Toolbox to Mitigate Bias in AI

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Materials: bit.ly/north-conf-toolbox

Agenda

- Responsible AI
- AI Fairness 360
- Demo
- Q&A

Responsible AI

- *AI Opportunities*
  - Increased Revenue
  - Efficiencies
- *AI Risks*
  - Harm to Users
  - Harm to Business
- *A Solution*
  - Regulation
  - Ethical & Moral Practices

Unwanted Bias

Places

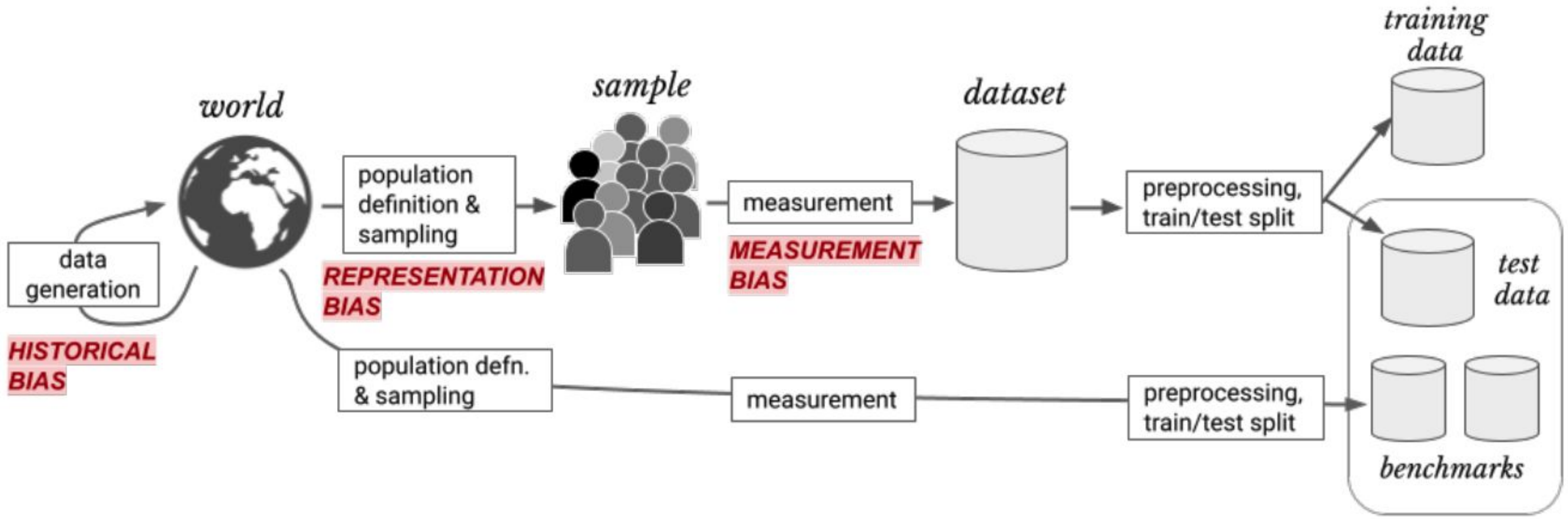
privileged groups at systematic **advantage**

