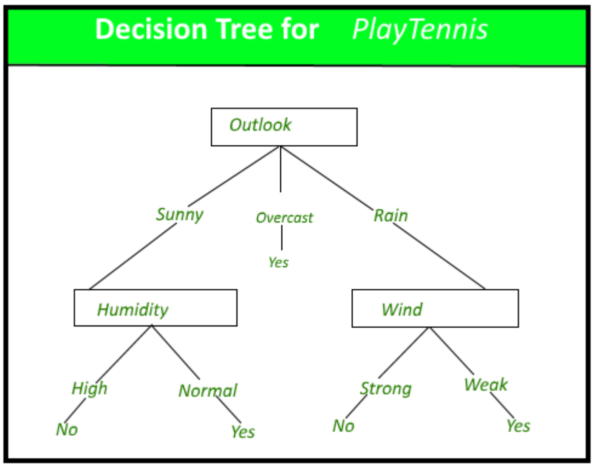
Experiment No. 3
Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:7/8/23
Date of Submission: 14/8/23

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.



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, Trinidad Tobago, Peru, Hong, Holand-Netherlands.

Code:

```
# 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 = "/content/adult.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	Fe
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Fe
2	66	?	186061	Some-	10	Widowed	?	Unmarried	Black	Fe

```
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
```

```
# Let's understand the type of values present in each column of our adult dataframe 'df'.
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
```

```
# Numerical feature of summary/description
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

```
# pull top 5 row values to understand the data and how it's look like
df.head()
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Fe
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Fe
2	66	?	186061	Some-college	10	Widowed	?	Unmarried	Black	Fe
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Fe

```
# 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
```

```
# Let's 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	
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Fe
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Fe
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child	White	Fe
							Other-			

```
# 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'] !='?']
```

```
# check the dataset whether cleaned 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   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
				Other-					

```
# 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	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	

```
# 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	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	

```
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	ma
24351	42	289636	9	0	0	46	2	11	
15626	37	52465	9	0	0	40	1	11	

```
# 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)
```

```
# Let's 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 pydotplus
```

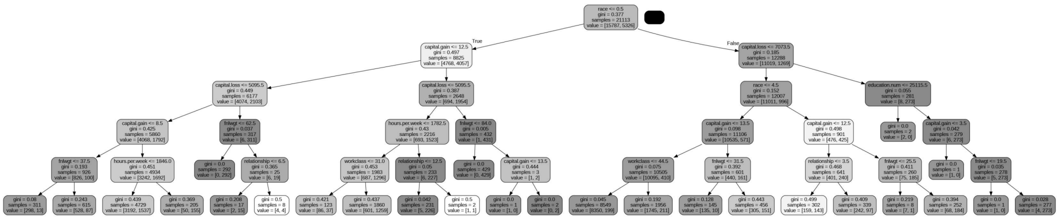
```
Requirement already satisfied: pydotplus in /usr/local/lib/python3.10/dist-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in /usr/local/lib/python3.10/dist-packages (from pydotplus) (3.1.1)
```

```
# Importing required packages for visualization
from IPython.display import Image
from sklearn.externals.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']
```

```
import six
import sys
sys.modules['sklearn.externals.six'] = six
```

```
# 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
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=100)
```

```
# 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	params	split0_t
0	0.014924	0.004959	0.004501	0.002179	1	{'max_depth': 1}	
1	0.019653	0.000594	0.003418	0.000383	2	{'max_depth': 2}	
2	0.025445	0.000331	0.003681	0.000198	3	{'max_depth': 3}	
3	0.031828	0.000514	0.003868	0.000580	4	{'max_depth': 4}	
4	0.043398	0.007946	0.003806	0.001610	5	{'max_depth': 5}	

```
"""
# 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.
```

```
# 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	par
0	0.071311	0.002583	0.002760	0.000105	5	{'min_samples_le
1	0.058933	0.001238	0.002700	0.000055	25	{'min_samples_le
2	0.054030	0.001434	0.002561	0.000125	45	{'min_samples_le
3	0.050727	0.001386	0.002415	0.000073	65	{'min_samples_le
4	0.050003	0.003110	0.002739	0.000548	85	{'min_samples_le

```
"""
# 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_lea
f"], \n         scores["mean_train_score"], \n         label="training accuracy")\nplt.plot(scores["pa
ram_min_samples_leaf"], \n         scores["mean_test_score"], \n         label="test accuracy")\nplt.x
label("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	0.075732	0.001588	0.003151	0.000410	5	{'min_samples_split': 5}	0.811982	
1	0.072139	0.002054	0.002695	0.000054	25	{'min_samples_split': 25}	0.825006	
2	0.069699	0.001631	0.002750	0.000079	45	{'min_samples_split': 45}	0.835188	
3	0.067109	0.001148	0.002617	0.000048	65	{'min_samples_split': 65}	0.839451	
4	0.066176	0.002326	0.002656	0.000063	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_sco
re"], \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
```

