Foundations of Data Science

Homework 5: Algorithmic fairness

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Part 1: Algorithmic fairness (15 points)

Data acquisition and preparation (4 points)

For this question we will use the "Adult" dataset from the UC Irvine repository.

This data is from the United States census, and we will examine the algorithmic fairness for an income prediction task. For more information about the dataset, see Here.

1. Download the data. (1 point)

Load data from the URL using the pandas read_csv method.

```
#Place code here
import pandas as pd
import io
import requests


url = "https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data"
url_data = requests.get(url).content
df=pd.read_csv(io.StringIO(url_data.decode('utf-8')), header=None)
```

```
df.head()
```

0	1	2	3	4	5	6

2. If the column headers are not correct, assign names to them (hint: use the readme from the source website). Compute descriptive statistics for the education level. (2 points).

2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-fami

README FILE

age: continuous.
workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
fnlwgt: continuous.
education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
education-num: continuous.
marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
sex: Female, Male.
capital-gain: continuous.
capital-loss: continuous.
hours-per-week: continuous.
native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

```
#Place code here
df.columns = ["age", "workclass", "fnlwgt", "education", "education-num", "marital-sta
df.head()

df.describe(include='all')
```

	age	workclass	fnlwgt	education	education-num	marital-status	occu
count	32561.000000	32561	3.256100e+04	32561	32561.000000	32561	
unique	NaN	9	NaN	16	NaN	7	
top	NaN	Private	NaN	HS-grad	NaN	Married-civ-spouse	Prof-s
freq	NaN	22696	NaN	10501	NaN	14976	
mean	38.581647	NaN	1.897784e+05	NaN	10.080679	NaN	
std	13.640433	NaN	1.055500e+05	NaN	2.572720	NaN	
min	17.000000	NaN	1.228500e+04	NaN	1.000000	NaN	
25%	28.000000	NaN	1.178270e+05	NaN	9.000000	NaN	
50%	37.000000	NaN	1.783560e+05	NaN	10.000000	NaN	
75%	48.000000	NaN	2.370510e+05	NaN	12.000000	NaN	
max	90.000000	NaN	1.484705e+06	NaN	16.000000	NaN	

```
df["education"].value_counts()
```

```
HS-grad         10501
Some-college     7291
Bachelors        5355
Masters          1723
Assoc-voc        1382
11th             1175
Assoc-acdm       1067
10th              933
7th-8th           646
Prof-school       576
9th               514
12th              433
Doctorate         413
5th-6th           333
1st-4th           168
Preschool          51
Name: education, dtype: int64
```

3. Select one attribute as protected. Explain the reason why you selected this attribute. (1 point)

Protected attributes require the prefix protected. The outcome attribute requires the prefix target. For example, if you need to measure fairness rankings of a dataset with the columns sex and credit_score, rename the columns to protected_sex and target_credit_Score. Update the column names for our dataset (hint: you may also have to convert the target to a binary variable and create dummy variables for those that are categorical, for upcoming steps). (1 point).

```
#Place code here
df["protected_sex"] = df["sex"]


cols = ["workclass", "education" ,"marital-status", "occupation", "relationship", "rac
df = pd.get_dummies(df, columns=cols)

df["class_binary"] = 0
df.loc[(df["class"]==' >50K'),"class_binary"] = 1


df.drop(columns=["sex","class"], inplace=True)



df["class_binary"].value_counts()
```

```
0    24720
1     7841
Name: class_binary, dtype: int64
```

There is race and gender that cna be chosen because I do not want the model to be biased towards that and to avoid Disparate treatment towards a particular class

But since here they have asked only one I chose gender since we are well aware of gender disparity in salaries

Build a Classifier (5 points)

4. Select a type of classifier to build for the income prediction task. Give reasoning for why you picked this type. (1 point)

I chose decision tree because its

1. fast,
2. there are not many attributes so its a lot simpler
3. only 2 classes so can easily classify them
4. lot of categorical variables so to split and to visualise will be easy

The training data is highly imbalanced I was thinking of Decision tree classifier but decision tree classifier are not sensitive to imbalanced datasets so tried XGB Boost and added balancing factor to it

5. Split the data into training and testing. Use pandas to create two data frames: train_df and test_df, where train_df has 80% of the data chosen uniformly at random without replacement

(test_df should have the other 20%). Also, make sure to write your own code to do the splits. You may use any random() function numpy but do not use the data splitting functions from Sklearn. (1 point)

```
#Place code here
import numpy as np
percent = np.random.rand(len(df)) <= 0.8
train_df = df[percent]
test_df = df[~percent]
```

```
df["class_binary"].value_counts()
```

```
0    24720
1     7841
Name: class_binary, dtype: int64
```

