Experiment No. 6
Apply Boosting Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:04–09–23
Date of Submission:25–09–23

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:

The accuracy of the model stands at 0.865, indicating that it effectively predicts income levels. The confusion matrix reveals that there are 637 true positive predictions, 144 true negatives, 379 false positives, and 854 false negatives.

In terms of precision, the model achieves a precision of 0.88 for predicting income level 0 and 0.79 for predicting income level 1. For recall, it attains a recall of 0.94 for income level 0 and 0.63 for income level 1. The F1-score, which combines precision and recall, is 0.91 for income level 0 and 0.70 for income level 1, indicating the model's overall effectiveness.

Both Random Forest and AdaBoost are capable of achieving high accuracy and are less prone to overfitting. However, Random Forest tends to be more robust to changes in hyperparameter tuning and often requires fewer adjustments in this regard. Additionally, Random Forest offers the benefit of feature importance analysis, making it more interpretable. In contrast, AdaBoost's sequential approach may result in lower interpretability.

In scenarios involving imbalanced data, AdaBoost outperforms Random Forest by giving more weight to minority class samples, effectively addressing class imbalance. In summary, AdaBoost and Random Forest are powerful ensemble algorithms, but their performance can vary based on hyperparameter settings and dataset characteristics.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import io
from sklearn.metrics import accuracy_score, precision_score, f1_score,confusion_matrix, classification_report
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error
```

```
import os
for dirname, _, filenames in os.walk('/content/adult.csv'):
    for filename in filenames:
       print(os.path.join(dirname, filename))
```

```
file = ('/content/adult.csv')
df = pd.read_csv(file)
```

```
print(df.head())
```

```
   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   

          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   

   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  
```

```
print(df.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
```

```
for i in df.columns:
        t = df[i].value_counts()
        index = list(t.index)
        print ("Count of ? in", i)
        for i in index:
            temp = 0
            if i == '?':
                    print (t['?'])
                    temp = 1
                    break
```

```
        if temp == 0:
            print ("0")
```

Streaming output truncated to the last 5000 lines.

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```

```
df=df.loc[(df['workclass'] != '?') & (df['native.country'] != '?')]
print(df.head())
```

```
   age workclass  fnlwgt     education  education.num marital.status  \
1   82   Private  132870       HS-grad              9        Widowed
3   54   Private  140359       7th-8th              4       Divorced
4   41   Private  264663  Some-college             10      Separated
5   34   Private  216864       HS-grad              9       Divorced
6   38   Private  150601          10th              6      Separated

          occupation   relationship   race     sex  capital.gain  \
1    Exec-managerial  Not-in-family  White  Female             0
3  Machine-op-inspct      Unmarried  White  Female             0
4     Prof-specialty      Own-child  White  Female             0
5      Other-service      Unmarried  White  Female             0
6       Adm-clerical      Unmarried  White    Male             0

   capital.loss  hours.per.week native.country income
1          4356              18  United-States  <=50K
3          3900              40  United-States  <=50K
4          3900              40  United-States  <=50K
```

```
     5         3770             45  United-States  <=50K
     6         3770             40  United-States  <=50K
```

```
df["income"] = [1 if i=='>50K' else 0 for i in df["income"]]
print(df.head())
```

```
        age workclass  fnlwgt     education  education.num marital.status  \
     1   82   Private  132870       HS-grad              9        Widowed
     3   54   Private  140359       7th-8th              4       Divorced
     4   41   Private  264663  Some-college             10      Separated
     5   34   Private  216864       HS-grad              9       Divorced
     6   38   Private  150601          10th              6      Separated

               occupation   relationship   race     sex  capital.gain  \
     1    Exec-managerial  Not-in-family  White  Female             0
     3  Machine-op-inspct      Unmarried  White  Female             0
     4     Prof-specialty      Own-child  White  Female             0
     5      Other-service      Unmarried  White  Female             0
     6       Adm-clerical      Unmarried  White    Male             0

        capital.loss  hours.per.week native.country  income
     1         4356             18  United-States      0
     3         3900             40  United-States      0
     4         3900             40  United-States      0
     5         3770             45  United-States      0
     6         3770             40  United-States      0
```