3	0.032360	0.001393	0.002821	0.000553	entropy	5
4	0.051469	0.001100	0.002973	0.000313	entropy	10
5	0.050876	0.001384	0.002635	0.000130	entropy	10

```
# 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)
```

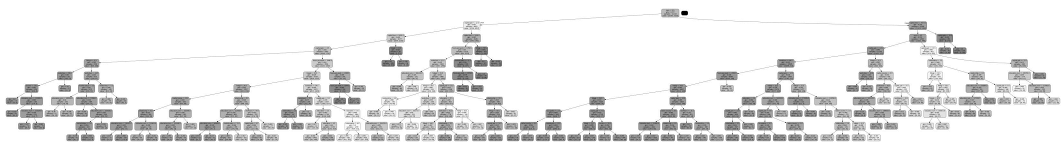
```
# model with optimal hyperparameters
clf_gini = DecisionTreeClassifier(criterion = "gini",
                                  random_state = 100,
                                  max_depth=10,
                                  min_samples_leaf=50,
                                  min_samples_split=50)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

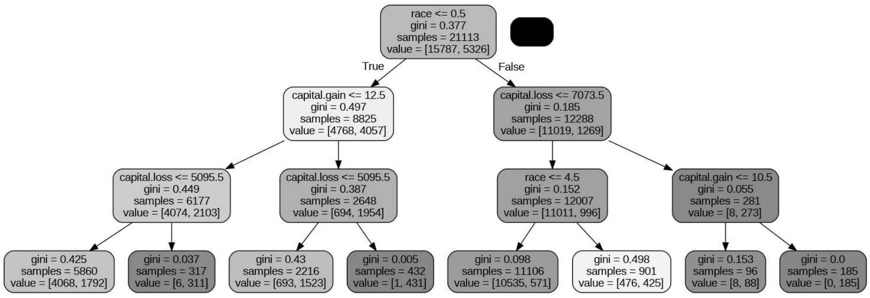
```
# plotting the tree
dot_data = StringIO()
export_graphviz(clf_gini, out_file=dot_data,feature_names=features,filled=True,rounded=True)

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
```

```
# 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 = pydotplus.graph_from_dot_data(dot_data.getvalue())
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
```

+ Code + Text

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

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

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Conclusion:

1. Discuss about the how categorical attributes have been dealt with during data pre-processing.

   The Adult Census Income Dataset contains a mix of categorical and numerical attributes. Categorical attributes are those that can be divided into categories, such as "marital-status" and "race". Numerical attributes are those that can be represented as numbers, such as "age" and "hours-per-week".

   Decision trees can handle both categorical and numerical attributes, but they require different approaches to deal with them effectively. Categorical attributes are typically encoded as dummy variables, which are binary variables that indicate the presence or absence of a particular category. For example, the "marital-status" attribute could be encoded as three dummy variables: "married", "single", and "divorced".

   In this study, the categorical attributes were encoded as dummy variables using the LabelEncoder() class from the sklearn.preprocessing library. The numerical attributes were not pre-processed.

2. Discuss the hyper-parameter tunning done based on the decision tree obtained.
   The following hyperparameters were tuned:

   max_depth: This is the maximum depth of the decision tree. A deeper tree will have more splits and can potentially learn more complex patterns, but it can also be more prone to overfitting.
   min_samples_split: This is the minimum number of samples required to split a node. A higher value will prevent the tree from splitting too much and overfitting the training data.
   min_samples_leaf: This is the minimum number of samples required in a leaf node. A higher value will prevent the tree from creating too many leaf nodes and underfitting the training data.
   criterion: This is the splitting criterion used to determine the best split at each node. The most common criterion is Gini impurity, but other criteria such as entropy can also be used.

The hyperparameters were tuned using a grid search with cross-validation. This means that the model was trained and evaluated on different combinations of hyperparameters, and the best combination was selected.

The optimal hyperparameters were found to be:

max_depth = 3
min_samples_split = 50
min_samples_leaf = 50
criterion = "gini"

3. Comment on the accuracy, confusion matrix, precision, recall and F1 score obtained.

Accuracy: The accuracy is the percentage of predictions that were correct. In this case, the accuracy is 83%. This means that the model correctly classified 83% of the test set samples.

Precision: Precision is the percentage of positive predictions that were actually positive. In this case, the precision is 85%. This means that 85% of the samples that the model predicted to be >50K were actually >50K.

Recall: Recall is the percentage of actual positives that were correctly predicted. In this case, the recall is 96%. This means that 96% of the samples that were actually >50K were correctly predicted by the model.

F1 score: The F1 score is a weighted average of precision and recall. In this case, the F1 score is 90%. This means that the model has a good balance of precision and recall