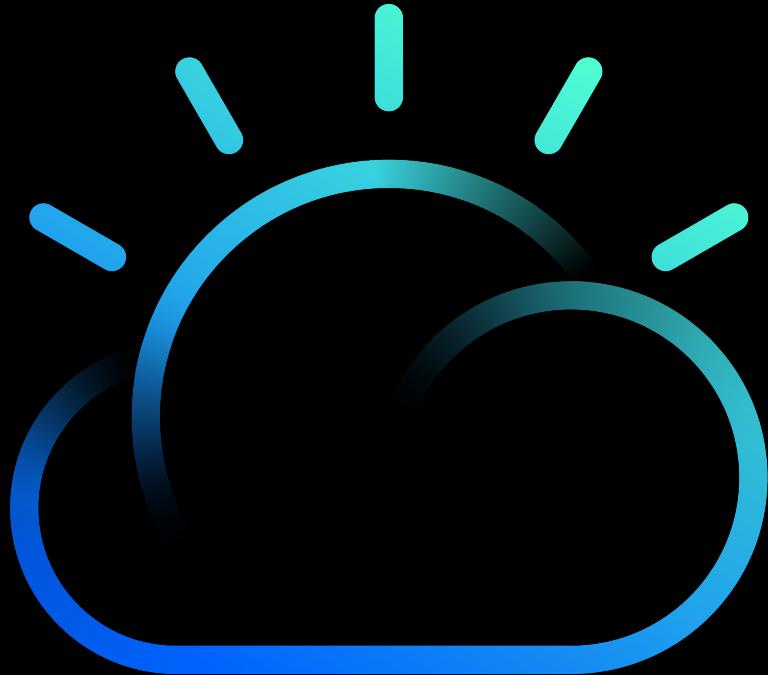


# Removing Unfair Bias in Machine Learning

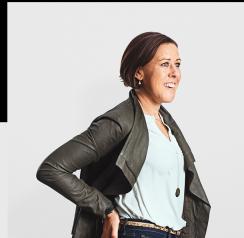


AI Fairness 360 Open Source Toolkit

# Today's Agenda

1. Intro to Fairness & Bias
2. Fairness Metrics & Algorithms
3. Fairness Guidelines
4. Metrics Interactive Demo
5. Medical Use Case - Python Tutorial

# Why Do We Care About Fairness?



# What is Fairness?

- There are 21 definitions of fairness
- Many of the definitions conflict
- The way you define fairness impacts bias



# Fairness in Machine Learning Algorithms

## Prediction Fails Differently for Black Defendants

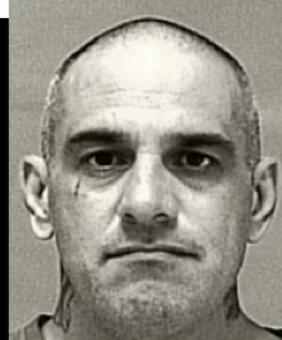
	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

*Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)*

<https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>



high risk 8



low risk 3

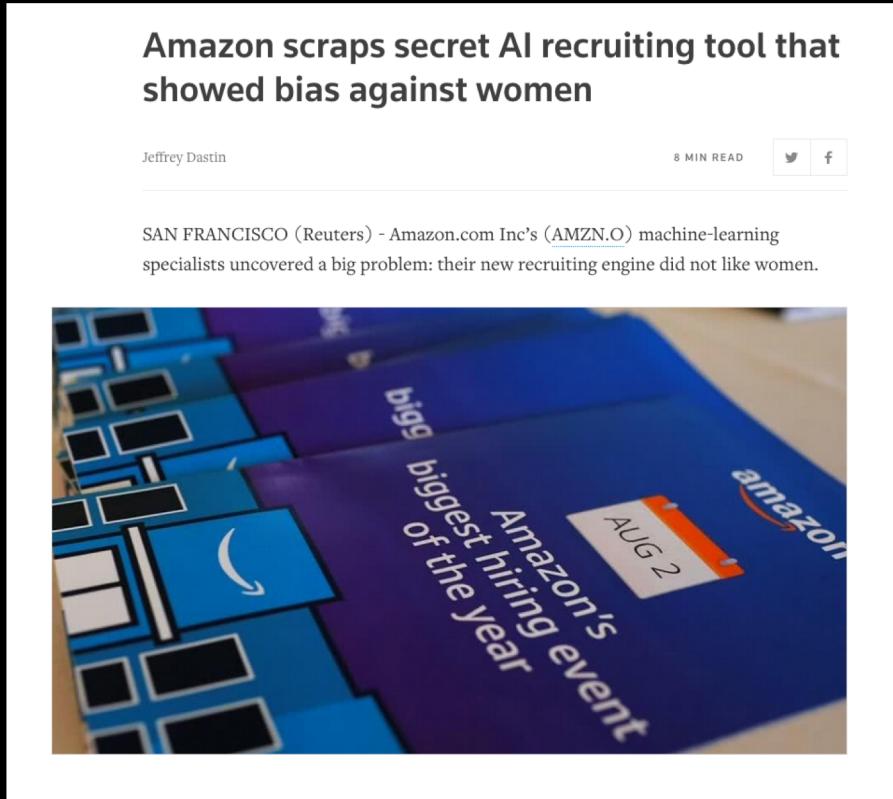
# Amazon's AI Recruiting Tool – Taught Gender Bias to Itself

**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.



“How to ensure that the algorithm is fair, how to make sure the algorithm is really interpretable and explainable - that’s still quite far off.”

# Apple's 'sexist' credit card investigated by US regulator



DHH ✅  
@dhh

The [@AppleCard](#) is such a fucking sexist program. My wife and I filed joint tax returns, live in a community-property state, and have been married for a long time. Yet Apple's black box algorithm thinks I deserve 20x the credit limit she does. No appeals work.

12:34 PM · Nov 7, 2019 · [Twitter for iPhone](#)

9.6K Retweets 29.1K Likes



DHH ✅ @dhh · Nov 7, 2019

Replies to @dhh

I'm surprised that they even let her apply for a card without the signed approval of her spouse? I mean, can you really trust women with a credit card these days??!