```
df_more=df.loc[df['income'] == 1]
print(df_more.head())
```

```
         age         workclass  fnlwgt    education  education.num marital.status  \
     7    74         State-gov   88638    Doctorate             16  Never-married
     10   45           Private  172274    Doctorate             16       Divorced
     11   38  Self-emp-not-inc  164526  Prof-school             15  Never-married
     12   52           Private  129177    Bachelors             13        Widowed
     13   32           Private  136204      Masters             14      Separated

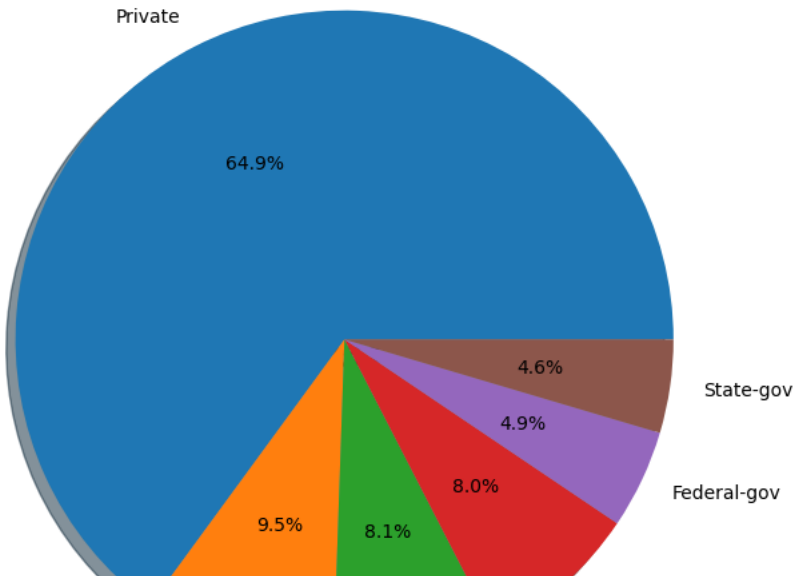
              occupation    relationship   race     sex  capital.gain  \
     7    Prof-specialty  Other-relative  White  Female             0
     10   Prof-specialty       Unmarried  Black  Female             0
     11   Prof-specialty   Not-in-family  White    Male             0
     12    Other-service   Not-in-family  White  Female             0
     13  Exec-managerial   Not-in-family  White    Male             0

         capital.loss  hours.per.week native.country  income
     7           3683             20  United-States      1
     10          3004             35  United-States      1
     11          2824             45  United-States      1
     12          2824             20  United-States      1
     13          2824             55  United-States      1
```

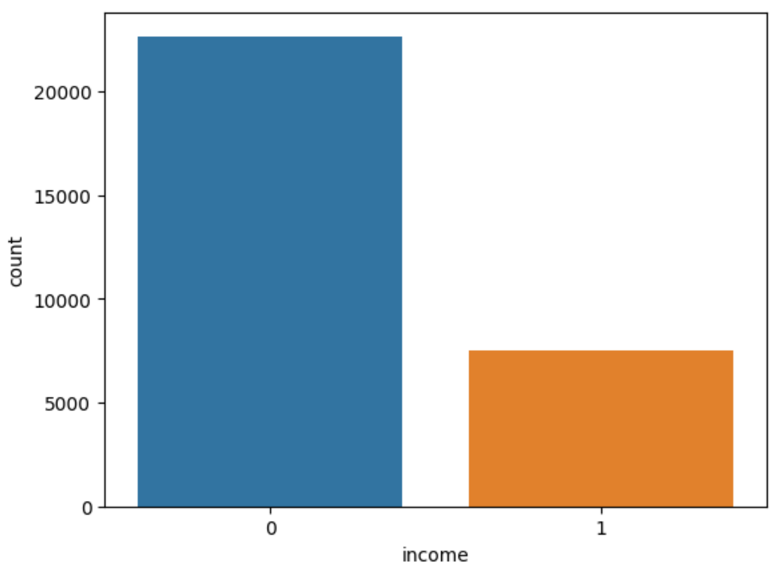
```
workclass_types = df_more['workclass'].value_counts()
labels = list(workclass_types.index)
aggregate = list(workclass_types)
print(workclass_types)
print(aggregate)
print(labels)
```

