Experiment No. 6
Apply Boosting Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:04/09/23
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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. The Gradient Boosting Classifier demonstrates the best performance on this dataset, boasting the highest accuracy (0.8732) and F1 score (0.71).
2. They exhibit commendable precision levels, implying their ability to accurately predict the positive class (1).
3. Among the classifiers, the Gradient Boosting Classifier stands out with the highest recall for the positive class (1), signifying its proficiency in correctly identifying more positive cases.
4. The F1 score, which strikes a balance between precision and recall, effectively gauges how well these classifiers perform in classifying both classes.

Comparison between Boosting Algorithm and Random Forest Classifier applied on the Adult Income Dataset :

1. Boosting algorithms, including Gradient Boosting, and XGBoost, consistently exhibit superior performance compared to the Random Forest Classifier, boasting higher accuracy, precision, and F1 scores.
2. The Random Forest Classifier maintains a respectable level of performance, achieving an accuracy rate of approximately 85% and a well-balanced F1 score. Nevertheless, it lags behind the boosting algorithms in terms of overall performance.
3. Boosting algorithms consistently demonstrate greater precision and recall for the positive class (income > 50K), signifying their enhanced capability to accurately classify individuals with high incomes.

4. Across the board, all these models deliver commendable results when applied to the Adult Census Income Dataset, with the boosting algorithms, particularly Gradient Boosting, showcasing slightly superior accuracy and F1 score compared to the Random Forest Classifier.

Random Forest Accuracy: 85.40
Boosting algorithm Accuracy: 87.05

```
# importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
```

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

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	ca
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Female	0	
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	
2	66	?	186061	Some-college	10	Widowed	?	Unmarried	Black	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	

```
df.describe()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.437456
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.347429
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

Data Treatment

```
df.isna().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
```

```
df.loc[df.duplicated() == True]
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain
8453	25	Private	308144	Bachelors	13	Never-married	Craft-repair	Not-in-family	White	Male	0
8645	90	Private	52386	Some-college	10	Never-married	Other-service	Not-in-family	Asian-Pac-Islander	Male	0
12202	21	Private	250051	Some-college	10	Never-married	Prof-specialty	Own-child	White	Female	0
14346	20	Private	107658	Some-college	10	Never-married	Tech-support	Not-in-family	White	Female	0
15603	25	Private	195994	1st-4th	2	Never-married	Priv-house-serv	Not-in-family	White	Female	0
17344	21	Private	243368	Preschool	1	Never-married	Farming-fishing	Not-in-family	White	Male	0
19067	46	Private	173243	HS-grad	9	Married-civ-spouse	Craft-repair	Husband	White	Male	0
20388	30	Private	144593	HS-grad	9	Never-married	Other-service	Not-in-family	Black	Male	0
20507	19	Private	97261	HS-grad	9	Never-married	Farming-fishing	Not-in-family	White	Male	0
22783	19	Private	138153	Some-college	10	Never-married	Adm-clerical	Own-child	White	Female	0
22934	19	Private	146679	Some-college	10	Never-married	Exec-managerial	Own-child	Black	Male	0
23276	49	Private	31267	7th-8th	4	Married-civ-spouse	Craft-repair	Husband	White	Male	0
23660	25	Private	195994	1st-4th	2	Never-married	Priv-house-serv	Not-in-family	White	Female	0
23720	44	Private	367749	Bachelors	13	Never-married	Prof-specialty	Not-in-family	White	Female	0
23827	49	Self-emp-not-inc	43479	Some-college	10	Married-civ-spouse	Craft-repair	Husband	White	Male	0
26738	23	Private	240137	5th-6th	3	Never-married	Handlers-cleaners	Not-in-family	White	Male	0
27133	28	Private	274679	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Male	0
28796	27	Private	255582	HS-grad	9	Never-married	Machine-op-inspct	Not-in-family	White	Female	0
29051	42	Private	204235	Some-	10	Married-civ-	Prof-	Husband	White	Male	0
29334	39	Private	30916	HS-grad	9	Married-civ-	Craft-repair	Husband	White	Male	0

```
df = df.drop_duplicates()
```

```
df.loc[df.duplicated() == True]
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.loss
31060	46	Private	133616		10	Divorced		Unmarried	White	Female	0	