89

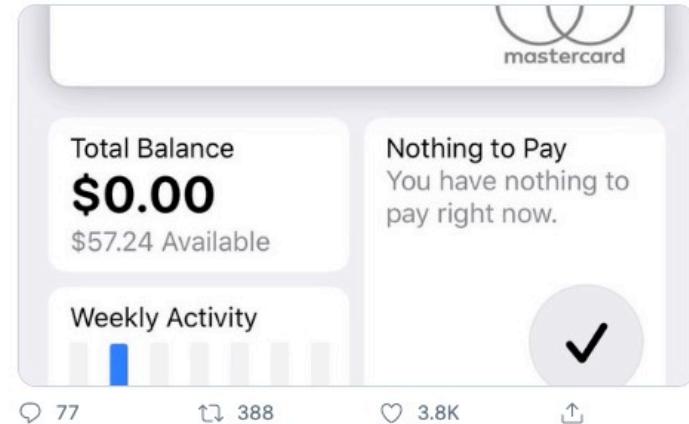
246

4.5K



DHH ✅ @dhh · Nov 7, 2019

It gets even worse. Even when she pays off her ridiculously low limit in full, the card won't approve any spending until the next billing period. Women apparently aren't good credit risks even when they pay off the fucking balance in advance and in full.



Steve Wozniak ✅  
@stevewoz

Replies to @dhh

The same thing happened to us. We have no separate bank accounts or credit cards or assets of any kind. We both have the same high limits on our cards, including our AmEx Centurion card. But 10x on the Apple Card.

10:58 PM · Nov 9, 2019 · [Twitter Web App](#)

# AI Fairness 360



## Open Source Toolbox to Mitigate Bias

- Demos & Tutorials on Industry Use Cases
- Fairness Guidance
- Comprehensive Toolbox
  - 75+ Fairness metrics
  - 10+ Bias Mitigation Algorithms
  - Fairness Metric Explanations

**Extensible Toolkit**  
for Detecting,  
Understanding, &  
Mitigating  
Unwanted  
**Algorithmic Bias**

**Leading Fairness**  
Metrics and  
Algorithms from  
**Industry &**  
**Academia**

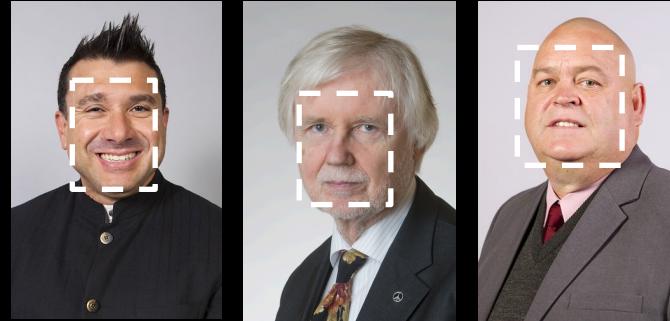
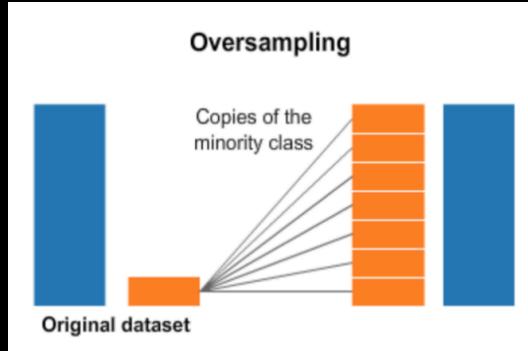
Designed to **translate new research** from the  
**lab to industry practitioners** (using Scikit  
Learn's fit/predict paradigm)

# **Next Section:**

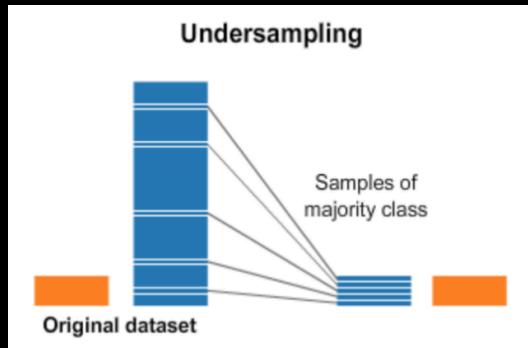
# How Do You Measure Bias & Where Does it Come From?

# Most Bias Come From Your Data – Over /Under Sampling, Label & User Generated Bias

## MIT Study of Top Face Recognition Services



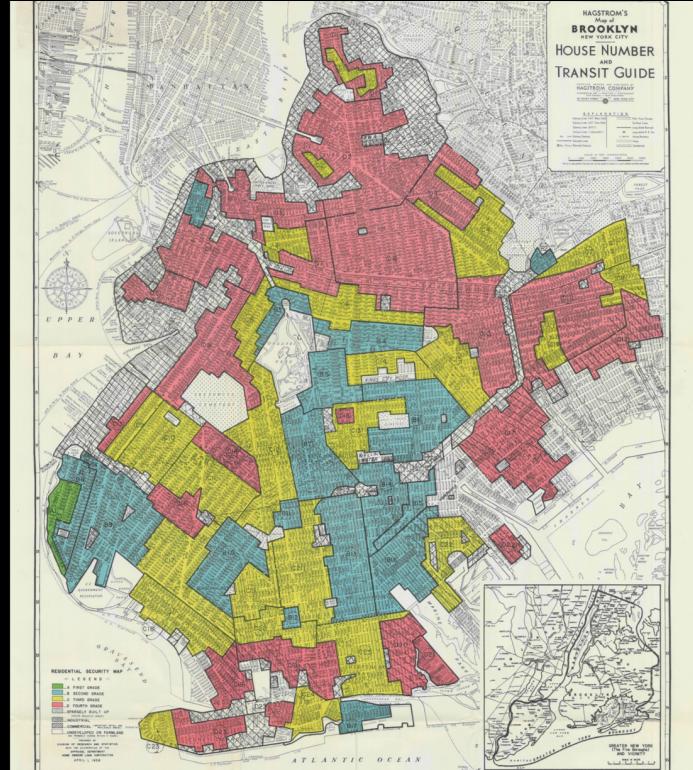
**99% accurate  
for lighter-skinned  
males**



**65% accurate  
for darker-skinned  
females**

# Why Not Just Remove Protected Attributes?

- You can't just drop protected attributes (gender, race); other features correlated with them
- Example: Buy using zip codes you can deconstruct individual's race or income



