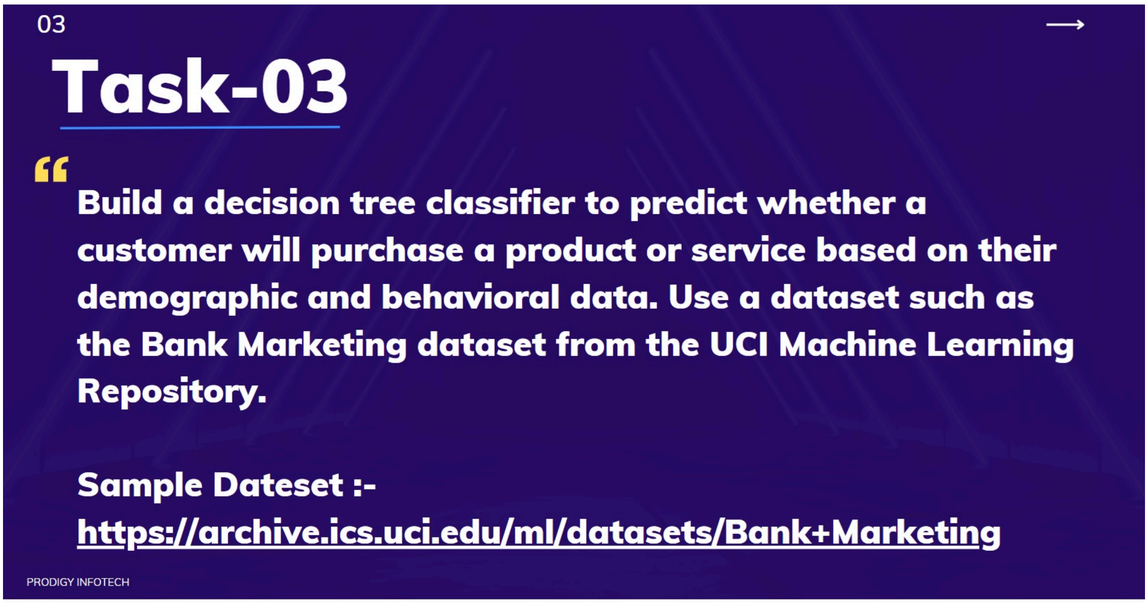
Project Name:Customer Purchase Prediction Using Decision Tree Classifier

By Mehul Chafekar



Project Introduction

- The ability to predict customer purchase behavior is a critical aspect of business success, enabling organizations to tailor marketing strategies, optimize resources, and enhance customer experiences.
- This project aims to build a Decision Tree Classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data.
- The dataset used for this project is the Bank Marketing dataset, sourced from the UCI Machine Learning Repository. It includes diverse features such as age, job type, marital status, education level, and past interactions, providing a comprehensive view of customer profiles.

Project Summary

- This project involves analyzing customer data, identifying patterns, and applying machine learning techniques to build a predictive model.
- The dataset is preprocessed to handle missing values, remove outliers, and encode categorical variables.
- Exploratory data analysis is conducted to understand feature distributions and correlations.
- Using a Decision Tree Classifier, the model predicts whether a customer will purchase a product or service.
- The model's performance is evaluated using accuracy scores, confusion matrices, and visualization of decision-making processes.

- The project also explores hyperparameter tuning to optimize the model's performance.

Business Objective

The primary objective is to assist businesses in:

- Predicting customer purchases based on their demographic and behavioral data.
- Enhancing marketing efficiency by identifying high-potential customers for targeted campaigns.
- Optimizing resources by focusing on customers most likely to convert, reducing marketing costs.
- Improving customer experience by personalizing offers and services based on predictive insights.

