```
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
```

```
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
<ipython-input-7-595c69654189>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus
  df["income"] = [1 if i=='>50K' else 0 for i in df["income"]]
```

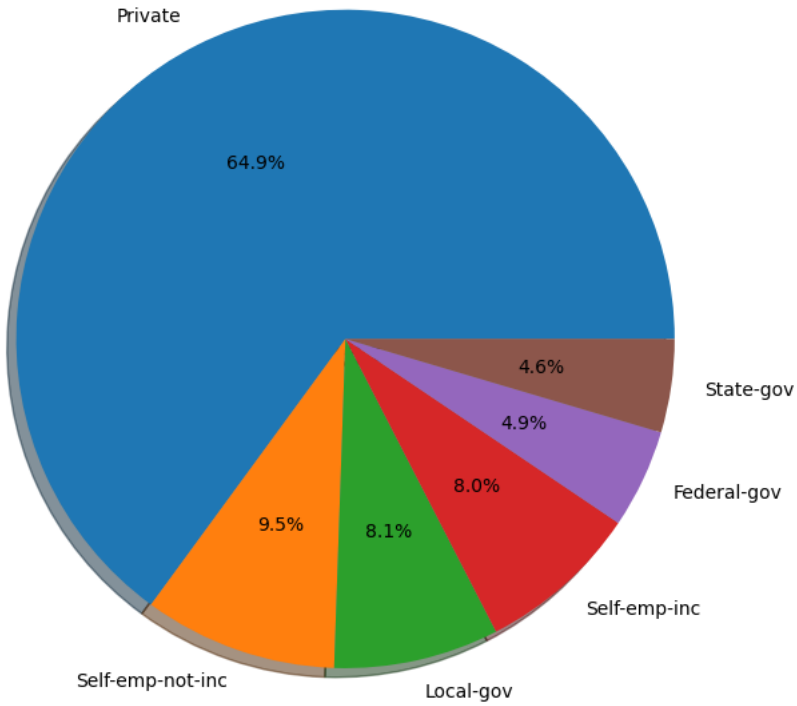
```
df_more=df.loc[df['income'] == 1]
print(df_more.head())
```

```
    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
```

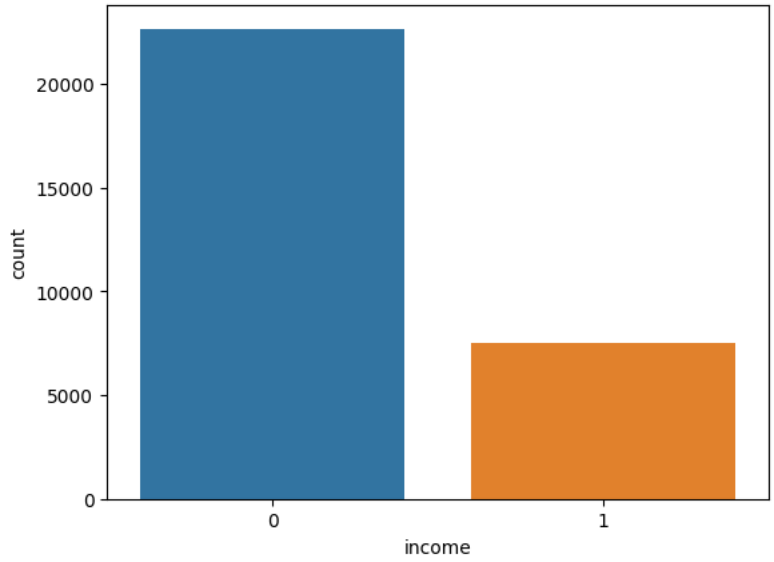
```
workclass_types = df_more['workclass'].value_counts()
labels = list(workclass_types.index)
aggregate = list(workclass_types)
print(workclass_types)
print(aggregate)
print(labels)
```

```
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()
```