# Fairness Terms You Need To Know

**Protected Attribute** – an attribute that partitions a population into groups whose outcomes should have parity (ex. race, gender, caste, and religion)

**Privileged Protected Attribute** – a protected attribute value indicating a group that has historically been at systemic advantage

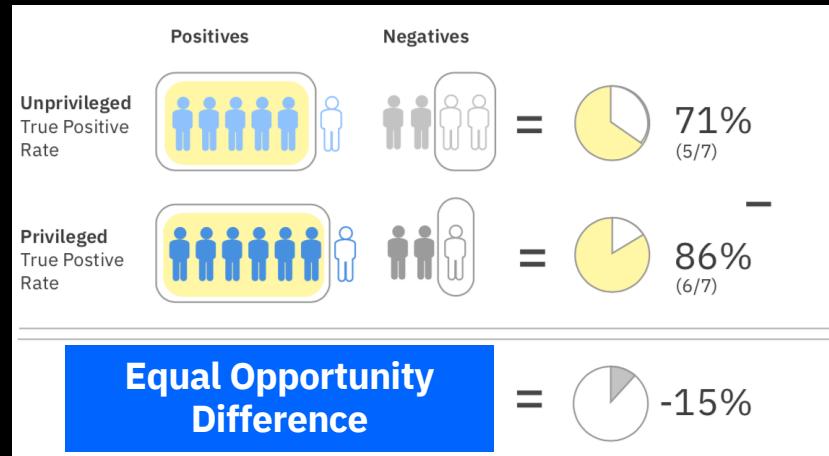
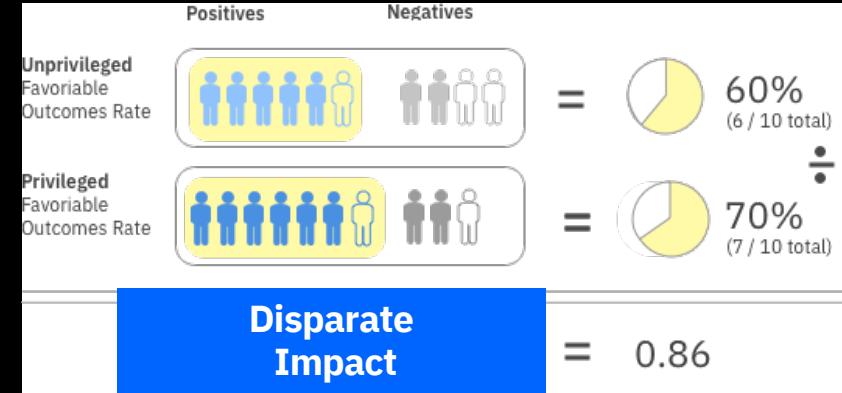
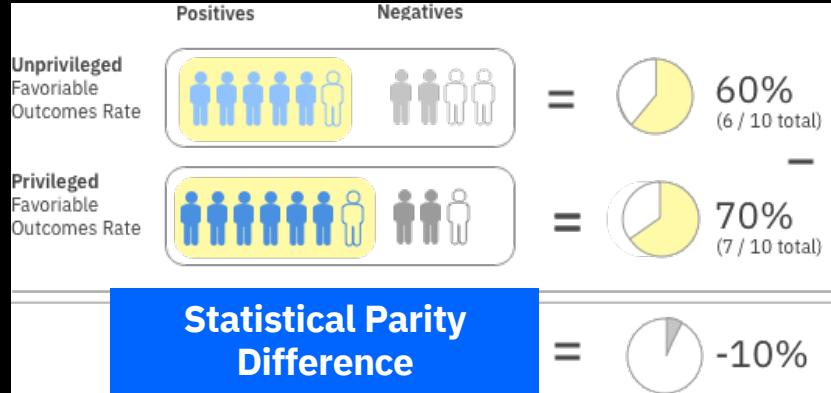
**Group Fairness** – Groups defined by protected attributes receiving similar treatments or outcomes

**Individual Fairness** – Similar individuals receiving similar treatments or outcomes

**Fairness Metric** – a measure of unwanted bias in training data or models

**Favorable Label** – a label whose value corresponds to an outcome that provides an advantage to the recipient

# How To Measure Fairness – Some Group Fairness Metrics



		LEGEND	
	Positives	Negatives	
Unprivileged			TRUE FALSE
Privileged			TRUE FALSE

# How You Define Fairness Impacts How You Measure It

Do SAT Scores Correctly Compare  
The Abilities of Applicants?

**YES**

SAT score correlates well with future success and correctly compare the abilities of applicants