Importing Libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

Loading the Dataset

In [2]:
```
df= pd.read_csv('bank-additional.csv',delimiter=';')
df.rename(columns={'y':'deposit'},inplace=True)
df
```

Out[2]:

	age	job	marital	education	default	housing	loan	contact	mont
0	30	blue-collar	married	basic.9y	no	yes	no	cellular	ma
1	39	services	single	high.school	no	no	no	telephone	ma
2	25	services	married	high.school	no	yes	no	telephone	ju
3	38	services	married	basic.9y	no	unknown	unknown	telephone	ju
4	47	admin.	married	university.degree	no	yes	no	cellular	nc
...	...	...	...	...	...	...	...	...	.
4114	30	admin.	married	basic.6y	no	yes	yes	cellular	j
4115	39	admin.	married	high.school	no	yes	no	telephone	j
4116	27	student	single	high.school	no	no	no	cellular	ma
4117	58	admin.	married	high.school	no	no	no	cellular	au
4118	34	management	single	high.school	no	yes	no	cellular	nc

4119 rows × 21 columns

Understanding the Data

In [3]:
```
df.head(10)
```

Out[3]:

	age	job	marital	education	default	housing	loan	contact	mor
0	30	blue-collar	married	basic.9y	no	yes	no	cellular	m
1	39	services	single	high.school	no	no	no	telephone	m
2	25	services	married	high.school	no	yes	no	telephone	j
3	38	services	married	basic.9y	no	unknown	unknown	telephone	j
4	47	admin.	married	university.degree	no	yes	no	cellular	n
5	32	services	single	university.degree	no	no	no	cellular	s
6	32	admin.	single	university.degree	no	yes	no	cellular	s
7	41	entrepreneur	married	university.degree	unknown	yes	no	cellular	n
8	31	services	divorced	professional.course	no	no	no	cellular	n
9	35	blue-collar	married	basic.9y	unknown	no	no	telephone	m

10 rows × 21 columns

In [4]:
```
df.tail()
```

Out[4]:

	age	job	marital	education	default	housing	loan	contact	month	day_o
4114	30	admin.	married	basic.6y	no	yes	yes	cellular	jul	
4115	39	admin.	married	high.school	no	yes	no	telephone	jul	
4116	27	student	single	high.school	no	no	no	cellular	may	
4117	58	admin.	married	high.school	no	no	no	cellular	aug	
4118	34	management	single	high.school	no	yes	no	cellular	nov	

5 rows × 21 columns

In [5]:
```
df.sample(5)
```

Out[5]:

	age	job	marital	education	default	housing	loan	contact	month
2725	59	blue-collar	married	basic.4y	unknown	no	no	cellular	jun
1484	28	admin.	single	university.degree	no	no	no	cellular	aug
291	46	admin.	married	professional.course	no	no	no	cellular	apr
216	43	management	married	university.degree	unknown	yes	yes	cellular	apr
2315	30	admin.	married	university.degree	no	no	no	cellular	jul

5 rows × 21 columns

Info of the dataframe

In [6]:
```
print("\nInfo of the dataframe:")
df.info()
```

```
Info of the dataframe:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4119 entries, 0 to 4118
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             4119 non-null   int64  
 1   job             4119 non-null   object 
 2   marital         4119 non-null   object 
 3   education       4119 non-null   object 
 4   default         4119 non-null   object 
 5   housing         4119 non-null   object 
 6   loan            4119 non-null   object 
 7   contact         4119 non-null   object 
 8   month           4119 non-null   object 
 9   day_of_week     4119 non-null   object 
 10  duration        4119 non-null   int64  
 11  campaign        4119 non-null   int64  
 12  pdays           4119 non-null   int64  
 13  previous        4119 non-null   int64  
 14  poutcome        4119 non-null   object 
 15  emp.var.rate    4119 non-null   float64
 16  cons.price.idx  4119 non-null   float64
 17  cons.conf.idx   4119 non-null   float64
 18  euribor3m       4119 non-null   float64
 19  nr.employed     4119 non-null   float64
 20  deposit         4119 non-null   object 
dtypes: float64(5), int64(5), object(11)
memory usage: 675.9+ KB
```

Shape of the dataframe

In [7]:
```
print("Shape of the dataframe:", df.shape)
```

```
Shape of the dataframe: (4119, 21)
```

Columns of the dataframe

In [8]:
```
print("\nColumns of the dataframe:")
print(df.columns)
```

```
Columns of the dataframe:
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'deposit'],
      dtype='object')
```

Datatypes of the columns

In [9]:
```
print("\nDatatypes of the columns:")
df.dtypes
```

```
Datatypes of the columns:
```