```
df['age'].describe()
```

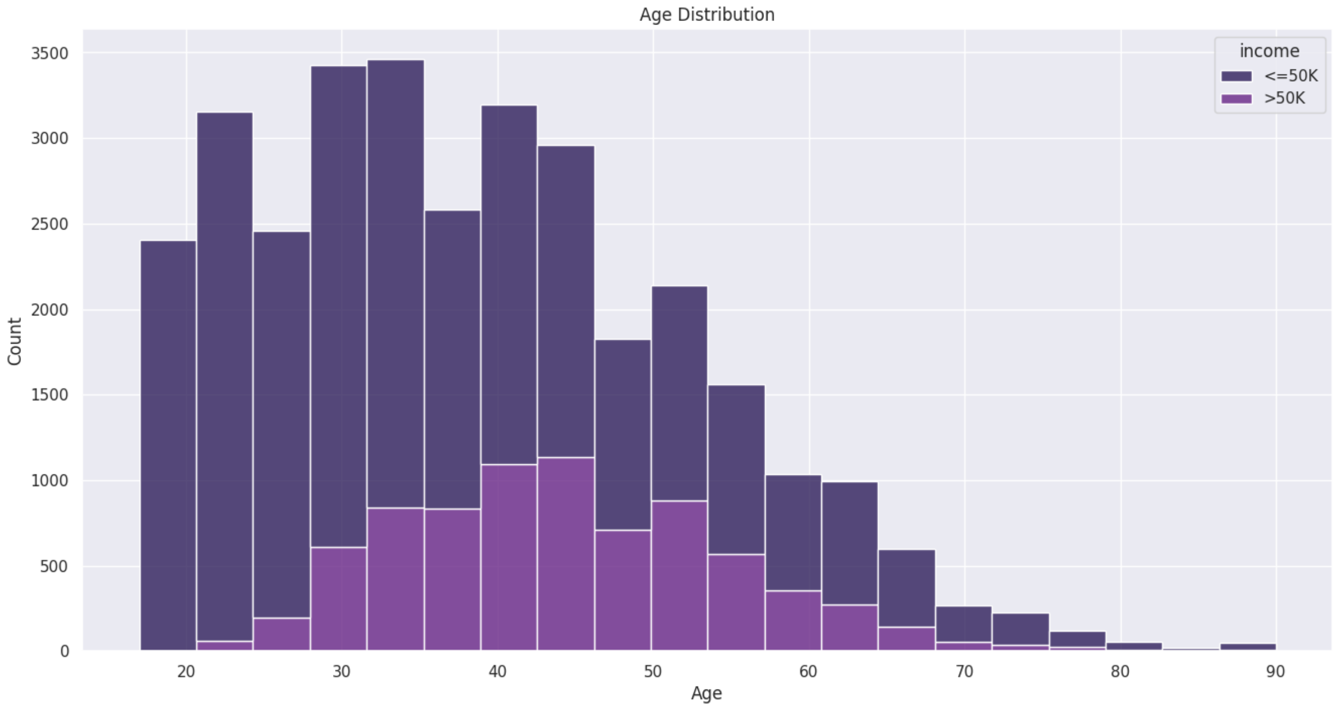
```
count    32537.000000
mean        38.585549
std         13.637984
min         17.000000
25%         28.000000
50%         37.000000
75%         48.000000
max         90.000000
Name: age, dtype: float64
```

Exploratory Data Analysis

Analysis per variable

```
# Age
plt.figure(figsize=(16, 8))
sns.set_theme(style="darkgrid")
sns.set_palette("magma")
sns.histplot(data=df, x='age', hue='income', bins=20, multiple='stack')
```

```
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Age Distribution')
plt.show()
```




```
# workclass
df.groupby('workclass').size()
```

```
workclass
?                    1836
Federal-gov           960
Local-gov            2093
Never-worked            7
Private             22673
Self-emp-inc         1116
Self-emp-not-inc     2540
State-gov            1298
Without-pay            14
dtype: int64
```

```
workclass_unknown = df.loc[df['workclass'] == '?']
print('**age distribution for workclass "?"** \n', workclass_unknown['age'].describe())
plt.figure(figsize=(16, 8))
plt.title('age distribution for workclass "?"')
plt.hist(workclass_unknown['age'], bins=20)
sns.histplot(data=df.loc[df['workclass'] == '?'], x='age', hue='income', bins=20, multiple='stack')
```

```
**age distribution for workclass "?"**
 count    1836.000000
mean       40.960240
std        20.334587
min        17.000000
25%        21.000000
50%        35.000000
75%        61.000000
max        90.000000
Name: age, dtype: float64
<Axes: title={'center': 'age distribution for workclass "?"'}, xlabel='age', ylabel='Count'>
```


```
print(df.query('age < 20').groupby('workclass').size())
print(df.query('age > 20 and age < 60').groupby('workclass').size())
print(df.query('age > 60').groupby('workclass').size())
```

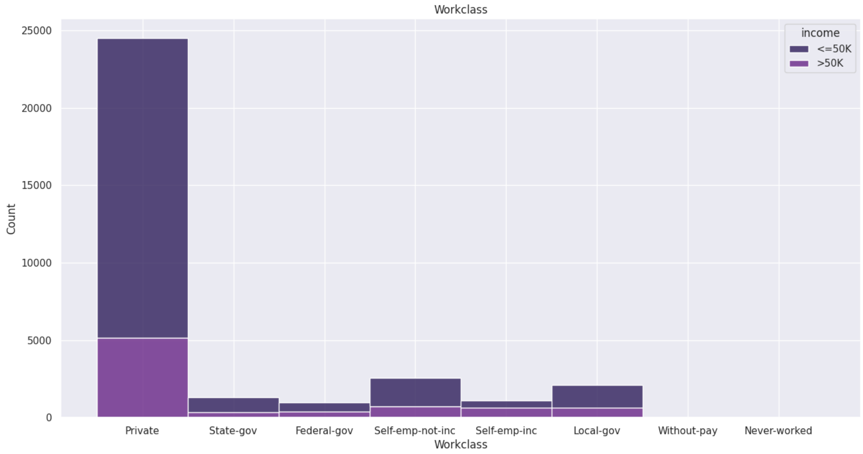
```
workclass
?                    269
Federal-gov            9
Local-gov             35
Never-worked           4
Private             1249
Self-emp-inc          16
Self-emp-not-inc      37
State-gov             32
Without-pay            2
dtype: int64
workclass
?                    928
Federal-gov          874
Local-gov           1875
Never-worked           2
Private            19599
Self-emp-inc         940
Self-emp-not-inc    2108
State-gov           1158
Without-pay            5
dtype: int64
workclass
?                    493
Federal-gov           58
Local-gov            151
Private             1070
Self-emp-inc         143
Self-emp-not-inc     338
State-gov             71
Without-pay            7
dtype: int64
```