**METRICS:**

average\_odds\_difference &  
average\_abs\_odds\_difference

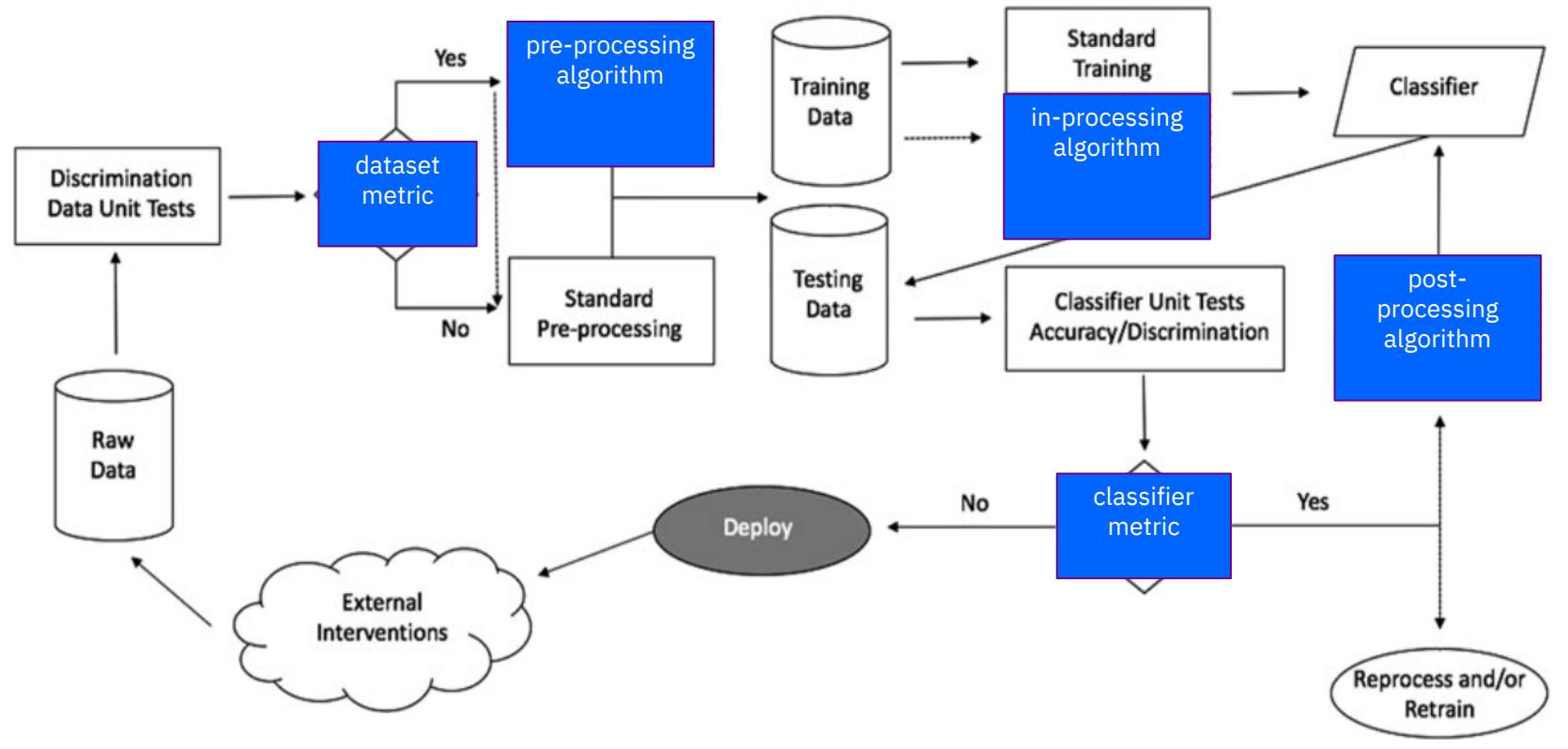
**NO**

SAT score may contain structural biases so its distribution is different across groups (*non-English speaking parents, single parents, low income, no SAT Prep*)

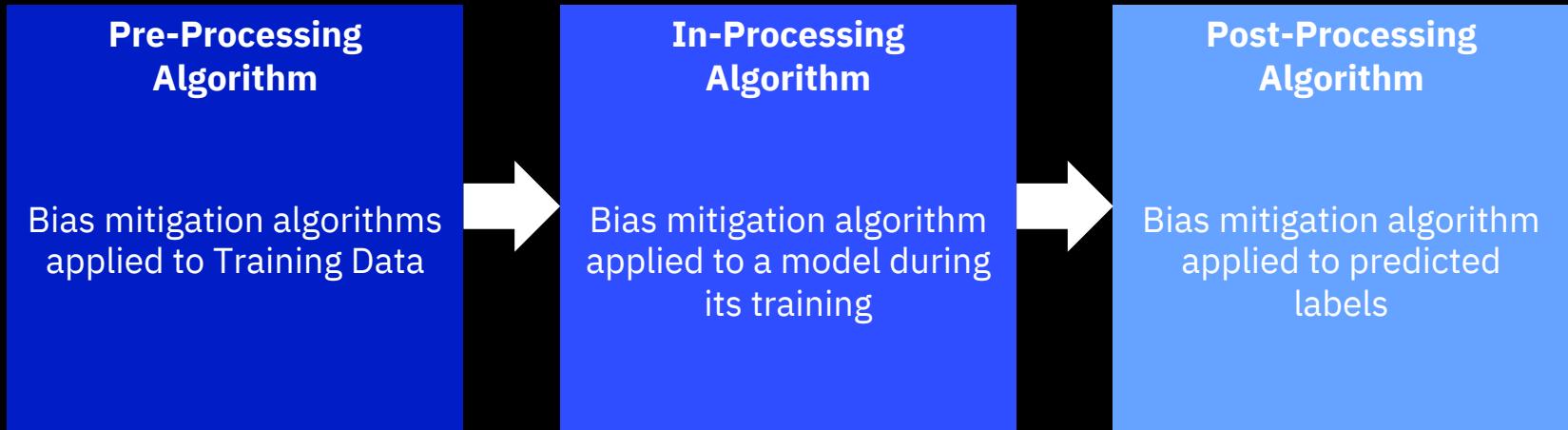
**METRICS:**

disparate\_impact &  
statistical\_parity\_difference

# Bias In the Machine Learning Pipeline



# Where Can You Intervene in the Pipeline?



- If you can modify the Training Data, then pre-processing can be used.
- If you can modify the Learning Algorithm, then in-processing can be used.
- If you can only treat the learned model as a black box and can't modify the training data or learning algorithm, then only post-processing can be used

# Bias Mitigation Algorithms For Each Phase of the Pipeline

## Pre-Processing Algorithms Mitigates Bias in **Training Data**

### Reweighting

Modifies the weights of different training examples

### Disparate Impact Remover

Edits feature values to improve group fairness

### Optimized Preprocessing

Modifies training data features & labels

### Learning Fair Representations

Learns fair representations by obfuscating information about protected attributes

## In-Processing Algorithms Mitigates Bias in **Classifiers**

### Adversarial Debiasing

Uses adversarial techniques to maximize accuracy & reduce evidence of protected attributes in predictions

### Prejudice Remover

Adds a discrimination-aware regularization term to the learning objective

### Meta Fair Classifier

Takes the fairness metric as part of the input & returns a classifier optimized for the metric

## Post-Processing Algorithms Mitigates Bias in **Predictions**

### Reject Option Classification

Changes predictions from a classifier to make them fairer

### Calibrated Equalized Odds

Optimizes over calibrated classifier score outputs that lead to fair output labels

### Equalized Odds

Modifies the predicted label using an optimization scheme to make predictions fairer

# AIF360 Includes The Top Algorithms In Industry/Academia

Optimized Preprocessing (Calmon et al., NIPS 2017) IBM Research

Meta-Algorithm for Fair Classification (Celis et al., FAT\* 2019) EPFL

Disparate Impact Remover (Feldman et al., KDD 2015) Haverford College THE UNIVERSITY OF UTAH THE UNIVERSITY OF ARIZONA

