Experiment No. 6
Apply Boosting Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:20-09-2023
Date of Submission:09-10-2023

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.

Conclusion:

1. Accuracy measures the ratio of correctly predicted instances to the total number of instances in the dataset. Accuracy is often expressed as a percentage and can be calculated using the following formula:

   $$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100\%$$

   Recall measures the model's ability to correctly identify all instances of a specific class among all the instances that truly belong to that class. It is defined as:

   $$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}}$$

   Precision measures the model's ability to correctly identify positive instances among all instances it predicts as positive. It is defined as:

   $$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}}$$

   A confusion matrix is a tabular representation used in machine learning to evaluate the performance of a classification model, especially for binary classification problems

2. The trade-offs must be taken into account when contrasting the outcomes of using the boosting and random forest algorithms on the Adult Census Income Dataset. Although there may be some interpretability trade-offs, boosting typically offers improved forecast accuracy, particularly for complex datasets. While maintaining better interpretability and durability to overfitting, random forests, on the other hand, provide accuracy that is competitive.

Exp 6 : Gradient Boosting

[134]:

```

```

Imports

[135]:

```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[136]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV, cross_val_score,␣
↪StratifiedKFold, learning_curve, train_test_split, KFold
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

Reading Csv File

[137]:

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

Data Preprocessing

[138]:

```
df.head()
```

[138]:

```
   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
```

[139]:
```
print ("Rows : " ,df.shape[0])
print ("Columns : " ,df.shape[1])
print ("\nFeatures : \n" ,df.columns.tolist())
print ("\nMissing values : ", df.isnull().sum().values.sum())
print ("\nUnique values : \n",df.nunique())
```

```
Rows :  32561
Columns :  15

Features :
 ['age', 'workclass', 'fnlwgt', 'education', 'education.num', 'marital.status',
'occupation', 'relationship', 'race', 'sex', 'capital.gain', 'capital.loss',
'hours.per.week', 'native.country', 'income']

Missing values :  0

Unique values :
 age                  73
workclass             9
fnlwgt            21648
education            16
education.num        16
marital.status        7
occupation           15
relationship          6
race                  5
sex                   2
capital.gain        119
capital.loss         92
hours.per.week       94
native.country       42
income                2
dtype: int64
```

[140]:
```
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
```

[141]:
```
df.describe
```

[141]:
```
<bound method NDFrame.describe of        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
…     …         …       …           …            …                  …
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  \
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
…                    …             …     …     …            …
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
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
…                 …               …            …     …
32556             0              40  United-States  <=50K
32557             0              38  United-States  <=50K
32558             0              40  United-States   >50K
32559             0              40  United-States  <=50K
32560             0              20  United-States  <=50K

[32561 rows x 15 columns]>
```

[142]:
```
df.isnull().sum()
```

[142]:
```
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
```

[143]:
```
df[df == '?'] = np.nan
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       30725 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      30718 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  31978 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

[144]:
```
df.isnull().sum()
```

[144]:
```
age                  0
workclass         1836
fnlwgt               0
education            0
education.num        0
marital.status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital.gain         0
capital.loss         0
hours.per.week       0
native.country     583
income               0
dtype: int64
```

[145]:
```
max_category = df['workclass'].value_counts().idxmax()
df['workclass'].fillna(max_category, inplace=True)
max_category = df['occupation'].value_counts().idxmax()
df['occupation'].fillna(max_category, inplace=True)
max_category = df['native.country'].value_counts().idxmax()
df['native.country'].fillna(max_category, inplace=True)
max_category = df['relationship'].value_counts().idxmax()
df['relationship'].fillna(max_category, inplace=True)
max_category = df['race'].value_counts().idxmax()
df['race'].fillna(max_category, inplace=True)
```