6. On the training set, implement your classifier. Give reasoning for your choice of any hyperparameter(s). (1 point)

Chose the balancing factor in xgb model as the dataset is highly imbalanced and also ran it through gridcv for it to choose the right hyperparameters

For decision tree chose min_samples_leaf 40 and min_samples_split 100 because dataset has around 30,000 data points and i did not want it to overfit

```
# DECISION TREE CLASSIFIER
import xgboost as xgb
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
dtc = DecisionTreeClassifier(criterion='entropy', min_samples_leaf = 40, min_samples_s

train_X = train_df.loc[:, train_df.columns != "class_binary"]
train_Y = train_df["class_binary"]

test_X = test_df.loc[:, test_df.columns != "class_binary"]
test_Y = test_df["class_binary"]

dtc.fit(train_X, train_Y)

predtest_Y = dtc.predict(test_X)
print("Test Accuracy", accuracy_score(test_Y, predtest_Y))
```

```
Test Accuracy 0.8619201725997843
```

```
# XGB CLASSIFIER
xgb_model = xgb.XGBClassifier(booster = 'dart', eta = 0.4, max_depth = 2, objective="b
eval_set = [(train_X, train_Y), (test_X, test_Y)]
xgb_model.fit(train_X, train_Y, eval_set=eval_set, eval_metric=["error", "logloss"])
predtest_Y = xgb_model.predict(test_X)
acc = accuracy_score(test_Y, predtest_Y)
print(acc)
```

```
[43]	validation_0-error:0.147745	validation_0-logloss:0.331848	validati
[44]	validation_0-error:0.147246	validation_0-logloss:0.330837	validati
[45]	validation_0-error:0.147016	validation_0-logloss:0.329899	validati
[46]	validation_0-error:0.147093	validation_0-logloss:0.32887	validati
[47]	validation_0-error:0.147169	validation_0-logloss:0.328011	validati
[48]	validation_0-error:0.146978	validation_0-logloss:0.327223	validati
[49]	validation_0-error:0.147323	validation_0-logloss:0.326476	validati
[50]	validation_0-error:0.147476	validation_0-logloss:0.325692	validati
[51]	validation_0-error:0.146326	validation_0-logloss:0.32484	validati
[52]	validation_0-error:0.146364	validation_0-logloss:0.324173	validati
[53]	validation_0-error:0.14621	validation_0-logloss:0.323542	validati
[54]	validation_0-error:0.146326	validation_0-logloss:0.322928	validati
[55]	validation_0-error:0.146479	validation_0-logloss:0.322223	validati
[56]	validation_0-error:0.146287	validation_0-logloss:0.321638	validati
[57]	validation_0-error:0.146479	validation_0-logloss:0.321093	validati
[58]	validation_0-error:0.146287	validation_0-logloss:0.320552	validati
[59]	validation_0-error:0.146249	validation_0-logloss:0.32006	validati
[60]	validation_0-error:0.146326	validation_0-logloss:0.319568	validati
[61]	validation_0-error:0.14621	validation_0-logloss:0.319054	validati
[62]	validation_0-error:0.14575	validation_0-logloss:0.318472	validati
[63]	validation_0-error:0.145635	validation_0-logloss:0.317996	validati
[64]	validation_0-error:0.145635	validation_0-logloss:0.317535	validati
[65]	validation_0-error:0.145443	validation_0-logloss:0.317018	validati
[66]	validation_0-error:0.145482	validation_0-logloss:0.316609	validati
[67]	validation_0-error:0.145674	validation_0-logloss:0.316165	validati
[68]	validation_0-error:0.145558	validation_0-logloss:0.315777	validati
[69]	validation_0-error:0.145443	validation_0-logloss:0.315405	validati
[70]	validation_0-error:0.145328	validation_0-logloss:0.315044	validati
[71]	validation_0-error:0.145405	validation_0-logloss:0.314707	validati
[72]	validation_0-error:0.145252	validation_0-logloss:0.314348	validati
[73]	validation_0-error:0.145175	validation_0-logloss:0.313985	validati
[74]	validation_0-error:0.14529	validation_0-logloss:0.313644	validati
[75]	validation_0-error:0.145213	validation_0-logloss:0.313349	validati
[76]	validation_0-error:0.145175	validation_0-logloss:0.313036	validati
[77]	validation_0-error:0.145175	validation_0-logloss:0.312754	validati
[78]	validation_0-error:0.144791	validation_0-logloss:0.312438	validati
[79]	validation_0-error:0.14483	validation_0-logloss:0.312154	validati
[80]	validation_0-error:0.144945	validation_0-logloss:0.311867	validati
[81]	validation_0-error:0.144715	validation_0-logloss:0.311583	validati
[82]	validation_0-error:0.144446	validation_0-logloss:0.311315	validati
[83]	validation_0-error:0.144178	validation_0-logloss:0.310978	validati
[84]	validation_0-error:0.144254	validation_0-logloss:0.310726	validati
[85]	validation_0-error:0.144216	validation_0-logloss:0.310487	validati
[86]	validation_0-error:0.144101	validation_0-logloss:0.310237	validati
[87]	validation_0-error:0.144216	validation_0-logloss:0.31001	validati
[88]	validation_0-error:0.144101	validation_0-logloss:0.309786	validati
[89]	validation_0-error:0.144178	validation_0-logloss:0.309546	validati
```

```
[90]	validation_0-error:0.144063	validation_0-logloss:0.309203	validati
[91]	validation_0-error:0.143756	validation_0-logloss:0.308968	validati
[92]	validation_0-error:0.143794	validation_0-logloss:0.308771	validati
[93]	validation_0-error:0.143756	validation_0-logloss:0.308564	validati
[94]	validation_0-error:0.143794	validation_0-logloss:0.308107	validati
[95]	validation_0-error:0.143564	validation_0-logloss:0.307908	validati
[96]	validation_0-error:0.143717	validation_0-logloss:0.307633	validati
[97]	validation_0-error:0.143526	validation_0-logloss:0.307345	validati
[98]	validation_0-error:0.143564	validation_0-logloss:0.307156	validati
[99]	validation_0-error:0.143295	validation_0-logloss:0.306758	validati
0.866235167206041
```

```
# GRID SEARCH XGB CLASSIFIER
from xgboost import XGBClassifier
from sklearn.utils.class_weight import compute_sample_weight
from sklearn.model_selection import GridSearchCV
estimator = XGBClassifier(
    objective= 'binary:logistic',
    nthread=4,
    seed=42
)

parameters = {
    'max_depth': range (2),
    'n_estimators': range(60),
    'learning_rate': [0.1]
}
grid_search = GridSearchCV(
    estimator=estimator,
    param_grid=parameters,
    scoring = 'roc_auc',
    n_jobs = 10,
    cv = 10,
    verbose=True
)
sample_weights = compute_sample_weight(
    class_weight='balanced',
    y=train_Y
)

grid_search.fit(train_X, train_Y, sample_weight=sample_weights)
print(grid_search.best_params_)
grid_search.score(test_X, test_Y)
```

```
Fitting 10 folds for each of 120 candidates, totalling 1200 fits
{'learning_rate': 0.1, 'max_depth': 1, 'n_estimators': 57}
0.9033226905320205
```