```
df.loc[df['workclass'] == '?', 'workclass'] = 'Private'
df.loc[df['workclass'] == '?' ]
```

age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.loss

```
plt.figure(figsize=(16, 8))
sns.histplot(data=df, x='workclass', hue='income', multiple='stack')
plt.xlabel('Workclass')
plt.title('Workclass')
```

```
Text(0.5, 1.0, 'Workclass')
```




```
df.groupby(df['workclass']).size()
```

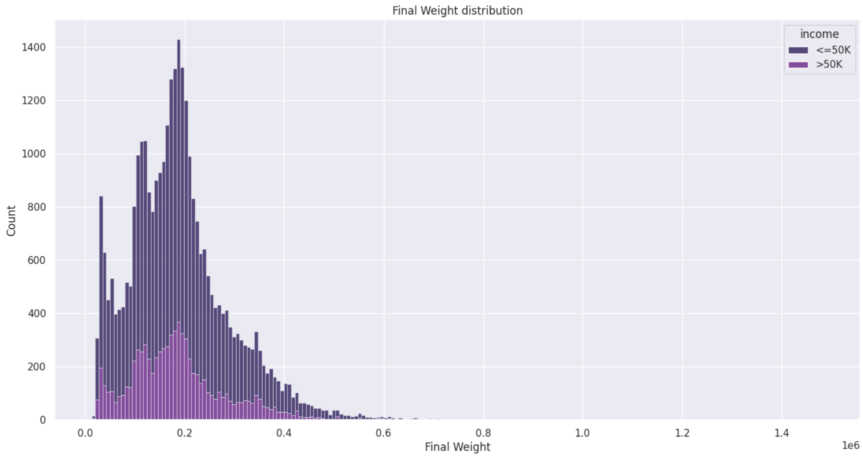
```
workclass
Federal-gov           960
Local-gov            2093
Never-worked            7
Private             24509
Self-emp-inc         1116
Self-emp-not-inc     2540
State-gov            1298
Without-pay            14
dtype: int64
```

```
df.head()
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.l
0	90	Private	77053	HS-grad	9	Widowed	?	Not-in-family	White	Female	0	4
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	4
2	66	Private	186061	Some-college	10	Widowed	?	Unmarried	Black	Female	0	4
							Machine-					

```
# Final Weight
plt.figure(figsize=(16, 8))
sns.histplot(x='fnlwgt', data=df, hue='income', multiple='stack')
plt.title('Final Weight distribution')
plt.xlabel('Final Weight')
```

```
Text(0.5, 0, 'Final Weight')
```




```
# Education
df.groupby('education').size()
```

```
education
10th             933
11th            1175
12th             433
1st-4th          166
5th-6th          332
7th-8th          645
9th              514
Assoc-acdm      1067
Assoc-voc       1382
Bachelors       5353
Doctorate        413
HS-grad        10494
Masters         1722
Preschool         50
Prof-school      576
Some-college    7282
dtype: int64
```

```
plt.figure(figsize=(16, 8))
plt.pie(df.groupby('education').size(), labels=df.groupby('education').size().index, autopct='%1.1f%%')
```

```
        Text(-0.7785868926457222, 0.7770472640710339, 'Doctorate'),
        Text(-1.0605252834929717, -0.2920378795159155, 'HS-grad'),
        Text(-0.13449613832544505, -1.091746668772359, 'Masters'),
        Text(0.05334950660702595, -1.0987055247630217, 'Preschool'),
        Text(0.11962081577950918, -1.0934765020027841, 'Prof-school'),
        Text(0.8391187061846062, -0.7112522737616188, 'Some-college')],
       [Text(0.5975670366161832, 0.05397811361795755, '2.9%'),
        Text(0.5743211004298473, 0.17365273853599109, '3.6%'),
        Text(0.540559772491962, 0.2603749841352626, '1.3%'),
        Text(0.5246052478260459, 0.29118608131806883, '0.5%'),
        Text(0.510002867060924, 0.3160649863392614, '1.0%'),
        Text(0.47796394868079695, 0.3626988609872665, '2.0%'),
        Text(0.4344705359375361, 0.4138059368860603, '1.6%'),
        Text(0.36649465623567234, 0.4750596456769363, '3.3%'),
        Text(0.2450065934522299, 0.547696785790216, '4.2%'),
        Text(-0.13658484476458072, 0.5842470198303414, '16.5%'),
        Text(-0.42468375962493937, 0.42384396222056386, '1.3%'),
        Text(-0.5784683364507117, -0.15929338882686297, '32.3%'),
        Text(-0.0733615299956973, -0.5954981829667412, '5.3%'),
        Text(0.029099730876559603, -0.5992939225980118, '0.2%'),
        Text(0.0652477176979141, -0.596441728365155, '1.8%'),
        Text(0.4577011124643306, -0.38795578568815564, '22.4%')])
```

```
plt.figure(figsize=(16, 8))
sns.countplot(x='education', data=df, hue='income')
```

```
<Axes: xlabel='education', ylabel='count'>
```


```
# Education Number
df.groupby('education.num').size()
```

