Experiment No. 6
Apply Boosting Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance: 04/09/2023
Date of Submission: 13/09/2023

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.**

The Adaboost model exhibited an overall accuracy of 86.37% in predicting income levels. In the specific category of income "= $50K," the model demonstrated commendable precision at 0.88, indicating a high accuracy of positive predictions. However, for the category "> $50K," the precision was slightly lower at 0.79, suggesting room for enhancement in correctly identifying instances within this income bracket.The model's recall, a measure of its ability to capture all relevant instances, was notably high at 0.94 for "= $50K," signifying effective identification of individuals with this income level. On the other hand, the recall for "> $50K" was 0.63, indicating a moderate performance in correctly identifying individuals in this income category.The F1 score, which balances precision and recall, was 0.91 for "= $50K," suggesting a harmonious blend of accuracy and completeness in predictions within this income range. For "> $50K," the F1 score was 0.70, indicating a reasonable balance but with room for improvement.

```
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:

The boosting algorithms—AdaBoost, Gradient Boosting, and XGBoost—demonstrate superior performance in terms of accuracy, precision, and F1 score compared to the Random Forest Classifier. While the Random Forest Classifier achieves a commendable accuracy of around 86.37% and maintains a balanced F1 score, it falls slightly behind the boosting algorithms in terms of overall predictive metrics.The boosting algorithms exhibit higher precision and recall for the positive class, reflecting their enhanced capability to accurately identify and categorize individuals with high incomes. This suggests that the boosting algorithms excel in pinpointing cases related to high-income individuals, showcasing a notable advantage over the Random Forest Classifier in this regard. Across the Adult Census Income Dataset, all models perform effectively, meeting expectations for accurate income level classification. Gradient Boosting, in particular, stands out with a slightly elevated accuracy and F1 score compared to the Random Forest Classifier. This implies that Gradient Boosting may provide a more refined and accurate prediction on this specific dataset, reinforcing its potential as a robust model for income classification.

[ ]:
```
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
```

[ ]:
```python
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
```

[ ]:
```python
#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
```

[ ]:

```
   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
4          3900              40  United-States       0
5          3900              40  United-States       0
6          3770              45  United-States       0
7          3770              40  United-States       0
```

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

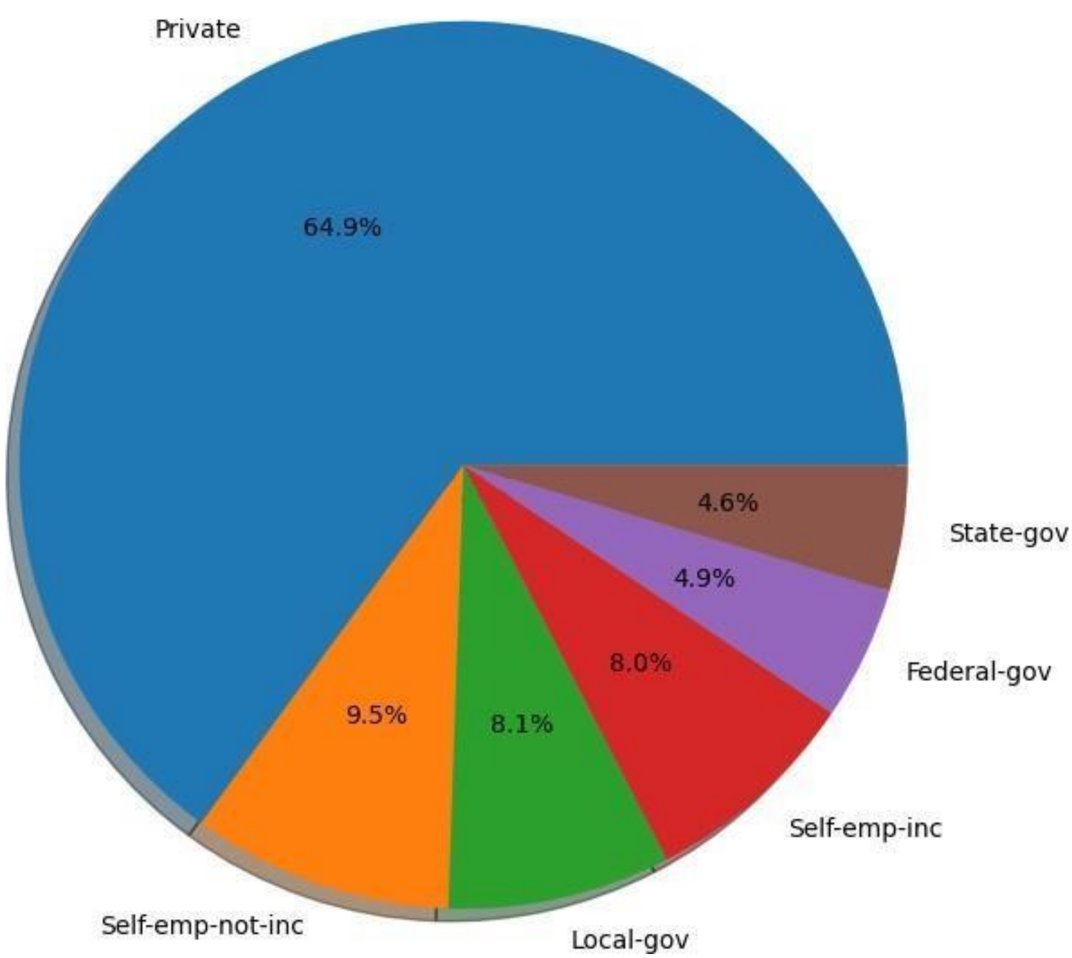
```
    age         workclass  fnlwgt    education  education.num marital.status  \
7    74         State-gov   88638    Doctorate             16  Never-married
10   45           Private  172274    Doctorate             16       Divorced
11   38  Self-emp-not-inc  164526  Prof-school             15 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