and

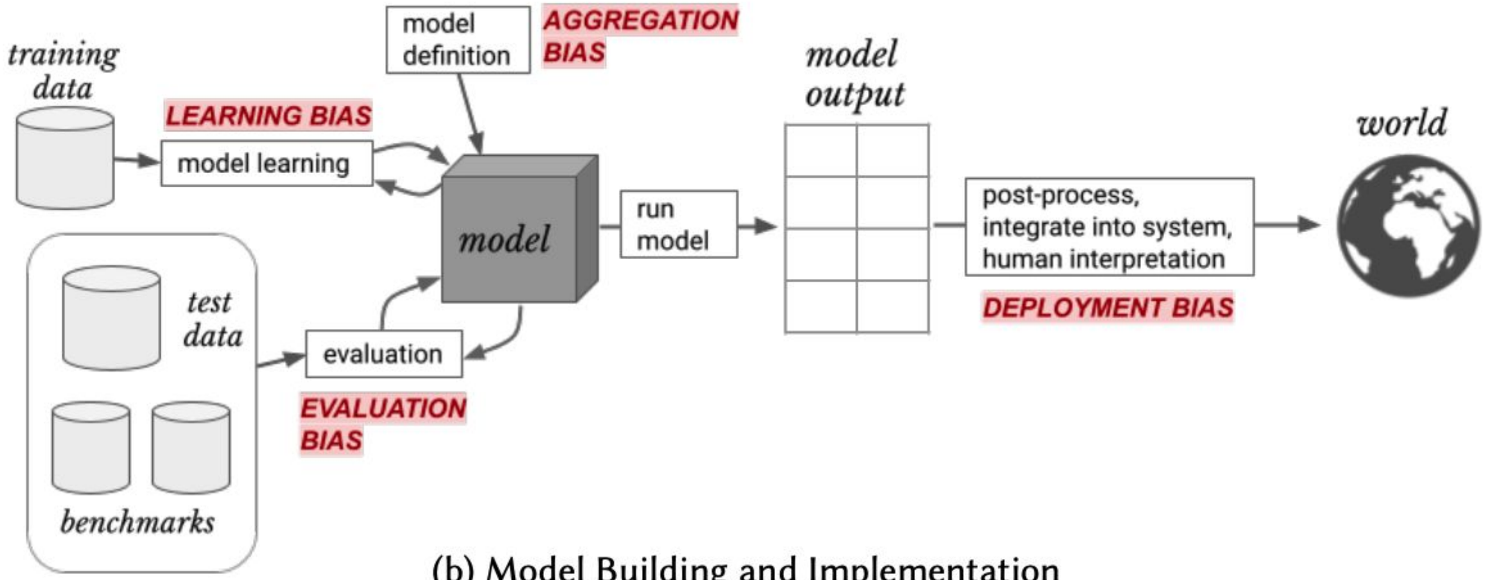
unprivileged groups at systematic **disadvantage.**

Types of Bias

A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle



(a) Data Generation



(b) Model Building and Implementation

https://arxiv.org/pdf/1901.10002.pdf

DESIGN

- Human Centric
- Optimization Metrics

DATA

- Representative
- Protected

MODEL

- Interpretable
- Fair

MONITORING

- Staged rollout
- Feedback loop

ACCOUNTABILITY

- Transparency
- Responsibilities

Responsible AI Pipeline

Responsible AI Benefits

- Prevent harm
- Build an inclusive product