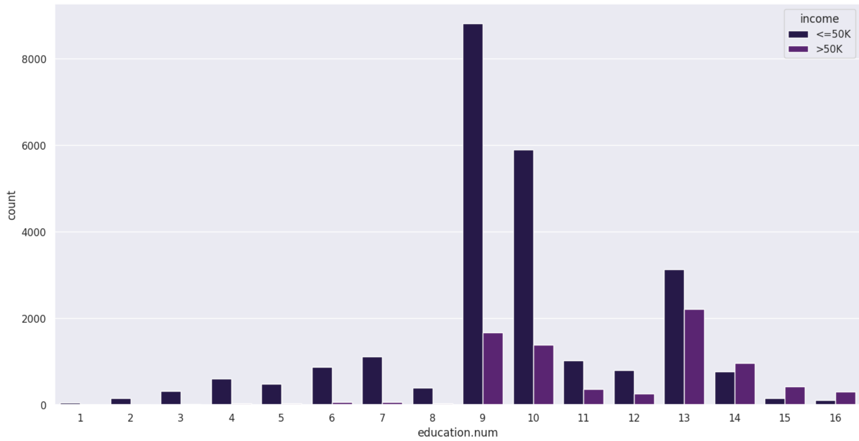
```
education.num
1        50
2       166
3       332
4       645
5       514
6       933
7      1175
8       433
9     10494
10     7282
11     1382
12     1067
13     5353
14     1722
15      576
16      413
dtype: int64
```

```
df['education.num'].describe()
```

```
count    32537.000000
mean        10.081815
std          2.571633
min          1.000000
25%          9.000000
50%         10.000000
75%         12.000000
max         16.000000
Name: education.num, dtype: float64
```

```
plt.figure(figsize=(16, 8))
sns.countplot(x='education.num', data=df, hue='income')
```

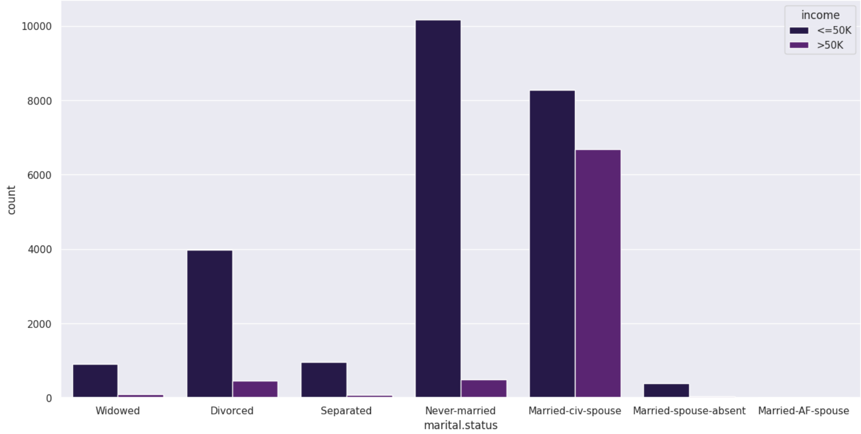
```
<Axes: xlabel='education.num', ylabel='count'>
```




```
# marital status
print(df.groupby('marital.status').size())
```