[ ]:
```python
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
```

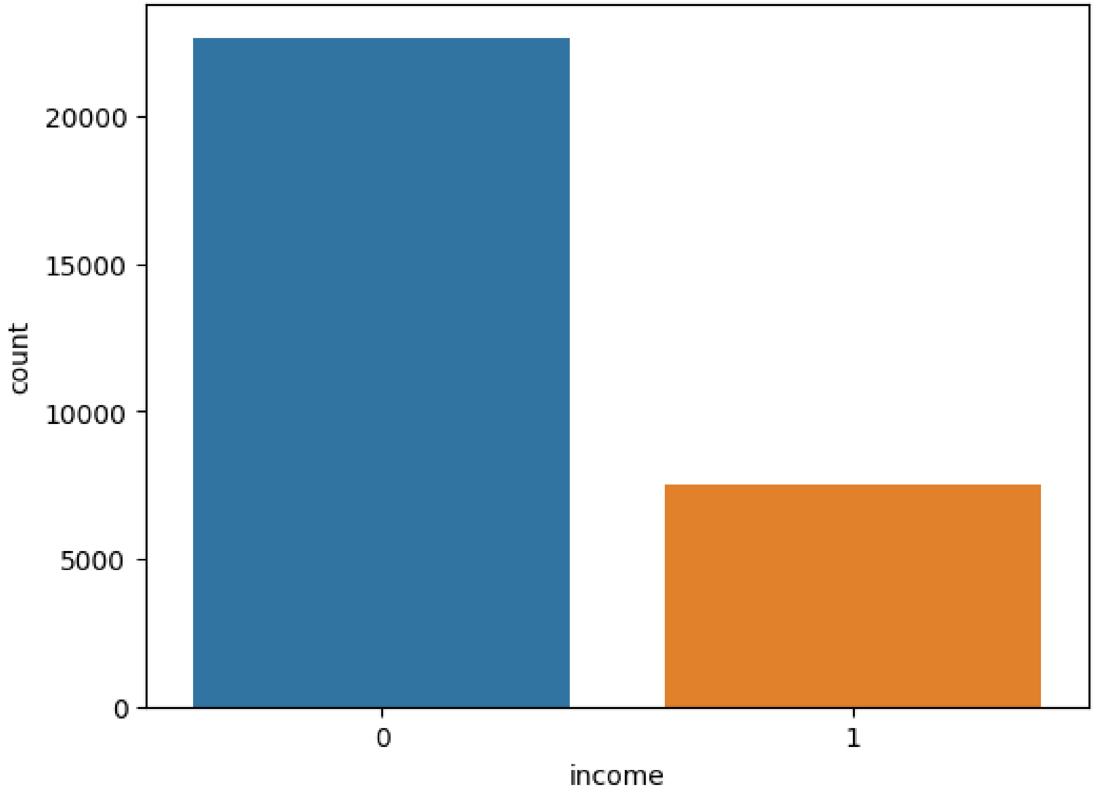
```
Local-gov              609
Self-emp-inc           600
Federal-gov            365
State-gov              344
Name: workclass, dtype: int64
[4876, 714, 609, 600, 365, 344]
['Private', 'Self-emp-not-inc', 'Local-gov', 'Self-emp-inc', 'Federal-gov',
'State-gov']
```

