Forward School

Program Code: J620-002-4:2020

Program Name: FRONT-END SOFTWARE DEVELOPMENT

Title : Exe19 - Decision Tree Exercise 1

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Date :

Introduction :

Conclusion :

Section 1

Reference: [https://www.kaggle.com/vinicius150987/bank-full-machine-learning/notebook (https://www.kaggle.com/vinicius150987/bank-full-machine-learning/notebook)](https://www.kaggle.com/vinicius150987/bank-full-machine-learning/notebook)

Decision Tree

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import plotly.graph_objects as go
import plotly.express as px
```

Read "bank-full.csv"

In [2]:
```
df = pd.read_csv("../Data files/bank-full.csv",delimiter=";")
df
```

Out[2]:

	age	job	marital	education	default	balance	housing	loan	contact	day	m
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	
1	44	technician	single	secondary	no	29	yes	no	unknown	5	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	
4	33	unknown	single	unknown	no	1	no	no	unknown	5	
...	...	...	...	...	...	...	...	...	...	...	
45206	51	technician	married	tertiary	no	825	no	no	cellular	17	
45207	71	retired	divorced	primary	no	1729	no	no	cellular	17	
45208	72	retired	married	secondary	no	5715	no	no	cellular	17	
45209	57	blue-collar	married	secondary	no	668	no	no	telephone	17	
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	

45211 rows × 17 columns

Check the distribution of labels (‘yes’, ‘no’) are distributed.

In [3]:
```
yesdist = len(df[df['y']=='yes'])
nodist = len(df[df['y']=='no'])
print(yesdist,nodist)
labels = ["Yes", "No"]
values = [yesdist, nodist]
fig = go.Figure(data=[
    go.Bar(x=['Yes', 'No'], y=values)
])

# Add labels and title to the graph
fig.update_layout(
    title='Number of "Yes" and "No" Responses',
    xaxis_title='Responses',
    yaxis_title='Count'
)