```
     Private             4876
     Self-emp-not-inc     714
     Local-gov            609
     Self-emp-inc         600
     Federal-gov          365
     State-gov            344
     Name: workclass, dtype: int64
     [4876, 714, 609, 600, 365, 344]
     ['Private', 'Self-emp-not-inc', 'Local-gov', 'Self-emp-inc', 'Federal-gov', 'State-gov']
```

```
plt.figure(figsize=(7,7))
plt.pie(aggregate, labels=labels, autopct='%1.1f%%', shadow = True)
plt.axis('equal')
plt.show()
```



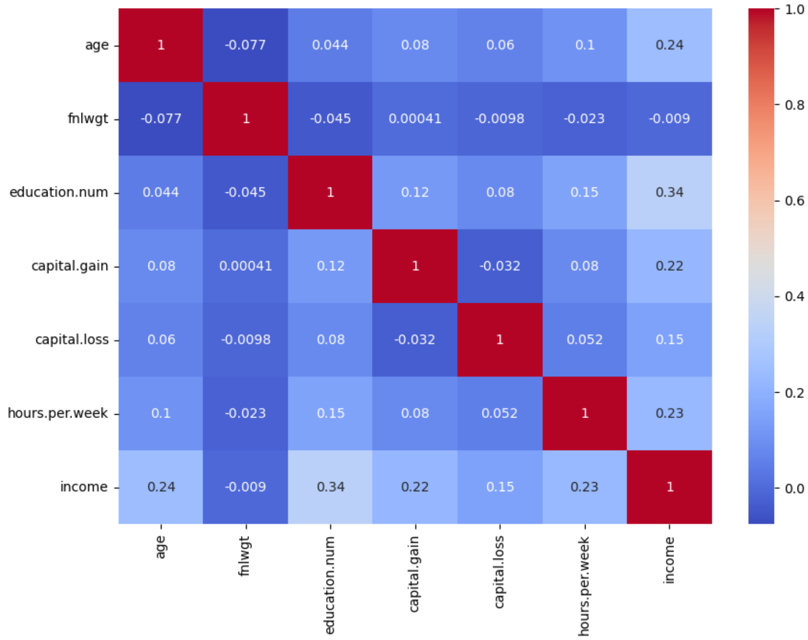

```
#Count plot on single categorical variable
sns.countplot(x ='income', data = df)
plt.show()
df['income'].value_counts()
```




```
0    22661
1     7508
Name: income, dtype: int64
```

```
#Plot figsize
plt.figure(figsize=(10,7))
sns.heatmap(df.corr(), cmap='coolwarm', annot=True)
print(plt.show())
plt.figure(figsize=(10,7))
sns.distplot(df['age'], color="red", bins=100)
plt.ylabel("Distribution", fontsize = 10)
plt.xlabel("Age", fontsize = 10)
plt.show()
```

```
<ipython-input-14-c01c35a847eb>:3: FutureWarning: The default value of numeric_c
  sns.heatmap(df.corr(), cmap='coolwarm', annot=True)
```



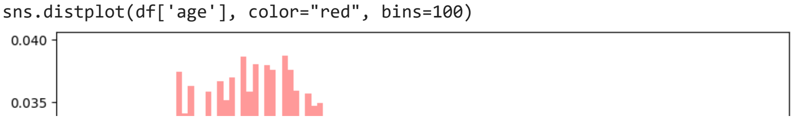

```
None
<ipython-input-14-c01c35a847eb>:6: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

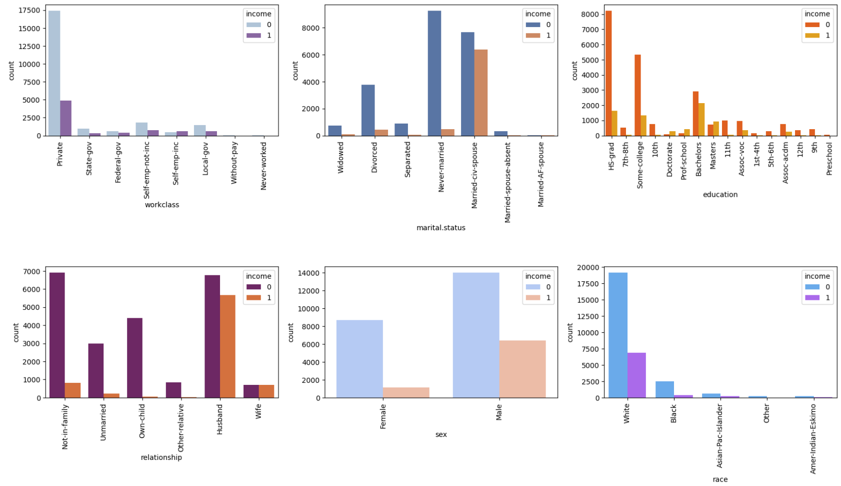
  sns.distplot(df['age'], color="red", bins=100)
```