- Delightful customer experiences
- Responsible branding

A Step Towards Building Trustworthy AI system

AI Fairness 360 Toolkit (AIF360)

AI Fairness 360 (AIF360)

An extensible, open source toolkit for measuring, understanding, and reducing AI bias. It combines the top bias metrics, bias mitigation algorithms, and metric explainers from fairness researchers across industry and academia

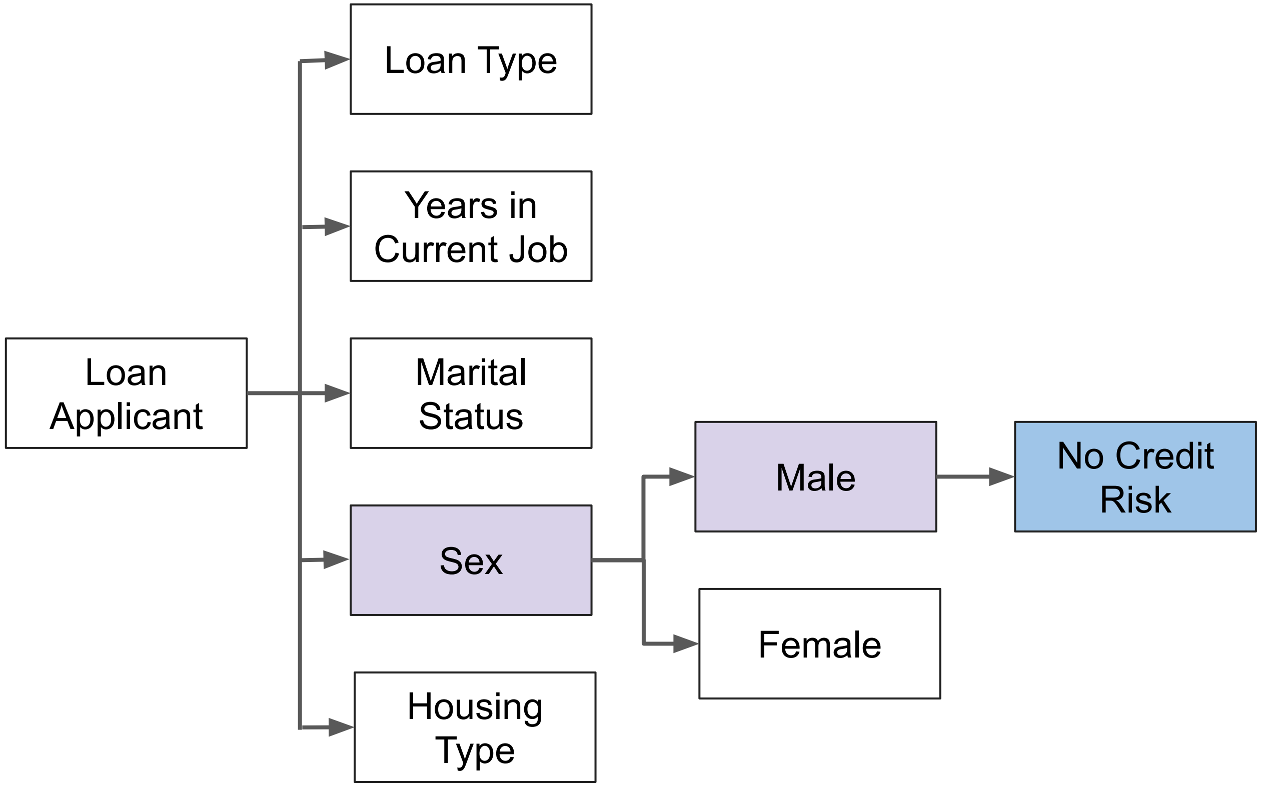
- Implement techniques from eight published papers across the greater AI fairness research community
- Available in Python and R