[ ]:
```
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)
```

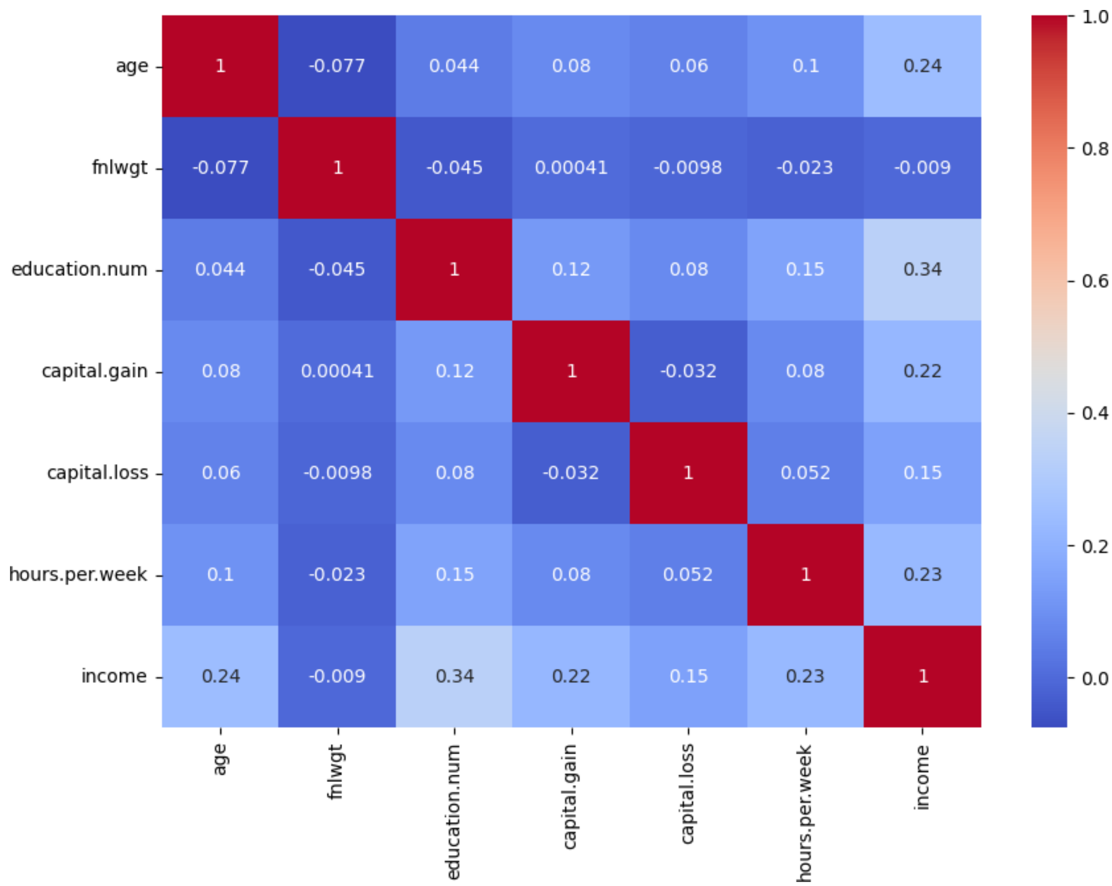
```
plt.show()
df['income'].value_counts()
```



