N

	Race			Creditability
1	**White**	**10**	**100**	**Y**
1	Black	10	100	N
1	Hispanic	10	100	Y

	Age (Priv: <60)			Creditability
1	**61**	**10**	**100**	**Y**
1	20	10	100	N
1	58	10	100	Y

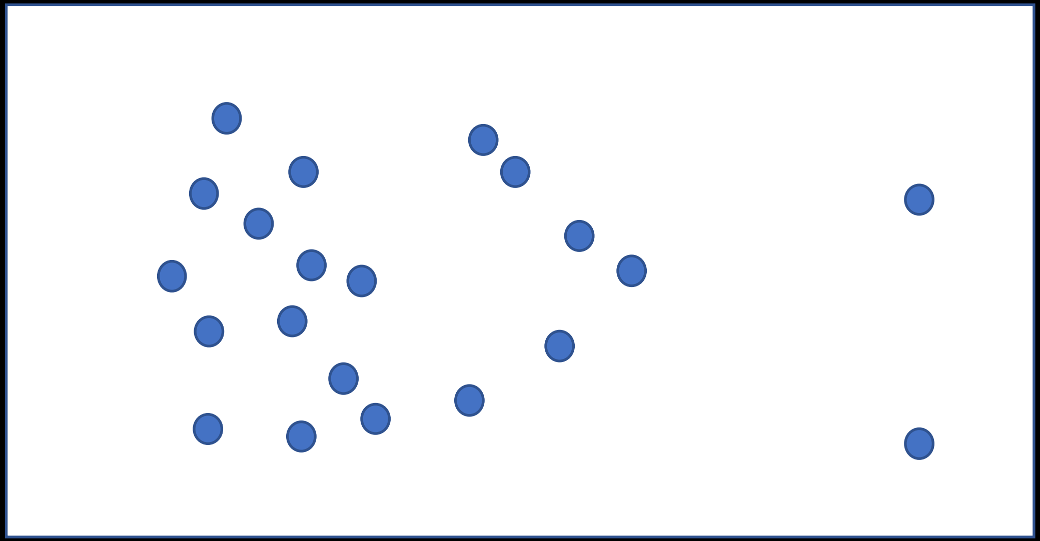
Given one sample (t) we can iteratively perturb it with values from the privileged/unprivileged class and generate test samples (t, t').

If M(t) != M(t') then t is called a discriminatory sample

Goal: Synthesize non-protected values for which we can find discriminatory sample

Themis

- Sample generation
  - Random
- Metric
  - $\frac{\text{\# Discriminatory samples}}{\text{\# samples}}$



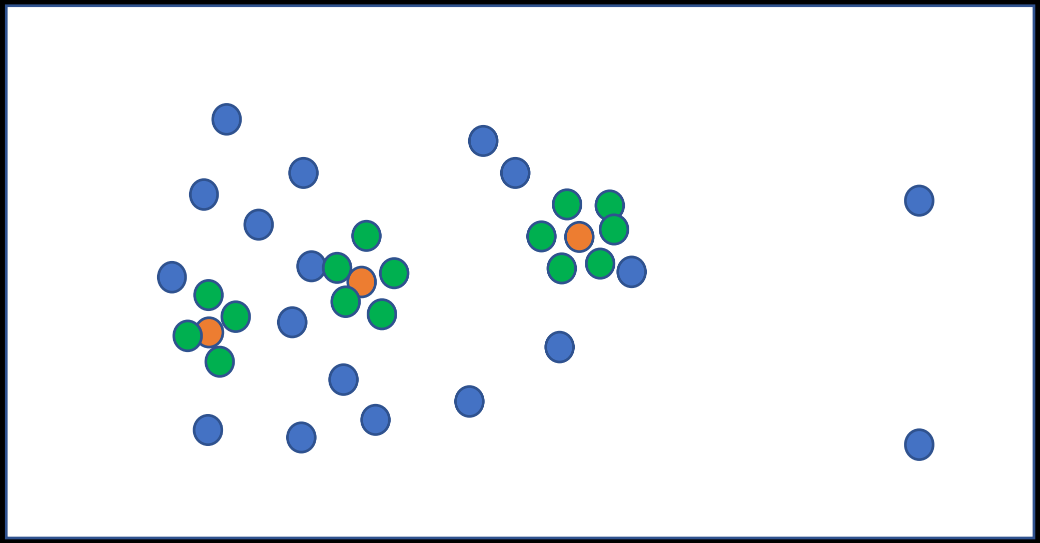
Key Result: 1000s of Discriminatory Input

Galhotra, Sainyam, Yuriy Brun, and Alexandra Meliou. "Fairness testing: testing software for discrimination." *FSE* 2017.