Terminology

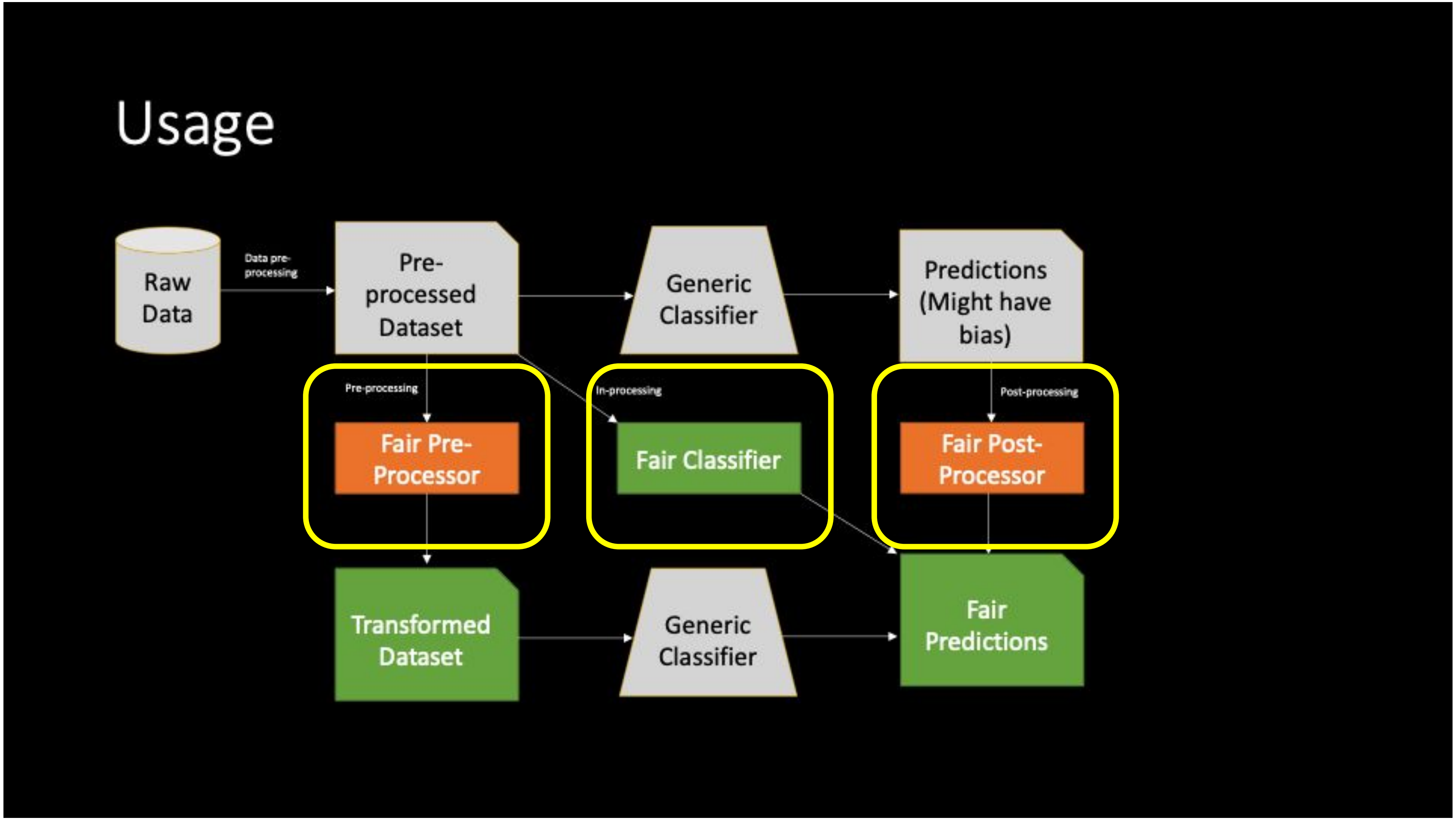
- **Favorable label**: A label whose value corresponds to an outcome that provides an advantage to the recipient (such as receiving a loan, being hired for a job, not being arrested)
- **Protected attribute**: An attribute that partitions a population into groups whose outcomes should have parity (such as race, sex, caste, and religion)
- **Privileged value** (of a protected attribute): A protected attribute value indicating a group that has historically been at a systemic advantage
- **Discrimination/unwanted bias**: When specific privileged groups are placed at a systematic advantage and specific unprivileged groups are placed at a systematic disadvantage. This relates to attributes such as race, sex, age, and sexual orientation.