[ ]:
```
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())
```

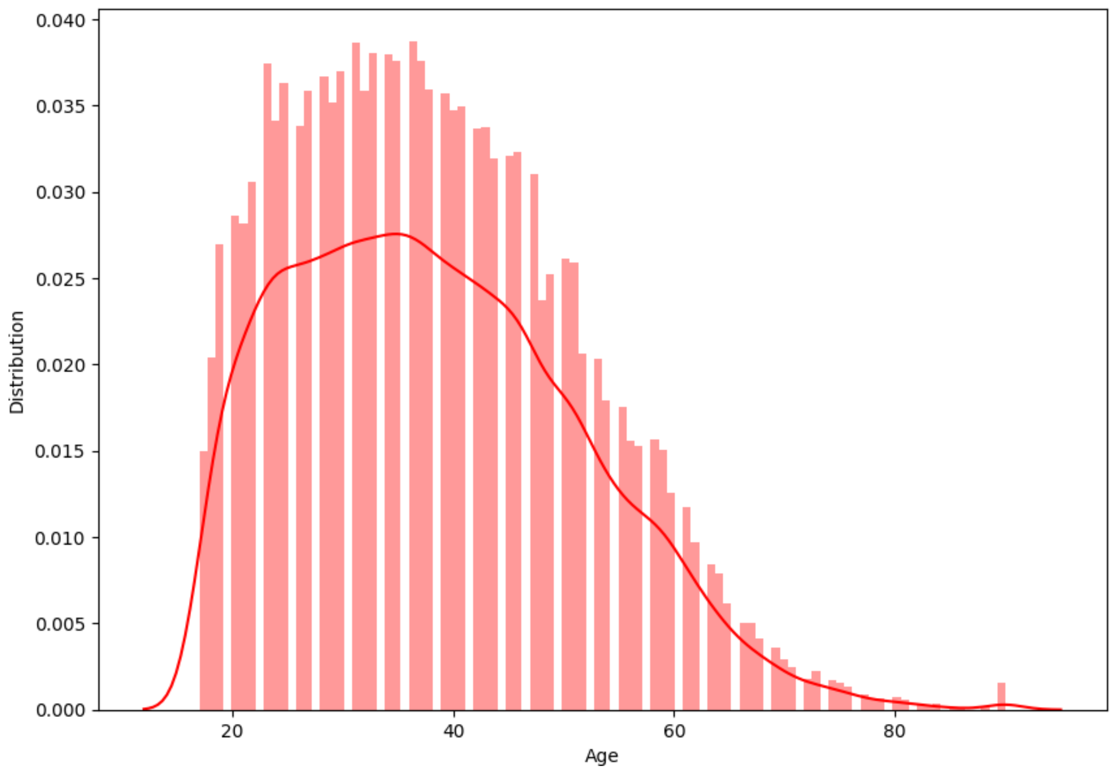
```
<ipython-input-91-6201d8194dba>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df.corr(), cmap='coolwarm', annot=True)
```



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()
```

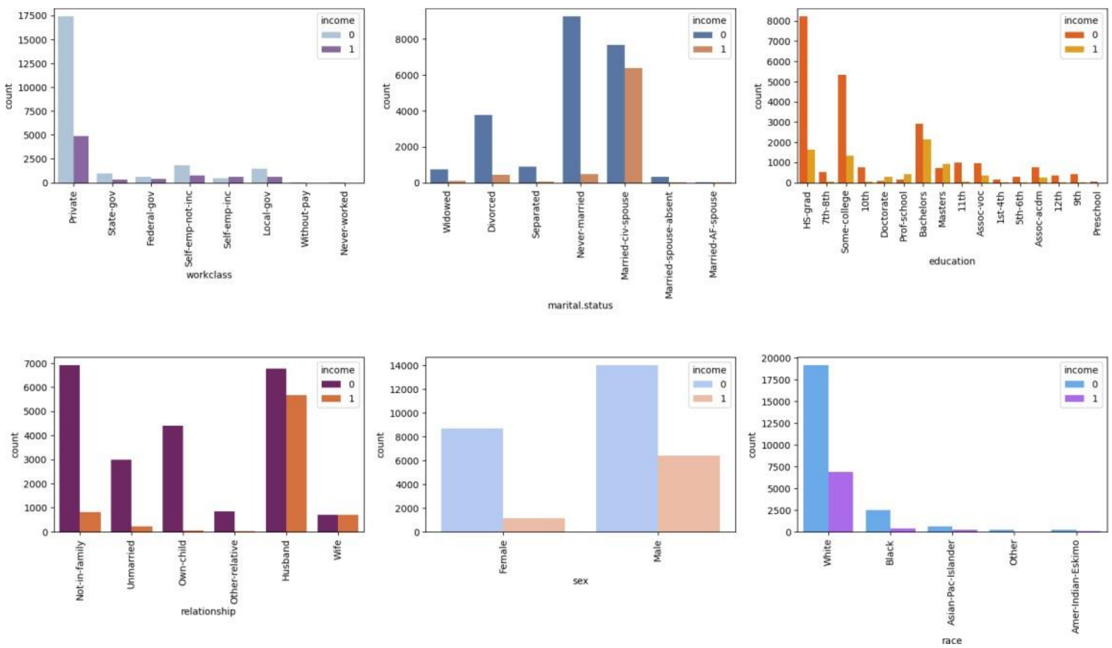
```
<ipython-input-92-1b72b8b67fa9>:2: UserWarning:

