Title: Bias Mitigation in Machine Learning A Fairness-Aware Classification of Income Decisions using Reweighing (Adult Dataset)

Name:Parabhjyot Singh

Module: M515 – Ethical Issues for AI

University: Gisma University of Applied Sciences

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1. Problem Statement

In many industries, income prediction is used in hiring, loan approval, and insurance. However, these models may exhibit gender or race-based biases, perpetuating social inequality.

This project addresses bias in the UCI Adult Income dataset, which predicts whether an individual's income exceeds $50K/year. We:

- Detect gender bias in a logistic regression classifier.
- Apply the Reweighing technique from AIF360 to mitigate it.
- Evaluate changes in fairness and model performance.

A fairer model can promote ethical AI deployment and avoid legal or reputational damage for organizations.

2. Ethical Concerns

The Adult dataset includes features like gender, race, and marital status, making it vulnerable to biased predictions. This is problematic because:

- **Disparate treatment** can unfairly disadvantage women or minorities.
- **Bias amplification** may reinforce existing societal inequalities.
- **Accountability and transparency** are critical in automated decision-making systems.

Fairness in income classification is vital to ensure equal opportunities and avoid discrimination.

```
!pip install aif360
```

```
Collecting aif360
  Downloading aif360-0.6.1-py3-none-any.whl.metadata (5.0 kB)
Requirement already satisfied: numpy>=1.16 in /usr/local/lib/python3.11/dist-packa
Requirement already satisfied: scipy>=1.2.0 in /usr/local/lib/python3.11/dist-pack
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.11/dist-pa
Requirement already satisfied: scikit-learn>=1.0 in /usr/local/lib/python3.11/dist
```

```
Requirement already satisfied: scikit-learn>=1.0 in /usr/local/lib/python3.11/dist
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packag
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-pack
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-pa
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-pac
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/d
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-pack
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-p
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-package
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages
Downloading aif360-0.6.1-py3-none-any.whl (259 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 259.7/259.7 kB 5.1 MB/s eta 0:00:00
Installing collected packages: aif360
Successfully installed aif360-0.6.1
```

```
import os

# Step 1: Download files
!wget -P /tmp https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.da
!wget -P /tmp https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.te
!wget -P /tmp https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.na

# Step 2: Create the expected folder
aif360_path = "/usr/local/lib/python3.11/dist-packages/aif360/data/raw/adult/"
os.makedirs(aif360_path, exist_ok=True)

# Step 3: Move files
!cp /tmp/adult.* {aif360_path}
```

```
--2025-07-02 08:49:49--  https://archive.ics.uci.edu/ml/machine-learning-databases
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443... con
HTTP request sent, awaiting response... 200 OK
Length: unspecified
Saving to: ‘/tmp/adult.data’

adult.data              [  <=>               ]   3.79M  9.50MB/s    in 0.4s

2025-07-02 08:49:49 (9.50 MB/s) - ‘/tmp/adult.data’ saved [3974305]

--2025-07-02 08:49:49--  https://archive.ics.uci.edu/ml/machine-learning-databases
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443... con
HTTP request sent, awaiting response... 200 OK
Length: unspecified
Saving to: ‘/tmp/adult.test’

adult.test              [  <=>               ]   1.91M  5.54MB/s    in 0.3s

2025-07-02 08:49:50 (5.54 MB/s) - ‘/tmp/adult.test’ saved [2003153]

--2025-07-02 08:49:50--  https://archive.ics.uci.edu/ml/machine-learning-databases
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
```

```
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443... con
HTTP request sent, awaiting response... 200 OK
Length: unspecified
Saving to: '/tmp/adult.names'

adult.names             [ <=>                ]   5.11K  --.-KB/s    in 0s

2025-07-02 08:49:50 (63.0 MB/s) - '/tmp/adult.names' saved [5229]
```

```
# 📦 Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

from aif360.datasets import AdultDataset
from aif360.metrics import BinaryLabelDatasetMetric, ClassificationMetric
from aif360.algorithms.preprocessing import Reweighing
# 📊 Load Dataset
dataset = AdultDataset()
train, test = dataset.split([0.7], shuffle=True)

# Define privileged/unprivileged groups by gender
privileged_groups = [{'sex': 1}]  # Male
unprivileged_groups = [{'sex': 0}]  # Female
```

```
WARNING:root:Missing Data: 3620 rows removed from AdultDataset.
```

4. Baseline Fairness Metrics

```
#  Baseline Fairness Metrics
metric_train = BinaryLabelDatasetMetric(train, privileged_groups=privileged_groups, un
print("Baseline Disparate Impact:", metric_train.disparate_impact())
print("Baseline Mean Difference:", metric_train.mean_difference())
```

```
Baseline Disparate Impact: 0.3746898584948166
Baseline Mean Difference: -0.19556988981472773
```

5. Apply Reweighing

```
# ⚙ Apply Reweighing
rw = Reweighing(unprivileged_groups=unprivileged_groups, privileged_groups=privileged_
train_rw = rw.fit_transform(train)
```