Equalized Odds Postprocessing (Hardt et al., NIPS 2016) Google TEXAS TOYOTA TECHNOLOGICAL INSTITUTE AT CHICAGO

Reweighting (Kamiran and Calders, KIS 2012) TU/e

Reject Option Classification (Kamiran et al., ICDM 2012) King Abdullah University of Science and Technology LUMS

Prejudice Remover Regularizer (Kamishima et al., ECML PKDD 2012) AIST

Calibrated Equalized Odds Postprocessing (Pleiss et al., NIPS 2017) Cornell University

Learning Fair Representations (Zemel et al., ICML 2013) UNIVERSITY OF TORONTO Microsoft Research

Adversarial Debiasing (Zhang et al., AIES 2018) Stanford University Google

# Pre-Processing is the Optimal Time to Mitigate Bias

## Pre-Processing Algorithms

Mitigates Bias in **Training Data**

### Reweighting

Modifies the weights of different training examples



**Reweighting** only changes **Weights** applied to training samples (no changes to feature/labels). Ideal if you cannot change values

### Disparate Impact Remover

Edits feature values to improve group fairness



**Disparate Impact Remover** and **Optimized Preprocessing** yield modified datasets in the same space as the input training data (provides transparency)

### Optimized Preprocessing

Modifies training data features & labels

### Learning Fair Representations

Learns fair representations by obfuscating information about protected attributes



**Learning Fair Representations** yields modified datasets in the latent space

# Tradeoffs - Bias vs. Accuracy

1. Is your model doing good things or bad things to people?
  - If your model is sending people to jail, may be better to have more false positives than false negatives
  - If your model is handing out loans, may be better to have more False Negatives than False Positives
2. Determine your threshold for accuracy vs. fairness based upon your legal, ethical and trust guidelines

## LEGAL

Doing what is legal is top priority (Penalties)

## ETHICAL

What's your company's Ethics (Amazon Echo)

## TRUST

Losing customer's Trust costly (Facebook)



## Preventing Bias Is Hard!

Work with your stakeholders early to define fairness, protected attributes & thresholds

Apply the earliest mitigation in the pipeline that you have permission to apply

Check for bias as often as possible using any metrics that are applicable

Caveat: AIF360 should only be used with well defined data sets & well defined use cases

# **Next Section:**

# Toolkit Overview

# & Interactive Demo

# AI Fairness 360 Toolkit Overview

<https://aif360.mybluemix.net/>

The screenshot shows the homepage of the AI Fairness 360 Open Source Toolkit. At the top, there's a navigation bar with links for Home, Demo, Resources, Events, Videos, and Community. The Home link is underlined, indicating it's the current page. Below the navigation, there's a main content area with a heading "AI Fairness 360 Open Source Toolkit" and a brief description of its purpose. Two buttons are visible: "API Docs" and "Get Code". A section titled "Not sure what to do first? Start here!" contains eight cards, each with a title, a brief description, and a right-pointing arrow. The cards are: "Read More" (about fairness and bias mitigation), "Try a Web Demo" (step through the process of checking and remediating bias), "Watch Videos" (watch videos to learn more about AI Fairness 360), "Read a paper" (read a paper describing how we designed AI Fairness 360), "Use Tutorials" (step through a set of in-depth examples that introduce developers to code that checks and mitigates bias in different industry and application domains), "Ask a Question" (join the AIF360 Slack Channel to ask questions, make comments, and tell stories about how you use the toolkit), "View Notebooks" (open a directory of Jupyter Notebooks in GitHub that provide working examples of bias detection and mitigation in sample datasets, then share your own notebooks!), and "Contribute" (add new metrics and algorithms in GitHub, share Jupyter notebooks showing how you have examined and mitigated bias in your machine learning application). Below this section, there's another row of three cards: "Credit Scoring" (detect and mitigate age bias in predictions of credit-worthiness using the German Credit dataset), "Medical Expenditure" (detect and mitigate racial bias in a care management scenario using Medical Expenditure Panel Survey data), and "Gender Bias in Face Images" (detect and mitigate bias in automatic gender classification of face images). Each card has a right-pointing arrow.

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AI Fairness 360 Open Source Toolkit

This extensible open source toolkit can help you examine, report, and mitigate discrimination and bias in machine learning models throughout the AI application lifecycle. Containing over 70 fairness metrics and 10 state-of-the-art bias mitigation algorithms developed by the research community, it is designed to translate algorithmic research from the lab into the actual practice of domains as wide-ranging as finance, human capital management, healthcare, and education. We invite you to use it and improve it.

API Docs ↗ Get Code ↗

Not sure what to do first? Start here!

<b>Read More</b> Learn more about fairness and bias mitigation concepts, terminology, and tools before you begin. →	<b>Try a Web Demo</b> Step through the process of checking and remediating bias in an interactive web demo that shows a sample of capabilities available in this toolkit. →	<b>Watch Videos</b> Watch videos to learn more about AI Fairness 360. →	<b>Read a paper</b> Read a paper describing how we designed AI Fairness 360. →	<b>Use Tutorials</b> Step through a set of in-depth examples that introduce developers to code that checks and mitigates bias in different industry and application domains. →	<b>Ask a Question</b> Join our AIF360 Slack Channel to ask questions, make comments, and tell stories about how you use the toolkit. →	<b>View Notebooks</b> Open a directory of Jupyter Notebooks in GitHub that provide working examples of bias detection and mitigation in sample datasets. Then share your own notebooks! →	<b>Contribute</b> You can add new metrics and algorithms in GitHub. Share Jupyter notebooks showing how you have examined and mitigated bias in your machine learning application. →
---	---	---	--	--	--	---	--

Learn how to put this toolkit to work for your application or industry problem. Try these tutorials.

<b>Credit Scoring</b> See how to detect and mitigate age bias in predictions of credit-worthiness using the German Credit dataset. →	<b>Medical Expenditure</b> See how to detect and mitigate racial bias in a care management scenario using Medical Expenditure Panel Survey data. →	<b>Gender Bias in Face Images</b> See how to detect and mitigate bias in automatic gender classification of face images. →
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# Interactive Demo

<https://aif360.mybluemix.net/data>

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Home

**Demo**

Resources

Events

Videos

Community

## AI Fairness 360 - Demo



Data    Check    Mitigate    Compare

### 1. Choose sample data set

Bias occurs in data used to train a model. We have provided three sample datasets that you can use to explore bias checking and mitigation. Each dataset contains attributes that should be protected to avoid bias.