Out[9]:
```
age                 int64
job                object
marital            object
education          object
default            object
housing            object
loan               object
contact            object
month              object
day_of_week        object
duration            int64
campaign            int64
pdays               int64
previous            int64
poutcome           object
emp.var.rate      float64
cons.price.idx    float64
cons.conf.idx     float64
euribor3m         float64
nr.employed       float64
deposit            object
dtype: object
```

Value counts of datatypes

In [10]:
```
print("\nValue counts of datatypes:")
df.dtypes.value_counts()
```

```
Value counts of datatypes:
```

Out[10]:
```
object     11
int64       5
float64     5
dtype: int64
```

Number of duplicated rows

In [11]:
```
print("\nNumber of duplicated rows:", df.duplicated().sum())
```

```
Number of duplicated rows: 0
```

find the Number of missing values in each column

In [12]:
```
# Check for missing values
print("\nNumber of missing values in each column:")
print(df.isnull().sum())
```

```
Number of missing values in each column:
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
deposit           0
dtype: int64
```

Separating Categorical and Numerical Columns

In [13]:
```
# Identifying categorical and numerical columns
categorical_cols = df.select_dtypes(include=('object')).columns
numerical_cols = df.select_dtypes(exclude=('object')).columns

print("\nCategorical columns:")
print(categorical_cols)

print("\nNumerical columns:")
print(numerical_cols)
```

```
Categorical columns:
Index(['job', 'marital', 'education', 'default', 'housing', 'loan', 'conta
ct',
       'month', 'day_of_week', 'poutcome', 'deposit'],
      dtype='object')

Numerical columns:
Index(['age', 'duration', 'campaign', 'pdays', 'previous', 'emp.var.rate',
       'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed'],
      dtype='object')
```

Description of the dataframe

In [14]:
```
print("\nDescription of the dataframe:")
df.describe()
```

```
Description of the dataframe:
```

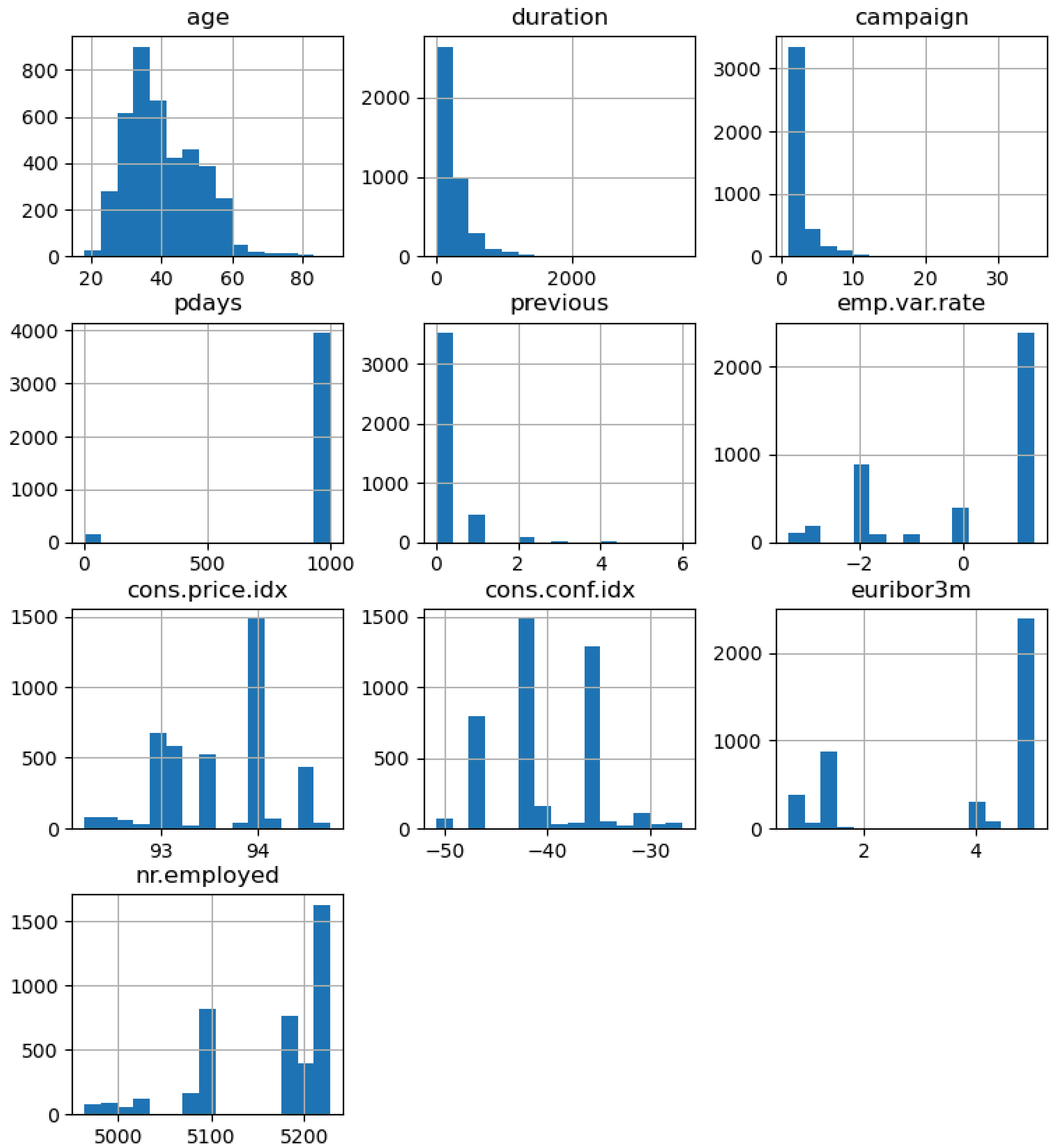
Out[14]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.p
count	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119
mean	40.113620	256.788055	2.537266	960.422190	0.190337	0.084972	93
std	10.313362	254.703736	2.568159	191.922786	0.541788	1.563114	0
min	18.000000	0.000000	1.000000	0.000000	0.000000	-3.400000	92
25%	32.000000	103.000000	1.000000	999.000000	0.000000	-1.800000	93
50%	38.000000	181.000000	2.000000	999.000000	0.000000	1.100000	93
75%	47.000000	317.000000	3.000000	999.000000	0.000000	1.400000	93
max	88.000000	3643.000000	35.000000	999.000000	6.000000	1.400000	94

