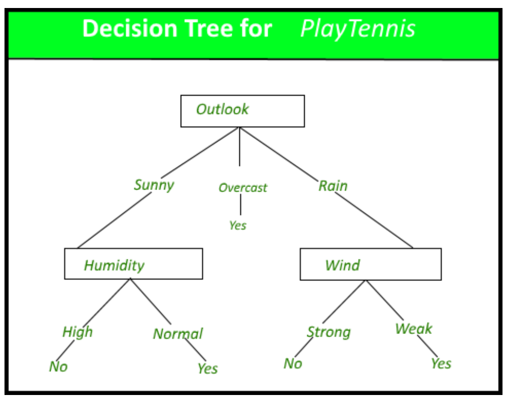
Experiment No. 3	
Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model	
Date of Performance:	14/08/23
Date of Submission:	22/08/23

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.



Decision Tree for *PlayTennis*

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.

```
# Import libraries
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# To ignore warning messages
import warnings
warnings.filterwarnings('ignore')
```

```
# Adult dataset path
adult_dataset_path = "adult_dataset.csv"

# Function for loading adult dataset
def load_adult_data(adult_path=adult_dataset_path):
    csv_path = os.path.join(adult_path)
    return pd.read_csv(csv_path)
```

```
# Calling load adult function and assigning to a new variable df
df = load_adult_data()
# load top 3 rows values from adult dataset
df.head(3)
```

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

```
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', 'capit

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
```

occupation 32561 non-null object

```
 6   relationship    32561 non-null  object
 7   race            32561 non-null  object
 8   sex             32561 non-null  object
 9   capital.gain    32561 non-null  int64
 10  capital.loss    32561 non-null  int64
 11  hours.per.week  32561 non-null  int64
 12  native.country  32561 non-null  object
 13  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

```
df.head()
```

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

```
# checking "?" total values present in particular 'workclass' feature
df_check_missing_workclass = (df['workclass']=='?').sum()
df_check_missing_workclass
```

```
1836
```

```
# checking "?" total values present in particular 'occupation' feature
df_check_missing_occupation = (df['occupation']=='?').sum()
df_check_missing_occupation
```

```
1843
```

```
# checking "?" values, how many are there in the whole dataset
df_missing = (df=='?').sum()
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
```

```
age               0.000000
workclass         5.638647
fnlwgt            0.000000
education         0.000000
education.num     0.000000
marital.status    0.000000
occupation        5.660146
relationship      0.000000
race              0.000000
sex               0.000000
capital.gain      0.000000
capital.loss      0.000000
hours.per.week    0.000000
native.country    1.790486
income            0.000000
dtype: float64
```

```
# find total number of rows which doesn't contain any missing value as '?'
df.apply(lambda x: x !='?',axis=1).sum()
```

```
age               32561
workclass         30725
fnlwgt            32561
education         32561
education.num     32561
marital.status    32561
occupation        30718
relationship      32561
race              32561
sex               32561
capital.gain      32561
capital.loss      32561
hours.per.week    32561
native.country    31978
income            32561
dtype: int64
```

```
# dropping the rows having missing values in workclass
df = df[df['workclass'] !='?']
df.head()
```

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

```
# select all categorical variables
df_categorical = df.select_dtypes(include=['object'])

# checking whether any other column contains '?' value
df_categorical.apply(lambda x: x=='?',axis=1).sum()
```

```
workclass           0
education           0
marital.status      0
occupation          7
relationship        0
race                0
sex                 0
native.country    556
income              0
dtype: int64
```

```
# dropping the "?"s from occupation and native.country
df = df[df['occupation'] !='?']
df = df[df['native.country'] !='?']
```

```
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   workclass       30162 non-null  object
 2   fnlwgt          30162 non-null  int64
 3   education       30162 non-null  object
 4   education.num   30162 non-null  int64
 5   marital.status  30162 non-null  object
 6   occupation      30162 non-null  object
 7   relationship    30162 non-null  object
 8   race            30162 non-null  object
 9   sex             30162 non-null  object
 10  capital.gain    30162 non-null  int64
 11  capital.loss    30162 non-null  int64
 12  hours.per.week  30162 non-null  int64
 13  native.country  30162 non-null  object
 14  income          30162 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
from sklearn import preprocessing