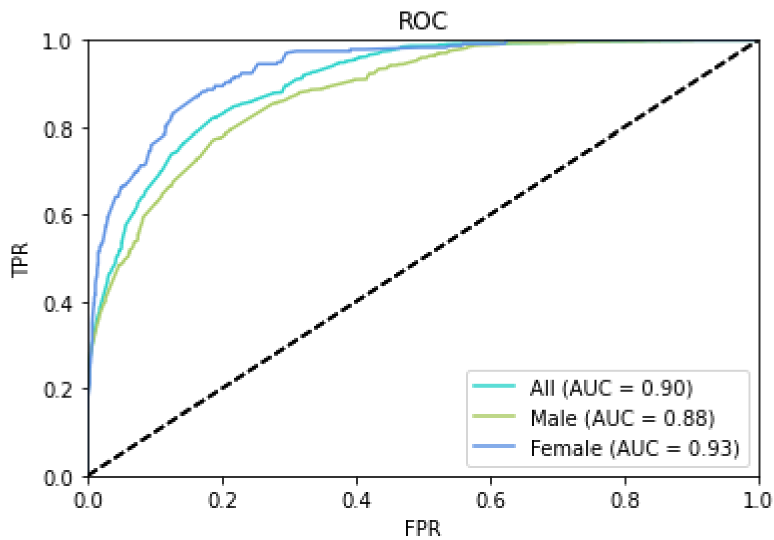
90.33% accuracy xgboost model compared to decision tree of 86.2%

