Experiment No. 6
Apply Boosting Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:
Date of Submission:

Aim: Apply Boosting algorithm on Adult Census Income Dataset and analyze the performance of the model.

Objective: Apply Boosting algorithm on the given dataset and maximize the accuracy, Precision, Recall, F1 score.

Theory:
Suppose that as a patient, you have certain symptoms. Instead of consulting one doctor, you choose to consult several. Suppose you assign weights to the value or worth of each doctor's diagnosis, based on the accuracies of previous diagnosis they have made. The final diagnosis is then a combination of the weighted diagnosis. This is the essence behind boosting. Algorithm: Adaboost- A boosting algorithm—create an ensemble of classifiers. Each one gives a weighted vote.

Input:
- D , a set of d class labelled training tuples
- k, the number of rounds (one classifier is generated per round)
- a classification learning scheme

Output: A composite model

Method

1. Initialize the weight of each tuple in D is 1/d
2. For i=1 to k do // for each round
3. Sample D with replacement according to the tuple weights to obtain D

4. Use training set D to derive a model M
5. Computer error(M), the error rate of M
6. Error(M)=∑w *err(X)
7. If Error(M)>0.5 then
8. Go back to step 3 and try again
9. endif
10. for each tuple in D that was correctly classified do
11. Multiply the weight of the tuple by error(Mi)/(1-error(M)
12. Normalize the weight of each tuple
13. end for

To use the ensemble to classify tuple X

1. Initialize the weight of each class to 0
2. for i=1 to k do // for each classifier
3. w =log((1-error(M))/error(M))//weight of the classifiers vote

4. C=M(X) // get class prediction for X from M i i
5. Add w to weight for class C
   i
6. end for
7. Return the class with the largest weight.

Dataset:

Predict whether income exceeds $50K/yr based on census data. Also known as "Adult" dataset.

Attribute Information: Listing of attributes:

>50K, <=50K.

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, Profspecialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transportmoving, 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, DominicanRepublic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad &Tobago, Peru, Hong, HolandNetherlands.

Code:

Conclusion:

1. Comment on the accuracy, confusion matrix, precision, recall and F1 score obtained.

• Accuracy Score: The model's accuracy stands at 0.854, signifying that it accurately predicts the income level (above or below $50K) for 85.4% of the samples in the test dataset.

• Confusion Matrix:

Confusion matrix is used to assess the performance of a classification model, in our case the TP is 904,TN is 4247, no. of FP is 286 and no. of FN are 596 which means our model is better in predicting negative cases than the positive cases.

• Precision: For class 1 (income above $50K), the precision is 0.76. This implies that 76% of the positive predictions made by the model are correct.

• Recall: The recall for class 1 is 0.60, indicating that the model accurately identifies 60% of the actual positive cases.

• F1-Score: The F1-score, a harmonic mean of precision and recall, provides a balanced single score for model assessment. The F1-score for class 1 is 0.67.

2. Compare the results obtained by applying boosting and random forest algorithm on the Adult Census Income Dataset

In the random forest algorithm, the accuracy, precision, recall and F1-score obtained respectively is 85.35%, 72.68%, 61%, 66%. and the accuracy, precision, recall and F1-score obtained by boosting algorithm is 85.3%,76%,60%,57%. In choosing between these algorithms, it's crucial to consider the specific objectives and requirements of the task at hand. If a balance between precision and recall is paramount, Random Forest may be preferred, whereas Boosting might be favored if precision is a higher priority.

```
[ ]: import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
```

```
[ ]: data = pd.read_csv('adult.csv')
print(data)
```

```
age workclass  fnlwgt    education  education.num     marital.status  \
0       90    ?     77053 HS-grad     9     Widowed
1       82  Private 132870 HS-grad 9 Widowed 2 66 ? 186061 Some-
        college 10 Widowed 3 54 Private 140359 7th-8th 4 Divorced
4       41  Private 264663 Some-college          10         Separated
…     …        …      …            …            …                …
  32556   22    Private 310152 Some-college 10    Never-married 32557
        27    Private 257302   Assoc-acdm 12 Married-civ-spouse
32558 40 Private 154374 HS-grad 9 Married-civ-spouse 32559 58 Private
151910 HS-grad 9 Widowed
32560  22  Private 201490     HS-grad            9      Never-married

          occupation relationship  race    sex capital.gain \
0                   ? Not-in-family White Female    0
1                   Exec-managerial Not-in-family White Female      0
2                   ?   Unmarried Black Female      0
3                   Machine-op-inspct   Unmarried White Female      0
4                   Prof-specialty Own-child White Female      0
…                …            …     …     …        …
32556      Protective-serv Not-in-family White      Male  0
32557      Tech-support Wife White Female      0
32558      Machine-op-inspct  Husband White    Male  0
32559      Adm-clerical Unmarried White Female      0
32560      Adm-clerical Own-child White  Male  0

       capital.loss hours.per.week native.country income
0            4356 40 United-States <=50K
1            4356 18 United-States <=50K
2            4356 40 United-States <=50K
3            3900 40 United-States <=50K
4            3900            40      United-States
                             <=50K
…            …           …            …    …
32556           0            40      United-States
                             <=50K
32557           0            38      United-States
                             <=50K
32558           0            40 United-States >50K
```

```
32559           0             40      United-States
                              <=50K
32560           0             20      United-States
                              <=50K
[32561 rows x 15 columns]
```