# encode categorical variables using label Encoder

# select all categorical variables
df_categorical = df.select_dtypes(include=['object'])
df_categorical.head()
```

	workclass	education	marital.status	occupation	relationship	race	sex	native.country	income
1	Private	HS-grad	Widowed	Exec-managerial	Not-in-family	White	Female	United-States	<=50K
3	Private	7th-8th	Divorced	Machine-op-inspct	Unmarried	White	Female	United-States	<=50K
4	Private	Some-college	Separated	Prof-specialty	Own-child	White	Female	United-States	<=50K
5	Private	HS-grad	Divorced	Other-service	Unmarried	White	Female	United-States	<=50K
6	Private	10th	Separated	Adm-clerical	Unmarried	White	Male	United-States	<=50K

```
# apply label encoder to df_categorical
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

```
# Next, Concatenate df_categorical dataframe with original df (dataframe)

# first, Drop earlier duplicate columns which had categorical values
df = df.drop(df_categorical.columns,axis=1)
df = pd.concat([df,df_categorical],axis=1)
df.head()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	marital.status	occupation	relatio
1	82	132870	9	0	4356	18	2	11	6	3	
3	54	140359	4	0	3900	40	2	5	0	6	
4	41	264663	10	0	3900	40	2	15	5	9	
5	34	216864	9	0	3770	45	2	11	0	7	
6	38	150601	6	0	3770	40	2	0	5	0	

```
# look at column type
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  int64
dtypes: int64(15)
memory usage: 3.7 MB
```

```
# convert target variable income to categorical
df['income'] = df['income'].astype('category')
```

```
# check df info again whether everything is in right format or not
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
```

```
# Importing train_test_split
from sklearn.model_selection import train_test_split
```

```
# Putting independent variables/features to X
X = df.drop('income',axis=1)

# Putting response/dependent variable/feature to y
y = df['income']
```

```
X.head(3)
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	marital.status	occupation	relatio
1	82	132870	9	0	4356	18	2	11	6	3	
3	54	140359	4	0	3900	40	2	5	0	6	
4	41	264663	10	0	3900	40	2	15	5	9	

```
y.head(3)
```

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

```
# Splitting the data into train and test
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.30,random_state=99)

X_train.head()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	education	marital.status	occupation	rel
24351	42	289636	9	0	0	46	2	11	2	13	
15626	37	52465	9	0	0	40	1	11	4	7	

```
# Importing decision tree classifier from sklearn library
from sklearn.tree import DecisionTreeClassifier

# Fitting the decision tree with default hyperparameters, apart from
# max_depth which is 5 so that we can plot and read the tree.
dt_default = DecisionTreeClassifier(max_depth=5)
dt_default.fit(X_train,y_train)
```

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

```
# check the evaluation metrics of our default model

# Importing classification report and confusion matrix from sklearn metrics
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score

# making predictions
y_pred_default = dt_default.predict(X_test)

# Printing classifier report after prediction
print(classification_report(y_test,y_pred_default))
```

```
              precision    recall  f1-score   support

           0       0.86      0.95      0.91      6867
           1       0.78      0.52      0.63      2182

    accuracy                           0.85      9049
   macro avg       0.82      0.74      0.77      9049
weighted avg       0.84      0.85      0.84      9049
```

```
# Printing confusion matrix and accuracy
print(confusion_matrix(y_test,y_pred_default))
print(accuracy_score(y_test,y_pred_default))
```

```
[[6553  314]
 [1039 1143]]
0.8504807161012267
```

```
!pip install my-package
```

```
Collecting my-package
  Downloading my_package-0.0.0-py3-none-any.whl (2.0 kB)
Installing collected packages: my-package
Successfully installed my-package-0.0.0
```

