```
# @title
!pip install -q aif360
```

```
# @title
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

from aif360.datasets import BinaryLabelDataset
from aif360.metrics import ClassificationMetric
from aif360.algorithms.preprocessing import Reweighing
```

```
# @title
data = load_breast_cancer()

X = pd.DataFrame(data.data, columns=data.feature_names)
y = pd.Series(data.target)

print("Healthcare Dataset")
X.head()
```

Healthcare Dataset

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883

5 rows × 30 columns

```
# @title
np.random.seed(42)
X["gender"] = np.random.choice(["Male","Female"], size=len(X))
```

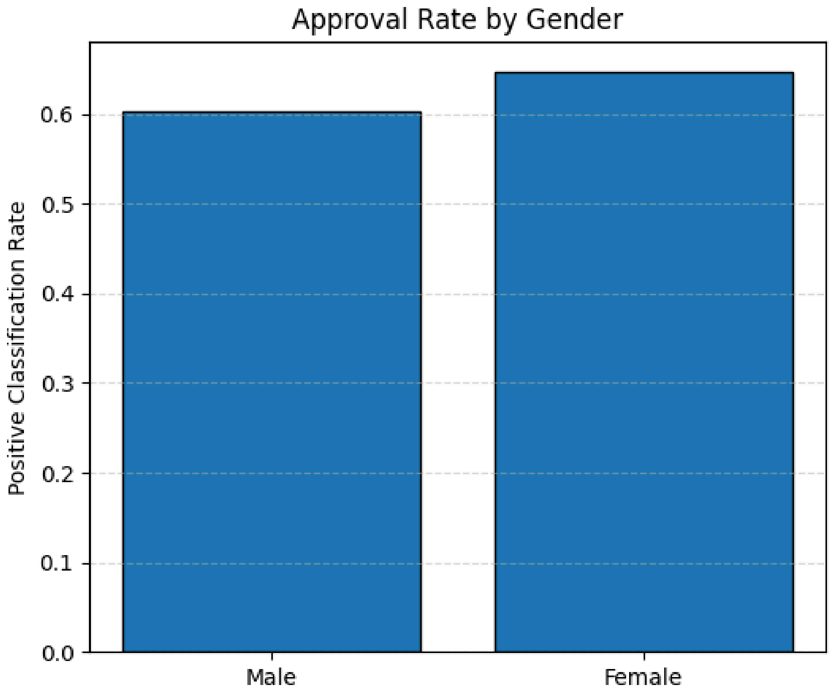
```
# @title
X_encoded = pd.get_dummies(X, drop_first=True)

X_train, X_test, y_train, y_test = train_test_split(
    X_encoded, y, test_size=0.3, random_state=42
)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

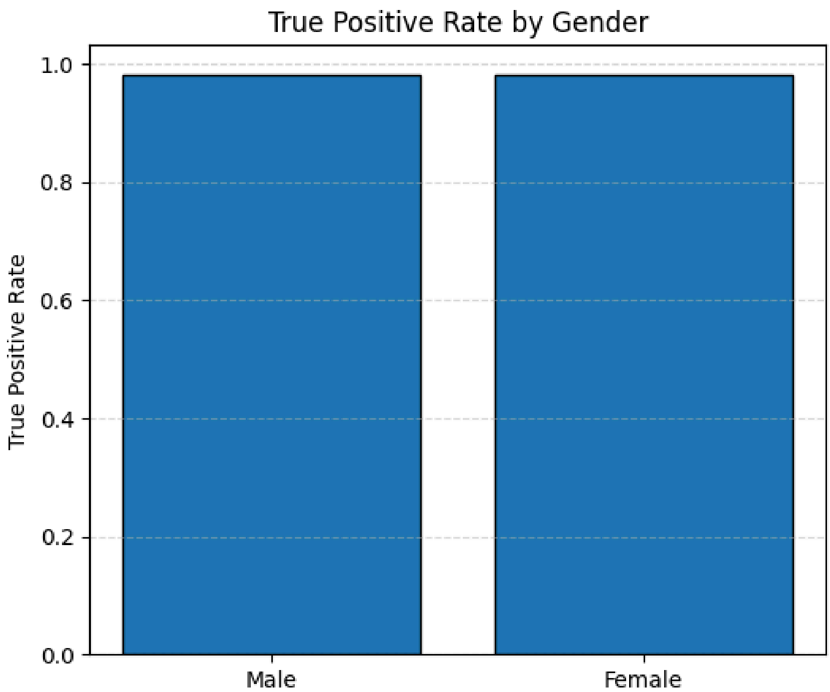
```
# @title
model = LogisticRegression(max_iter=2000)
model.fit(X_train, y_train)

preds = model.predict(X_test)
```

```
# @title
results = pd.DataFrame({
    "actual": y_test,
    "pred": preds,
    "gender": X.loc[y_test.index]["gender"].values
})

male = results[results["gender"]=="Male"]
female = results[results["gender"]=="Female"]

def approval_rate(g):
    return g["pred"].mean()

def tpr(g):
    tp = ((g["pred"]==1) & (g["actual"]==1)).sum()
    pos = (g["actual"]==1).sum()
    return tp/pos

spd = approval_rate(male) - approval_rate(female)
di = approval_rate(female) / approval_rate(male)
eod = tpr(male) - tpr(female)

print("FAIRNESS METRICS")
print("Statistical Parity Difference:", round(spd,3))
print("Disparate Impact:", round(di,3))
print("Equal Opportunity Difference:", round(eod,3))
```