Terminologies

- Favorable label: No Credit Risk
- Unfavorable label: Credit Risk
- Protected Attribute: Sex
- Privileged Protected Attribute: Male



Mitigating bias throughout the AI application lifecycle



Metrics

A quantification of unwanted bias in training data or models.

Group fairness

Partitions a population into groups defined by protected attributes & seeks for some statistical measure to be equal across groups.

Individual fairness

Seeks for similar individuals to be treated similarly.

Metrics

Group Fairness

Data Vs Model

Measure fairness on the training data

Vs

Measure fairness on the learned model

Metrics

Group Fairness

We are all Equal

All groups have similar abilities with respect to the task

(even if we cannot observe this properly)

Vs

What You See is What You Get

Observations reflect ability with respect to the task

Group Fairness Metrics

- Difference
- Number of instance
- Ratio
- Base Rate
- Consistency
- Difference
- Disparate Impact
- Mean Difference

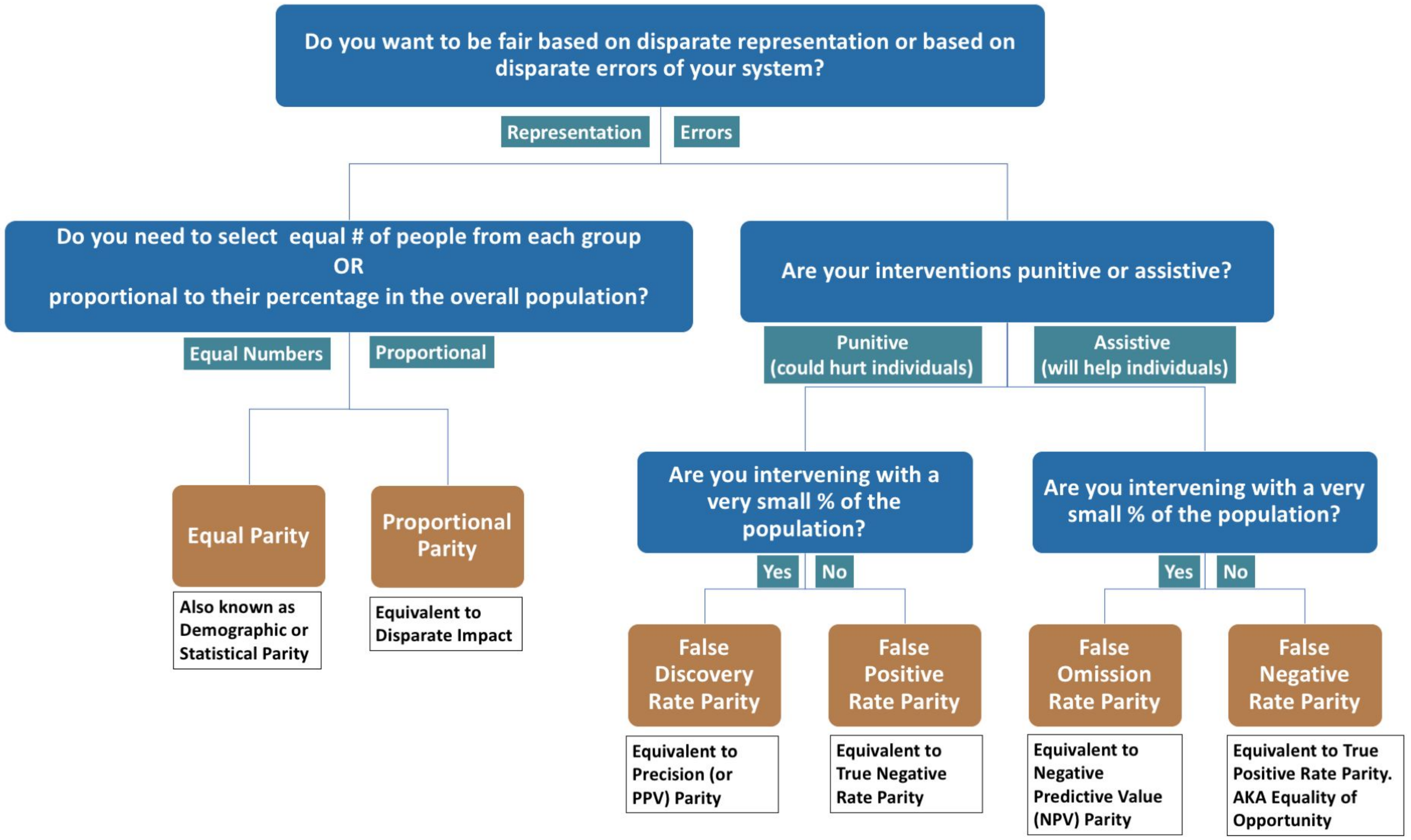
- Number of negatives
- Number of Positives
- Ratio
- Smoothed empirical differential fairness
- Statistical Parity Difference
- Rich Subgroup
- false_negative_rate
- false_negative_rate