7. To demonstrate the performance of your classifier, we will now plot the AUROC. Below are two functions which you can use. What you need to add is code to plot the AUROC for all the data and as well for each value of the protected attribute (on one set of axes). (2 points)

```
#Code for computing the AUCROC

from sklearn.metrics import roc_auc_score, roc_curve, auc
import matplotlib.pyplot as plt

def getAUC(truth, pred):
    fpr, tpr, thresholds = roc_curve(truth, pred)
    return auc(fpr, tpr)


def plotAUC(truth, pred, lab):
    fpr, tpr, thresholds = roc_curve(truth, pred)
    roc_auc = auc(fpr, tpr)
    c = (np.random.rand(), np.random.rand(), np.random.rand())
    plt.plot(fpr, tpr, color=c, label= lab+' (AUC = %0.2f)' % roc_auc)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.0])
    plt.xlabel('FPR')
    plt.ylabel('TPR')
    plt.title('ROC')
    plt.legend(loc="lower right")
```

```
test_df["prediction"] = predtest_Y
test_df["score"] = grid_search.predict_proba(test_X)[:,1]

# For all values
print("All ", getAUC(test_Y, test_df["score"]))
plotAUC(test_Y, test_df["score"],'All')


# For every value in protected attribute
print("Male ", getAUC(test_df[test_df["protected_sex_ Male"]==1]["class_binary"],test_
plotAUC(test_df[test_df["protected_sex_ Male"]==1]["class_binary"],test_df[test_df["pr


print("Female ",getAUC(test_df[test_df["protected_sex_ Female"]==1]["class_binary"],te
plotAUC(test_df[test_df["protected_sex_ Female"]==1]["class_binary"],test_df[test_df['
plt.show()
```

```
<ipython-input-200-e5e84d334034>:27: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
  test_df["prediction"] = predtest_Y
<ipython-input-200-e5e84d334034>:28: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
  test_df["score"] = grid_search.predict_proba(test_X)[:,1]
All  0.9033226905320205
Male  0.8797646810657971
Female  0.9332041001170831
```



Assessing algorithmic fairness (5 points)

8. Algorithmic Fairness metrics (2 points)

Pick a fairness metric to apply to the income prediction task and your selected protected attribute. Explain why you selected this metric.

ANSWER

Statistical parity, Equalized odds, Equality of opportunity, Calibration

With all the possibilities, Statistical parity is what I am favouring because I want to know if irrespective of sex the people belong to the same income bracket or not and SPD helps in even understanding which group is underpriveleged or priveleged based on the sign of value. We can also determine the impact by calculating disparate impact ratio

SPD = P(Y pred =1 | A=minority)−P(Y pred=1 | A=majority)

9. Compute the chosen metric for your protected attribute. Hint: this will require you to first find the threshold wiith the best when predicting on the entire data, and then computing the TPR/FPR or other necessary parameters at that threshold for each value of the protected attribute. (2 points)

There are many ways we could locate the threshold with the optimal balance between the false positive rate (FPR) and true positive rate (TPR).

As a reminder, the TPR is called the Sensitivity. The inverse of the false-positive rate (1-FPR) is called the Specificity.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad \text{Specificity} = \frac{TN}{FP+TN}$$

where:

$$\text{Sensitivity} = \text{TPR and Specificity} = 1 - \text{FPR}$$

The Geometric Mean or g-mean is a metric for imbalanced classification that, if optimized, will seek a balance between the sensitivity and the specificity.

$$\text{g-mean} = \sqrt{Sensitivity * Specificity}$$

Using Imblearn Package

```
from imblearn.metrics import geometric_mean_score
import math
result_proba = grid_search.predict_proba(test_X)
df_threshold = pd.DataFrame()
threshold_lis = []
gmean = []

for i in range(0,100,1):
  threshold = i/100
  threshold_lis.append(threshold)
  result_boolean2 = (result_proba[:,1] > threshold)
  gmean.append(geometric_mean_score(test_Y,result_boolean2))
df_threshold["threshold"] = threshold_lis
df_threshold["gmean"] = gmean
```

```
df_threshold
```

	threshold	gmean
0	0.00	0.000000
1	0.01	0.000000
2	0.02	0.000000
3	0.03	0.000000
4	0.04	0.000000
...	...	...
95	0.95	0.284935

Withot imblearn and manually calcuating

```
import math
result_proba = grid_search.predict_proba(test_X)
df_threshold = pd.DataFrame()
threshold_lis = []
gmean = []

for i in range(0,100,1):
  threshold = i/100
  threshold_lis.append(threshold)
  y_pred = (result_proba[:,1] > threshold)
  y_true = test_Y

  fp = np.sum((y_pred == 1) & (y_true == 0))
  tp = np.sum((y_pred == 1) & (y_true == 1))

  fn = np.sum((y_pred == 0) & (y_true == 1))
  tn = np.sum((y_pred == 0) & (y_true == 0))

  fpr = fp / (fp + tn)
  tpr = tp / (tp + fn)
  gmean.append(math.sqrt((1-fpr)*tpr))

df_threshold["threshold"] = threshold_lis
df_threshold["gmean"] = gmean


df_threshold
```