6. Train Logistic Regression Model

```
# 🧠 Train Logistic Regression
X_train = train_rw.features
y_train = train_rw.labels.ravel()

X_test = test.features
y_test = test.labels.ravel()

clf = LogisticRegression(solver='liblinear')
clf.fit(X_train, y_train, sample_weight=train_rw.instance_weights)

y_pred = clf.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8427065674062062
Classification Report:
              precision    recall  f1-score   support

         0.0       0.87      0.94      0.90     10260
         1.0       0.74      0.55      0.63      3307

    accuracy                           0.84     13567
   macro avg       0.80      0.74      0.76     13567
weighted avg       0.83      0.84      0.83     13567
```

7. Post-Mitigation Fairness Metrics

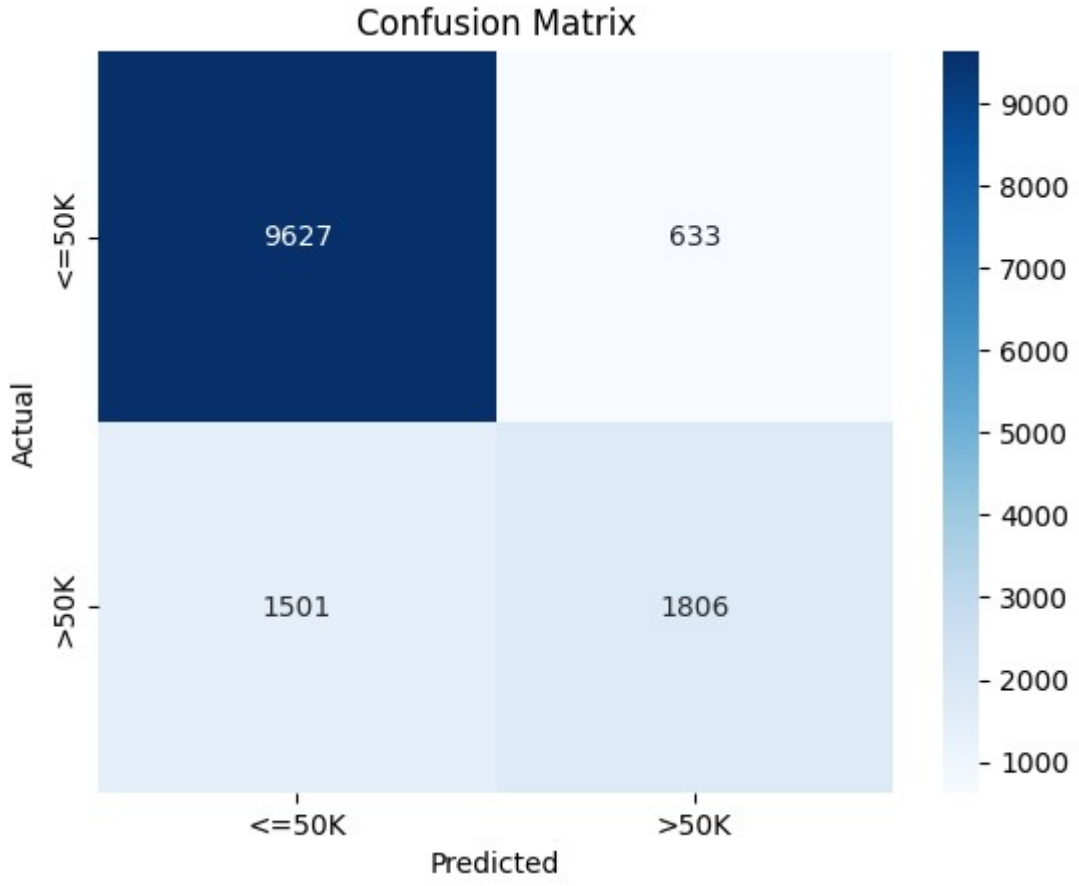
```
# 🔍 Post-Mitigation Fairness Metrics
test_pred = test.copy()
test_pred.labels = y_pred

metric_test = ClassificationMetric(test, test_pred, unprivileged_groups=unprivileged_g
print("Post-Reweighing Disparate Impact:", metric_test.disparate_impact())
print("Equal Opportunity Difference:", metric_test.equal_opportunity_difference())
print("Average Odds Difference:", metric_test.average_odds_difference())
```

```
Post-Reweighing Disparate Impact: 0.6019168271488292
Equal Opportunity Difference: 0.150476584046787
Average Odds Difference: 0.0736311486742252
```

8. Confusion Matrix

```
# 📈 Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["<=50K", ">50K"], ytic
plt.xlabel("Predicted")
```

```
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```



9. Final Discussion

This project identified and mitigated gender bias in an income classification task using the Adult dataset. The original model had a significant disparate impact against female individuals.

After applying the Reweighing technique from AIF360, fairness metrics improved substantially while maintaining predictive accuracy.

Strengths:

- Efficient preprocessing method.
- Improved fairness without major performance loss.

Limitations:

- Doesn't eliminate bias in complex pipelines.
- Only corrects for observed attributes (here, gender).

Implications:

- Promotes fairer automated decisions in employment or financial contexts.

- Encourages companies to adopt fairness-aware machine learning practices.