```
!pip install pydotplus
```

```
Requirement already satisfied: pydotplus in /usr/local/lib/python3.10/dist-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in /usr/local/lib/python3.10/dist-packages (from pydotplus) (3.1.1)
```

```
# Importing required packages for visualization
from IPython.display import Image
from six import StringIO
from sklearn.tree import export_graphviz
import pydotplus,graphviz

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

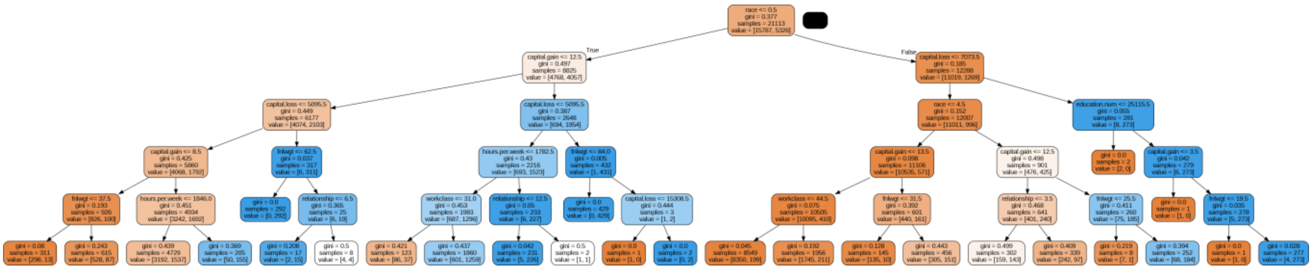
```
['fnlwgt',
 'education.num',
 'capital.gain',
 'capital.loss',
 'hours.per.week',
 'workclass',
 'education',
 'marital.status',
 'occupation',
 'relationship',
 'race',
 'sex',
```

```
       'native.country',
       'income']
```

```
!pip install graphviz
```

```
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (0.20.1)
```

```
# plotting tree with max_depth=3
dot_data = StringIO()
export_graphviz(dt_default, out_file=dot_data,
                feature_names=features, filled=True,rounded=True)

graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```



```
# GridSearchCV to find optimal max_depth
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV


# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'max_depth': range(1, 40)}

# instantiate the model
dtree = DecisionTreeClassifier(criterion = "gini",
                               random_state = 100)

# fit tree on training data
tree = GridSearchCV(dtree, parameters,
                    cv=n_folds,
                   scoring="accuracy")
tree.fit(X_train, y_train)
```

▸ **GridSearchCV**

▸ **estimator: DecisionTreeClassifier**

▸ DecisionTre eClassifier

```
# scores of GridSearch CV
scores = tree.cv_results_
pd.DataFrame(scores).head()
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	p rams	split0_test_score	split1_test_score
0	0.017606	0.003309	0.004545	0.000778	1	{'max_(pth': 1}	0.747810	0.747810
1	0.019553	0.002510	0.003388	0.000431	2	{'max_(pth': 2}	0.812219	0.818612
2	0.024394	0.001255	0.003224	0.000196	3	{'max_(pth': 3}	0.828558	0.834241
3	0.031005	0.003047	0.003377	0.000224	4	{'max_(pth': 4}	0.832583	0.840871
4	0.038414	0.004430	0.003606	0.000638	5	{'max_(pth': 5}	0.834241	0.844897

```
"""
# plotting accuracies with max_depth
plt.figure()
plt.plot(scores["param_max_depth"],
         scores["mean_train_score"],
         label="training accuracy")
plt.plot(scores["param_max_depth"],
         scores["mean_test_score"],
         label="test accuracy")
plt.xlabel("max_depth")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
"""
```

```
'\n# plotting accuracies with max_depth\nplt.figure()\nplt.plot(scores["param_max_depth"], \n         scores["mean_train_score"],
\n         label="training accuracy")\nplt.plot(scores["param_max_depth"], \n         scores["mean_test_score"], \n         label
="test accuracy")\nplt xlabel("max depth")\nplt ylabel("Accuracy")\nplt legend()\nplt show()\n'
```

```
# GridSearchCV to find optimal max_depth
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV


# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'min_samples_leaf': range(5, 200, 20)}

# instantiate the model
dtree = DecisionTreeClassifier(criterion = "gini",
                               random_state = 100)

# fit tree on training data
tree = GridSearchCV(dtree, parameters,
                    cv=n_folds,
                   scoring="accuracy")
tree.fit(X_train, y_train)
```

```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