Individual Fairness Metrics

- average_euclidean_distance
- average_mahalanobis_distance
- average_manhattan_distance
- difference
- euclidean_distance
- mahalanobis_distance
- manhattan_distance
- mean_euclidean_distance_difference
- mean_euclidean_distance_ratio
- mean_mahalanobis_distance_difference
- mean_mahalanobis_distance_ratio
- mean_manhattan_distance_difference
- mean_manhattan_distance_ratio

Full Guidance Available Here: https://aif360.mybluemix.net/resources#guidance

Fairness Metrics Tree

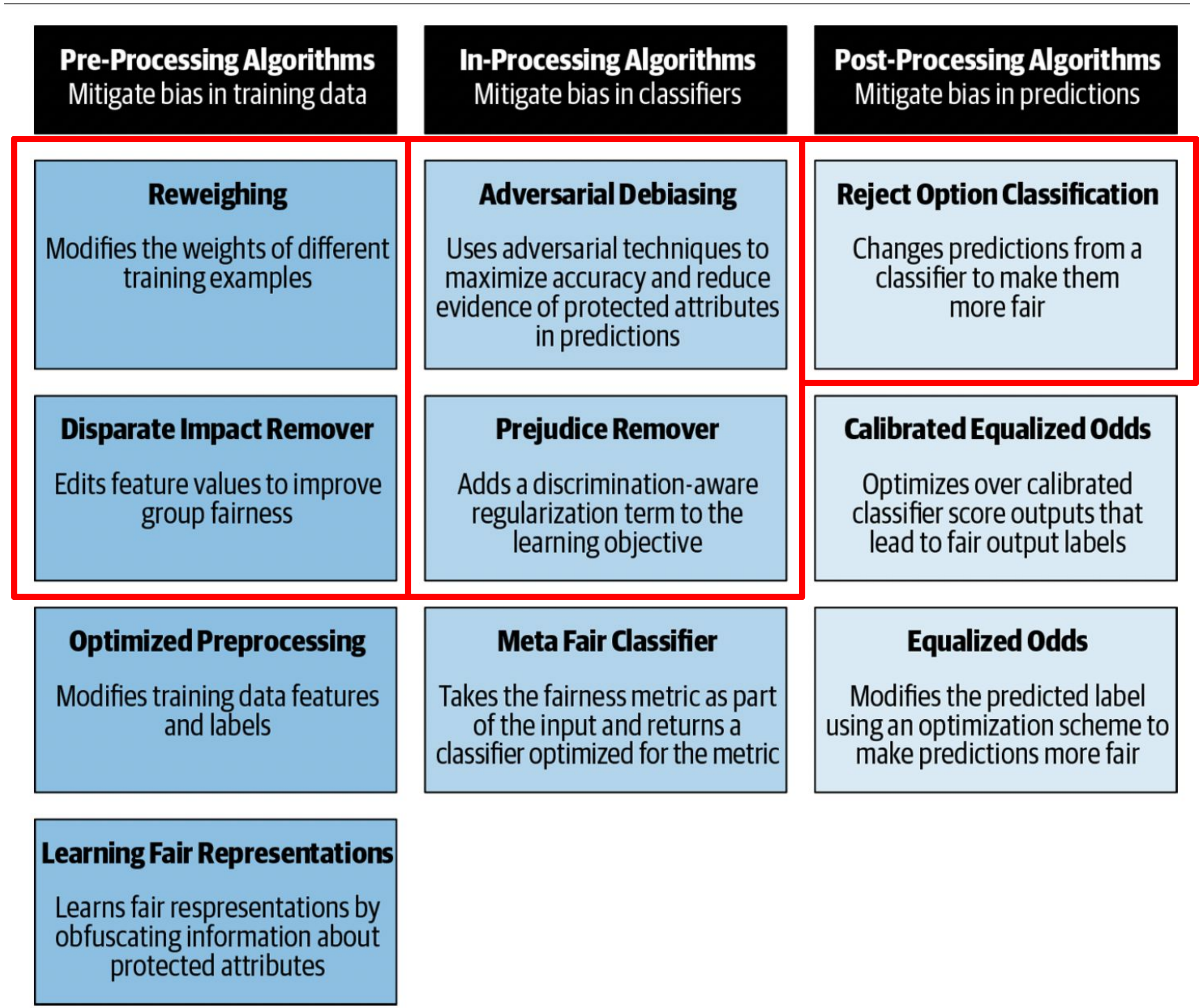


Full Guidance Available Here: https://aif360.mybluemix.net/resources#guidance

Algorithms

- Bias mitigation algorithms attempt to improve the fairness metrics by modifying the training data, the learning algorithm, or the predictions.
- These algorithm categories are known as pre-processing, in-processing, and post-processing, respectively.

Algorithms


Pre-Processing Algorithms
Mitigate bias in training data
In-Processing Algorithms
Mitigate bias in classifiers
Post-Processing Algorithms
Mitigate bias in predictions
Reweighing
Modifies the weights of different training examples
Adversarial Debiasing
Uses adversarial techniques to maximize accuracy and reduce evidence of protected attributes in predictions
Reject Option Classification
Changes predictions from a classifier to make them more fair
Disparate Impact Remover
Edits feature values to improve group fairness
Prejudice Remover
Adds a discrimination-aware regularization term to the learning objective
Calibrated Equalized Odds
Optimizes over calibrated classifier score outputs that lead to fair output labels
Optimized Preprocessing
Modifies training data features and labels
Meta Fair Classifier
Takes the fairness metric as part of the input and returns a classifier optimized for the metric
Equalized Odds
Modifies the predicted label using an optimization scheme to make predictions more fair
Learning Fair Representations
Learns fair respresentations by obfuscating information about protected attributes

Using AIF360 in R

R Package Installation

You can install the **aif360** R package in your machine

Or you can use **Docker** for example and install the package

Example Use-Case

Business use-case

Select customers who are likely to buy our new product.

Target Audience

Those whose income is over $50,000.

Dataset

https://archive.ics.uci.edu/ml/datasets/adult

Example Attributes

- Age
- Work Classification (e.g. Private, Self-Employed, Never worked, etc.)
- Education (e.g. Bachelors, Some college, High School graduate, etc.)
- Years of Education
- Marital Status
- Occupation
- Race
- Sex
- Hours-per-week
- Native country