[146]:
```
df.isnull().sum()
```

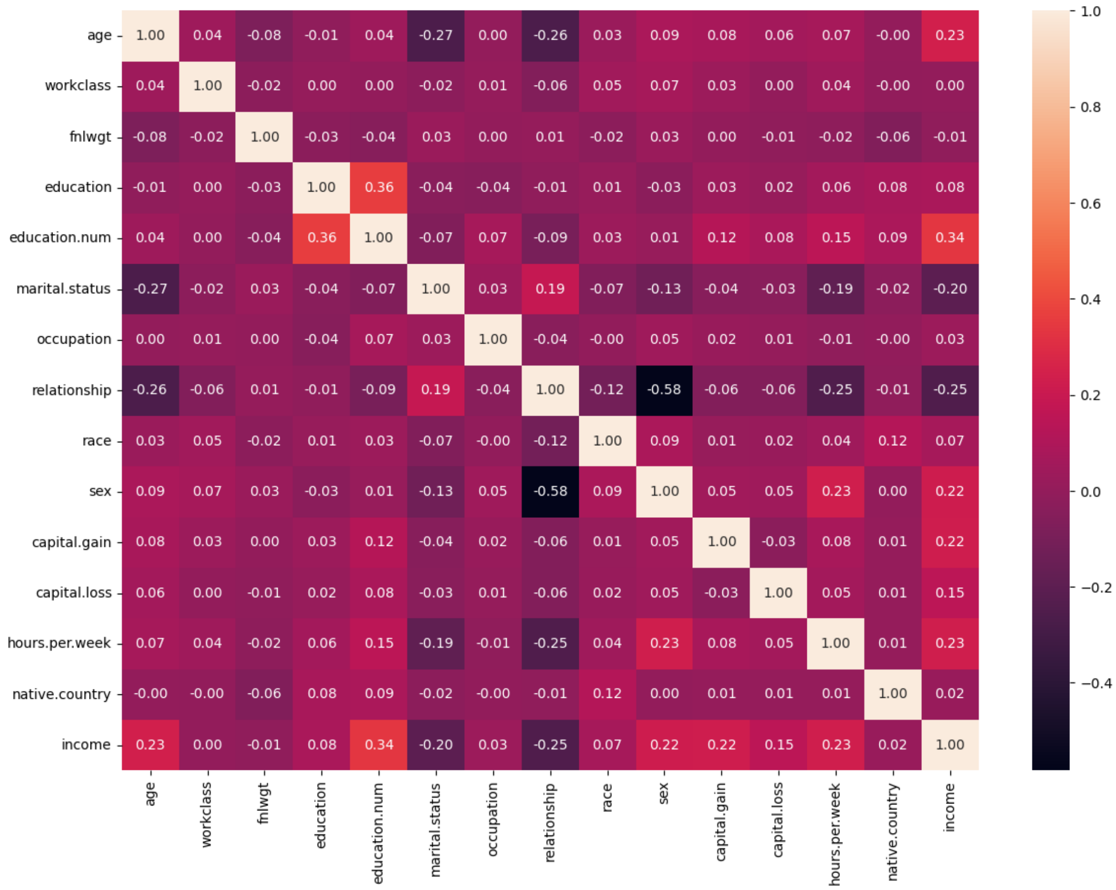
[146]:
```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
```

Label Encoding

[147]:
```
from sklearn.preprocessing import LabelEncoder
```

[148]:
```
labelencoder_x=LabelEncoder()
df["workclass"]=labelencoder_x.fit_transform(df["workclass"])
df["education"]=labelencoder_x.fit_transform(df["education"])
df["relationship"]=labelencoder_x.fit_transform(df["relationship"])
df["occupation"]=labelencoder_x.fit_transform(df["occupation"])
df["sex"]=labelencoder_x.fit_transform(df["sex"])
df["income"]=labelencoder_x.fit_transform(df["income"])
df["marital.status"]=labelencoder_x.fit_transform(df["marital.status"])
df["race"]=labelencoder_x.fit_transform(df["race"])
df["native.country"]=labelencoder_x.fit_transform(df["native.country"])
```

[149]:
```
plt.figure(figsize=(14,10))
sns.heatmap(df.corr(),annot=True,fmt='.2f')
plt.show()
```