# Display the graph
fig.show()
```

```
5289 39922
```

In [ ]:

Counts of "yes" and "no" with "age"

In [4]:
```
df.groupby('age')['y'].value_counts()
```

Out[4]:
```
age  y  
18   yes     7
     no      5
19   no     24
     yes    11
20   no     35
            ..
92   yes     2
93   yes     2
94   no      1
95   no      1
     yes     1
Name: y, Length: 148, dtype: int64
```

Correlation between the data

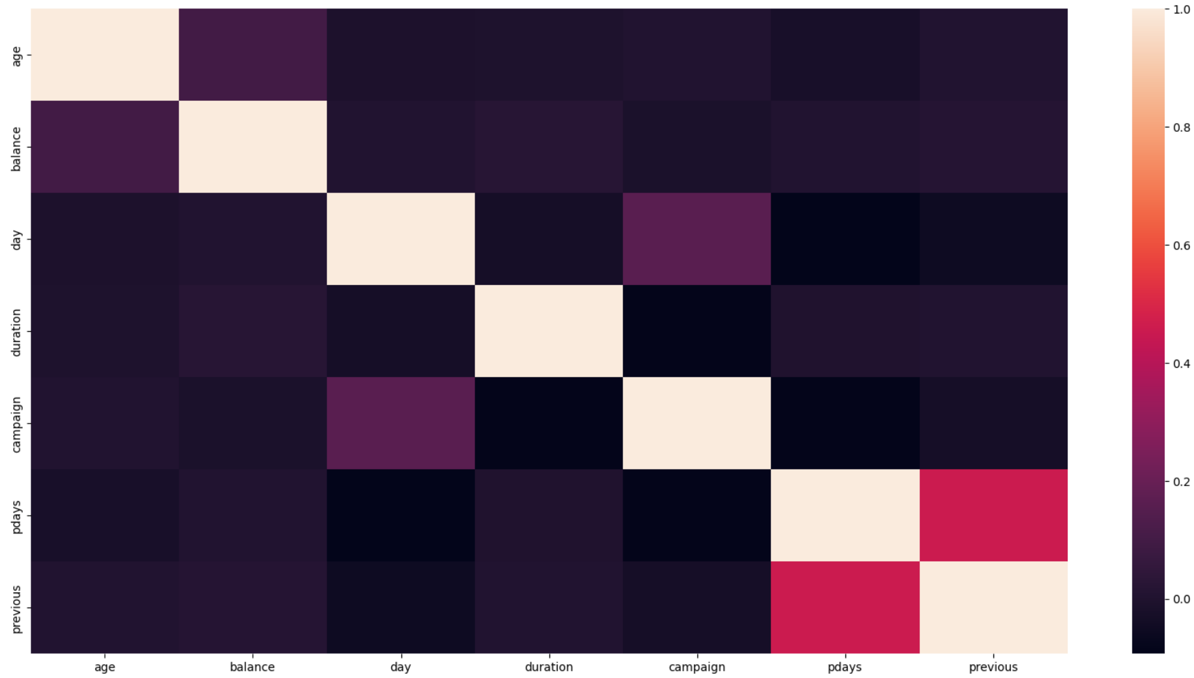
In [5]:
```
cor=df.corr(numeric_only=True)
cor
```

Out[5]:

	age	balance	day	duration	campaign	pdays	previous
age	1.000000	0.097783	-0.009120	-0.004648	0.004760	-0.023758	0.001288
balance	0.097783	1.000000	0.004503	0.021560	-0.014578	0.003435	0.016674
day	-0.009120	0.004503	1.000000	-0.030206	0.162490	-0.093044	-0.051710
duration	-0.004648	0.021560	-0.030206	1.000000	-0.084570	-0.001565	0.001203
campaign	0.004760	-0.014578	0.162490	-0.084570	1.000000	-0.088628	-0.032855
pdays	-0.023758	0.003435	-0.093044	-0.001565	-0.088628	1.000000	0.454820
previous	0.001288	0.016674	-0.051710	0.001203	-0.032855	0.454820	1.000000

Plot the heatmap

In [6]:
```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(20,10))
sns.heatmap(cor)
plt.show()
```



Convert categorical data into numerical

In [7]:
```
replace_response = {'yes': 1, 'no': 0}
df = df.replace({'default': replace_response, 'housing': replace_response, 'loa
                 'y': replace_response,})
replace_marital = {'single': 1, 'married': 2, 'divorced': 3}
df['marital'] = df['marital'].replace(replace_marital)
replace_education = {'primary': 1, 'secondary': 2, 'tertiary': 3, 'unknown': No
df['education'] = df['education'].replace(replace_education)
replace_contact = {'telephone': 1, 'cellular': 2, 'unknown': None}
df['contact'] = df['contact'].replace(replace_contact)
df
```

Out[7]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mont
0	58	management	2	3.0	0	2143	1	0	NaN	5	ma
1	44	technician	1	2.0	0	29	1	0	NaN	5	ma
2	33	entrepreneur	2	2.0	0	2	1	1	NaN	5	ma
3	47	blue-collar	2	NaN	0	1506	1	0	NaN	5	ma
4	33	unknown	1	NaN	0	1	0	0	NaN	5	ma
...	...	...	...	...	...	...	...	...	...	...	
45206	51	technician	2	3.0	0	825	0	0	2.0	17	nc
45207	71	retired	3	1.0	0	1729	0	0	2.0	17	nc
45208	72	retired	2	2.0	0	5715	0	0	2.0	17	nc
45209	57	blue-collar	2	2.0	0	668	0	0	1.0	17	nc
45210	37	entrepreneur	2	2.0	0	2971	0	0	2.0	17	nc

45211 rows × 17 columns

Next step is to select features and labels

In [8]:
```
da = df.copy()
da.dropna(subset=['education', 'contact'], inplace=True)
feature_cols = ['age', 'marital', 'education', 'balance', 'housing', 'loan', 'c
X = da[feature_cols]
y = da.y
```

Drop "poutcome"

In [9]:
```
del df['poutcome']
df
```

Out[9]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mont
0	58	management	2	3.0	0	2143	1	0	NaN	5	ma
1	44	technician	1	2.0	0	29	1	0	NaN	5	ma
2	33	entrepreneur	2	2.0	0	2	1	1	NaN	5	ma
3	47	blue-collar	2	NaN	0	1506	1	0	NaN	5	ma
4	33	unknown	1	NaN	0	1	0	0	NaN	5	ma
...	...	...	...	...	...	...	...	...	...	...	
45206	51	technician	2	3.0	0	825	0	0	2.0	17	nc
45207	71	retired	3	1.0	0	1729	0	0	2.0	17	nc
45208	72	retired	2	2.0	0	5715	0	0	2.0	17	nc
45209	57	blue-collar	2	2.0	0	668	0	0	1.0	17	nc
45210	37	entrepreneur	2	2.0	0	2971	0	0	2.0	17	nc

45211 rows × 16 columns

Split the data into train and test

In [10]:
```
# Target variable
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree Classifi
from sklearn.model_selection import train_test_split # Import train_test_split
from sklearn import metrics,tree
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, randon
```

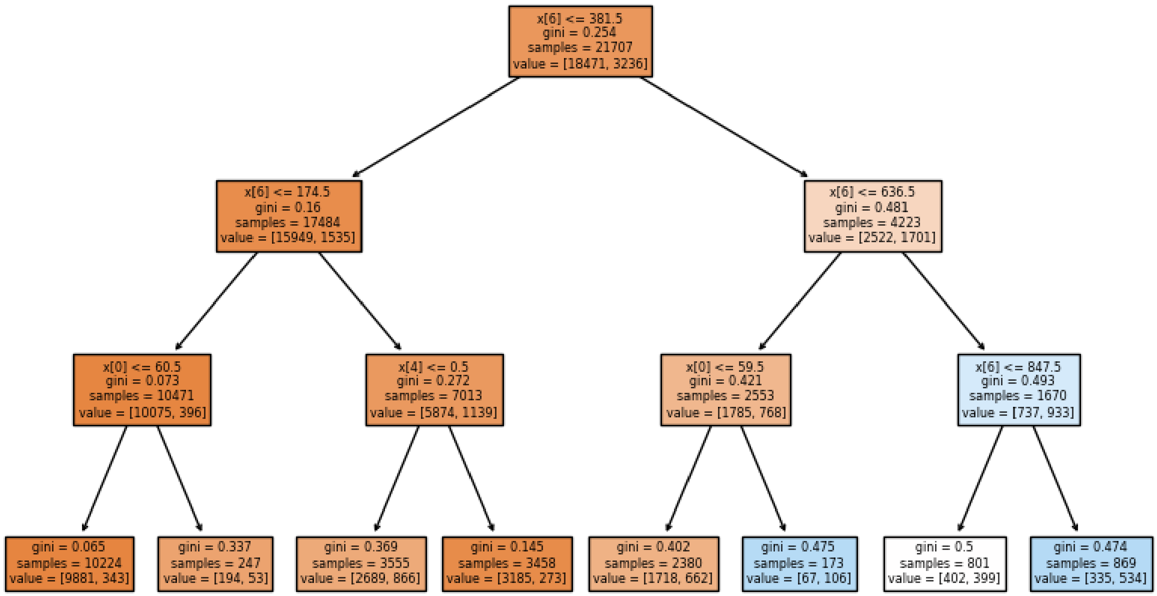
Applying Decision Tree Classifier:

Next, I created a pipeline of StandardScaler (standardize the features) and DT Classifier (see a note below regarding Standardization of features). We can import DT classifier as from sklearn.tree import DecisionTreeClassifier from Scikit-Learn. To determine the best parameters (criterion of split and maximum tree depth) for DT classifier, I also used Grid Search Cross Validation. The code snippet below is self-explanatory.

In [11]:
```
# Create Decision Tree classifer object
clf = DecisionTreeClassifier(max_depth =3)
clf = clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
```

To display

In [12]:
```
plt.figure(figsize=(10,6))
tree.plot_tree(clf,filled=True)
plt.show()
```



The number of nodes and the maximum depth

In [13]:
```
print(clf.tree_.node_count,clf.tree_.max_depth)
```