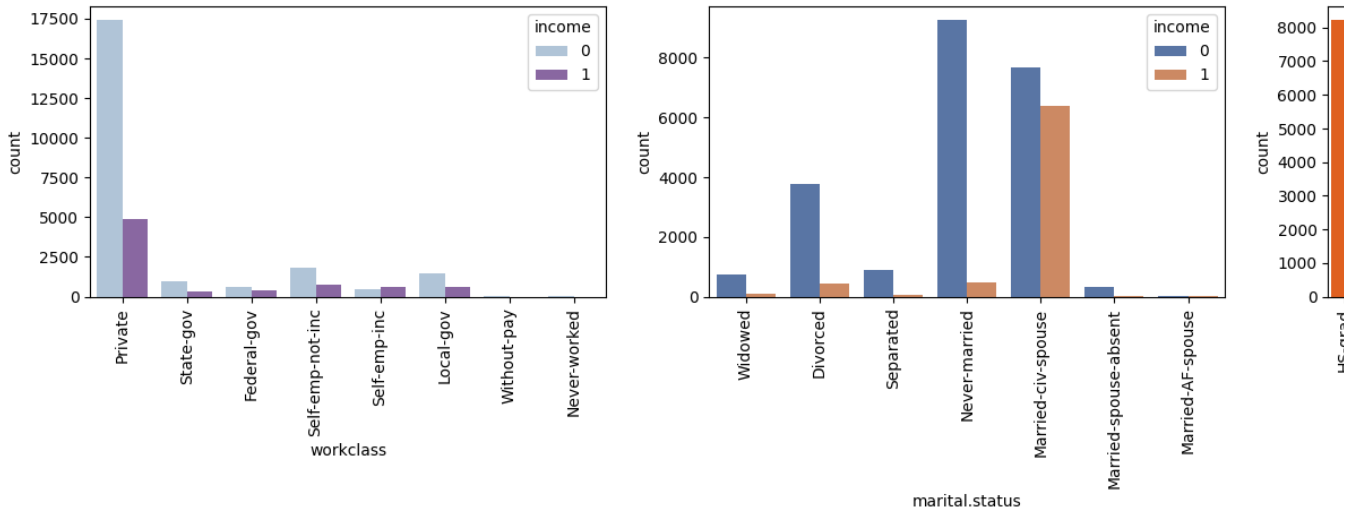


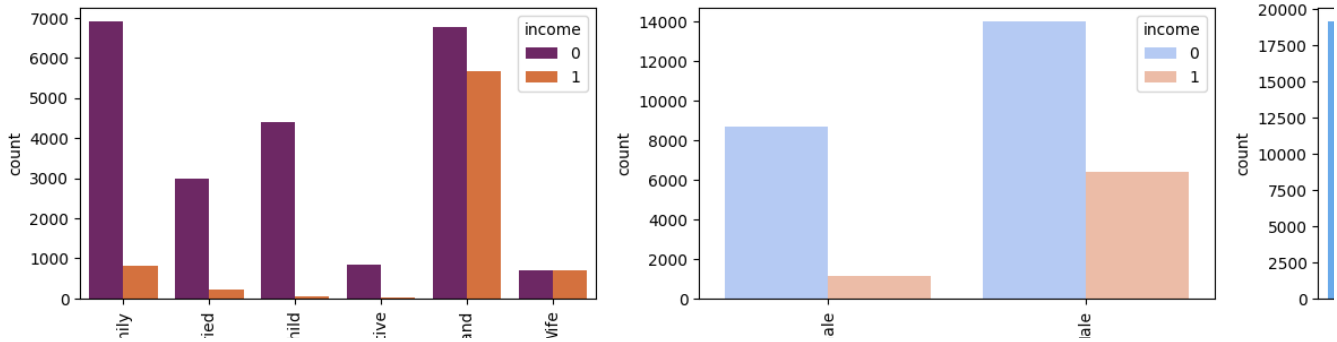

```
0    22661
1     7508
Name: income, dtype: int64
```

```
#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-13-e1b6d1f0108f>:3: MatplotlibDeprecationWarning: Auto-removal of overlapping axes is deprecated since 3.6 and will b
  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	occupation	relationship	race	sex	capital.gain	capit
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Female	0	
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child	White	Female	0	
5	34	Private	216864	HS-grad	9	Divorced	Other-service	Unmarried	White	Female	0	
6	38	Private	150601	10th	6	Separated	Adm-clerical	Unmarried	White	Male	0	
...	...	...	...	...	...	...	...	...	...	...	...	...
32556	22	Private	310152	Some-	10	Never-married	Protective-	Not-in-family	White	Male	0	

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

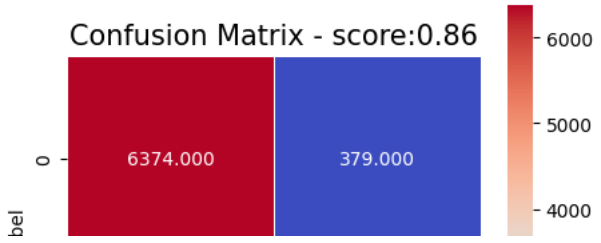
```
X = df1.drop(columns = ['income'])
y = df1['income'].values
# Splitting the data set into train and test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,random_state = 0)
print ("Train set size: ", X_train.shape)
print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

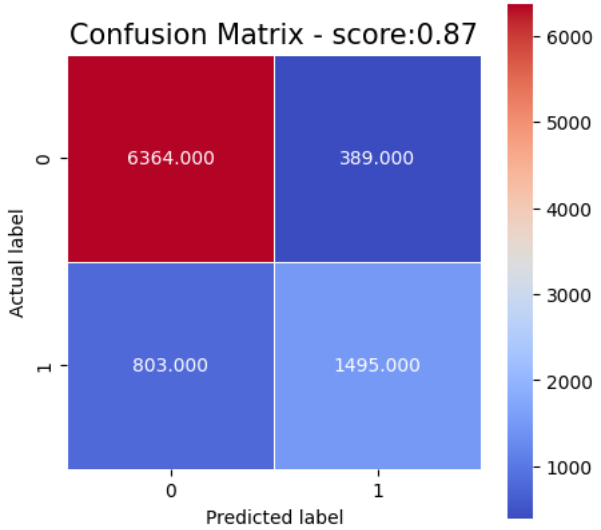



```
import xgboost as xgb
from xgboost import XGBClassifier
#Training the model with gradient boosting
xgboost = XGBClassifier(learning_rate=0.01,
colsample_bytree = 0.4,
n_estimators=1000,
max_depth=20,
gamma=1)
xgboost_model = xgboost.fit(X_train, y_train)
```

Predicted label

```
# 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 :  0.868301845099989
F1 score :  0.7149689143950263
Precision :  0.7935244161358811
RMSE for xgboost:  0.3629024040978663
```



	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	0.80	0.81	9051
weighted avg	0.86	0.87	0.86	9051