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_i
4. Use training set D_i to derive a model M_i
5. Computer error(M_i), the error rate of M_i
6. Error(M_i)=$\sum w_j$*err(X_j)
7. If Error(M_i)>0.5 then
8. Go back to step 3 and try again
9. endif
10. for each tuple in D_i that was correctly classified do
11. Multiply the weight of the tuple by error(Mi)/(1-error(M_i)

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_i=log((1-error(M_i))/error(M_i))//weight of the classifiers vote
4. C=M_i(X) // get class prediction for X from M_i
5. Add w_i to weight for class C
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, 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.

Code:

Conclusion:

Accuracy: 0.85, indicating that the model correctly predicts the income level.

Precision: For class 0, the precision is 88%, indicating that when the model predicts class 0, it is correct 88% of the time. For class 1, the precision is 76%, suggesting that the model's ability to correctly predict class 1 is not as high as for class 0.

Recall: For class 0, the recall is 94%, indicating that the model effectively captures 94% of all instances of class 0. For class 1, the recall is 60%, suggesting that the model's ability to identify all instances of class 1 is not as high as for class 0.

F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a balance between these two metrics and is particularly useful when dealing with imbalanced datasets. For class 0, the F1 score is 0.91, indicating a good balance between precision and recall. For class 1, the F1 score is 0.67, which is lower and suggests room for improvement.

AdaBoost is a boosting algorithm that iteratively corrects errors by assigning greater weight to misclassified instances, making it more prone to overfitting if the base learner is complex. In contrast, Random Forest employs bagging to build multiple independent decision trees and combines their predictions by averaging or majority voting, reducing variance and overfitting. AdaBoost tends to balance both bias and variance, while Random Forest primarily reduces variance.

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

```
# Load the dataset
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	hours.p
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99

```
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])
```

```
# Split the data into training and testing sets
X = data.drop("income", axis=1)
y = data["income"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score, classification_report
```

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

```
# Fit the classifier to the training data
ada_boost_classifier.fit(X_train, y_train)
```

```
▾        AdaBoostClassifier
AdaBoostClassifier(random_state=42)
```

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

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
```

```
print("The Accuracy for boosting algo is :", accuracy)
```

```
The Accuracy for boosting algo is : 0.8538040775733466
```

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

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

```
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay
```

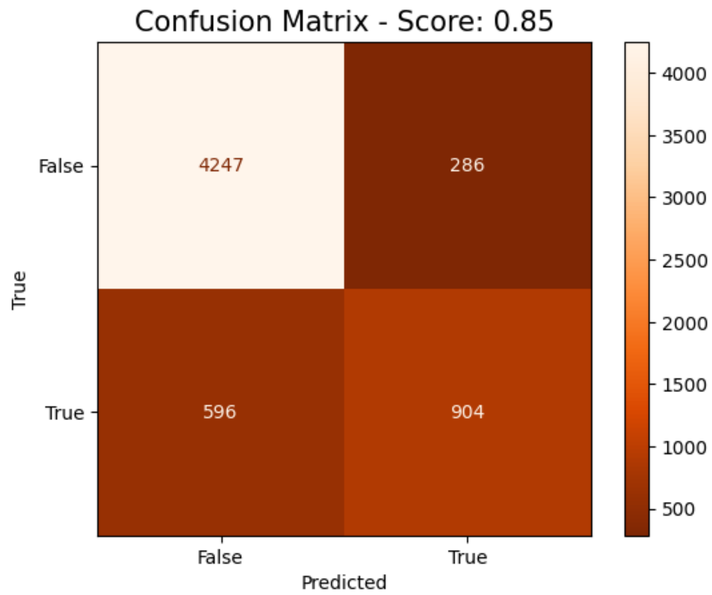
```
# Assuming you already have the y_test and y_pred values from your AdaBoost classifier
confusion_matrix = confusion_matrix(y_test, y_pred)
```

```
# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
```

```
# Create a title for the plot with accuracy score
title = f'Confusion Matrix - Score: {round(accuracy, 2)}'
```

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

```
# Plot the confusion matrix with the specified title plt.figure(figsize=(8, 6))
cm_display.plot(cmap='Oranges_r', values_format='d')
plt.title(title, size=15)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```




```
# Print the accuracy score
print("Accuracy Score:", accuracy)
```

```
Accuracy Score: 0.8538040775733466
```

```
print("Classification Report:\n", report)
```

```
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
```