```
#To find distribution of categorical columns w.r.t income
fig, axes = plt.subplots(figsize=(20, 10))
plt.subplot(231)
sns.countplot(x ='workclass',
hue='income',
data = df,
palette="BuPu")
plt.xticks(rotation=90)
plt.subplot(232)
sns.countplot(x ='marital.status',
hue='income',
data = df,
palette="deep")
plt.xticks(rotation=90)
plt.subplot(233)
sns.countplot(x ='education',
hue='income',
data = df,
palette = "autumn")
plt.xticks(rotation=90)
plt.subplot(234)
sns.countplot(x ='relationship',
hue='income',
data = df,
palette = "inferno")
plt.xticks(rotation=90)
plt.subplot(235)
sns.countplot(x ='sex',
hue='income',
data = df,
palette = "coolwarm")
plt.xticks(rotation=90)
plt.subplot(236)
sns.countplot(x ='race',
```

```
hue='income',
data = df,
palette = "cool")
plt.xticks(rotation=90)
plt.subplots_adjust(hspace=1)
plt.show()
```

```
<ipython-input-16-e1b6d1f0108f>:3: MatplotlibDeprecationWarning: Auto-removal of o
  plt.subplot(231)
```




```
df1 = df.copy()
categorical_features = list(df1.select_dtypes(include=['object']).columns)
print(categorical_features)
df1
```

```
['workclass', 'education', 'marital.status', 'occupation', 'relationship', 'race',
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupatio
1	82	Private	132870	HS-grad	9	Widowed	Exec managerial
3	54	Private	140359	7th-8th	4	Divorced	Machine op-inspc
4	41	Private	264663	Some-college	10	Separated	Pro specialt
5	34	Private	216864	HS-grad	9	Divorced	Other servic
6	38	Private	150601	10th	6	Separated	Adm clerica
...	...	...	...	...	...	...	.
32556	22	Private	310152	Some-college	10	Never-married	Protective ser
32557	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech suppo

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for feat in categorical_features:
        df1[feat] = le.fit_transform(df1[feat].astype(str))
        df1
```

```
X = df1.drop(columns = ['income'])
y = df1['income'].values
# Splitting the data set into train and test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,random_state = 0)
print ("Train set size: ", X_train.shape)
print ("Test set size: ", X_test.shape)

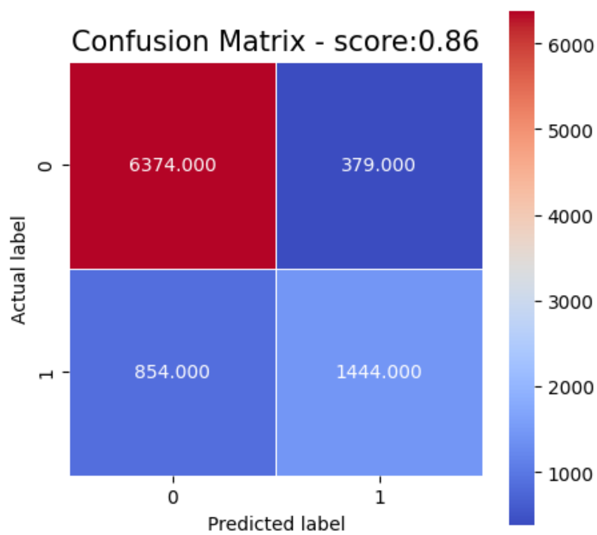
from sklearn.ensemble import AdaBoostClassifier
# Train Adaboost Classifer
abc = AdaBoostClassifier(n_estimators = 300, learning_rate=1)
abc_model = abc.fit(X_train, y_train)
#Prediction
y_pred_abc = abc_model.predict(X_test)
```