AEQUITAS

- Sample generation
  - Two Steps
    - Global: Random
    - Local:
      - For each discriminatory Input
        - Random small perturbation to non-protected attributes
- Metric
  - # Discriminatory samples / # gen. samples

Global non-discriminatory samples
Global discriminatory samples
Local samples



Key Result: > 70% Discriminatory Inputs

Sakshi Udeshi, Pryanshu Arora, and Sudipta Chattopadhyay. "Automated directed fairness testing." *ASE*. 2018.

Summary and Next Class

Summary

- Types of Fairness
- Reason for Bias
- AIF360
- Metrics
- Mitigation Algorithms
- Individual Discrimination Testing

Next Class

- Explainability
- AIF360 Tour
    - Common Fairness Datasets
    - Metrics computation using AIF360
    - Fairness-Accuracy Tradeoff
    - Hands-on Group Bias Mitigation

Backup

Explainability

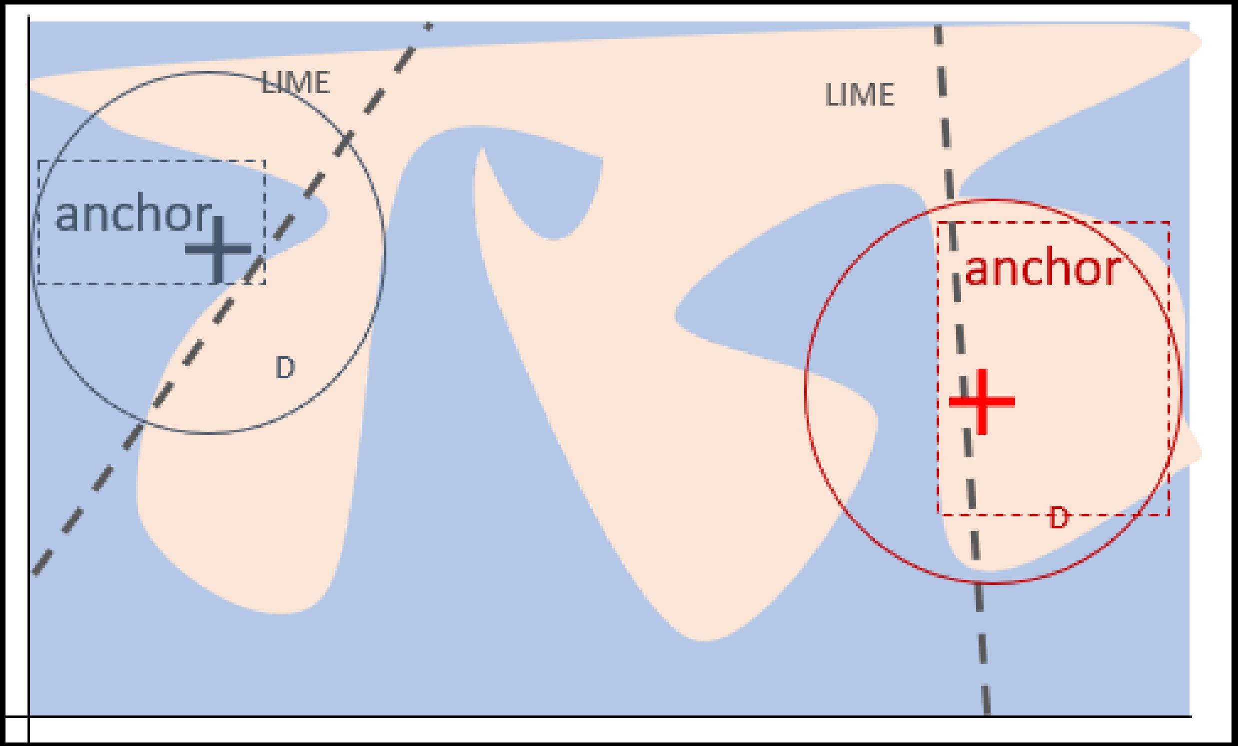
LOCAL

GLOBAL

COUNTERFACTUAL

ANCHOR

- ANCHOR computes the region where the same prediction holds

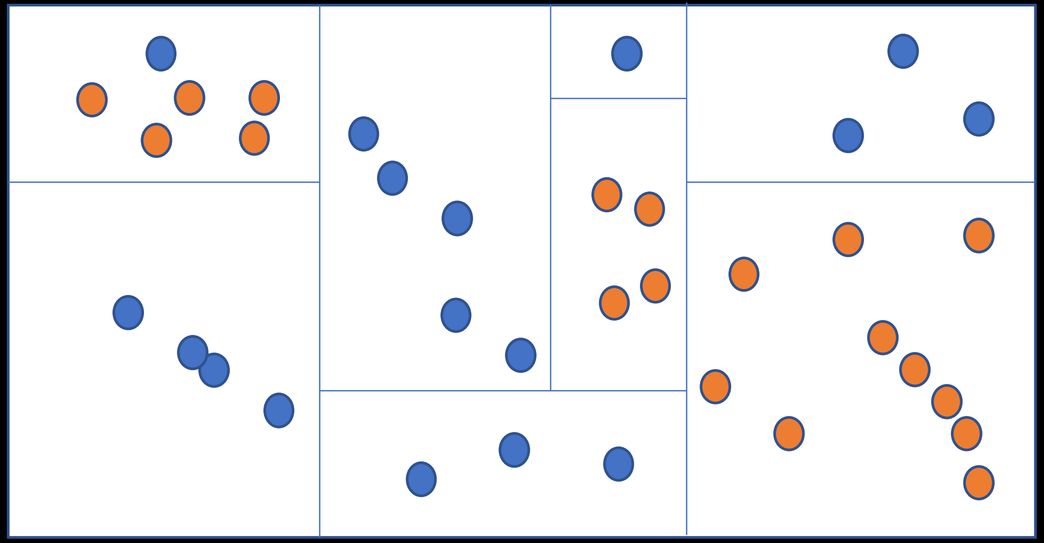


Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "Anchors: High-precision model-agnostic explanations." *AAAI* 2018.