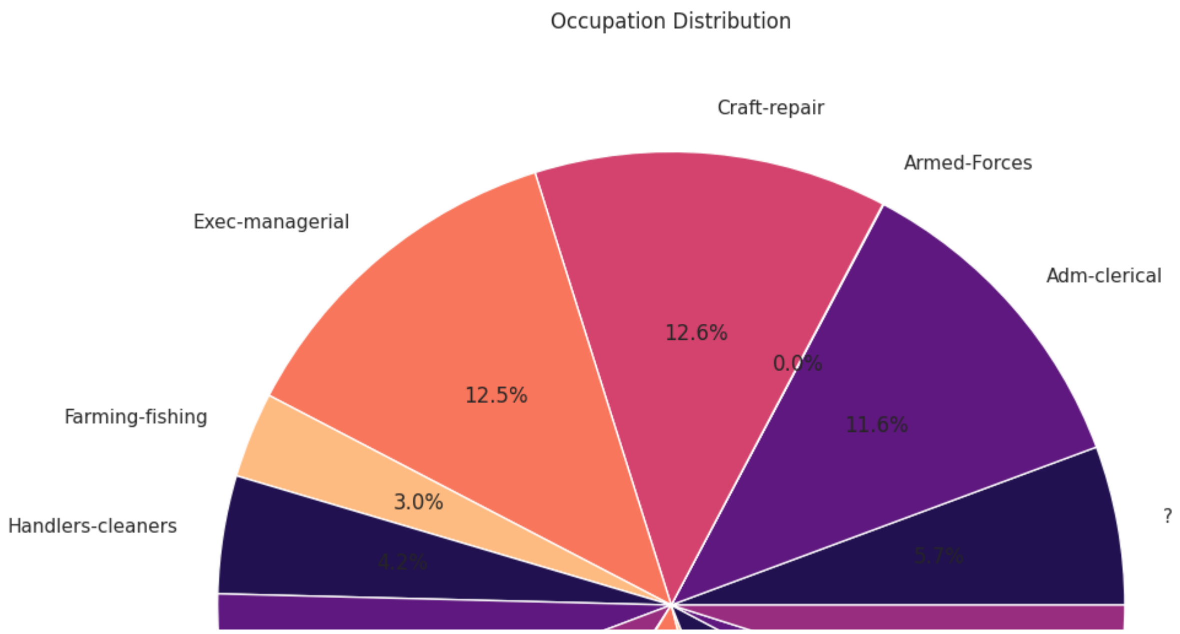
```
plt.figure(figsize=(16, 8))
sns.countplot(data=df, x='marital.status', hue='income')
```

```
marital.status
Divorced                  4441
Married-AF-spouse           23
Married-civ-spouse       14970
Married-spouse-absent      418
Never-married            10667
Separated                 1025
Widowed                    993
dtype: int64
<Axes: xlabel='marital.status', ylabel='count'>
```



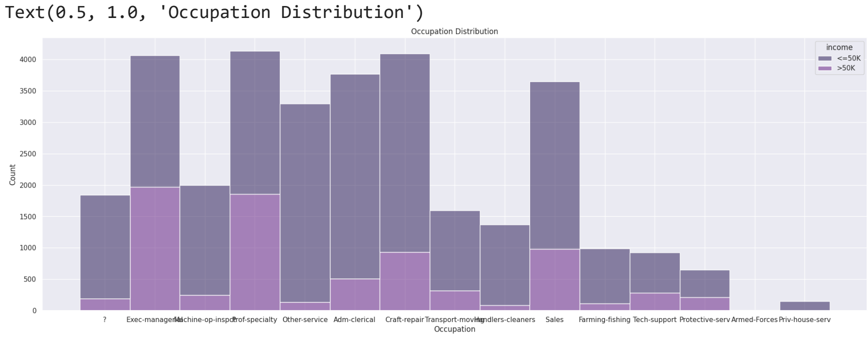

```
# Occupation
print(df.groupby('occupation').size())
plt.figure(figsize=(16, 12))
plt.pie(df.groupby('occupation').size(), labels=df.groupby('occupation').size().index, autopct='%1.1f%%')
plt.title('Occupation Distribution')
```

```
occupation
?                    1843
Adm-clerical         3768
Armed-Forces            9
Craft-repair         4094
Exec-managerial      4065
Farming-fishing       992
Handlers-cleaners    1369
Machine-op-inspct    2000
Other-service        3291
Priv-house-serv       147
Prof-specialty       4136
Protective-serv       649
Sales                3650
Tech-support          927
Transport-moving     1597
dtype: int64
Text(0.5, 1.0, 'Occupation Distribution')
```




```
plt.figure(figsize=(24, 8))
sns.histplot(data=df, x='occupation', hue='income', multiple='stack', alpha=0.5)
plt.xlabel('Occupation')
plt.title('Occupation Distribution')
```

```
Text(0.5, 1.0, 'Occupation Distribution')
```

