| |
|---|
| 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:13/09/23 |

**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:**

1. **Accuracy, confusion matrix, precision, recall and F1 score obtained.**

   With an accuracy rate of 86.37%, the Adaboost model successfully forecasted income levels. For income "= $50K," it showed good precision (0.88) but somewhat lower precision (0.79) for income "> $50K." With a recall of 0.94 for "= $50K" cases, it performed exceptionally well; but, its recall for "> $50K" instances (0.63) was just fair. A decent balance was suggested for "= $50K" (F1-Score: 0.91), however there was potential for improvement for "> $50K" (0.70). Adaboost delivered a generally well-balanced performance, with space for improvement to improve estimates of "> $50K".

```
confusion matrix
 [[6374  379]
 [ 854 1444]]
              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
```

**2. Comparison of Boosting and Random Forest Algorithms:**

In terms of accuracy, precision, and F1 score, the boosting algorithms (AdaBoost, Gradient Boosting, and XGBoost) perform better than the Random Forest Classifier. The Handom Forest Classifier performs admirably, with a bulinced Fl score and an accuracy of about 86.37%. However, it lags the boosting algorithms a little bit. For the positive class the boosting algorithms tend to have greater precision and recall, indicating a stronger capacity to accurately identify and classify high-income people.On the Adult Census Income Dataset, all of these models perform about as well as they should. Gradient Boosting, in particular, seems to offer somewhat greater accuracy and an F1 score than Random Forest Classifier.

```
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

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    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
```

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

```
 Count of ? in age 0
 Count of ? in workclass 1836
 Count of ? in fnlwgt 0
 Count of ? in education 0
 Count of ? in education.num 0
 Count of ? in marital.status 0
 Count of ? in occupation 1843
 Count of ? in relationship 0
 Count of ? in race 0
 Count of ? in sex 0
 Count of ? in capital.gain 0
 Count of ? in capital.loss 0
 Count of ? in hours.per.week 0
 Count of ? in native.country 583
 Count of ? in income 0
```

```
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())
```

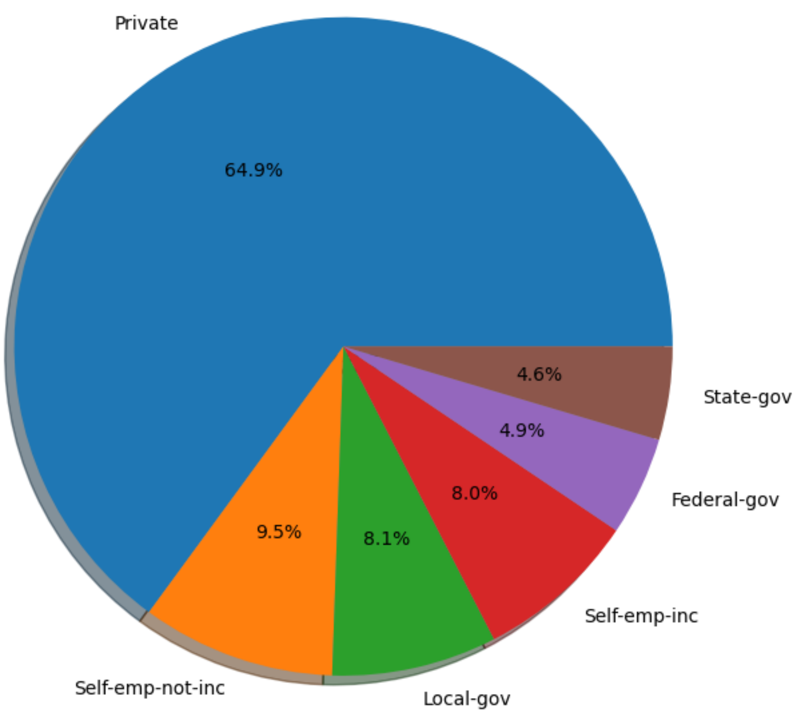
```
    age         workclass  fnlwgt    education  education.num marital.status  \
7    74         State-gov   88638    Doctorate             16  Never-married
10   45           Private  172274    Doctorate             16       Divorced
11   38  Self-emp-not-inc  164526  Prof-school             15  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
```

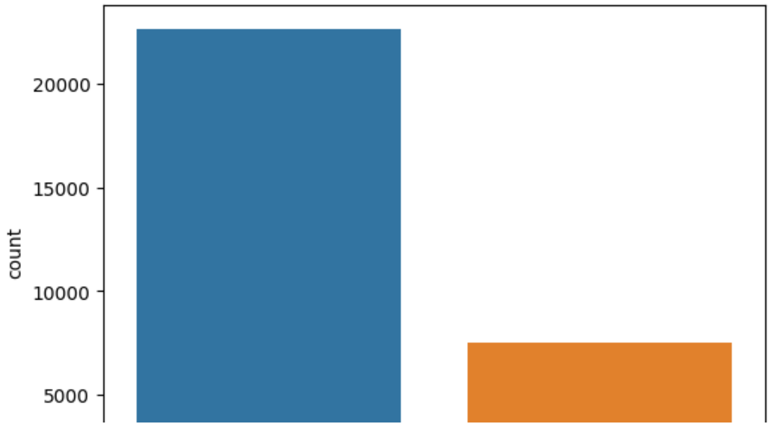
```
workclass_types = df_more['workclass'].value_counts()
labels = list(workclass_types.index)
aggregate = list(workclass_types)
print(workclass_types)
print(aggregate)
print(labels)
```

```
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()
```

