Vidyavardhini's College of Engineering & Technology Department of Computer Engineering

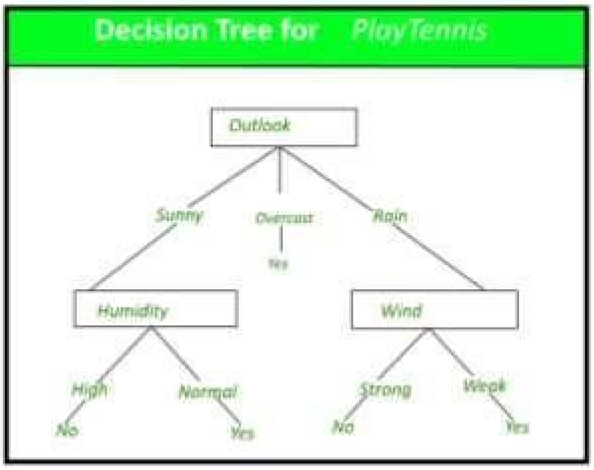
Experiment No. 3
Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:
Date of Submission:

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:

```
import os

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

adult_dataset_path = "../input/adult_dataset.csv"

def load_adult_data(adult_path=adult_dataset_path):

    csv_path = os.path.join(adult_path)

    return pd.read_csv(csv_path)
```

df = load_adult_data()

df.head(3)

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.loss	hours.per.week
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Female	0	4356	40
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	4356	18
2	66	?	186061	Some-college	10	Widowed	?	Unmarried	Black	Female	0	4356	40

df = df[df['workclass'] !='?']

df.head()

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.loss	hours.per.week
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	4356	18
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Female	0	3900	40
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child	White	Female	0	3900	40
5	34	Private	216864	HS-grad	9	Divorced	Other-service	Unmarried	White	Female	0	3770	45
6	38	Private	150601	10th	6	Separated	Adm-clerical	Unmarried	White	Male	0	3770	40

df = df[df['occupation'] !='?']

df = df[df['native.country'] !='?']

from sklearn import preprocessing

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

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.head()

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

df['income'] = df['income'].astype('category')

from sklearn.model_selection import train_test_split

X = df.drop('income',axis=1)

y = df['income']

X.head(3)

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

```
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.30,random_state=99)

from sklearn.tree import DecisionTreeClassifier

dt_default = DecisionTreeClassifier(max_depth=5)

dt_default.fit(X_train,y_train)

from sklearn.metrics import
classification_report,confusion_matrix,accuracy_score

y_pred_default = dt_default.predict(X_test)

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
```

```
print(confusion_matrix(y_test,y_pred_default))

print(accuracy_score(y_test,y_pred_default))
```

```
[[6553  314]
 [1038 1144]]
0.8505912255497845
```

from IPython.display import Image

from sklearn.externals.six import StringIO

from sklearn.tree import export_graphviz

import graphviz

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']
```

Tuning max_depth

from sklearn.model_selection import KFold

from sklearn.model_selection import GridSearchCV

n_folds = 5

parameters = {'max_depth': range(1, 40)}

dtree = DecisionTreeClassifier(criterion = "gini",random_state = 100)

```
tree = GridSearchCV(dtree, parameters,cv=n_folds,scoring="accuracy")

tree.fit(X_train, y_train)
```

Tuning min_samples_leaf

```
from sklearn.model_selection import KFold

from sklearn.model_selection import GridSearchCV

n_folds = 5

parameters = {'min_samples_leaf': range(5, 200, 20)}

dtree = DecisionTreeClassifier(criterion = "gini",random_state = 100)

tree = GridSearchCV(dtree, parameters cv=n_folds, scoring="accuracy")

tree.fit(X_train, y_train)
```

Tuning min_samples_split

```
from sklearn.model_selection import KFold

from sklearn.model_selection import GridSearchCV

n_folds = 5

parameters = {'min_samples_split': range(5, 200, 20)}

dtree = DecisionTreeClassifier(criterion = "gini", random_state = 100)

tree = GridSearchCV(dtree, parameters, cv=n_folds, scoring="accuracy")
```

tree.fit(X_train, y_train)

Grid Search to Find Optimal Hyperparameters