[150]:
```
x=df.drop("income",axis=1)
y=df["income"]
```

[151]:
```
df.head(10)
```

[151]:
```
   age  workclass  fnlwgt  education  education.num  marital.status  \
0   90          3   77053         11              9               6
1   82          3  132870         11              9               6
2   66          3  186061         15             10               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
7   74          6   88638         10             16               4
8   68          0  422013         11              9               0
9   41          3   70037         15             10               4

   occupation  relationship  race  sex  capital.gain  capital.loss  \
0           9             1     4    0             0          4356
```

```
1          3           1    4   0           0         4356
2          9           4    2   0           0         4356
3          6           4    4   0           0         3900
4          9           3    4   0           0         3900
5          7           4    4   0           0         3770
6          0           4    4   1           0         3770
7          9           2    4   0           0         3683
8          9           1    4   0           0         3683
9          2           4    4   1           0         3004

   hours.per.week  native.country  income
0              40              38       0
1              18              38       0
2              40              38       0
3              40              38       0
4              40              38       0
5              45              38       0
6              40              38       0
7              20              38       1
8              40              38       0
9              60              38       1
```

Data Accuracy

[152]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=0,test_size=0.3)
```

[153]:
```
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score,classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
```

[154]:
```
features = list(df.columns[1:])
features
```

[154]:
```
['workclass',
 'fnlwgt',
 'education',
 'education.num',
 'marital.status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'capital.gain',
 'capital.loss',
```

```
 'hours.per.week',
 'native.country',
 'income']
```

[155]:
```
gbm=GradientBoostingClassifier(n_estimators=10)
gbm.fit(x_train,y_train)
y_gbmp=gbm.predict(x_test)
```

[156]:
```
print('Gradient Boosting : ' ,accuracy_score(y_test,y_gbmp)*100)
```

```
Gradient Boosting :  83.86733544886887
```

[157]:
```
print('Recall : ' ,recall_score(y_test,y_gbmp)*100)
```

```
Recall :  42.51801610852056
```

[158]:
```
print('Precision : ' ,precision_score(y_test,y_gbmp)*100)
```

```
Precision :  82.01144726083402
```

[159]:
```
print('F1-Score : ' ,f1_score(y_test,y_gbmp)*100)
```

```
F1-Score :  56.00223338916807
```

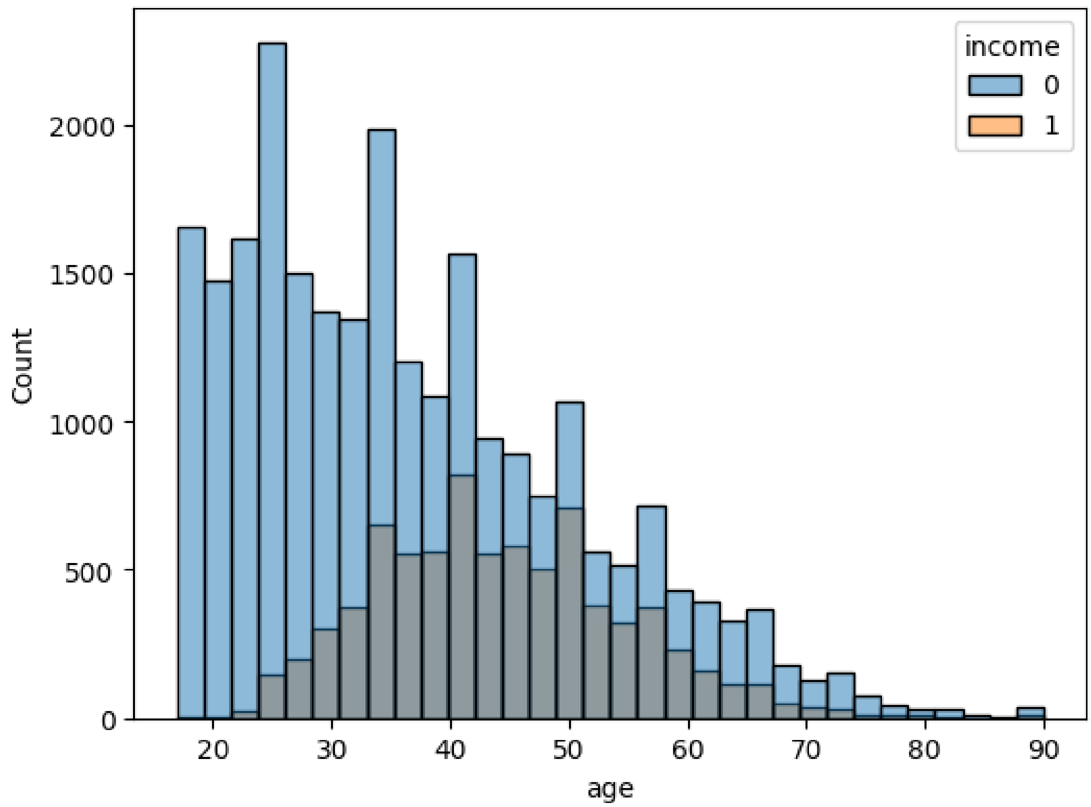
[160]:
```
print(classification_report(y_test,y_gbmp))
```