In [15]:
```
df.describe(include='object')
```
Out[15]:

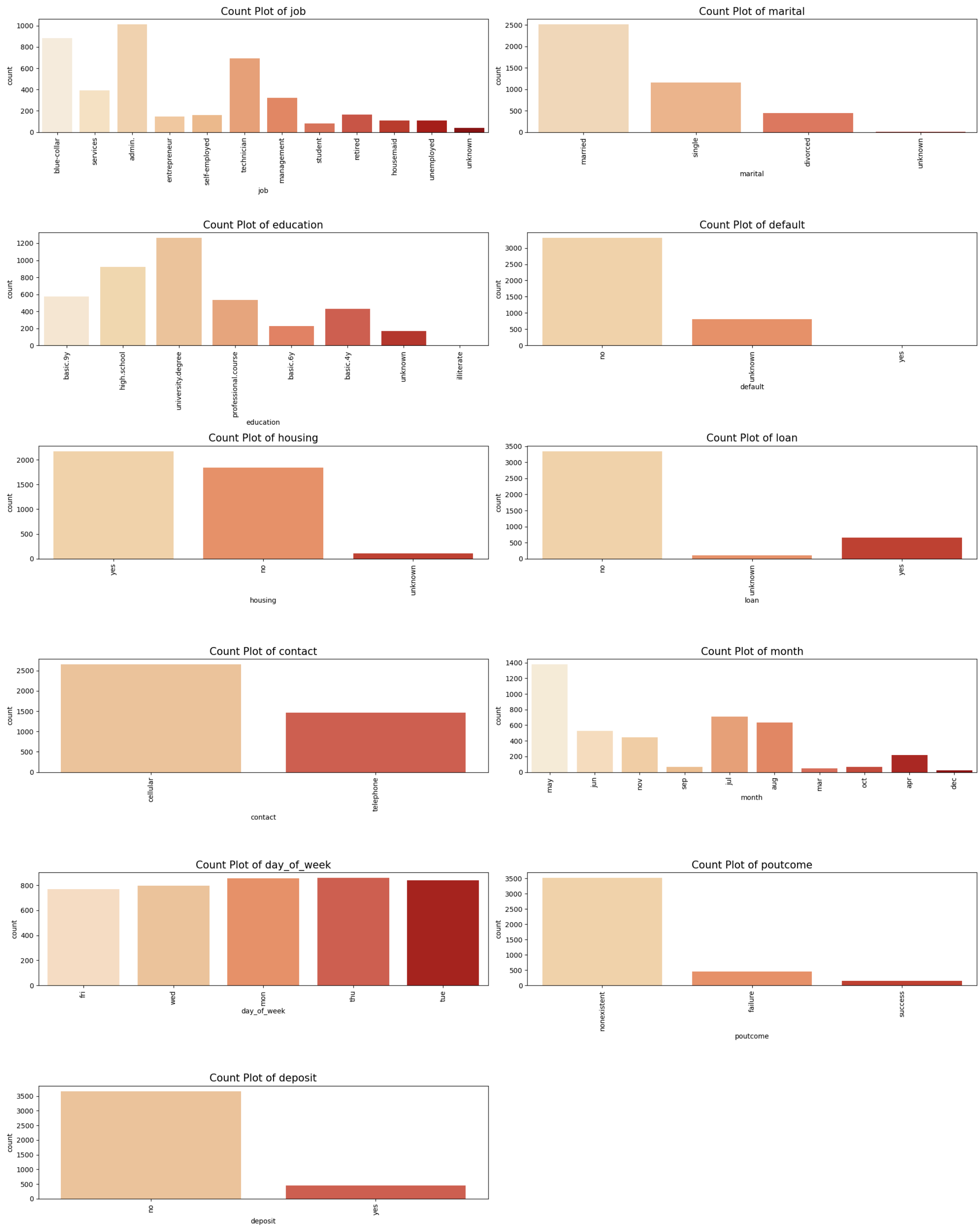
	job	marital	education	default	housing	loan	contact	month	day_of_wee
count	4119	4119	4119	4119	4119	4119	4119	4119	411
unique	12	4	8	3	3	3	2	10	
top	admin.	married	university.degree	no	yes	no	cellular	may	th
freq	1012	2509	1264	3315	2175	3349	2652	1378	86

