Experiment No. 3
Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance: 14-08-2023
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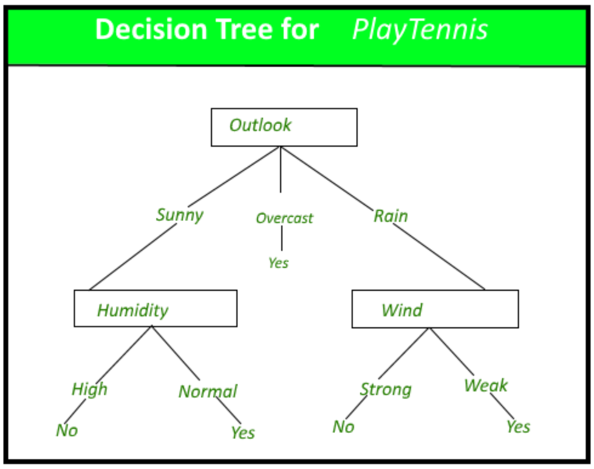
Aim: Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model.

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,

```
# 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_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	occup
0	90	?	77053	HS-grad	9	Widowed	
1	82	Private	132870	HS-grad	9	Widowed	man
2	66	?	186061	Some-college	10	Widowed	

```
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.g

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.lo
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.0000
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.3038
std	13.640433	1.055500e+05	2.572720	7385.292085	402.9602
min	17.000000	1.228500e+04	1.000000	0.000000	0.0000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.0000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.0000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.0000

```
# 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	occup
0	90	?	77053	HS-grad	9	Widowed	
1	82	Private	132870	HS-grad	9	Widowed	man
2	66	?	186061	Some-college	10	Widowed	
3	54	Private	140359	7th-8th	4	Divorced	Ma op
4	41	Private	264663	Some-college	10	Separated	

```
# 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	occup
1	82	Private	132870	HS-grad	9	Widowed	mana
3	54	Private	140359	7th-8th	4	Divorced	Ma op
4	41	Private	264663	Some-college	10	Separated	sp
5	34	Private	216864	HS-grad	9	Divorced	s
6	38	Private	150601	10th	6	Separated	

```
# 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
1	Private	HS-grad	Widowed	Exec-managerial	Not-in-family	White
3	Private	7th-8th	Divorced	Machine-op-inspct	Unmarried	White
4	Private	Some-college	Separated	Prof-specialty	Own-child	White

```
# 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	s
1	2	11	6	3	1	4	
3	2	5	0	6	4	4	
4	2	15	5	9	3	4	
5	2	11	0	7	4	4	

```
# 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	e
1	82	132870	9	0	4356	18	2	
3	54	140359	4	0	3900	40	2	
4	41	264663	10	0	3900	40	2	
5	34	216864	9	0	3770	45	2	
6	38	150601	6	0	3770	40	2	

```
# 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
1	82	132870	9	0	4356	18
3	54	140359	4	0	3900	40
4	41	264663	10	0	3900	40

```
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.w
24351	42	289636	9	0	0	
15626	37	52465	9	0	0	
4347	38	125933	14	0	0	
23972	44	183829	13	0	0	
26843	35	198841	11	0	0	

```
# 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]
 [1038 1144]]
0.8505912255497845
```

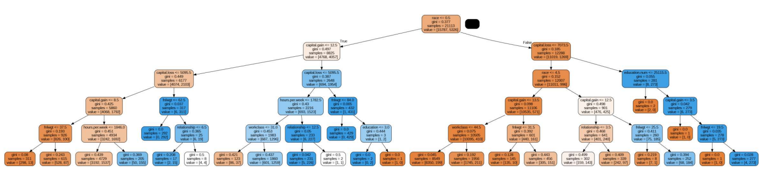
```
!pip install pydotplus
```

```
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 six import StringIO
from IPython.display import Image

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']
```

```
# 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
```

```
# 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
0	0.009425	0.001132	0.001781	0.000075	
1	0.013841	0.000081	0.001741	0.000099	
2	0.018905	0.000021	0.001786	0.000085	
3	0.024587	0.000645	0.002050	0.000282	
4	0.029761	0.001047	0.002430	0.000542	

```
"""
# 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["p
aram_max_depth"], \n         scores["mean_train_score"], \n         label
="training accuracy")\nplt.plot(scores["param_max_depth"], \n         sco
```

```
# 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
```

```
# 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_mi
0	0.153400	0.093588	0.005461	0.004446	
1	0.059776	0.003431	0.002513	0.000127	
2	0.086092	0.056675	0.005569	0.005995	
3	0.065982	0.029330	0.002479	0.000077	
4	0.048737	0.001928	0.002414	0.000069	