Live Demo

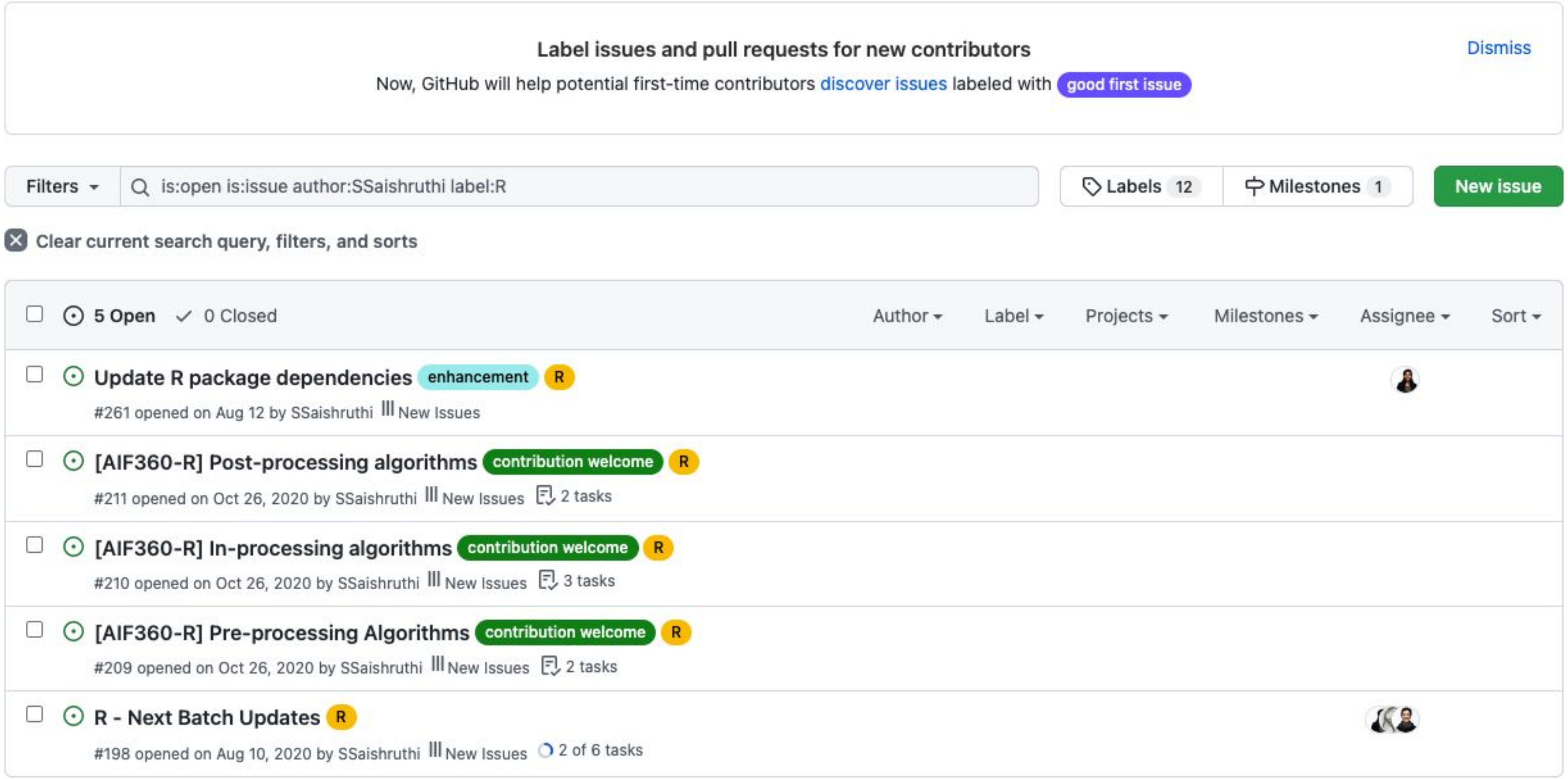
```r
## 3) Calculate the mean  difference
metric_train <- binary_label_dataset_metric(data_aif_train,
                                            privileged_groups = privileged_groups,
                                            unprivileged_groups = unprivileged_groups)
metric_train$mean_difference()
# [1] -0.1932321
# The difference between the proportion of positive outcomes for the unprivileged vs
# the  privileged group
# P(Y =1| D =unprivileged) - P ( Y =1| D =privileged)



### 4) Apply Adversarial debiasing is an in-processing technique that learns a classifier
## to maximize prediction accuracy and simultaneously reduce an adversary's ability to determine
### the protected attribute from the predictions
sess <- tf$compat$v1$Session()

debiased_model <- adversarial_debiasing(privileged_groups = privileged_groups,
                                        unprivileged_groups = unprivileged_groups,
                                        scope_name = 'debiased_classifier',
                                        debias = TRUE,
                                        sess = sess)

debiased_model$fit(data_aif_train)
# predictions
data_aif_train_debiasing <- debiased_model$predict(data_aif_train)

# Right now we are just caring about fairness
metric_preds <- binary_label_dataset_metric(data_aif_train_debiasing,
                                            privileged_groups = privileged_groups,
                                            unprivileged_groups = unprivileged_groups)

metric_preds$mean_difference()
# [1] -0.08583602 after
# [1] -0.1932321 before
```