#### Compas (ProPublica recidivism)

Predict a criminal defendant's likelihood of reoffending.

##### Protected Attributes:

- **Sex**, privileged: **Female**, unprivileged: **Male**
- **Race**, privileged: **Caucasian**, unprivileged: **Not Caucasian**

[Learn more](#)

#### German credit scoring

Predict an individual's credit risk.

##### Protected Attributes:

- **Sex**, privileged: **Male**, unprivileged: **Female**
- **Age**, privileged: **Old**, unprivileged: **Young**

[Learn more](#)

#### Adult census income

Predict whether an individual makes over \$50K/year based on their features.

# Toolkit API – Definitions, Formulas & References

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[API Docs](#) [Get Code](#)

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---	---	---	--	---	---

**View Notebooks**  
Open a directory of Jupyter Notebooks in GitHub that provide working examples of bias detection and mitigation  
[View Notebooks](#)

**Contribute**  
You can add new metrics and algorithms in GitHub. Share Jupyter notebooks showcasing how you have implemented them.  
[Contribute](#)

## aif360.algorithms.preprocessing

### Disparate Impact Remover

```
class aif360.algorithms.preprocessing.DisparateImpactRemover(repair_level=1.0) [source]
```

Disparate impact remover is a preprocessing technique that edits feature values increase group fairness while preserving rank-ordering within groups [\[1\]](#).

#### References

[1] M. Feldman, S. A. Friedler, J. Moeller, C. Scheidegger, and S. Venkatasubramanian, "Certifying and removing disparate impact." ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2015.

## fit\_transform(dataset) [source]

Run a repainer on the non-protected features and return the transformed dataset.

**Parameters:** dataset (*BinaryLabelDataset*) – Dataset that needs repair.

**Returns:** Transformed Dataset.

**Return type:** dataset (*BinaryLabelDataset*)

#### Note

In order to transform test data in the same manner as training data, the distributions of attributes conditioned on the protected attribute must be the same.

### Learning Fair Representations

```
class aif360.algorithms.preprocessing.LFR(unprivileged_groups, privileged_groups, k=5, Ax=0.01, Ay=1.0, Az=50.0, print_interval=250, verbose=1, seed=None) [source]
```

Learning fair representations is a pre-processing technique that finds a latent representation which encodes the data well but obfuscates information about protected attributes [\[2\]](#).

# **Next Section:**

# Medical Use Case

# Python Tutorial

# Toolkit API – Definitions, Formulas & References

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Home Demo Resources Events Videos Community

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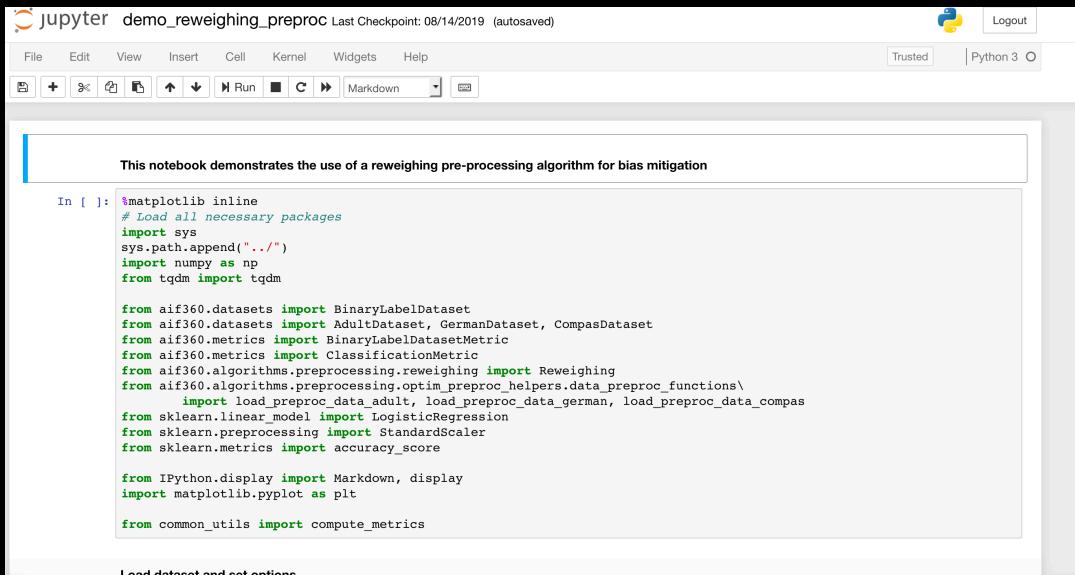
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class aif360.algorithms.preprocessing.LFR(unprivileged_groups, privileged_groups, k=5, Ax=0.01, Ay=1.0, Az=50.0, print_interval=250, verbose=1, seed=None) [source]
```

Learning fair representations is a pre-processing technique that finds a latent representation which encodes the data well but obfuscates information about protected attributes [\[2\]](#).

# Reweighting Preprocessing Algorithm

- Demonstrate how AIF 360 Toolkit can be used to detect and reduce bias with a learning classifier using a fairness metrics and algorithms
- Classifiers are built using Logistic Regression
- Bias Detection Metrics Used:
  - Disparate Impact
  - Average Odds Difference
- Bias Mitigation Algorithm Used:
  - Reweighting (pre-processing algorithm)



This notebook demonstrates the use of a reweighting pre-processing algorithm for bias mitigation

```
In [ ]: %matplotlib inline
# Load all necessary packages
import sys
sys.path.append("../")
import numpy as np
from tqdm import tqdm