[ ]:
```
data.describe()
```

[ ]:
```
                 age    fnlwgt education.num capital.gain capital.loss \
count 32561.000000             32561.000000            32561.000000
3.256100e+04                   32561.000000
mean   38.581647 1.897784e+05   10.080679 1077.648844    87.303830
std    13.640433 1.055500e+05    2.572720 7385.292085   402.960219
min    17.000000 1.228500e+04    1.000000    0.000000     0.000000
25%    28.000000 1.178270e+05    9.000000    0.000000     0.000000
50%    37.000000 1.783560e+05   10.000000    0.000000     0.000000
75%    48.000000 2.370510e+05   12.000000    0.000000     0.000000
max     90.000000              16.000000 99999.000000 4356.000000
      1.484705e+06
      hours.per.week
count   32561.000000

mean       40.437456

std        12.347429

min         1.000000

25%        40.000000

50%        40.000000

75%        45.000000

max        99.000000
```

[ ]:
```
print(data.info())
```

```
<class
'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to
32560 Data columns (total 15
columns):
 #  Column         Non-Null Count Dtype
--- ------         -------------- -----
 0   age            32561 non-null
                    int64
 1  workclass       32561      non-null
                    object
 2   fnlwgt         32561 non-null
                    int64
```

```
 3  education      32561      non-null
                   object
 4  education.num  32561 non-null
                   int64
 5 marital.status 32561 non-null
 object 6 occupation 32561 non-null
 object
 7   relationship  32561 non-null object
 8   race     32561 non-null object
 9   sex      32561 non-null object
 10  capital.gain  32561 non-null int64
 11  capital.loss  32561 non-null int64
 12  hours.per.week 32561 non-null int64
 13  native.country 32561 non-null object 14 income 32561 non-null
     object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
None
```

[ ]:
```
data.isnull().sum()
```

[ ]:
```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
```

```
dtype: int64
```

[ ]:
```
# Replace '?' with NaN in the dataset
data.replace('?', pd.NA, inplace=True)
```

[ ]:
```
# Drop rows with missing values
data.dropna(inplace=True)
```

[ ]:
```
# Encode categorical variables
label_encoder = LabelEncoder()
categorical_columns = data.select_dtypes(include=['object']).columns

for column in categorical_columns:
    data[column] = label_encoder.fit_transform(data[column])
```

[ ]:
```
X = data.drop("income", axis=1)
y = data["income"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[ ]:
```
print(X)
print(y)
```

```
   age workclass fnlwgt education education.num marital.status \
1       82          2 132870        11              9              6
3       54     2 140359    5     4     0
4       41     2 264663    15    10    5
5       34     2 216864    11    9     0
6       38     2 150601    0     6     5
…    …        …     …       …          …         …
32556   22     2 310152    15    10    4 32557     27    2 257302    7
  12    2
32558  40     2 154374    11    9     2
32559  58     2 151910    11    9     6
32560  22     2 201490    11    9     4

   occupation relationship race sex capital.gain capital.loss \
1              3             1    4    0             0         4356
3              6    4     4     0     0     3900
4              9    3     4     0     0     3900
5              7    4     4     0     0     3770
6              0  4  4  1  0  3770 … … … … … … …
32556          10   1     4     1     0     0
32557          12   5     4     0     0     0
```

```
32558          6    0     4     1     0     0
32559          0    4     4     0     0     0
32560          0    3     4     1     0     0

      hours.per.week native.country
1                18             38
3                40     38
4                40     38
5                45     38
6                40     38
…              …            …
32556            40     38
32557            38     38
32558            40     38
32559            40     38
32560            20     38

[30162 rows x 14 columns]
1        0
3        0
4        0
5        0
6        0
        ..
32556   0
32557   0
32558   1
32559   0
32560   0
```