Histogram Plot for Numerical Columns

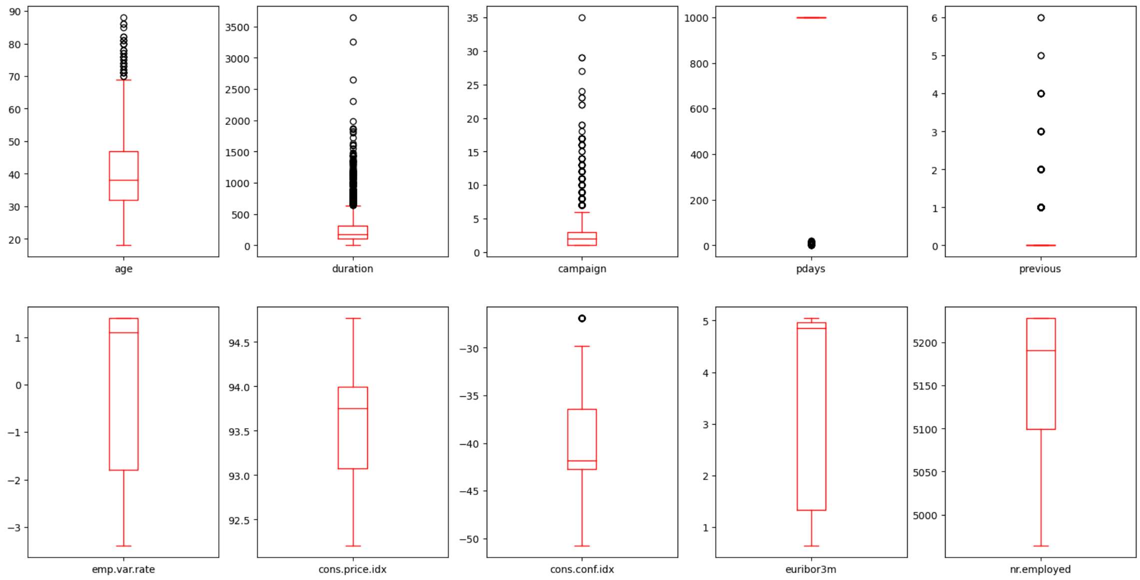
In [16]:
```
df[numerical_cols].hist(bins=15, figsize=(9, 10))
plt.show()
```