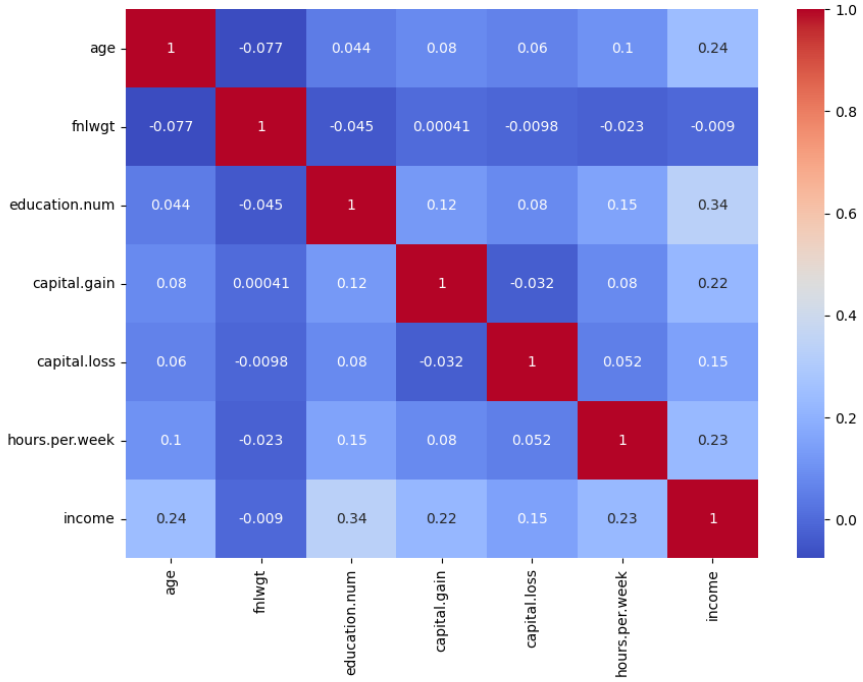



```
#Count plot on single categorical variable
sns.countplot(x ='income', data = df)
plt.show()
df['income'].value_counts()
```




```
#Plot figsize
plt.figure(figsize=(10,7))
sns.heatmap(df.corr(), cmap='coolwarm', annot=True)
print(plt.show())
```

```
<ipython-input-91-6201d8194dba>:3: FutureWarning: The default value of numeric_only i
  sns.heatmap(df.corr(), cmap='coolwarm', annot=True)
```

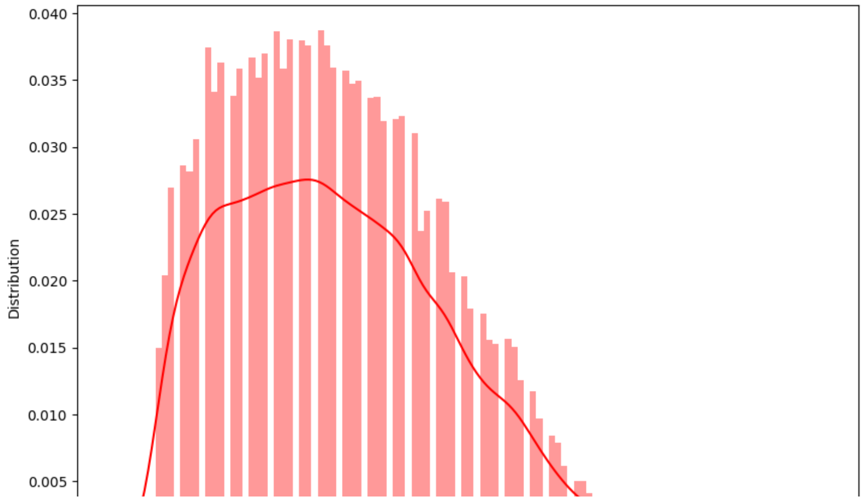



| | age | fnlwgt | education.num | capital.gain | capital.loss | hours.per.week | income |
|---|---|---|---|---|---|---|---|
| age | 1 | -0.077 | 0.044 | 0.08 | 0.06 | 0.1 | 0.24 |
| fnlwgt | -0.077 | 1 | -0.045 | 0.00041 | -0.0098 | -0.023 | -0.009 |
| education.num | 0.044 | -0.045 | 1 | 0.12 | 0.08 | 0.15 | 0.34 |
| capital.gain | 0.08 | 0.00041 | 0.12 | 1 | -0.032 | 0.08 | 0.22 |
| capital.loss | 0.06 | -0.0098 | 0.08 | -0.032 | 1 | 0.052 | 0.15 |
| hours.per.week | 0.1 | -0.023 | 0.15 | 0.08 | 0.052 | 1 | 0.23 |
| income | 0.24 | -0.009 | 0.34 | 0.22 | 0.15 | 0.23 | 1 |

```
None
```

