PRODIGY INFOTECH INTERNSHIP

TASK 3:Build a decision tree classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Use a dataset such as the Bank Marketing dataset from the UCI Machine Learning Repository.

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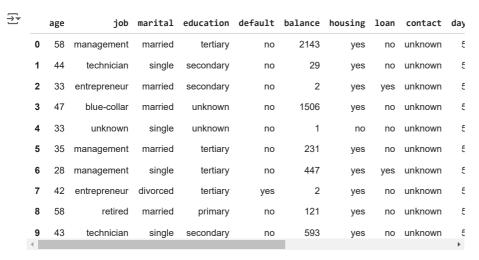
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```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier,plot_tree
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder

df=pd.read_csv('bank-full.csv', sep=';')
df
```

7		age	job	marital	education	default	balance	housing	loan	contact
	0	58	management	married	tertiary	no	2143	yes	no	unknowr
	1	44	technician	single	secondary	no	29	yes	no	unknowr
	2	33	entrepreneur	married	secondary	no	2	yes	yes	unknowr
	3	47	blue-collar	married	unknown	no	1506	yes	no	unknowr
	4	33	unknown	single	unknown	no	1	no	no	unknowr
	45206	51	technician	married	tertiary	no	825	no	no	cellulaı
	45207	71	retired	divorced	primary	no	1729	no	no	cellulaı
	45208	72	retired	married	secondary	no	5715	no	no	cellulaı
	45209	57	blue-collar	married	secondary	no	668	no	no	telephone
	45210	37	entrepreneur	married	secondary	no	2971	no	no	cellulaı
	45211 rows × 17 columns									
	4									>

df.head(10)

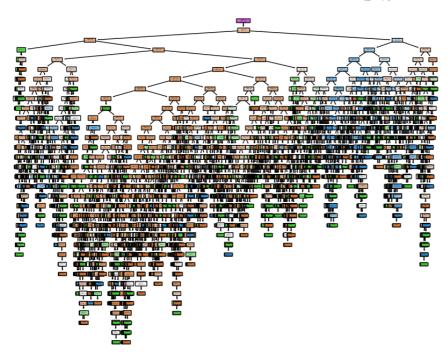


df.isna().sum()

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     education
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     default
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     balance
     housing
     loan
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    day
                   0
    month
    duration
                   0
                   0
     campaign
     pdays
                   0
     previous
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poutcome
                  0
     dtype: int64
df.dropna(inplace=True)
df_1=df.drop_duplicates()
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     [45211 rows x 17 columns]>
#Preprocess the data
X=df.drop('poutcome', axis=1)
v=df['poutcome']
X=pd.get_dummies(X)
X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.2, random_state=42)
#Create the classifier
clf=DecisionTreeClassifier()
#Train the classifier
clf.fit(X_train, y_train)
#Make predictions
y_pred=clf.predict(X_test)
#Calculate accuracy
accuracy=accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
Accuracy: 0.9183899148512662
#Visualize the decision tree
plt.figure(figsize=(10,8))
\verb|plot_tree(clf,feature_names=list(X.columns), class_names=df['education'].unique().tolist(),filled=True,rounded=True)|
```





#Create the classsifier with pruning enabled
clf=DecisionTreeClassifier(ccp_alpha=0.01)
#Train the classifier
clf.fit(X_train,y_train)
#Make predictions
y_pred=clf.predict(X_test)
#Calculate accuracy
accuracy=accuracy_score(y_test,y_pred)
print("Accuracy:",accuracy)

→ Accuracy: 0.928674112573261

#Visualize the pruned decision tree
plt.figure(figsize=(10,8))
plot_tree(clf,feature_names=list(X.columns),class_names=df['education'].unique().tolist(),filled=True,rounded=True)
plt.show()