```
FAIRNESS METRICS
Statistical Parity Difference: -0.045
Disparate Impact: 1.075
Equal Opportunity Difference: -0.002
```

```
# @title
plt.figure(figsize=(6,5))
plt.bar(
    ["Male","Female"],
    [approval_rate(male), approval_rate(female)],
    edgecolor="black"
)
plt.title("Approval Rate by Gender")
plt.ylabel("Positive Classification Rate")
plt.grid(axis="y", linestyle="--", alpha=0.5)
plt.show()

plt.figure(figsize=(6,5))
plt.bar(
    ["Male","Female"],
    [tpr(male), tpr(female)],
    edgecolor="black"
)
plt.title("True Positive Rate by Gender")
plt.ylabel("True Positive Rate")
plt.grid(axis="y", linestyle="--", alpha=0.5)
plt.show()
```






```
from aif360.datasets import BinaryLabelDataset
from aif360.algorithms.preprocessing import Reweighing
from aif360.metrics import ClassificationMetric
```

```
# Create numeric-only copy for AIF360
aif_df = results.copy()

# Convert gender to numeric (0 = Female, 1 = Male)
aif_df["gender"] = aif_df["gender"].map({"Male":1, "Female":0})

# Ensure all columns are numeric
aif_df = aif_df.select_dtypes(include=["number"])

print("Numeric DataFrame for AIF360 ready")
print(aif_df.head())
```

```
Numeric DataFrame for AIF360 ready
     actual  pred  gender
204       1     1       0
70        0     0       0
131       0     0       1
431       1     1       0
540       1     1       1
```

```
# Build numeric-only copy for AIF360 (NO TEXT ALLOWED)
aif_df = results.copy()

# Convert gender
aif_df["gender"] = aif_df["gender"].map({"Male":1, "Female":0})

# Drop any accidental leftover non-numeric columns if present
aif_df = aif_df.select_dtypes(include=["number"])

print("Remaining columns for AIF360:")
print(aif_df.columns.tolist())
```

```
Remaining columns for AIF360:
['actual', 'pred', 'gender']
```

```
from aif360.datasets import BinaryLabelDataset
from aif360.metrics import ClassificationMetric

# Build true dataset
true_dataset = BinaryLabelDataset(
    df=aif_df,
    label_names=['actual'],
    protected_attribute_names=['gender']
)

# Build predicted dataset (must be float)
pred_dataset = true_dataset.copy()
pred_dataset.labels = aif_df['pred'].values.reshape(-1,1).astype(float)

# Calculate fairness metrics
clf_metric = ClassificationMetric(
    true_dataset,
    pred_dataset,
    unprivileged_groups=[{'gender':0}],   # Female
    privileged_groups=[{'gender':1}]      # Male
)

print("\nFAIRNESS METRICS")
print("SPD:", round(clf_metric.statistical_parity_difference(),3))
print("DI:", round(clf_metric.disparate_impact(),3))
print("EOD:", round(clf_metric.equal_opportunity_difference(),3))



print("SPD:", round(clf_metric.statistical_parity_difference(),3))
print("DI:", round(clf_metric.disparate_impact(),3))
print("EOD:", round(clf_metric.equal_opportunity_difference(),3))
```

```
FAIRNESS METRICS
SPD: 0.045
DI: 1.075
EOD: 0.002
SPD: 0.045
DI: 1.075
EOD: 0.002
```

Gemini

```
from aif360.algorithms.preprocessing import Reweighing
```

```
from aif360.datasets import BinaryLabelDataset
from aif360.metrics import ClassificationMetric
from sklearn.linear_model import LogisticRegression

# -----------------------------
# Keep original gender column
# -----------------------------
# If 'gender' column is missing from X (due to previous cell issues or overwriting), re-add it.
# This assumes the original data and random seed for gender assignment.
if "gender" not in X.columns:
    # Recreate the gender series deterministically using the original seed and length of X
    np.random.seed(42)
    original_gender_series = pd.Series(np.random.choice(["Male","Female"], size=len(X)), index=X.inde
    gender_to_split = original_gender_series
else:
    # If gender is present, use it as intended
    gender_to_split = X["gender"].copy()

# Split dataset
X_train, X_test, y_train, y_test, gender_train, gender_test = train_test_split(
    X_encoded, y, gender_to_split, test_size=0.3, random_state=42
)

# -----------------------------
# Build training DataFrame for AIF360
# -----------------------------
train_df = pd.DataFrame({
    "actual": y_train,
    "gender": gender_train
})