Countplot for Categorical Columns

In [17]:
```
# Calculate number of plots, rows, and columns
num_plots = len(categorical_cols)
num_rows = (num_plots+1)//2
num_cols = 2

# create new figure
plt.figure(figsize=(20,25))

# Create count plots for each categorical column
for i, col in enumerate(categorical_cols,1):
    plt.subplot(num_rows,num_cols,i)
    sns.countplot(x= col,data=df, palette = 'OrRd')
    plt.title(f"Count Plot of {col}", fontsize=15)
    plt.xlabel(col)
    plt.ylabel('count')
    plt.xticks(rotation=90)

#Adjust layout to prevent overlap of subplots
plt.tight_layout()
plt.show()
```


Count Plot of job
count
job
blue-collar
services
admin.
entrepreneur
self-employed
technician
management
student
retired
housemaid
unemployed
unknown
Count Plot of marital
marital
married
single
divorced
unknown
Count Plot of education
education
basic.9y
high.school
university.degree
professional.course
basic.6y
basic.4y
unknown
illiterate
Count Plot of default
default
no
unknown
yes
Count Plot of housing
housing
yes
no
unknown
Count Plot of loan
loan
no
unknown
yes
Count Plot of contact
contact
cellular
telephone
Count Plot of month
month
may
jun
nov
sep
jul
aug
mar
oct
apr
dec
Count Plot of day_of_week
day_of_week
fri
wed
mon
thu
tue
Count Plot of poutcome
poutcome
nonexistent
failure
success
Count Plot of deposit
deposit
no
yes

In [19]:
```python
df.plot(kind='box',subplots= True,layout=(2,5),figsize=(20,10),color='r')
plt.show()
```



In [25]:
```python
for col in numerical_cols:
    Q1 = df[col].quantile(0.25)
    Q2 = df[col].quantile(0.5)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    print(f"{col}: Q1={Q1}, Q2={Q2}, Q3={Q3}, IQR={IQR}, Lower Bound={lower
```

```
age: Q1=32.0, Q2=38.0, Q3=47.0, IQR=15.0, Lower Bound=9.5, Upper Bound=69.
5
duration: Q1=103.0, Q2=181.0, Q3=317.0, IQR=214.0, Lower Bound=-218.0, Upp
er Bound=638.0
campaign: Q1=1.0, Q2=2.0, Q3=3.0, IQR=2.0, Lower Bound=-2.0, Upper Bound=
6.0
pdays: Q1=999.0, Q2=999.0, Q3=999.0, IQR=0.0, Lower Bound=999.0, Upper Bou
nd=999.0
previous: Q1=0.0, Q2=0.0, Q3=0.0, IQR=0.0, Lower Bound=0.0, Upper Bound=0.
0
emp.var.rate: Q1=-1.8, Q2=1.1, Q3=1.4, IQR=3.2, Lower Bound=-6.60000000000
00005, Upper Bound=6.200000000000001
cons.price.idx: Q1=93.075, Q2=93.749, Q3=93.994, IQR=0.9189999999999969, L
ower Bound=91.69650000000001, Upper Bound=95.3725
cons.conf.idx: Q1=-42.7, Q2=-41.8, Q3=-36.4, IQR=6.300000000000004, Lower
Bound=-52.150000000000006, Upper Bound=-26.949999999999992
euribor3m: Q1=1.334, Q2=4.857, Q3=4.961, IQR=3.6270000000000002, Lower Bou
nd=-4.1065000000000005, Upper Bound=10.4015
nr.employed: Q1=5099.1, Q2=5191.0, Q3=5228.1, IQR=129.0, Lower Bound=4905.
6, Upper Bound=5421.6
```