```
              precision    recall  f1-score   support

           0       0.84      0.97      0.90      7410
           1       0.82      0.43      0.56      2359

    accuracy                           0.84      9769
   macro avg       0.83      0.70      0.73      9769
weighted avg       0.84      0.84      0.82      9769
```

Data Visualization

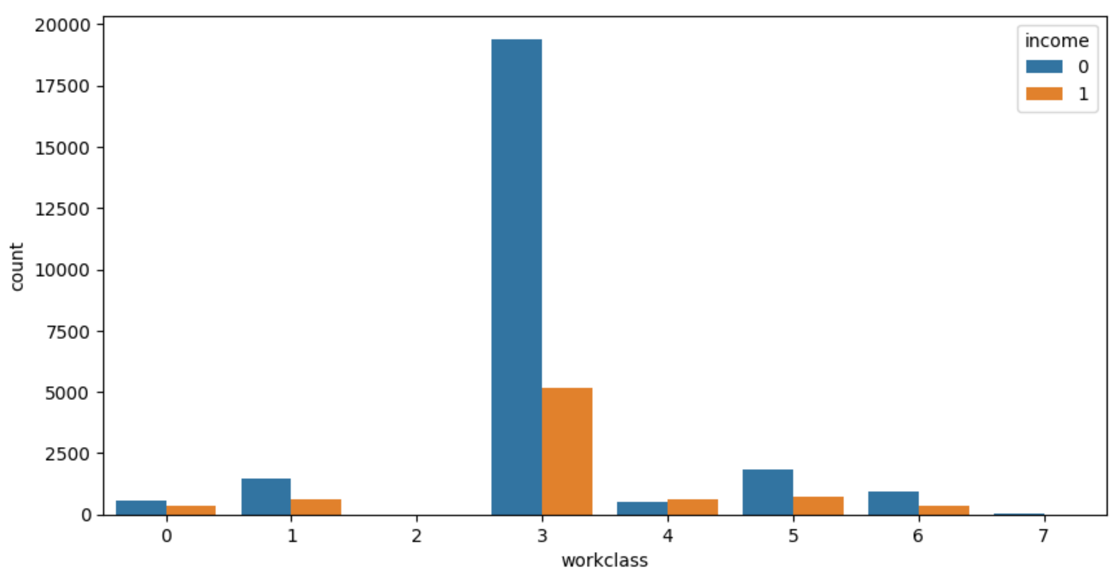
[161]:
```
sns.histplot(df, x='age', hue='income', bins= 32)
```

[161]: <Axes: xlabel='age', ylabel='Count'>

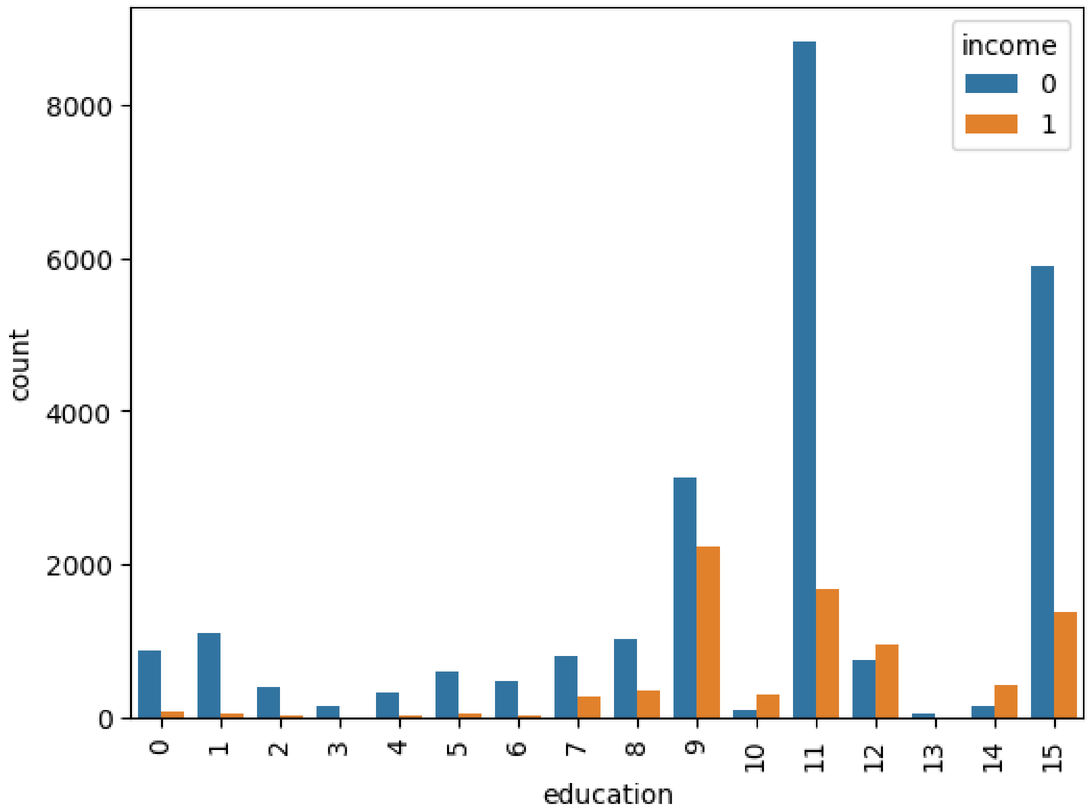


[162]:
```
fig=plt.figure(figsize=(10,5))
sns.countplot(data = df, x = 'workclass', hue = 'income')
```

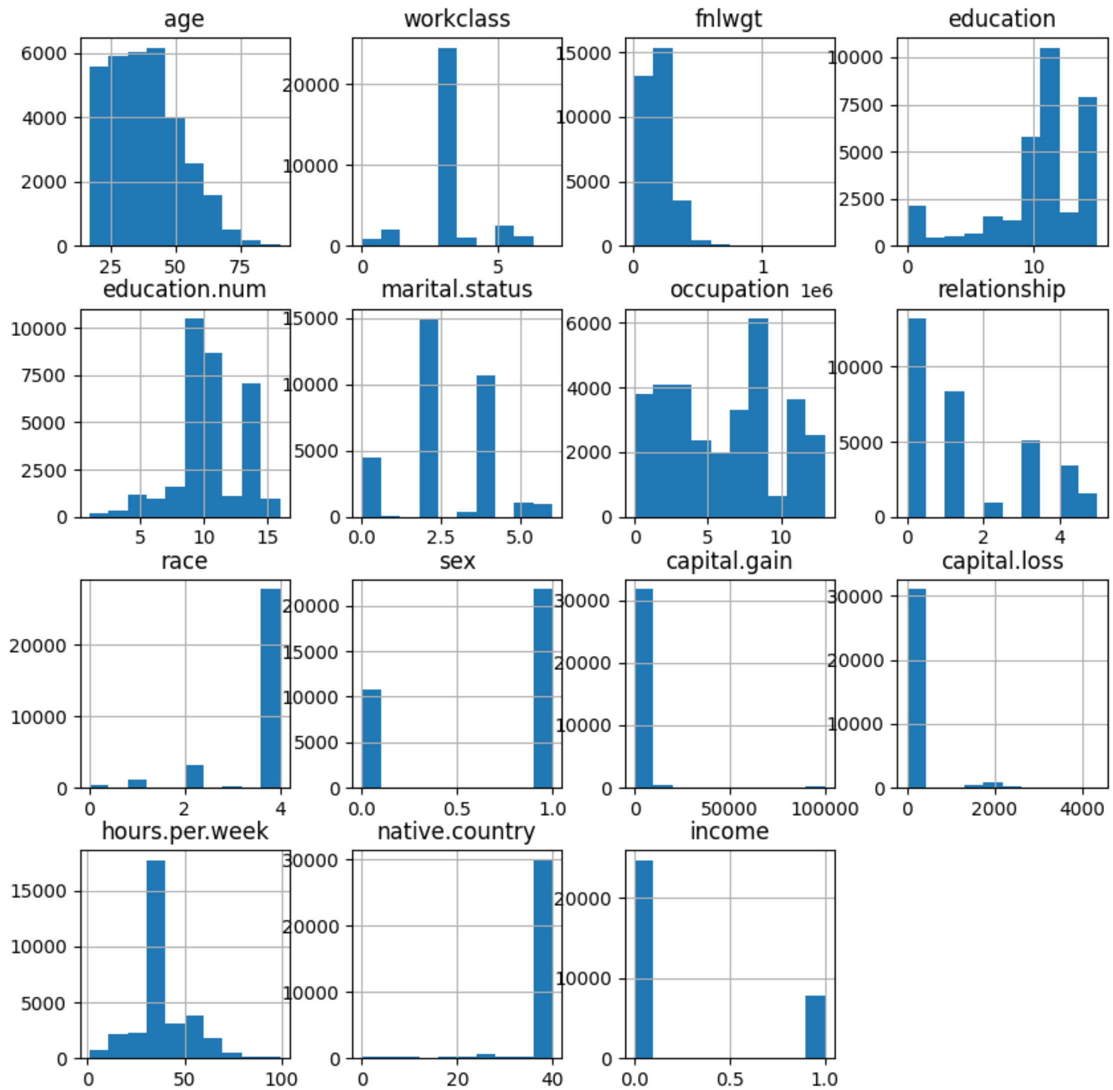
[162]: <Axes: xlabel='workclass', ylabel='count'>