```
Name: income, Length: 30162, dtype: int64
```

[ ]:
```python
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score, classification_report
```

[ ]:
```python
# Create the AdaBoost classifier
ada_boost_classifier = AdaBoostClassifier(n_estimators=50, random_state=42)
```

[ ]:
```python
# Make predictions on the test data
y_pred = ada_boost_classifier.predict(X_test)
```

[ ]:
```python
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪ConfusionMatrixDisplay
```

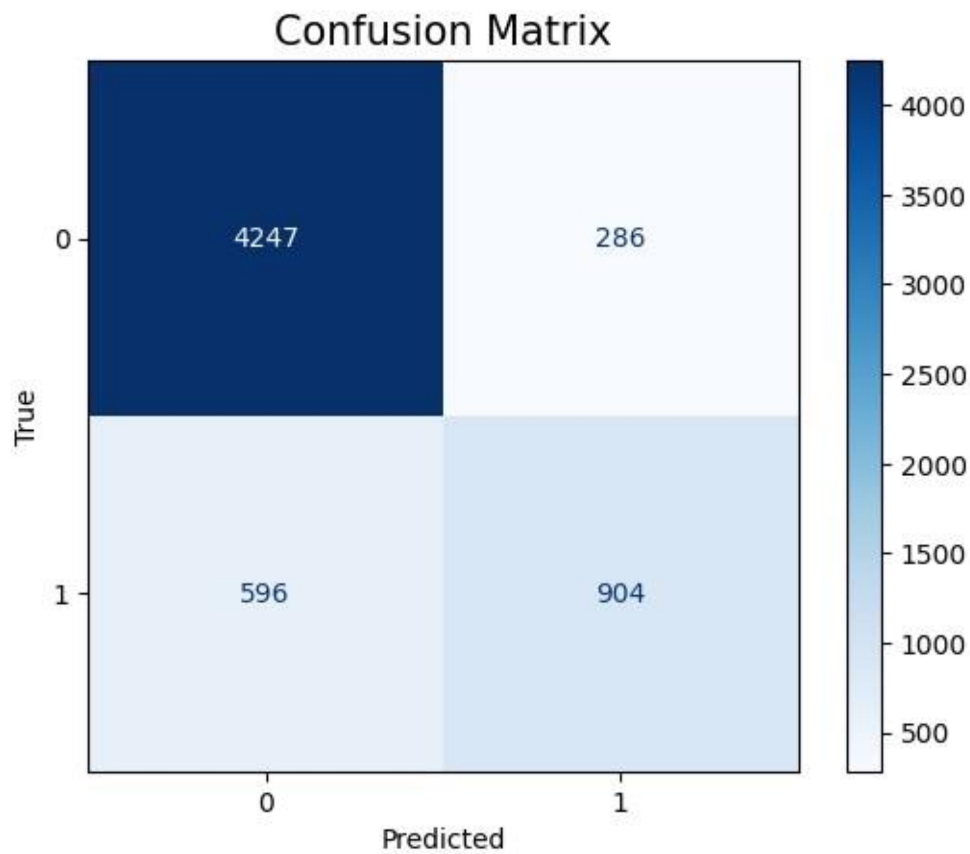
[ ]:
```python
accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
```

```
0.8538040775733466
```

[ ]:
```python
# Create the ConfusionMatrixDisplay cm_display =
ConfusionMatrixDisplay(confusion_matrix=confusion_matrix,␣
 ↪display_labels=[False, True])
```

[ ]:
```python
# Plot the confusion matrix with the specified title
cm_display =
ConfusionMatrixDisplay(confusion_matrix=conf_matrix,␣
 ↪display_labels=None)
plt.figure(figsize=(8, 6))
cm_display.plot(cmap='Blues',
values_format='d') plt.title("Confusion
Matrix", size=15) plt.xlabel('Predicted')
plt.ylabel('True') plt.show()
```

```
<Figure size 800x600 with 0 Axes>
```




```
[ ]: # Calculate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
Confusion Matrix:
[[4247 286]
 [ 596 904]]
```

```
[ ]: accuracy = accuracy_score(y_test,
y_pred) report =
classification_report(y_test, y_pred)
print("Accuracy :", accuracy)
print("Classification Report:\n",
report)
```

```
Accuracy : 0.8538040775733466
Classification Report:
              precision   recall f1-score support
```

```
          0       0.88    0.94      0.91     4533
          1       0.76    0.60      0.67     1500
   accuracy 0.85 6033 macro avg 0.82 0.77 0.79
6033 weighted avg 0.85 0.85 0.85 6033
```