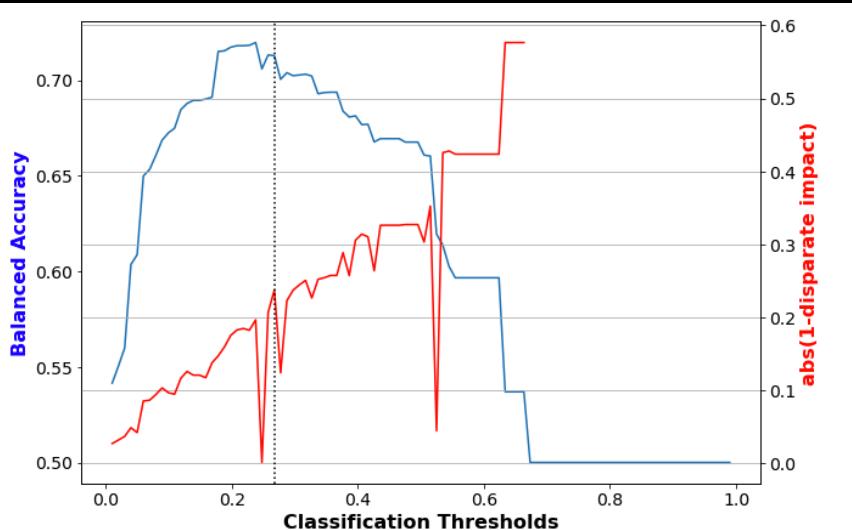
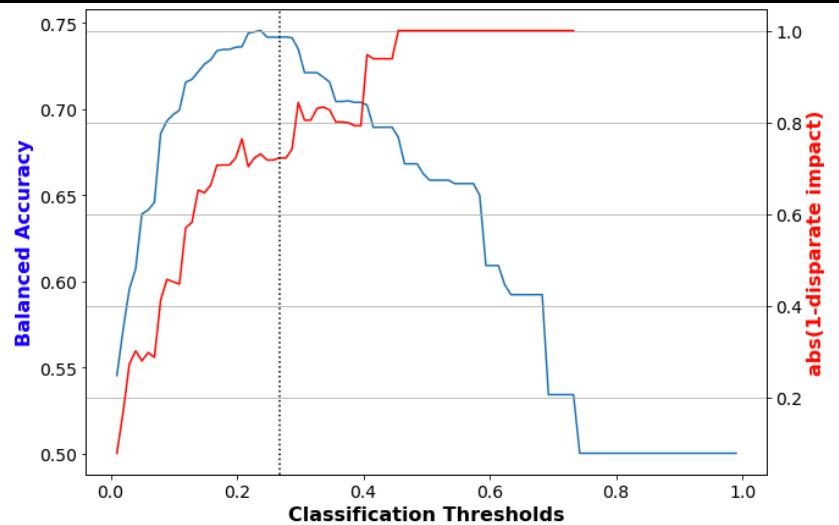
from aif360.datasets import BinaryLabelDataset
from aif360.datasets import AdultDataset, GermanDataset, CompasDataset
from aif360.metrics import BinaryLabelDatasetMetric
from aif360.metrics import ClassificationMetric
from aif360.algorithms.preprocessing.reweighing import Reweighting
from aif360.algorithms.preprocessing.optim_preproc_helpers.data_preproc_functions \
    import load_preproc_data_adult, load_preproc_data_german, load_preproc_data_compas
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score