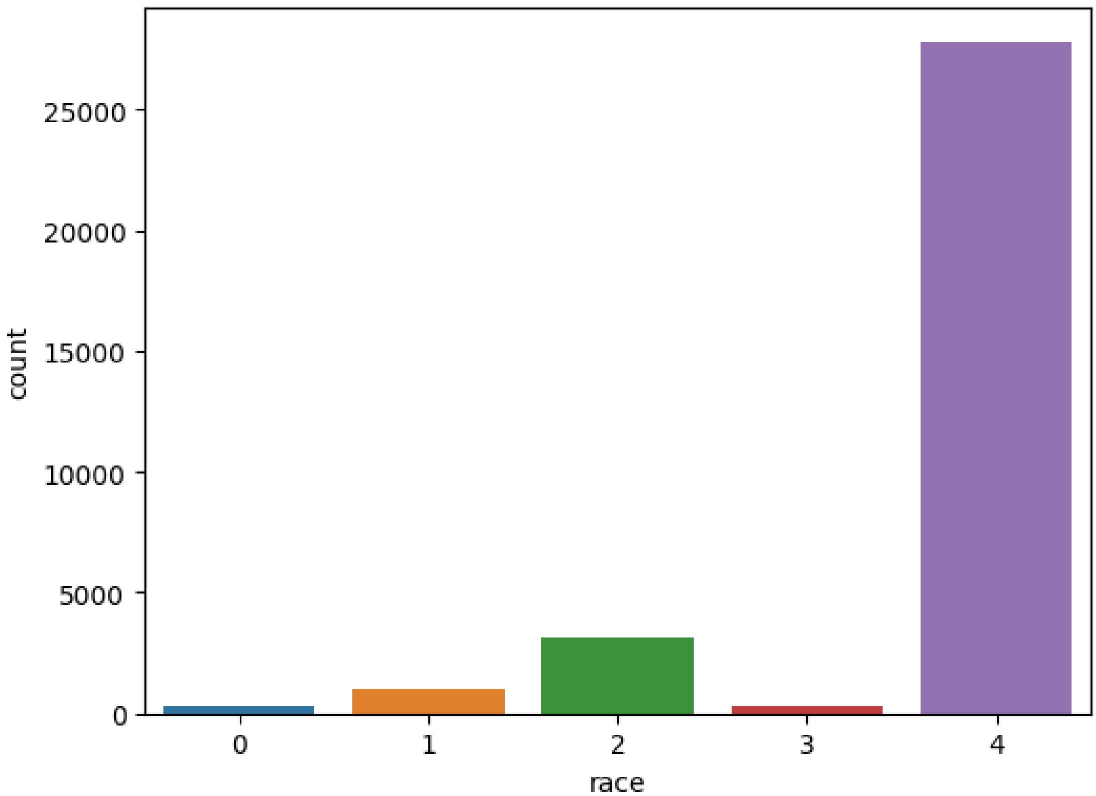
[163]:
```
sns.countplot(data = df, x = 'education', hue = 'income')
plt.tick_params(axis='x', rotation=90)
```



[164]:
```
df.hist(bins=10, figsize=(10, 10))
plt.show()
```

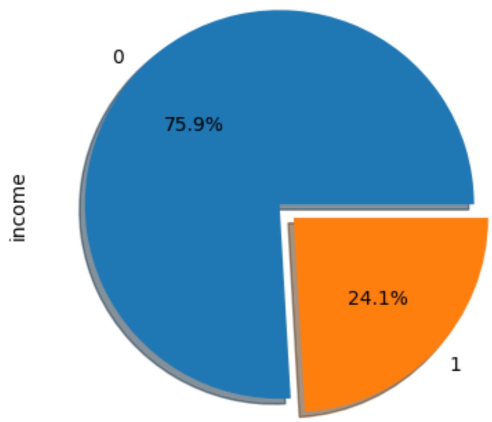


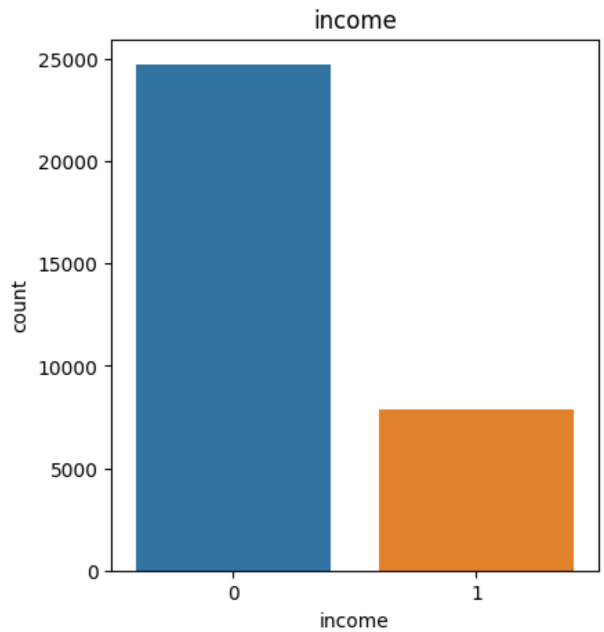
[165]:
```
sns.countplot(x = "race", data=df);
```



[166]:
```
f, ax = plt.subplots(1, 2, figsize=(10, 5))
df['income'].value_counts().plot.pie(explode=[0, 0.1], autopct='%1.1f%%',␣
 ↪ax=ax[0], shadow=True)
sns.countplot(x='income', data=df, ax=ax[1])
ax[1].set_title('income')
```

[166]: `Text(0.5, 1.0, 'income')`


income
0
75.9%
24.1%
1


income
25000
20000
15000
10000
5000
0
count
0
1
income