Image Source https://drive.google.com/file/d/1QdBRUCn_yYtUlJaTyWghcp9XJZ4K2kY9/view

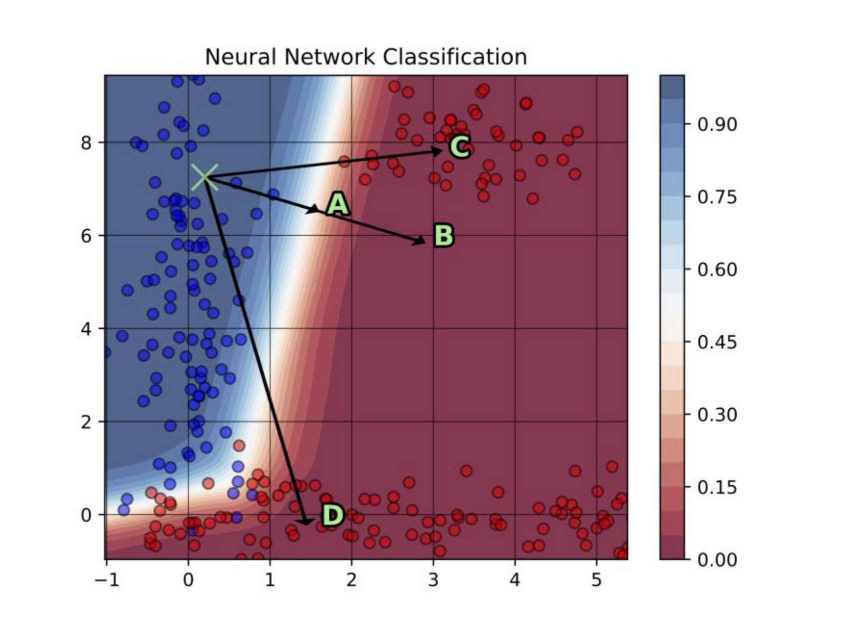
Global Explainability thru TrePan

- Approximate black-box model's decision boundary by decision tree
- Model Agnostic path coverage criteria
- TrePan
  - Modified decision tree algorithm
    - Uses target model's decision (instead of training data's decision)
  - Decision tree algorithm forms boundary based on fewer number of samples near the leaf levels
    - TrePan generates more synthetic data to increase density to create more accurate boundary



Craven, Mark, and Jude W. Shavlik. "Extracting tree-structured representations of trained networks." *Advances in neural information processing systems*. 1996.

Counterfactual Explainability



- A counterfactual explanation of a prediction describes the smallest change to the feature values that changes the prediction to a predefined output

Wachter et al. suggest minimizing the following loss:

$$L(x, x', y', \lambda) = \lambda \cdot (\hat{f}(x') - y')^2 + d(x, x')$$