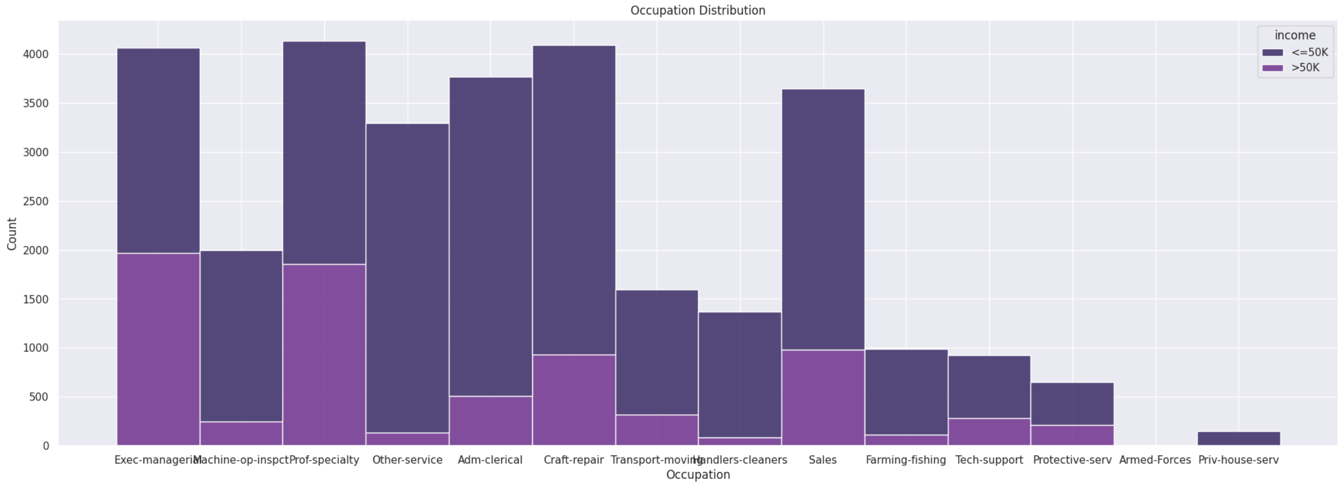



```
df.drop(df.loc[df['occupation'] == '?'].index, inplace=True)
```

```
plt.figure(figsize=(24, 8))
sns.histplot(data=df, x='occupation', hue='income', multiple='stack')
```

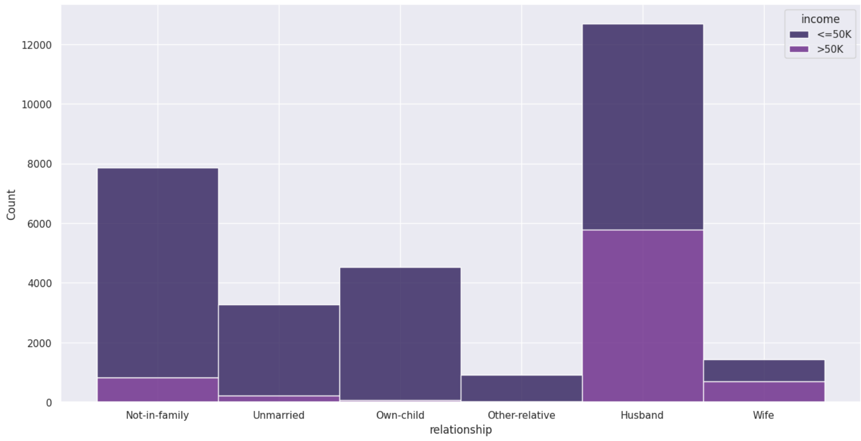
```
plt.xlabel('Occupation')
plt.title('Occupation Distribution')
```

```
Text(0.5, 1.0, 'Occupation Distribution')
```



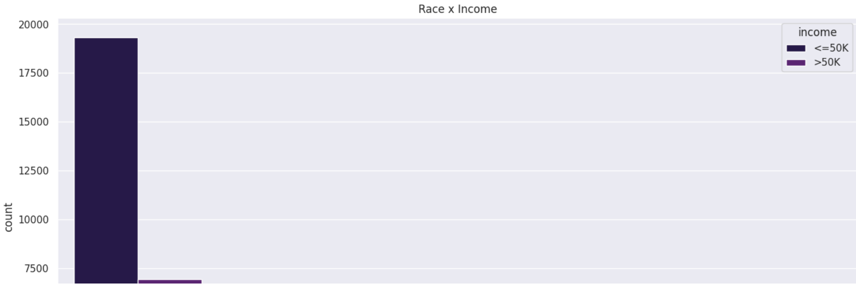

```
# Relationship
print(df.groupby('relationship').size())
plt.figure(figsize=(16, 8))
sns.histplot(data=df, x='relationship', hue='income', multiple='stack')
```

```
relationship
Husband           12698
Not-in-family      7852
Other-relative      918
Own-child          4521
Unmarried          3270
Wife               1435
dtype: int64
<Axes: xlabel='relationship', ylabel='Count'>
```



```
# Race and Sex
plt.figure(figsize=(16, 8))
print(df.groupby(df.race).size())
sns.countplot(data=df, x='race', hue='income')
plt.title('Race x Income')
plt.show()
plt.figure(figsize=(16, 8))
print(df.groupby(df.sex).size())
sns.countplot(data=df, x='sex', hue='income')
plt.title('Sex x Income')
```