# Convert gender to numeric
train_df["gender"] = train_df["gender"].map({"Male":1,"Female":0})

# Build BinaryLabelDataset for training
train_dataset = BinaryLabelDataset(
    df=train_df,
    label_names=['actual'],
    protected_attribute_names=['gender']
)

# Apply Reweighing
rw = Reweighing(
    unprivileged_groups=[{'gender':0}],  # Female
    privileged_groups=[{'gender':1}]     # Male
)
rw_train = rw.fit_transform(train_dataset)

print("✅ Reweighing applied. Sample weights for training:")
print("Reweighing applied. Sample weights for training:")
print(rw_train.instance_weights[:10])

# -----------------------------
# Train model with instance weights
# -----------------------------
model_rw = LogisticRegression(max_iter=2000)
# Increased max_iter to prevent ConvergenceWarning
model_rw = LogisticRegression(max_iter=5000)
model_rw.fit(X_train, y_train, sample_weight=rw_train.instance_weights)

# Predict on test set
preds_rw = model_rw.predict(X_test)

# -----------------------------
# Build test results DataFrame
# -----------------------------
results_rw = pd.DataFrame({
    "actual": y_test,
    "pred": preds_rw,
    "gender": gender_test
```

```
})

# Convert gender to numeric for AIF360
results_rw["gender_num"] = results_rw["gender"].map({"Male":1,"Female":0})

# Prepare numeric-only DataFrame for AIF360
aif_df_rw = results_rw.copy()
aif_df_rw["gender"] = aif_df_rw["gender_num"]
aif_df_rw = aif_df_rw.select_dtypes(include=["number"])

# Build BinaryLabelDataset for test set
true_dataset_rw = BinaryLabelDataset(
    df=aif_df_rw,
    label_names=['actual'],
    protected_attribute_names=['gender']
)
pred_dataset_rw = true_dataset_rw.copy()
pred_dataset_rw.labels = aif_df_rw['pred'].values.reshape(-1,1).astype(float)

# ------------------------------
# Compute post-mitigation metrics
# ------------------------------
clf_metric_rw = ClassificationMetric(
    true_dataset_rw,
    pred_dataset_rw,
    unprivileged_groups=[{'gender':0}],
    privileged_groups=[{'gender':1}]
)

print("\nFAIRNESS METRICS AFTER REWEIGHING")
print("SPD:", round(clf_metric_rw.statistical_parity_difference(),3))
print("DI:", round(clf_metric_rw.disparate_impact(),3))
print("EOD:", round(clf_metric_rw.equal_opportunity_difference(),3))
```

```
Reweighing applied. Sample weights for training:
[0.97635907 1.02667182 0.97635907 0.97635907 0.97635907 1.04217031
 0.97635907 1.02667182 0.97635907 1.02667182]

FAIRNESS METRICS AFTER REWEIGHING
SPD: 0.068
DI: 1.113
EOD: 0.039
```

```
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score

# ------------------------------
# Accuracy Comparison
# ------------------------------
acc_before = accuracy_score(y_test, preds)
acc_after = accuracy_score(y_test, preds_rw)

print("Accuracy Comparison")
print("Accuracy Before Mitigation:", round(acc_before, 3))
print("Accuracy After Mitigation:", round(acc_after, 3))

# ------------------------------
# Fairness Metrics Comparison
# ------------------------------
metrics = ['Statistical Parity Difference (SPD)',
           'Disparate Impact (DI)',
           'Equal Opportunity Difference (EOD)']

before_values = [
    clf_metric.statistical_parity_difference(),
    clf_metric.disparate_impact(),
    clf_metric.equal_opportunity_difference()
]

after_values = [
```

```
    clf_metric_rw.statistical_parity_difference(),
    clf_metric_rw.disparate_impact(),
    clf_metric_rw.equal_opportunity_difference()
]

# Print metrics
print("\nFairness Metrics Comparison")
for m, b, a in zip(metrics, before_values, after_values):
    print(f"{m}: Before = {round(b,3)}, After = {round(a,3)}")

# ------------------------------
# Visual Comparison: Bar Chart
# ------------------------------
import numpy as np

x = np.arange(len(metrics))
width = 0.35

plt.figure(figsize=(8,5))
plt.bar(x - width/2, before_values, width, label='Before', edgecolor='black')
plt.bar(x + width/2, after_values, width, label='After', edgecolor='black')

plt.xticks(x, metrics, rotation=20, ha='right')
plt.ylabel('Metric Value')
plt.title('Fairness Metrics Before vs After Reweighing')
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```

```
Accuracy Comparison
Accuracy Before Mitigation: 0.982
Accuracy After Mitigation: 0.971

Fairness Metrics Comparison
Statistical Parity Difference (SPD): Before = 0.045, After = 0.068
Disparate Impact (DI): Before = 1.075, After = 1.113
Equal Opportunity Difference (EOD): Before = 0.002, After = 0.039
```