Skewness and Data Distribution

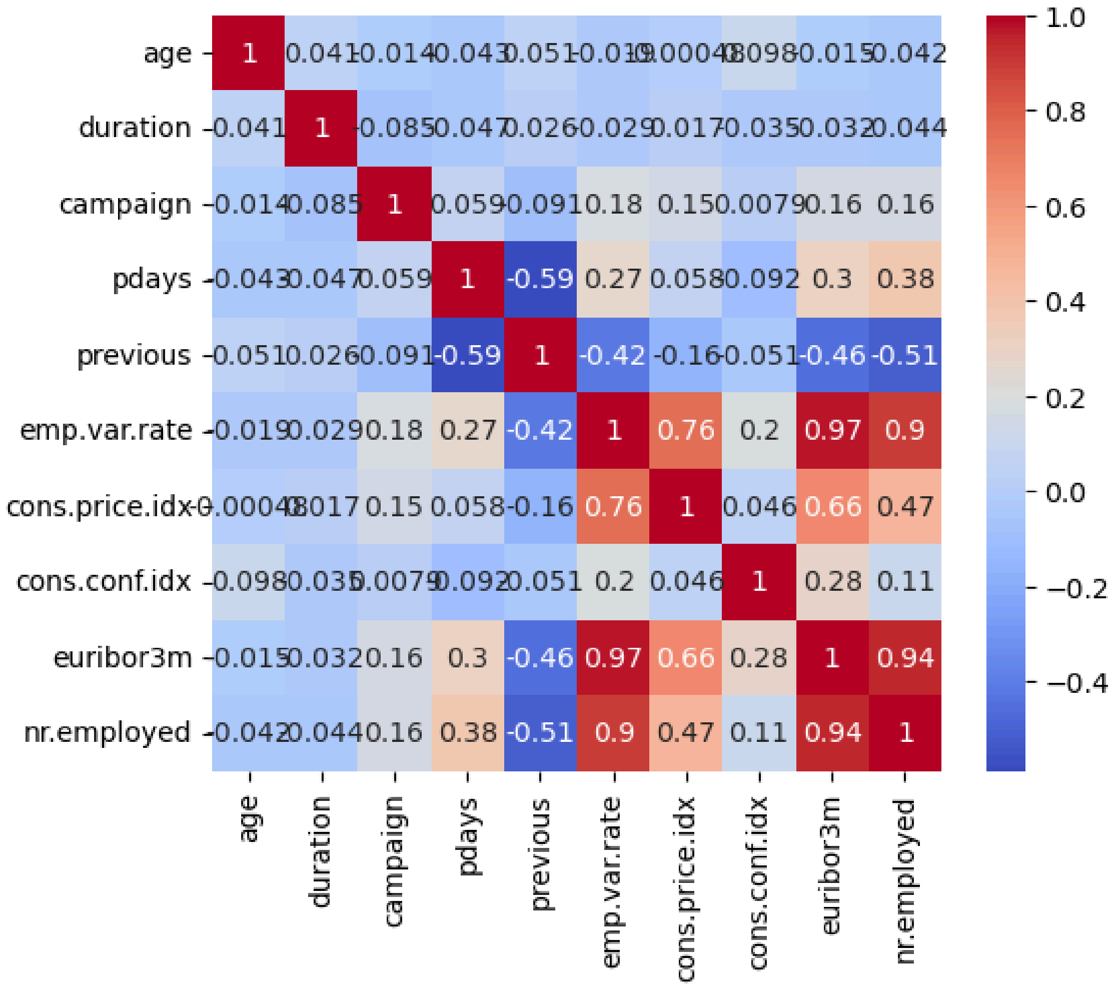
In [28]:
```
skewness = df[numerical_cols].skew()
print("\nSkewness of numerical columns:\n", skewness)
```

```
Skewness of numerical columns:
 age               0.715694
duration          3.294781
campaign          4.003185
pdays            -4.775139
previous          4.022979
emp.var.rate     -0.727688
cons.price.idx   -0.216641
cons.conf.idx     0.287309
euribor3m        -0.715080
nr.employed      -1.075877
dtype: float64
```