`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 overlapping axes is deprecated since 3.6 and will be removed two minor releases later; explicitly call ax.remove() as needed.
  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', 'sex', 'native.country']
```

[ ]:
```
       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
...    ...       ...     ...           ...            ...                 ...
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  \
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
...                   ...            ...    ...    ...     ...
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
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
...             ...             ...             ...     ...
32556             0              40   United-States       0
32557             0              38   United-States       0
32558             0              40   United-States       1
32559             0              40   United-States       0
32560             0              20   United-States       0

[30169 rows x 15 columns]
```

[ ]:
```python
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  \
1       82          3  132870         11              9               6
3       54          3  140359          5              4               0
4       41          3  264663         15             10               5
5       34          3  216864         11              9               0
6       38          3  150601          0              6               5
...    ...        ...     ...        ...            ...             ...
32556   22          3  310152         15             10               4
32557   27          3  257302          7             12               2
32558   40          3  154374         11              9               2
32559   58          3  151910         11              9               6
32560   22          3  201490         11              9               4

       occupation  relationship  race  sex  capital.gain  capital.loss  \
1               4             1     4    0             0          4356
3               7             4     4    0             0          3900
4              10             3     4    0             0          3900
```

```
5                8          4    4    0          0        3770
6                1          4    4    1          0        3770
...            ...    ...  ...  ...    ...       ...
32556           11          1    4    1          0           0
32557           13          5    4    0          0           0
32558            7          0    4    1          0           0
32559            1          4    4    0          0           0
32560            1          3    4    1          0           0

       hours.per.week  native.country  income
1                  18              38       0
3                  40              38       0
4                  40              38       0
5                  45              38       0
6                  40              38       0
...               ...             ...     ...
32556              40              38       0
32557              38              38       0
32558              40              38       1
32559              40              38       0
32560              20              38       0

[30169 rows x 15 columns]
```

[ ]:
```python
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)
```

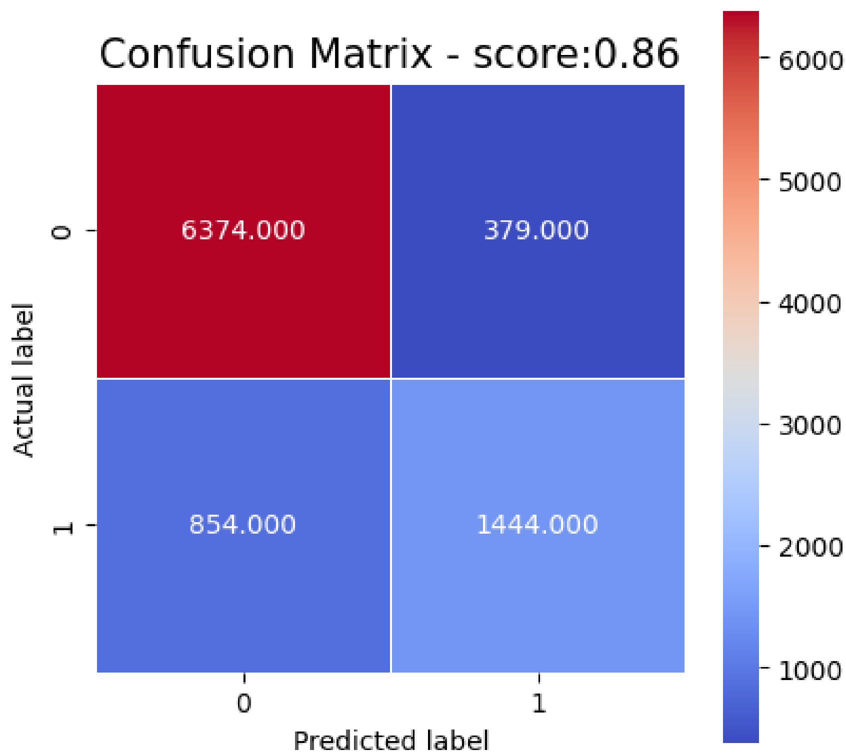
```
Train set size:  (21118, 14)
Test set size:  (9051, 14)
```

[ ]:
```python
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)
```

```python
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
```

[ ]:
```python
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))
```



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