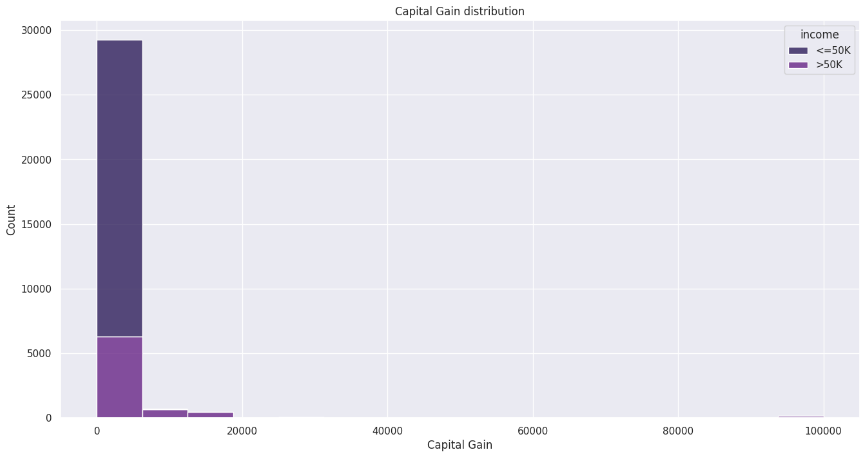
```
race
Amer-Indian-Eskimo      286
Asian-Pac-Islander      973
Black                  2907
Other                   248
White                 26280
dtype: int64
```



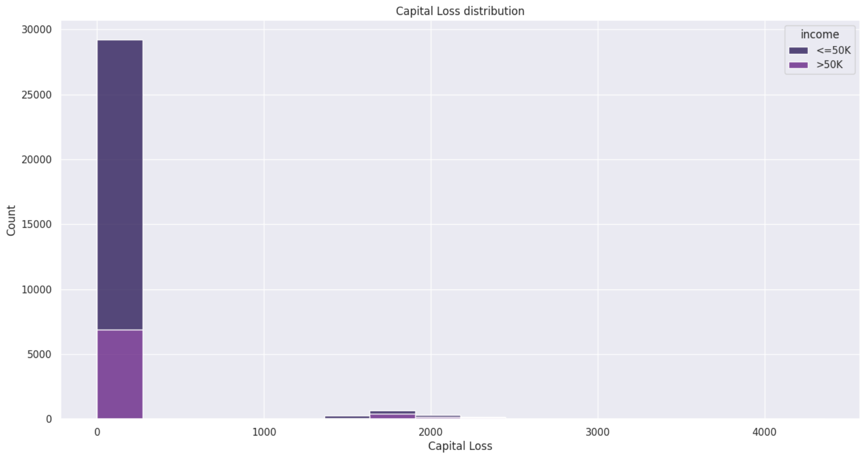

```
# Capital Gain & Capital Loss
print('**** capital gain **** \n ', df.groupby('capital.gain').size(), '\n')
print('**** capital loss **** \n ', df.groupby('capital.loss').size(), '\n')
```

```
**** capital gain ****
  capital.gain
0        28105
114          6
401          1
594         29
914          8
         ...
25236       11
27828       33
34095        3
41310        2
99999      155
Length: 118, dtype: int64

**** capital loss ****
  capital.loss
0       29233
155         1
213         4
323         3
419         1
        ...
3004        2
3683        2
3770        2
3900        2
4356        1
Length: 90, dtype: int64
```

```
plt.figure(figsize=(16, 8))
sns.histplot(x='capital.gain', data=df, hue='income', multiple='stack')
plt.title('Capital Gain distribution')
plt.xlabel('Capital Gain')
plt.show()
plt.figure(figsize=(16, 8))
sns.histplot(x='capital.loss', data=df, hue='income', multiple='stack')
plt.title('Capital Loss distribution')
plt.xlabel('Capital Loss')
```




```
Text(0.5, 0, 'Capital Loss')
```




```
df.head()
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	rela
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	No
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	U
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	

```
# Hours per week
df.groupby('hours.per.week').size()
```

```
hours.per.week
1      8
2     15
3     24
4     28
5     39
      ..
95     2
96     5
```

```
97     2
98    11
99    80
Length: 94, dtype: int64
```

```
df = df.drop(columns=['hours.per.week'])
```

```
# Native Country
df.groupby('native.country').size()
```

```
native.country
?                              555
Cambodia                        18
Canada                         107
China                           68
Columbia                        56
Cuba                            92
Dominican-Republic              67
Ecuador                         27
El-Salvador                    100
England                         86
France                          27
Germany                        128
Greece                          29
Guatemala                       61
Haiti                           42
Holand-Netherlands               1
Honduras                        12
Hong                            19
Hungary                         13
India                          100
Iran                            42
Ireland                         24
Italy                           68
Jamaica                         80
Japan                           59
Laos                            17
Mexico                         606
Nicaragua                       33
Outlying-US(Guam-USVI-etc)      14
Peru                            30
Philippines                    188
Poland                          56
Portugal                        34
Puerto-Rico                    109
Scotland                        11
South                           71
Taiwan                          42
Thailand                        17
Trinadad&Tobago                 18
United-States                27487
Vietnam                         64
Yugoslavia                      16
dtype: int64
```

```
#plt.figure(figsize=(16, 8))
#plt.pie(df.groupby('native.country').size(), labels=df.groupby('native.country').size().index, autopct='%1.1f%%')
```

Model preparation & building

```
label_encoder = LabelEncoder()
categorical_columns = ['income', 'workclass', 'education', 'marital.status', 'occupation', 'relationship', 'race', 'sex', 'native.country
df[categorical_columns] = df[categorical_columns].apply(label_encoder.fit_transform)
```