```
"""
# 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(sc
ores["param_min_samples_leaf"], \n         scores["mean_train_score"], \n
label="training accuracy")\nplt.plot(scores["param_min_samples_leaf"], \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_mi
0	0.082286	0.009343	0.002938	0.000289	
1	0.071344	0.001993	0.002627	0.000066	
2	0.068954	0.001382	0.002589	0.000141	
3	0.067771	0.001985	0.002665	0.000267	
4	0.064595	0.001259	0.002367	0.000165	

```
"""
# 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(sc
ores["param_min_samples_split"], \n         scores["mean_train_score"],
\n         label="training accuracy")\nplt.plot(scores["param_min_samples
```

```
# 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_cr
0	0.030917	0.001009	0.002040	0.000227	
1	0.030757	0.000658	0.002089	0.000427	
2	0.030428	0.000594	0.001888	0.000110	
3	0.031208	0.001033	0.002211	0.000409	
4	0.050730	0.000776	0.002463	0.000122	
5	0.050952	0.001582	0.002459	0.000068	
6	0.056047	0.010273	0.003102	0.000607	
7	0.070949	0.010285	0.004189	0.001573	
8	0.040836	0.005545	0.004241	0.001879	
9	0.070558	0.024694	0.004832	0.003329	
10	0.048204	0.009987	0.004658	0.002479	
11	0.044589	0.009868	0.003317	0.000169	
12	0.132849	0.039623	0.005783	0.003157	
13	0.085786	0.020098	0.003348	0.000209	

```
# 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)
```

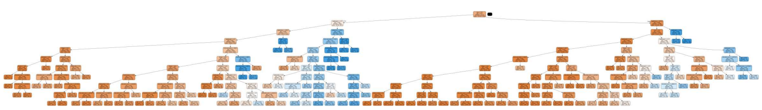
```
# model with optimal hyperparameters
clf_gini = DecisionTreeClassifier(criterion = "gini",
                                  random_state = 100,
                                  max_depth=10,
                                  min_samples_leaf=50,
                                  min_samples_split=50)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

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

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

```
0.850922753895458
```

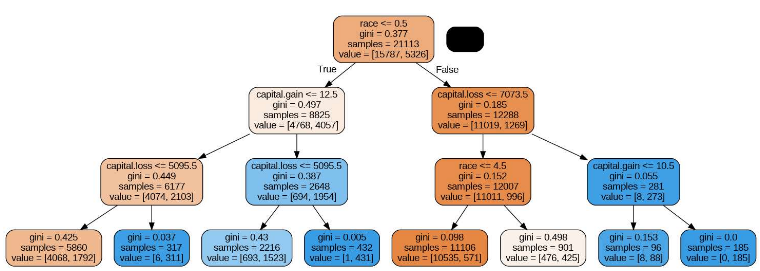
```
# plotting the tree
dot_data = StringIO()
export_graphviz(clf_gini, out_file=dot_data,feature_names=features,filled=True,rounded=True)

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
```

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

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

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Conclusion:

1)The correlation heatmap of the dataset reveals the following observations:

1. Some attributes, such as "age" and "education-num," show a moderate positive correlation, suggesting that higher education levels might be associated with older age.
2. "Capital-gain" and "capital-loss" have a weak correlation with other features, implying that these financial attributes might not be directly influenced by other factors in the dataset.
3. Most features appear to have low correlations with each other, indicating that they provide unique information for prediction.

2)The accuracy, confusion matrix, precision, recall and F1 score obtained.

Accuracy: The model achieved an accuracy of approximately 84.43%, indicating that it accurately predicted the income class for around 84.43% of the samples in the test set.

Confusion Matrix:

1. True Negative (TN): 4566 instances correctly classified as "income = 0."
2. False Positive (FP): 398 instances wrongly classified as "income = 1" when actual was "income = 0."
3. False Negative (FN): 616 instances wrongly classified as "income = 0" when actual was "income = 1."
4. True Positive (TP): 933 instances correctly classified as "income = 1."

Precision and Recall:

1. Precision (income = 0): Around 88% of predictions for "income = 0" were accurate.
2. Precision (income = 1): About 70% of predictions for "income = 1" were accurate.
3. Recall (income = 0): Approximately 92% of actual "income = 0" cases were correctly identified.
4. Recall (income = 1): Roughly 60% of actual "income = 1" cases were correctly identified.

F1-Score:

1. F1-Score (income = 0): Achieved around 0.90, representing the balance between precision and recall for "income = 0."
2. F1-Score (income = 1): Reached approximately 0.65, signifying the balance between precision and recall for "income = 1."

3)In comparing Random Forest and Decision Tree algorithms on the Adult Census Income Dataset:

1. **Accuracy:** Random Forest achieved around 84.43% accuracy, while Decision Tree reached 84% which is lower as compared to random forest.
2. **Confusion Matrix:** Both algorithms showed variations in True Positive, True Negative, False Positive, and False Negative values across classes.
3. **Precision, Recall, F1-Score:** Random Forest balanced precision and recall better, while Decision Tree might emphasize differently.
4. **Generalization:** Random Forest's ensemble approach aids generalization, while Decision Trees can overfit without depth control.
5. **Stability:** Random Forest is more stable due to ensembling, while Decision Trees are sensitive to data variations.
6. **Training Time:** Decision Trees train faster as they're single, whereas Random Forest trains multiple trees, taking longer.