```
# scores of GridSearch CV
scores = tree.cv_results_
pd.DataFrame(scores).head()
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_min_samples_leaf	params	split0_test_score	split
0	0.206307	0.049675	0.006364	0.001320	5	{'min_samples_leaf': 5}	0.825716	
1	0.130202	0.019363	0.006910	0.002911	25	{'min_samples_leaf': 25}	0.841819	
2	0.109869	0.021408	0.005161	0.000183	45	{'min_samples_leaf': 45}	0.843003	
3	0.106612	0.017281	0.008429	0.006759	65	{'min_samples_leaf': 65}	0.841108	
4	0.116716	0.018254	0.009106	0.005065	85	{'min_samples_leaf': 85}	0.838030	

```
"""
# plotting accuracies with min_samples_leaf
plt.figure()
plt.plot(scores["param_min_samples_leaf"],
         scores["mean_train_score"],
         label="training accuracy")
plt.plot(scores["param_min_samples_leaf"],
         scores["mean_test_score"],
         label="test accuracy")
plt.xlabel("min_samples_leaf")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
"""
```

```
'\n# plotting accuracies with min_samples_leaf\nplt.figure()\nplt.plot(scores["param_min_samples_leaf"], \nscores["mean_t
rain_score"], \nlabel="training accuracy")\nplt.plot(scores["param_min_samples_leaf"], \n                 scores["mean_test_scor
e"], \n         label="test accuracy")\nplt.xlabel("min_samples_leaf")\nplt.ylabel("Accuracy")\nplt.legend()\nplt.show()\n'
```

```
# GridSearchCV to find optimal min_samples_split
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV


# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'min_samples_split': range(5, 200, 20)}

# instantiate the model
dtree = DecisionTreeClassifier(criterion = "gini",
                               random_state = 100)

# fit tree on training data
tree = GridSearchCV(dtree, parameters,
                    cv=n_folds,
                   scoring="accuracy")
tree.fit(X_train, y_train)
```

```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
  ▸ DecisionTreeClassifier
```

```
# scores of GridSearch CV
scores = tree.cv_results_
pd.DataFrame(scores).head()
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_min_samples_split	params	split0_test_score	spli
0	0.135789	0.007802	0.005833	0.000620	5	{'min_samples_split': 5}	0.811982	
1	0.129377	0.003017	0.005809	0.000127	25	{'min_samples_split': 25}	0.825006	
2	0.127084	0.003051	0.005815	0.000104	45	{'min_samples_split': 45}	0.835188	
3	0.124147	0.005110	0.006897	0.001300	65	{'min_samples_split': 65}	0.839451	
4	0.090817	0.015012	0.004403	0.000369	85	{'min_samples_split': 85}	0.846081	

```
"""
# plotting accuracies with min_samples_leaf
plt.figure()
plt.plot(scores["param_min_samples_split"],
         scores["mean_train_score"],
         label="training accuracy")
plt.plot(scores["param_min_samples_split"],
        scores["mean_test_score"],
         label="test accuracy")
plt.xlabel("min_samples_split")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
"""
```

```
'\n# plotting accuracies with min_samples_leaf\nplt.figure()\nplt.plot(scores["param_min_samples_split"], \n scores["mean_
train_score"], \n      label="training accuracy")\nplt.plot(scores["param_min_samples_split"], \n      scores["mean_test_score"],
\n label="test accuracy")\nplt.xlabel("min_samples_split")\nplt.ylabel("Accuracy")\nplt.legend()\nplt.show()\n'
```