from IPython.display import Markdown, display
import matplotlib.pyplot as plt

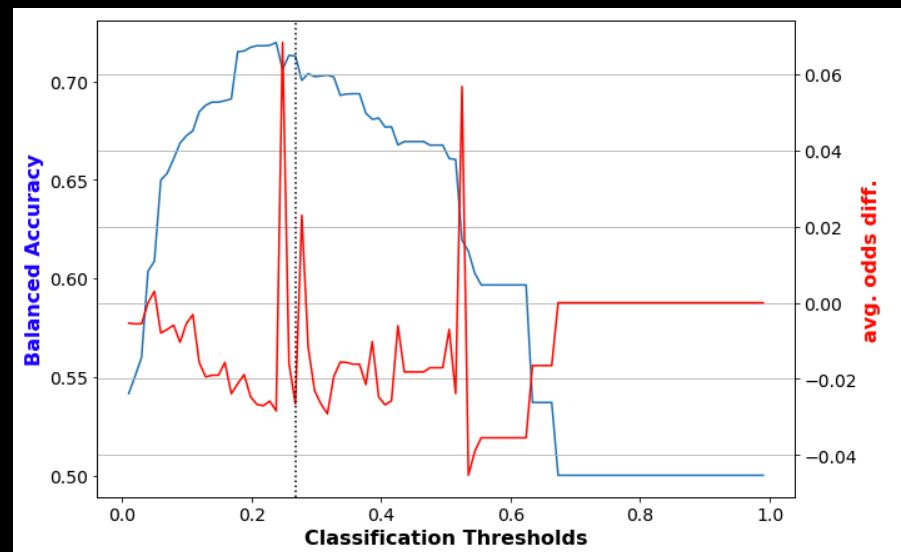
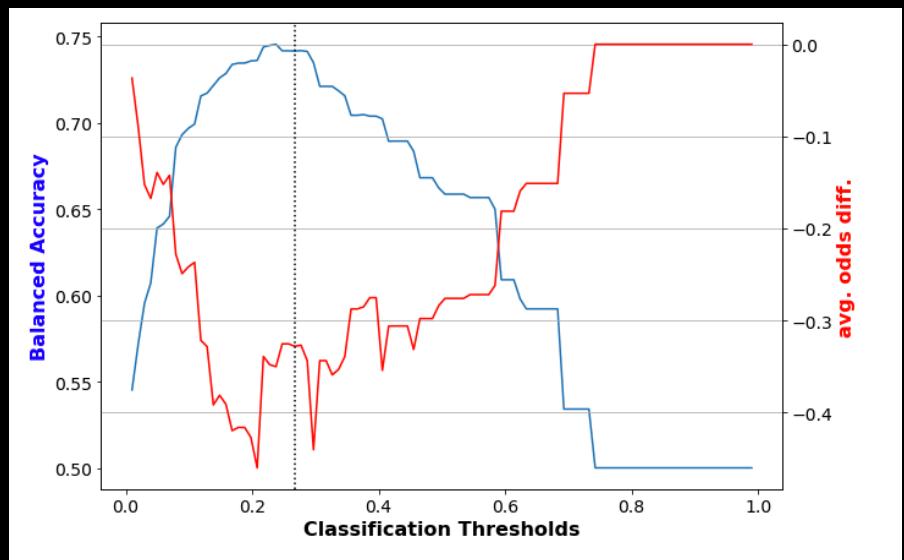
from common_utils import compute_metrics
```

Load dataset and set options

# Bias Metric – Disparate Impact



# Bias Metric - Average Odds Difference



# Bias Metric - Average Odds Difference

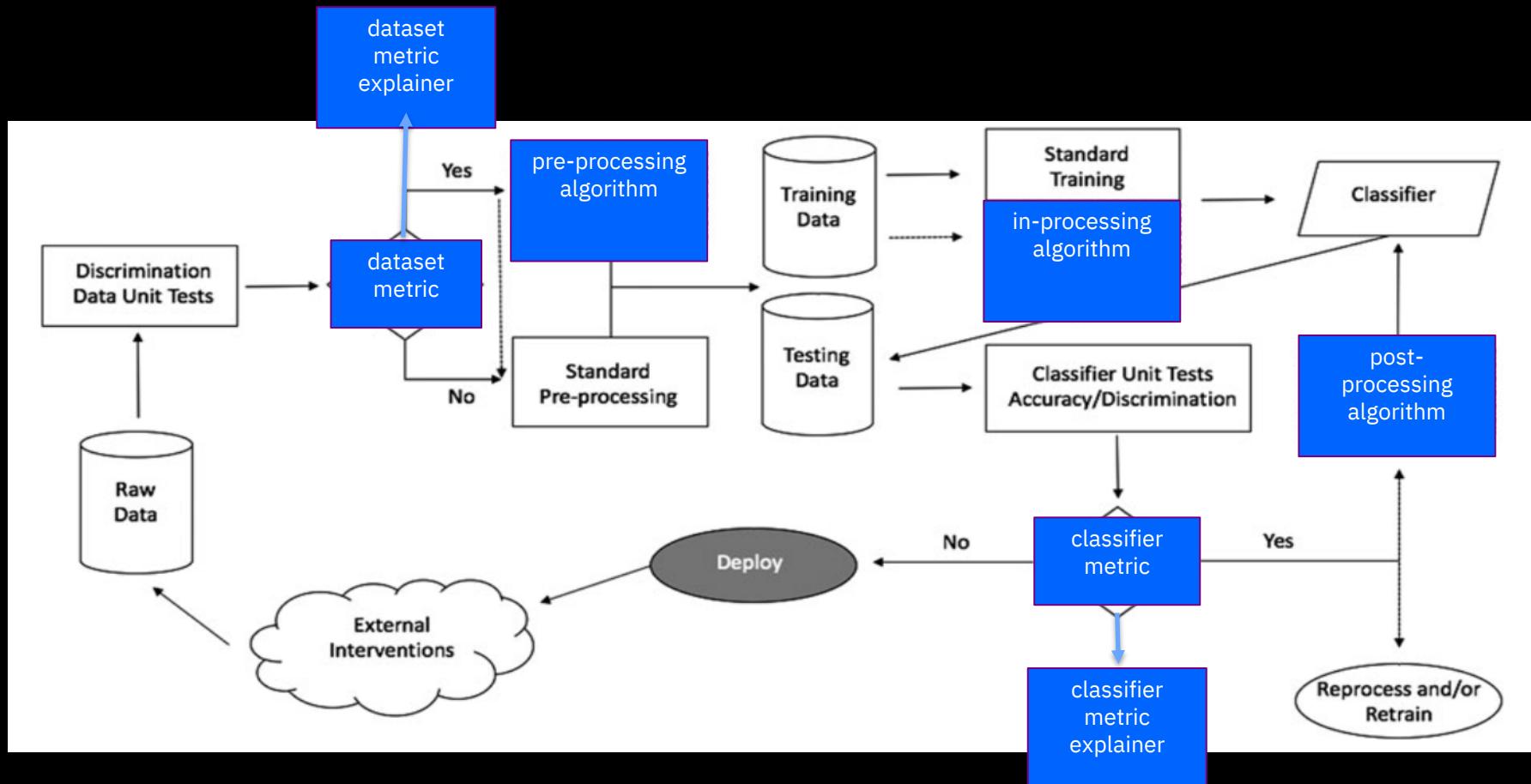
	Disparate Impact	
“Sex”	Before	After
Accuracy	0.7417	0.7128
Fairness	0.2774	0.7625

*Disparate Impact  
Fairness is Closer to 1 (Ratio)*

	Average Odds Difference	
“Sex”	Before	After
Accuracy	0.7417	0.7128
Fairness	-0.3281	-0.0266

*Average Odds Difference  
Fairness is Closer to 0 (Difference)*

# Metrics, Algorithms & Explainers



# Join the AI Fairness Slack Channel

Join the AIF360 Slack <https://aif360.slack.com/>

Ask questions and speak to AI Fairness 360 researchers, experts, and developers


Change photo

# Build Smart



Part of **IBM Developer** - 43 groups [?](#)

## IBM Developer SF Bay Area

 San Francisco, CA

 8,426 members · Public group [?](#)

 Organized by Angie K and 6 others

## IBM Developer



Share:   

WED, JAN 22, 9:30 AM

### Online Meetup: Kubernetes hands-on workshop with OpenShift on IBM Cloud



 Needs a location

Please do not forget to register on Crowdcast and join us using Chrome browser via Crowdcast on the event date! RSVP on Crowdcast NOW: <https://www.crowdcast.io/e/kubernetes-hands-on> Red Hat OpenShift on IBM Cloud is an extension of the IBM Cloud Kubernetes Service, whe...



Manage 

Attend



Manage 

Attend



Manage 

Going 

THU, JAN 23, 6:00 PM

### Meetup: Data wrangling and exploration with Pandas



 Hacker Dojo

Prerequisites - Curious minds ! Bring your laptop, and the rest happens on the cloud! This is an introductory session on exploring and analyzing data using Python, Pandas and Jupyter Notebooks. We will go over: - how to obtain/read a data file using python in Watson Studio - ho...

THU, JAN 30, 9:30 AM

### Online Meetup: Deep Learning Master Class I - Introduction



 Needs a location

Please do not forget to register on Crowdcast and join us using Chrome browser via Crowdcast on the event date! RSVP on Crowdcast NOW: <https://www.crowdcast.io/e/deep-learning-master> This series takes engineers from zero to expert in machine learning in 5 sessions. The world...

# IBM Partners

Enabling Independent Software Vendors (ISVs)  
and tech companies for growth

## Target audience

- ISVs and tech companies building and selling cloud solutions
- New to IBM Cloud
- Startups who aspire to build and sell their own solutions

## Offers to help you get started



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Integrate your solutions with leading-edge IBM Cloud technologies to deliver more innovation and value to your clients. Access more than **130 unparalleled services** including Watson™, Analytics and Security.



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