```
15 3
```

Accuracy measurement

In [14]:
```
# Model Accuracy, how often is the classifier correct?
metrics.accuracy_score(y_test,y_pred)
```

Out[14]:
```
0.869518486672399
```

Prediction

In [15]:
```
y_pred
```

Out[15]:
```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

Grid Search

In [16]:
```
# from sklearn.metrics import confusion_matrix
# print(confusion_matrix(y_test,y_pred))
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline

pipe = Pipeline(steps=[('dec_tree',clf)])
criterion = ['gini','entropy']
max_depth = [2,4,6,8,10,12]
parameters = dict(dec_tree__criterion = criterion,dec_tree__max_depth=max_deptł
grid_search = GridSearchCV(pipe,parameters)
grid_search.fit(X_train,y_train)
```

Out[16]:
```
GridSearchCV(estimator=Pipeline(steps=[('dec_tree',
                                        DecisionTreeClassifier(max_depth=
3))]),
             param_grid={'dec_tree__criterion': ['gini', 'entropy'],
                         'dec_tree__max_depth': [2, 4, 6, 8, 10, 12]})
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Display the best features

In [17]:
```
for feature, importance in zip(feature_cols,clf.feature_importances_):
    print(f"{feature}:{importance}")
```

```
age:0.0472818139419897
marital:0.0
education:0.0
balance:0.0
housing:0.08656876612385284
loan:0.0
duration:0.8661494199341575
campaign:0.0
```

Run DecisionTreeClassifier using the obtained features

In [18]:
```
optimized_classifier = DecisionTreeClassifier(criterion='gini',max_depth=2)
optimized_classifier.fit(X_train,y_train)
```

Out[18]:
```
DecisionTreeClassifier(max_depth=2)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Concat train test results