```
df
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation
1	82	2	132870	11	9	6	3
3	54	2	140359	5	4	0	6
4	41	2	264663	15	10	5	9
5	34	2	216864	11	9	0	7

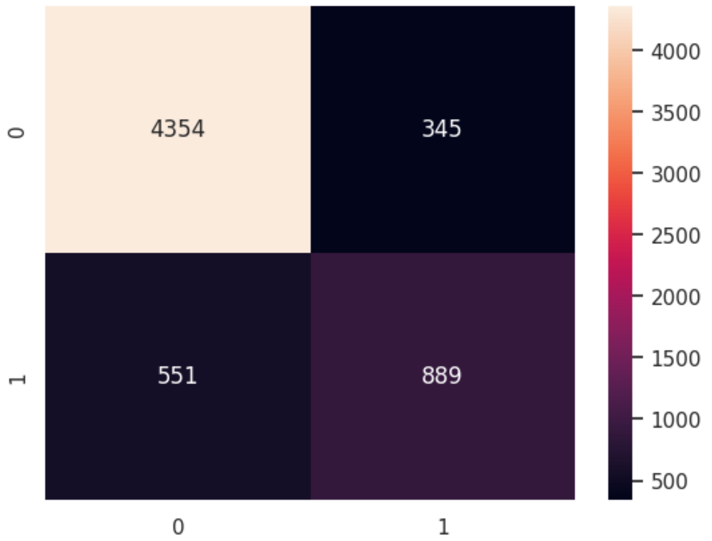
```
x_train, x_test, y_train, y_test = train_test_split(df.drop(columns=['income']), df['income'], test_size=0.2, random_state=42)
```

```
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

rfc = RandomForestClassifier()
rfc.fit(x_train, y_train)
y_pred = rfc.predict(x_test)
print('**** ACCURACY_SCORE **** \n\n', accuracy_score(y_test, y_pred), '\n')
print('**** CLASSIFICATION_REPORT **** \n\n', classification_report(y_test, y_pred), '\n')
print('**** CONFUSION MATRIX ****')
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d')
```

```
**** ACCURACY_SCORE ****

 0.8540478905359179

**** CLASSIFICATION_REPORT ****

               precision    recall  f1-score   support

           0       0.89      0.93      0.91      4699
           1       0.72      0.62      0.66      1440

    accuracy                           0.85      6139
   macro avg       0.80      0.77      0.79      6139
weighted avg       0.85      0.85      0.85      6139


**** CONFUSION MATRIX ****
<Axes: >
```

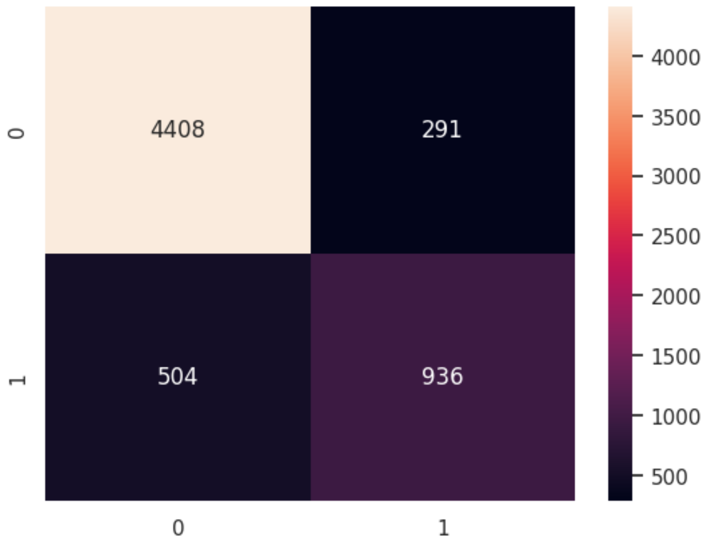


XGBoost Classifier

```
from xgboost import XGBClassifier

xgb = XGBClassifier()
xgb.fit(x_train, y_train)
y_pred = xgb.predict(x_test)
```

```
print('**** ACCURACY_SCORE **** \n\n', accuracy_score(y_test, y_pred), '\n')
print('**** CLASSIFICATION_REPORT **** \n\n', classification_report(y_test, y_pred), '\n')
print('**** CONFUSION MATRIX ****')
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d')
```

```
**** ACCURACY_SCORE ****

 0.8705000814464896

**** CLASSIFICATION_REPORT ****

              precision    recall  f1-score   support

           0       0.90      0.94      0.92      4699
           1       0.76      0.65      0.70      1440

    accuracy                           0.87      6139
   macro avg       0.83      0.79      0.81      6139
weighted avg       0.87      0.87      0.87      6139


**** CONFUSION MATRIX ****
<Axes: >
```




```
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('**** CLASSIFICATION_REPORT **** \n\n', classification_report(y_test, y_pred_gbc), '\n')
print('**** CONFUSION MATRIX ****')
sns.heatmap(confusion_matrix(y_test, y_pred_gbc), annot=True, fmt='d')
```