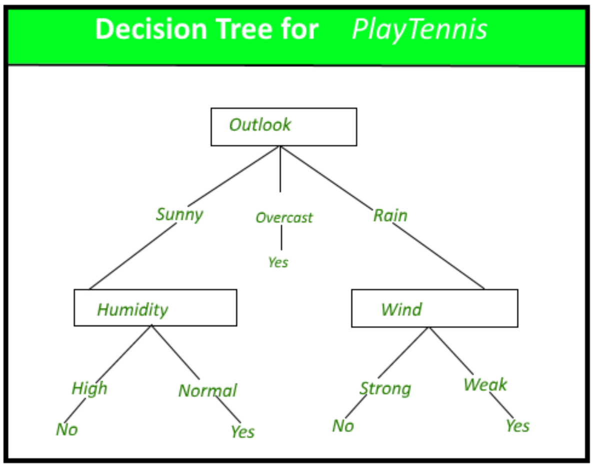
Experiment No. 3
Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:
Date of Submission:

Aim: Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model.

Objective: To perform various feature engineering tasks, apply Decision Tree Algorithm on the given dataset and maximize the accuracy, Precision, Recall, F1 score. Improve the performance by performing different data engineering and feature engineering tasks.

Theory:

Decision Tree is the most powerful and popular tool for classification and prediction. A Decision tree is a flowchart-like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.



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:

Importing lib

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

Load the dataset

```
df = pd.read_csv('adult.csv')
df.head(10)
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relatio
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-
2	66	?	186061	Some-college	10	Widowed	?	Unm
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unm
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Owi
5	34	Private	216864	HS-grad	9	Divorced	Other-service	Unm
6	38	Private	150601	10th	6	Separated	Adm-clerical	Unm

Understanding Dataset

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

```
Total Rows     :  32561
Total Columns  :  15

Features :
 ['age', 'workclass', 'fnlwgt', 'education', 'education.num', 'marital.status', 'occupation', 'relationship', 'race', 'sex', 'capital.ga

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
```

```
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
```

```
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

Missing Values

```
df_missing = (df=='?').sum()
print(df_missing)
```

```
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
```

percent_missing = (df=='?').sum() * 100/len(df) percent_missing

```
#droping row having missing values from dataset
df = df[df['workclass'] !='?']
df = df[df['occupation'] !='?']
df = df[df['native.country'] !='?']
df.head()
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race

```
df_missing = (df=='?').sum()
print(df_missing)
```

```
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
```

```
print ("Total Rows after droping rows : " ,df.shape[0])
print("Numbers of rows drop: ", dataset_row -df.shape[0])
```

```
Total Rows after droping rows :  30162
Numbers of rows drop:  2399
```

Data Preparation

```
from sklearn import preprocessing
```

```
df_categorical = df.select_dtypes(include=['object'])
df_categorical.head()
```

	workclass	education	marital.status	occupation	relationship	race	sex	native.country	incom
1	Private	HS-grad	Widowed	Exec-managerial	Not-in-family	White	Female	United-States	<=50
3	Private	7th-8th	Divorced	Machine-op-inspct	Unmarried	White	Female	United-States	<=50
4	Private	Some-college	Separated	Prof-specialty	Own-child	White	Female	United-States	<=50
[illegible]	[illegible]	[illegible]	[illegible]	Other-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

```
le = preprocessing.LabelEncoder()
df_categorical = df_categorical.apply(le.fit_transform)
df_categorical.head()
```

	workclass	education	marital.status	occupation	relationship	race	sex	native.country	income
1	2	11	6	3	1	4	0	38	0
3	2	5	0	6	4	4	0	38	0
4	2	15	5	9	3	4	0	38	0
5	2	11	0	7	4	4	0	38	0
6	2	0	5	0	4	4	1	38	0