```
Train set size:  (21118, 14)
Test set size:  (9051, 14)
```

```
print("Accuracy: ", accuracy_score(y_test, y_pred_abc))
print("F1 score :",f1_score(y_test, y_pred_abc, average='binary'))
print("Precision : ", precision_score(y_test, y_pred_abc))
```

```
Accuracy:  0.8637719588995691
F1 score : 0.7008007765105557
Precision :  0.7921009325287987
```

```
cm = confusion_matrix(y_test, y_pred_abc)
plt.figure(figsize=(5,5))
sns.heatmap(cm, annot=True, fmt=".3f", linewidths=.5, square = True, cmap ="coolwarm");
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
plt.title('Confusion Matrix - score:' + str(round(accuracy_score(y_test,y_pred_abc), 2)), size = 15);
plt.show()
print(classification_report(y_test, y_pred_abc))
```




```
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      6753
           1       0.79      0.63      0.70      2298

    accuracy                           0.86      9051
   macro avg       0.84      0.79      0.81      9051
weighted avg       0.86      0.86      0.86      9051
```

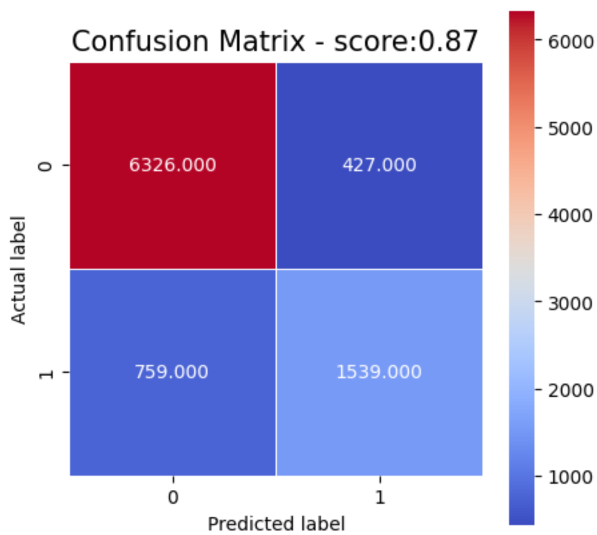
```
from sklearn.ensemble import GradientBoostingClassifier
#Training the model with gradient boosting
gbc = GradientBoostingClassifier(
learning_rate = 0.1,
n_estimators = 500,
max_depth = 5,
subsample = 0.9,
min_samples_split = 100,
max_features='sqrt',
random_state=10)
gbc.fit(X_train,y_train)
# Predictions
y_pred_gbc = gbc.predict(X_test)
print("Accuracy : ",accuracy_score(y_test, y_pred_gbc))
print("F1 score : ", f1_score(y_test, y_pred_gbc, average = 'binary'))
print("Precision : ", precision_score(y_test, y_pred_gbc))
```

```
Accuracy :  0.8689647552756602
F1 score :  0.7218574108818011
Precision :  0.7828077314343845
```

```
rms = np.sqrt(mean_squared_error(y_test, y_pred_gbc))
print("RMSE for gradient boost: ", rms)

cm = confusion_matrix(y_test, y_pred_gbc)
plt.figure(figsize=(5,5))
sns.heatmap(cm, annot = True, fmt=".3f", linewidths = 0.5, square = True, cmap= "coolwarm");
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
plt.title('Confusion Matrix - score:' + str(round(accuracy_score(y_test,y_pred_gbc),2)), size = 15);
plt.show()
print(classification_report(y_test, y_pred_gbc))
```