adult_dataset.R

Source on Save

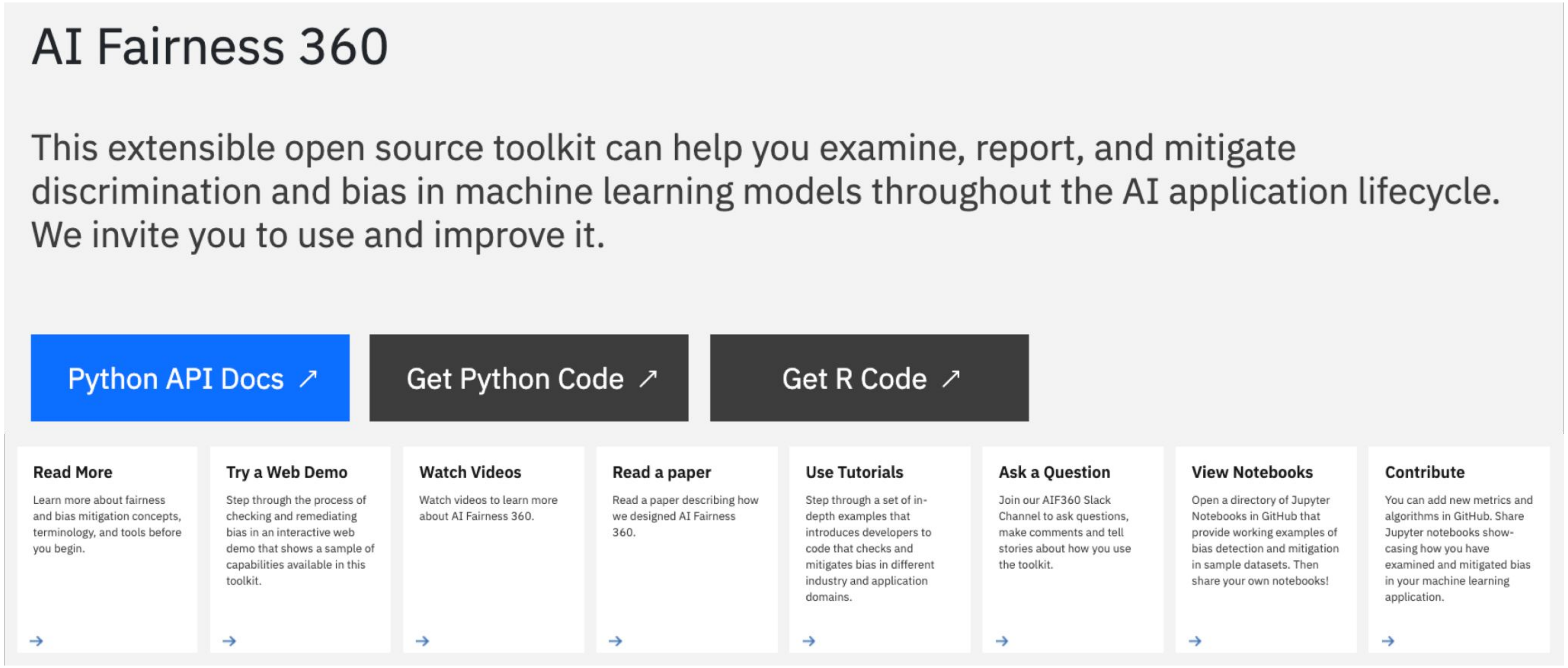
```r
### Load the library
library(aif360)
load_aif360_lib()

### Load the data
original_data <- readr::read_csv(
  "https://www.dropbox.com/s/ga8tr1glji7nrgk/adult_data_preprocessed.csv?dl=1"
  )
original_data <- original_data[, -1]
head(original_data)
str(original_data)

# Predict whether income exceeds $50K/yr based on census data.
# Variables:
## sex: 1 male, 0 female
## income binary: 1 > 50k, 0 <= 50k

privileged_groups <- list('sex', 1)
unprivileged_groups <- list('sex', 0)

### 1) Convert the dataframe into the aif360 format ----------------------------
data_aif <- aif_dataset(data_path = original_data,
                        favor_label = 1,
                        unfavor_label = 0,
                        privileged_protected_attribute = 1,
                        unprivileged_protected_attribute = 0,
                        target_column = "Income Binary",
                        protected_attribute = "sex")

### 2) Let's  split in train and test ------------------------------------------
# train should be 70%
# test should be 30%
set.seed(1234)
data_aif_split <- data_aif$split(num_or_size_splits = list(0.70))
data_aif_train <- data_aif_split[[1]]
data_aif_test <- data_aif_split[[2]]
```

Call To Action



AIF360 - Interactive Demo

aif360.mybluemix.net



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Thank You!

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