```
# Create the parameter grid
param_grid = {
    'max_depth': range(5, 15, 5),
    'min_samples_leaf': range(50, 150, 50),
    'min_samples_split': range(50, 150, 50),
    'criterion': ["entropy", "gini"]
}

n_folds = 5
```

```
# Instantiate the grid search model
dtree = DecisionTreeClassifier()
grid_search = GridSearchCV(estimator = dtree, param_grid = param_grid,
                          cv = n_folds, verbose = 1)

# Fit the grid search to the data
grid_search.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

```
# cv results
cv_results = pd.DataFrame(grid_search.cv_results_)
cv_results
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_criterion	param_max_depth	param_min_samples_leaf	param_m
0	0.040022	0.005139	0.003463	0.000684	entropy	5	50	
1	0.038898	0.002205	0.003150	0.000035	entropy	5	50	
2	0.039383	0.001463	0.003649	0.000590	entropy	5	100	
3	0.038811	0.001748	0.003635	0.000666	entropy	5	100	

```
# printing the optimal accuracy score and hyperparameters
print("best accuracy", grid_search.best_score_)
print(grid_search.best_estimator_)
```

```
best accuracy 0.8510400232064759
DecisionTreeClassifier(max_depth=10, min_samples_leaf=50, min_samples_split=50)
```

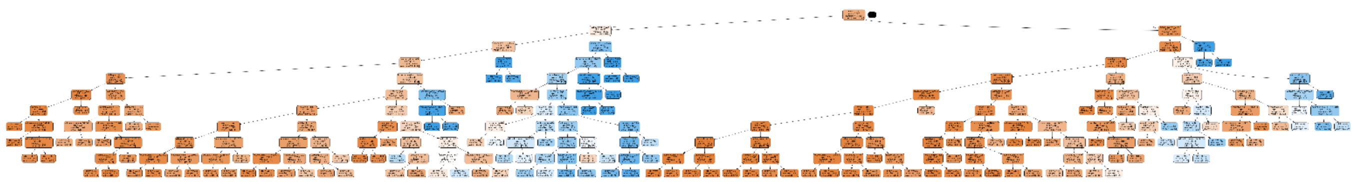
```
# model with optimal hyperparameters
clf_gini = DecisionTreeClassifier(criterion = "gini",
                                  random_state = 100,
                                  max_depth=10,
                                  min_samples_leaf=50,
                                  min_samples_split=50)
clf_gini.fit(X_train, y_train)
```

```
▾                    DecisionTreeClassifier
DecisionTreeClassifier(max_depth=10, min_samples_leaf=50, min_samples_split=50,
                       random_state=100)
```

```
# accuracy score
clf_gini.score(X_test,y_test)
```

```
0.850922753895458
```

```
#plotting the tree
dot_data = StringIO()
export_graphviz(clf_gini, out_file=dot_data,feature_names=features,filled=True,rounded=True)

graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```



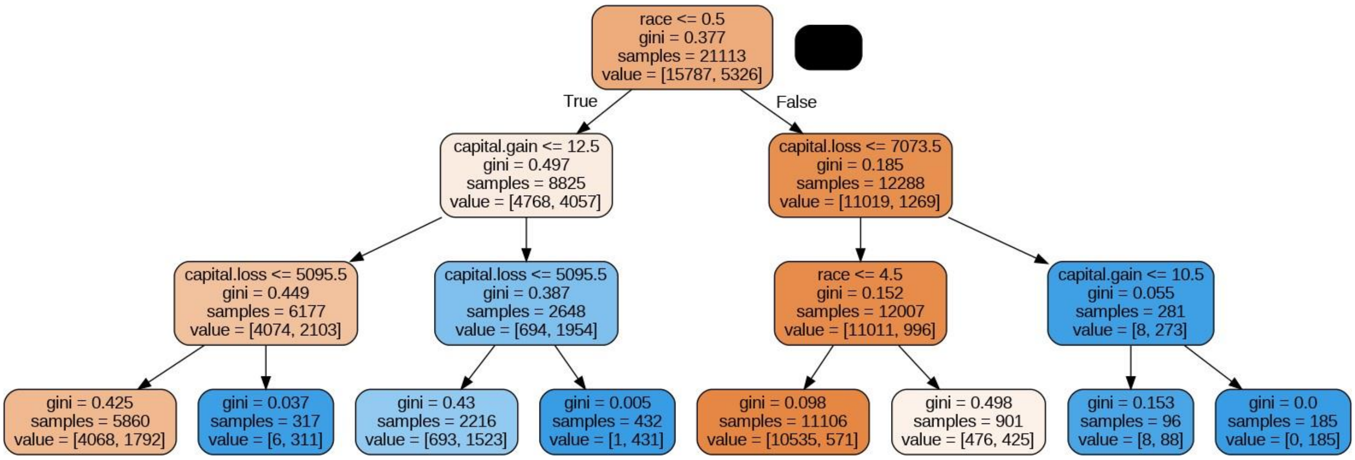
```
# tree with max_depth = 3
clf_gini = DecisionTreeClassifier(criterion = "gini",
                                  random_state = 100,
                                  max_depth=3,
                                  min_samples_leaf=50,
                                  min_samples_split=50)
clf_gini.fit(X_train, y_train)

# score
print(clf_gini.score(X_test,y_test))
```

```
0.8393192617968837
```

15	0.056551	0.001851	0.004291	0.000614	gini	10	100

```
# plotting tree with max_depth=3
dot_data = StringIO()
export_graphviz(clf_gini, out_file=dot_data,feature_names=features,filled=True,rounded=True)
```

```
graph =
Image(graph.create_png())
```




```
# classification metrics
from sklearn.metrics import classification_report,confusion_matrix
y_pred = clf_gini.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.96      0.90      6867
           1       0.77      0.47      0.59      2182

    accuracy                           0.84      9049
   macro avg       0.81      0.71      0.74      9049
weighted avg       0.83      0.84      0.82      9049
```

```
# confusion matrix
print(confusion_matrix(y_test,y_pred))
```

```
[[6564  303]
 [1151 1031]]
```

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Conclusion:

1. Utilizing the Label Encoder technique, categorical attributes have been converted into numerical representations, enabling their utilization in machine learning algorithms that require numerical input by assigning unique integers to distinct categorical values.
2. Hyper-parameter tuning was conducted based on the decision tree model, optimizing key parameters such as Max Depth, Min Samples Split, Min Samples Leaf, and Criterion to enhance model effectiveness:
    - Max Depth: This parameter controls the tree's depth, preventing it from becoming overly complex and overfitting.
    - Min Samples Split: Setting the minimum number of samples required in a node before further splitting helps maintain decision tree balance.
    - Min Samples Leaf: This parameter establishes the minimum number of samples in a leaf node, preventing overly specific decisions.
    - Criterion: This parameter specifies the function used to evaluate split quality, commonly "Gini impurity" or "entropy."
3. The model's accuracy stands at around 84%, implying that it correctly predicted class labels for 84% of the test dataset instances.
4. Breaking down the confusion matrix, we observe:
    - True Positives (TP): 1031
    - True Negatives (TN): 6564
    - False Positives (FP): 303
    - False Negatives (FN): 1151

   The model excels in predicting class 0 (high TP and TN), but struggles with class 1 predictions (high FN).
5. Precision for class 1 is relatively strong, at approximately 0.77, indicating that when the model predicts class 1, it is correct about 77% of the time.
6. However, the recall for class 1 is lower, approximately 0.47, signifying that the model misses a substantial portion of actual class 1 instances. In other words, it correctly identifies only around 47% of all class 1 instances.
7. The F1 score for class 1 serves as a balanced metric, considering both precision and recall, offering a comprehensive view of the model's performance.

   In summary, while the model shows overall accuracy, it requires improvement in correctly identifying class 1 instances. It excels in avoiding false positives but falls short in capturing all actual positive cases. Further optimization is necessary to enhance its performance, particularly in classifying instances belonging to class 1.