```
RMSE for gradient boost:  0.3619879068758235
```




```
              precision    recall  f1-score   support

           0       0.89      0.94      0.91      6753
           1       0.78      0.67      0.72      2298

    accuracy                           0.87      9051
   macro avg       0.84      0.80      0.82      9051
weighted avg       0.86      0.87      0.87      9051
```

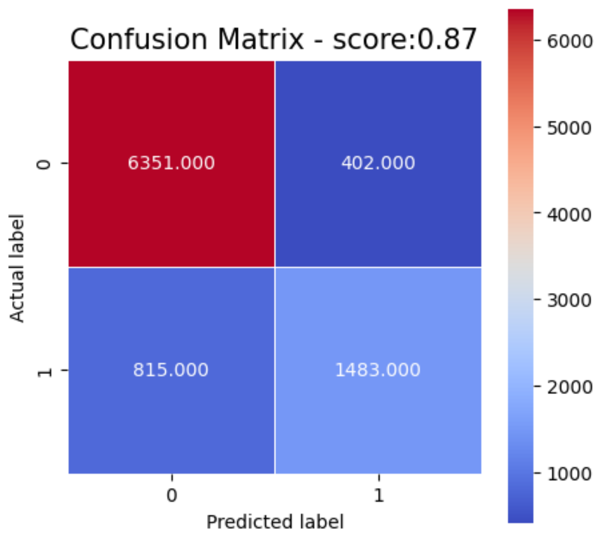
```
import xgboost as xgb
from xgboost import XGBClassifier
#Training the model with gradient boosting
xgboost = XGBClassifier(learning_rate=0.01,
colsample_bytree = 0.4,
n_estimators=1000,
max_depth=20,
gamma=1)
xgboost_model = xgboost.fit(X_train, y_train)
```

```
# Predictions
y_pred_xgboost = xgboost_model.predict(X_test)
print("Accuracy : ",accuracy_score(y_test, y_pred_xgboost))
print("F1 score : ", f1_score(y_test, y_pred_xgboost, average = 'binary'))
print("Precision : ", precision_score(y_test, y_pred_xgboost))

rms = np.sqrt(mean_squared_error(y_test, y_pred_xgboost))
print("RMSE for xgboost: ", rms)

cm = confusion_matrix(y_test, y_pred_xgboost)
plt.figure(figsize=(5,5))
sns.heatmap(cm, annot=True, fmt=".3f", linewidths=.5, square = True, cmap ="coolwarm");
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
plt.title('Confusion Matrix - score:'+str(round(accuracy_score(y_test,y_pred_xgboost),2)), size = 15);
plt.show()
print(classification_report(y_test,y_pred_xgboost))
```

```
Accuracy :  0.8655397193680257
F1 score :  0.7090604829070045
Precision :  0.786737400530504
RMSE for xgboost:  0.3666882608319693
```

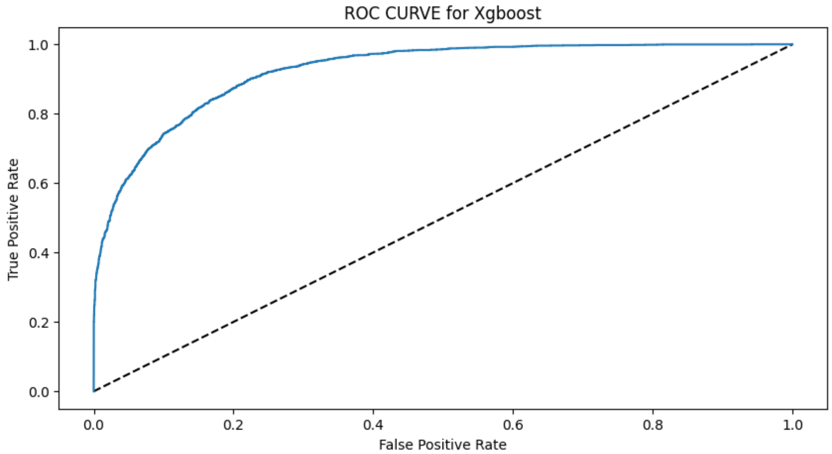



```
              precision    recall  f1-score   support

           0       0.89      0.94      0.91      6753
           1       0.79      0.65      0.71      2298

    accuracy                           0.87      9051
   macro avg       0.84      0.79      0.81      9051
weighted avg       0.86      0.87      0.86      9051
```

```
from sklearn.metrics import roc_curve
fpr, tpr, thresholds = roc_curve(y_test, xgboost.predict_proba(X_test)[:,1])
plt.figure(figsize = (10,5))
plt.plot([0,1],[0,1], 'k--')
plt.plot(fpr, tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC CURVE for Xgboost')
plt.show()
```


ROC CURVE for Xgboost
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0