In [19]:
```
y_pred_train = optimized_classifier.predict(X_train)
y_pred_test = optimized_classifier.predict(X_test)
y_pred_train = y_pred_train.reshape(len(y_pred_train),1)
y_pred_test = y_pred_test.reshape(len(y_pred_test),1)
print('train result')
print(np.concatenate((y_pred_train,y_train.to_numpy().reshape(len(y_train),1)),
print('test result')
print(np.concatenate((y_pred_test,y_test.to_numpy().reshape(len(y_test),1)),1)
```

```
train result
[[0 0]
 [0 0]
 [1 1]
 ...
 [0 0]
 [0 0]
 [0 0]]
test result
[[0 0]
 [0 0]
 [0 0]
 ...
 [0 0]
 [0 0]
 [0 0]]
```

Section 2

1. Read "petrol_consumption.csv" file

In [20]:
```
petrol_df = pd.read_csv('../Data files/petrol_consumption.csv')
```

2. Display the first 5 records

In [21]:
```
petrol_df.head()
```

Out[21]:

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol_Consumptio
0	9.0	3571	1976	0.525	54
1	9.0	4092	1250	0.572	52
2	9.0	3865	1586	0.580	56
3	7.5	4870	2351	0.529	41
4	8.0	4399	431	0.544	41

4. Identify the label (Petrol_Consumption)

In [22]:
```
petrol_df['Petrol_Consumption']
```

Out[22]:
```
0     541
1     524
2     561
3     414
4     410
5     457
6     344
7     467
8     464
9     498
10    580
11    471
12    525
13    508
14    566
15    635
16    603
17    714
18    865
19    640
20    649
21    540
22    464
23    547
24    460
25    566
26    577
27    631
28    574
29    534
30    571
31    554
32    577
33    628
34    487
35    644
36    640
37    704
38    648
39    968
40    587
41    699
42    632
43    591
44    782
45    510
46    610
47    524
Name: Petrol_Consumption, dtype: int64
```

5. Identify the features.

In [23]:
```
petrol_features = petrol_df.columns.to_list()
petrol_features
```

Out[23]:
```
['Petrol_tax',
 'Average_income',
 'Paved_Highways',
 'Population_Driver_licence(%)',
 'Petrol_Consumption']
```

6. Use of describe method to describe the dataset.

In [24]:
```
petrol_df.describe()
```

Out[24]:

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol_Consum
count	48.000000	48.000000	48.000000	48.000000	48.0
mean	7.668333	4241.833333	5565.416667	0.570333	576.7
std	0.950770	573.623768	3491.507166	0.055470	111.8
min	5.000000	3063.000000	431.000000	0.451000	344.0
25%	7.000000	3739.000000	3110.250000	0.529750	509.5
50%	7.500000	4298.000000	4735.500000	0.564500	568.5
75%	8.125000	4578.750000	7156.000000	0.595250	632.7
max	10.000000	5342.000000	17782.000000	0.724000	968.0

7. Display the first 5 records of the features

In [25]:
```
petrol_df[petrol_features].head()
```

Out[25]:

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol_Consumptio
0	9.0	3571	1976	0.525	54
1	9.0	4092	1250	0.572	52
2	9.0	3865	1586	0.580	56
3	7.5	4870	2351	0.529	41
4	8.0	4399	431	0.544	41

8. Split the data into training (80%) and testing (20%) sets.

In [26]:
```
X3=petrol_df[petrol_features]
y3=petrol_df.Petrol_Consumption

X3_train, X3_test, y3_train, y3_test = train_test_split(X3, y3, test_size=0.2,
```

9. Build your model and train the training data

In [27]:
```
from sklearn.tree import DecisionTreeRegressor
clf2 = DecisionTreeRegressor(max_depth =3)
clf2 = clf2.fit(X3_train,y3_train)
y_pred2 = clf2.predict(X3_test)
```

10. Prediction using the testing set

In [28]:
```
y_pred2
```

Out[28]:
```
array([640.        , 525.75      , 640.        , 640.        ,
       582.5       , 377.        , 582.5       , 582.5       ,
       705.66666667, 640.        ])
```

11. Display Actual and Predictied price side by side in df

In [29]:
```
compare_df = pd.DataFrame({'Actual': y3_test, 'Predicted': y_pred2}).reset_inde
compare_df
```

Out[29]:

	Actual	Predicted
0	628	640.000000
1	547	525.750000
2	648	640.000000
3	640	640.000000
4	561	582.500000
5	414	377.000000
6	554	582.500000
7	577	582.500000
8	782	705.666667
9	631	640.000000

12. Evaluate the model using mean_absulate_error

In [30]:
```
from sklearn.metrics import mean_absolute_error

mean_absolute_error(y3_test,y_pred2)
```

Out[30]:
```
21.908333333333334
```

13. Display the predicted output using first 5 features.

In [31]:
```
clf2.predict(X3[:5])
```

Out[31]:
```
array([525.75, 525.75, 582.5 , 377.  , 377.  ])
```