```
df = df.drop(df_categorical.columns,axis=1)
df = pd.concat([df,df_categorical],axis=1)
df['income'] = df['income'].astype('category')
df.head()
```

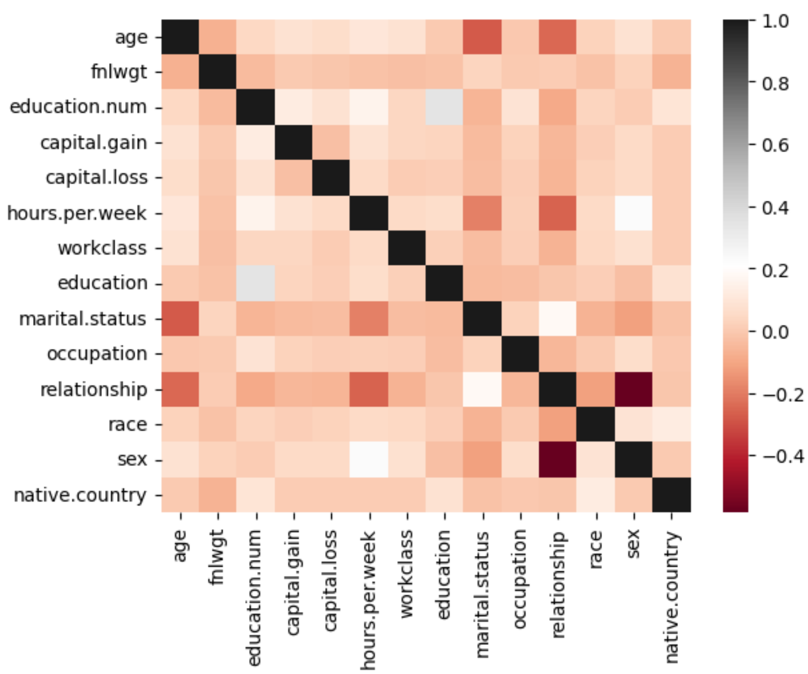
	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	marita
1	82	132870	9	0	4356	18	2	11	
3	54	140359	4	0	3900	40	2	5	
4	41	264663	10	0	3900	40	2	15	
5	34	216864	9	0	3770	45	2	11	
6	38	150601	6	0	3770	40	2	0	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30162 entries, 1 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype   
---  ------          --------------  -----   
 0   age             30162 non-null  int64   
 1   fnlwgt          30162 non-null  int64   
 2   education.num   30162 non-null  int64   
 3   capital.gain    30162 non-null  int64   
 4   capital.loss    30162 non-null  int64   
 5   hours.per.week  30162 non-null  int64   
 6   workclass       30162 non-null  int64   
 7   education       30162 non-null  int64   
 8   marital.status  30162 non-null  int64   
 9   occupation      30162 non-null  int64   
 10  relationship    30162 non-null  int64   
 11  race            30162 non-null  int64   
 12  sex             30162 non-null  int64   
 13  native.country  30162 non-null  int64   
 14  income          30162 non-null  category
dtypes: category(1), int64(14)
memory usage: 3.5 MB
```

```
sns.heatmap(df.corr(), cmap = 'RdGy')
```

```
<ipython-input-101-b22fcbbd6ef9>:1: FutureWarning: The default value of numeric_only in DataFrame.corr
  sns.heatmap(df.corr(), cmap = 'RdGy')
<Axes: >
```



Spliting dataset

```
from sklearn.model_selection import train_test_split
```

```
X = df.drop('income',axis=1)
X = X.drop('sex',axis=1)
y = df['income']
```

```
X.head()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	marita
1	82	132870	9	0	4356	18	2	11	
3	54	140359	4	0	3900	40	2	5	
4	41	264663	10	0	3900	40	2	15	
5	34	216864	9	0	3770	45	2	11	
6	38	150601	6	0	3770	40	2	0	

```
y.head()
```

```
1    0
3    0
4    0
5    0
6    0
Name: income, dtype: category
Categories (2, int64): [0, 1]
```

```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.20)
```

Appling Decision Tree Algo

```
from sklearn.tree import DecisionTreeClassifier
```

```
dt_default = DecisionTreeClassifier(max_depth=5)
dt_default.fit(X_train,y_train)
```

```
▾      DecisionTreeClassifier
DecisionTreeClassifier(max_depth=5)
```

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

```
y_pred_default = dt_default.predict(X_test)
print("confusion matrix\n",confusion_matrix(y_test,y_pred_default))
print(classification_report(y_test,y_pred_default))
```

```
confusion matrix
 [[4310  243]
 [ 713  767]]
              precision    recall  f1-score   support

           0       0.86      0.95      0.90      4553
           1       0.76      0.52      0.62      1480

    accuracy                           0.84      6033
   macro avg       0.81      0.73      0.76      6033
weighted avg       0.83      0.84      0.83      6033
```

```
print("accuracy score: ",accuracy_score(y_test,y_pred_default))
```

```
accuracy score:  0.8415382065307475
```

Conclusion:

1. **Dealing with Categorical Attributes during Data Pre-processing:**

In the code, categorical attributes are handled as follows:

Label Encoding: Categorical attributes are transformed into numerical format using label encoding. The LabelEncoder from Scikit-Learn is applied to convert categorical values into unique integers.

Dropping Missing Values: Rows containing missing values in categorical columns ('workclass', 'occupation', 'native.country') are dropped from the dataset to maintain data quality.

2. **Hyper parameter Tuning:**

Hyperparameter tuning is minimal in the code. The Decision Tree classifier is created with a max_depth of 5. However, there's no comprehensive hyperparameter tuning process, such as grid search or random search, to optimize the model's performance. Tuning hyperparameters like max_depth, min_samples_split, and min_samples_leaf could potentially improve the model's accuracy.

3. **Accuracy, Confusion Matrix, Precision, Recall, and F1-Score**:

Accuracy: Measures overall correctness of predictions.

Confusion Matrix: Summarizes true positives, true negatives, false positives, and false negatives.

Precision: Measures accurate positive classifications.

Recall (Sensitivity): Measures identifying relevant instances.

F1-Score: Balances precision and recall, especially useful for imbalanced classes.

Obtain output:

```
confusion matrix
 [[4310  243]
 [ 713  767]]
              precision    recall  f1-score

           0       0.86      0.95      0.90
           1       0.76      0.52      0.62

    accuracy                           0.84
   macro avg       0.81      0.73      0.76
weighted avg       0.83      0.84      0.83
```