```
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
dtree = DecisionTreeClassifier()
grid_search = GridSearchCV(estimator = dtree, param_grid = param_grid,cv = n_folds, verbose = 1)
grid_search.fit(X_train,y_train)
print("best accuracy", grid_search.best_score_)
print(grid_search.best_estimator_)
```

best accuracy 0.8514659214701843

```
# 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)

clf_gini.score(X_test,y_test)
```

Accuracy: 0.850922753895458

```
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)

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

0.8393192617968837

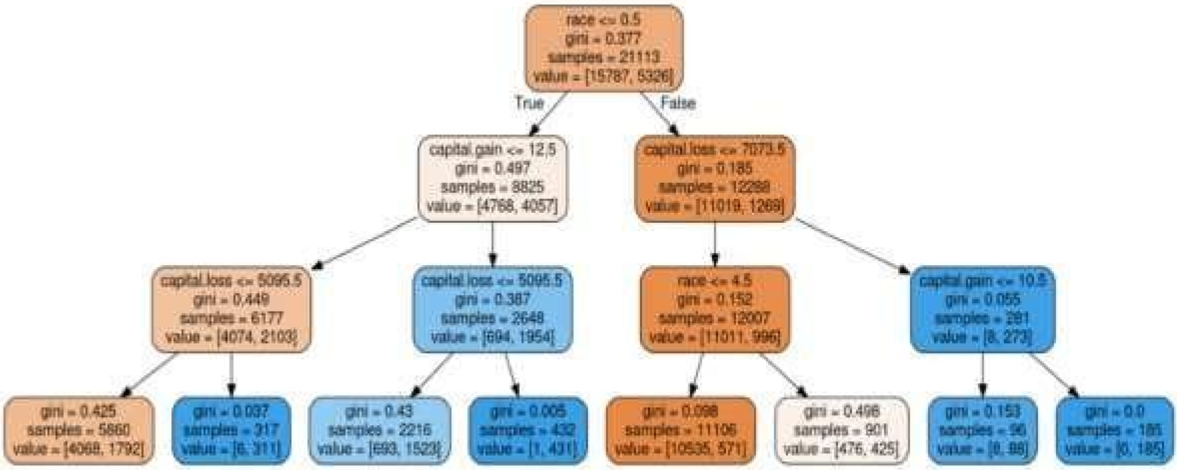
```
dot_data = StringIO()

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())
```

#Decision Tree Considering max_depth = 3



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
```

print(confusion_matrix(y_test,y_pred))

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

Conclusion:

1. 1. By using the Label Encoder technique, categorical attributes have been transformed from their original text-based representations into numerical representations by assigning a unique integer to each unique categorical value within each column. This makes it possible to use these categorical variables in machine learning algorithms that require numerical input.
2. Hyper-parameter tuning done based on the decision tree obtained:
   ● Max Depth: This parameter restricts the depth of the decision tree, preventing it from becoming too complex and overfitting the training data.
   ● Min Samples Split: This parameter sets the minimum number of samples required in a node to be eligible for further splitting. It helps prevent the tree from making overly specific decisions based on a small number of instances.
   ● Min Samples Leaf: This parameter sets the minimum number of samples to be in a leaf node. Similar to min samples split, this can prevent the tree from creating nodes with very few instances.
   ● Criterion: This parameter defines the function used to measure the quality of a split. "Gini impurity" and "entropy" are common criteria.
   3. The accuracy of the model is approximately 84%. This means that the model correctly predicted the class labels for 84% of the instances in the test dataset.
   4. True Positive (TP): 1031, True Negative (TN): 6564, False Positive (FP): 303, False Negative (FN): 1151. The confusion matrix indicates that the model is performing well in predicting class 0 (high true negatives and true positives), but it struggles with class 1 prediction (high false negatives).
   5. The precision for class 1 is relatively good, indicating that when the model predicts class 1, it's often correct. For class 1, the precision is approximately 0.77, indicating that out of all instances predicted as class 1, around 77% are actually class 1.
   6. The recall for class 1 is lower, suggesting that the model misses a significant number of actual class 1 instances. For class 1, the recall is approximately 0.47. This means that the model was able to correctly identify only about 47% of all actual instances that belong to class 1.
   7. The F1 score for class 1 is in between precision and recall, providing a balanced view of the model's performance.