51 to 75 of 100 entries Filter

index	threshold	gmean
50	0.5	0.8061284503086985
51	0.51	0.8063641488364729
52	0.52	0.8117287268898862
53	0.53	0.81413814935931
54	0.54	0.8153436084688543
55	0.55	0.8152920127201502
56	0.56	0.8160783714833416
57	0.57	0.8087105461628338
58	0.58	0.8043432490590281
59	0.59	0.8037007121671583
60	0.6	0.7891138178160744
61	0.61	0.7872998126228338
62	0.62	0.7671833342596796
63	0.63	0.762624012939201
64	0.64	0.7505317193512874
65	0.65	0.7348109491712191
66	0.66	0.7240792778501726
67	0.67	0.7143294671057079
68	0.68	0.7106754372621845
69	0.69	0.7024692430974895
70	0.7	0.699323085142228
71	0.71	0.6933245809878108

ANSWER

0.56 is a threshold that gives the highest geometric mean between sensitivy and specificity, so considering that threshold

P(Y pred =1 | A=minority)−P(Y pred=1 | A=majority)

```
test_df["prediction_threshold"] =0
test_df.loc[(test_df["score"]>0.56),"prediction_threshold"] = 1

test_minority = test_df[test_df["protected_sex_ Female"]==1]
test_minority_class_binary = test_minority[test_minority["prediction_threshold"]==1]


test_majority = test_df[test_df["protected_sex_ Male"]==1]
test_majority_class_binary = test_majority[test_majority["prediction_threshold"]==1]
```

```
<ipython-input-203-2e47796b02fc>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
  test_df["prediction_threshold"] =0
/usr/local/lib/python3.8/dist-packages/pandas/core/indexing.py:1817: SettingWith
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
  self._setitem_single_column(loc, value, pi)
```

```
SPD = len(test_minority_class_binary)/len(test_minority) - len(test_majority_class_bi
print(SPD)
```

```
-0.33824944428794945
```

10. Is there a disparity? How can we interpret its magnitude? Is such a disparity a bad thing/avoidable? (1 point)

ANSWER

There is disparity, so SPD should be 0 for it to be fair but in our case it is 0.366 which means there is disparity of income bracket between men and women

-0.338 when it is supposed to be 0 shows the magnitude of it. A negative value of statistical parity difference indicates that the unprivileged group is at a disadvantage and a positive value indicates that the privileged group is at a disadvantage.

it is sessentially calculating probabilities of a positive outcome across two groups and if its negative shows how much of disparity exists like in our case underpriveleged that is women here experiety parity difference

Disparity is quite bad as it shows that women are less likely to have an income range in the >50K bracket though they are equally qualified as men. And when an ML model

Disparate Impact (DI) compares the proportion of individuals that receive a favorable outcome for two groups, a majority group and a minority group. This measure must be equal to 1 to be fair.

```
DI = len(test_minority_class_binary)/len(test_minority)/len(test_majority_class_binar
print(DI)
```

```
1.5429836854912323e-08
```

ANSWER

Value for DI was supposed to be 1 for the model to be fair but here its close to 0 so its not

Here, a value of indicates fairness, values less than indicate disadvantage faced by the unprivileged group, and values greater than indicate disadvantage faced by the privileged group. The disparate impact ratio is also sometimes known as the relative risk ratio or the adverse impact ratio.

Other Fairness Metrics

Equal Opportunity Difference (EOD) measures the deviation from the equality of opportunity, which means that the same proportion of each population receives the favorable outcome. This measure must be equal to 0 to be fair.

```
test_minority_prediction = test_df[test_df["protected_sex_ Female"]==1]
test_minority_class_gt = test_minority_prediction[test_minority_prediction["class_bina
test_minority = test_minority_class_gt[test_minority_class_gt["prediction_threshold"]=


test_majority_prediction = test_df[test_df["protected_sex_ Male"]==1]
test_majority_class_gt = test_majority_prediction[test_majority_prediction["class_bina
test_majority = test_majority_class_gt[test_majority_class_gt["prediction_threshold"]=

EOD = len(test_minority)/len(test_minority_class_gt) - len(test_majority)/len(test_ma
print(EOD)
```

```
-0.17569976822963096
```

Value for EOD was supposed to be 0 for the model to be fair but here its 0.27 indicating it is no fair