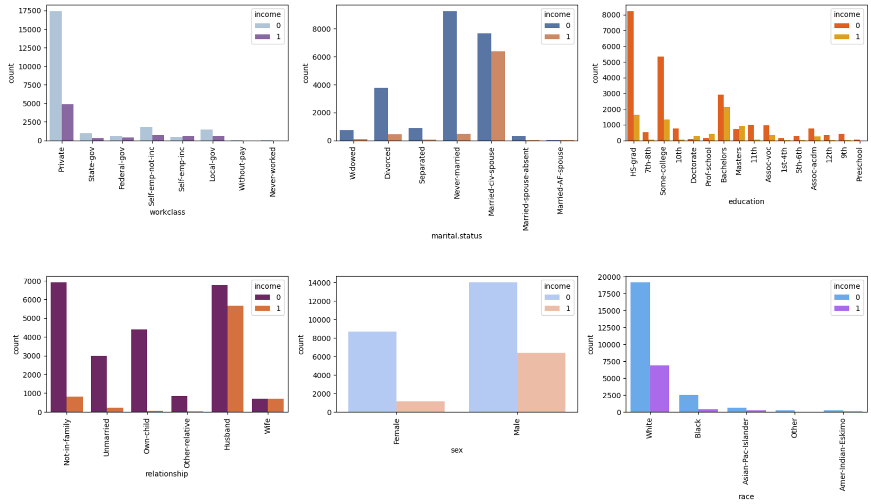
```
plt.figure(figsize=(10,7))
sns.distplot(df['age'], color="red", bins=100)
plt.ylabel("Distribution", fontsize = 10)
plt.xlabel("Age", fontsize = 10)
plt.show()
```

```
<ipython-input-92-1b72b8b67fa9>:2: 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-93-42defcd4889b>:4: MatplotlibDeprecationWarning: Auto-removal of over
  plt.subplot(231)
```




```
df1 = df.copy()
```

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

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
for feat in categorical_features:
    df1[feat] = le.fit_transform(df1[feat].astype(str))
df1
```

| | age | workclass | fnlwgt | education | education.num | marital.status | occupation |
|---|---|---|---|---|---|---|---|
| **1** | 82 | 3 | 132870 | 11 | 9 | 6 | 4 |
| **3** | 54 | 3 | 140359 | 5 | 4 | 0 | 7 |
| **4** | 41 | 3 | 264663 | 15 | 10 | 5 | 10 |
| **5** | 34 | 3 | 216864 | 11 | 9 | 0 | 8 |
| **6** | 38 | 3 | 150601 | 0 | 6 | 5 | 1 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **32556** | 22 | 3 | 310152 | 15 | 10 | 4 | 11 |
| **32557** | 27 | 3 | 257302 | 7 | 12 | 2 | 13 |
| **32558** | 40 | 3 | 154374 | 11 | 9 | 2 | 7 |
| **32559** | 58 | 3 | 151910 | 11 | 9 | 6 | 1 |
| **32560** | 22 | 3 | 201490 | 11 | 9 | 4 | 1 |

30169 rows × 15 columns

32559 58 Private 151910 HS-grad 9 Widowed

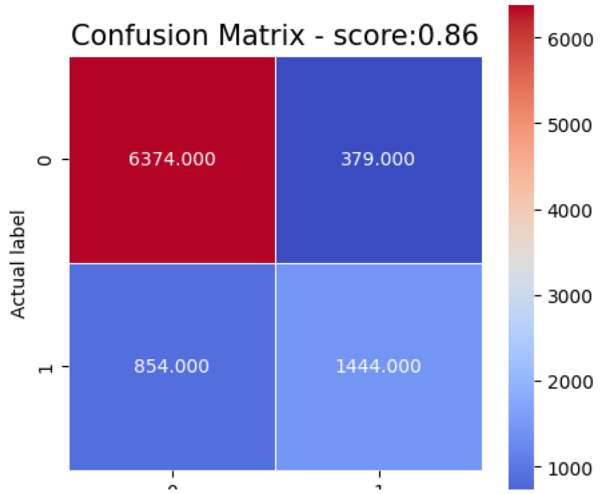
```
X = df1.drop(columns = ['income'])
y = df1['income'].values

# 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)
```

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

```
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)

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("confusion matrix\n",confusion_matrix(y_test,y_pred_abc))
print(classification_report(y_test, y_pred_abc))
```




```
# 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))


# 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))


# 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))
```