Correlation Matrix and Heatmap

In [34]:
```
# Exclude non-numeric columns for correlation matrix
corr_matrix = df[numerical_cols].corr()
print(corr_matrix)
plt.figure(figsize=(6, 5))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.show()
```

```
                     age  duration  campaign     pdays  previous  \
age             1.000000  0.041299 -0.014169 -0.043425  0.050931   
duration        0.041299  1.000000 -0.085348 -0.046998  0.025724   
campaign       -0.014169 -0.085348  1.000000  0.058742 -0.091490   
pdays          -0.043425 -0.046998  0.058742  1.000000 -0.587941   
previous        0.050931  0.025724 -0.091490 -0.587941  1.000000   
emp.var.rate   -0.019192 -0.028848  0.176079  0.270684 -0.415238   
cons.price.idx -0.000482  0.016672  0.145021  0.058472 -0.164922   
cons.conf.idx   0.098135 -0.034745  0.007882 -0.092090 -0.051420   
euribor3m      -0.015033 -0.032329  0.159435  0.301478 -0.458851   
nr.employed    -0.041936 -0.044218  0.161037  0.381983 -0.514853   

                emp.var.rate  cons.price.idx  cons.conf.idx  euribor3m  \
age                -0.019192       -0.000482       0.098135  -0.015033   
duration           -0.028848        0.016672      -0.034745  -0.032329   
campaign            0.176079        0.145021       0.007882   0.159435   
pdays               0.270684        0.058472      -0.092090   0.301478   
previous           -0.415238       -0.164922      -0.051420  -0.458851   
emp.var.rate        1.000000        0.755155       0.195022   0.970308   
cons.price.idx      0.755155        1.000000       0.045835   0.657159   
cons.conf.idx       0.195022        0.045835       1.000000   0.276595   
euribor3m           0.970308        0.657159       0.276595   1.000000   
nr.employed         0.897173        0.472560       0.107054   0.942589   

                nr.employed  
age               -0.041936  
duration          -0.044218  
campaign           0.161037  
pdays              0.381983  
previous          -0.514853  
emp.var.rate       0.897173  
cons.price.idx     0.472560  
cons.conf.idx      0.107054  
euribor3m          0.942589  
nr.employed        1.000000  
```



High Correlation Columns

In [35]:
```
# Filter highly correlated columns
high_corr_cols = [col for col in corr_matrix.columns if any(corr_matrix[col
print("\nHighly correlated columns:", high_corr_cols)

# Create a copy and drop high correlation columns
data_copy = df.drop(high_corr_cols, axis=1)
print("\nShape after dropping high correlation columns:", data_copy.shape)
```

```
Highly correlated columns: ['age', 'duration', 'campaign', 'pdays', 'previ
ous', 'emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.
employed']

Shape after dropping high correlation columns: (4119, 11)
```

Encode Categorical Data

In [40]:
```
from sklearn.preprocessing import LabelEncoder

encoder = LabelEncoder()

df_new= data_copy.apply(encoder.fit_transform)
df_new
```

Out[40]:

	job	marital	education	default	housing	loan	contact	month	day_of_week	poutcom
0	1	1	2	0	2	0	0	6	0	
1	7	2	3	0	0	0	1	6	0	
2	7	1	3	0	2	0	1	4	4	
3	7	1	2	0	1	1	1	4	0	
4	0	1	6	0	2	0	0	7	1	
...	...	...	...	...	...	...	...	...	...	
4114	0	1	1	0	2	2	0	3	2	
4115	0	1	3	0	2	0	1	3	0	
4116	8	2	3	0	0	0	0	6	1	
4117	0	1	3	0	0	0	0	1	0	
4118	4	2	3	0	2	0	0	7	4	

4119 rows × 11 columns

In [41]:
```
# Check the values in the target column
print(df_new['deposit'].value_counts())
```

```
0    3668
1     451
Name: deposit, dtype: int64
```

Drop Independent Variable and Check Shape and Type

In [42]:
```
# Drop target variable 'deposit' from features
X = df_new.drop('deposit', axis=1)
y = df_new['deposit']

print("\nShape of X:", X.shape)
print("\nShape of y:", y.shape)
print("\nType of X:", type(X))
print("\nType of y:", type(y))
```

```
Shape of X: (4119, 10)

Shape of y: (4119,)

Type of X: <class 'pandas.core.frame.DataFrame'>

Type of y: <class 'pandas.core.series.Series'>
```

Model Selection and Training

In [43]:
```
from sklearn.model_selection import train_test_split


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
print("Training Shape:", X_train.shape)
print("Testing Shape:", X_test.shape)
```

```
Training Shape: (2883, 10)
Testing Shape: (1236, 10)
```

Build Decision Tree Classifier

Model Training and Evaluation

In [44]:

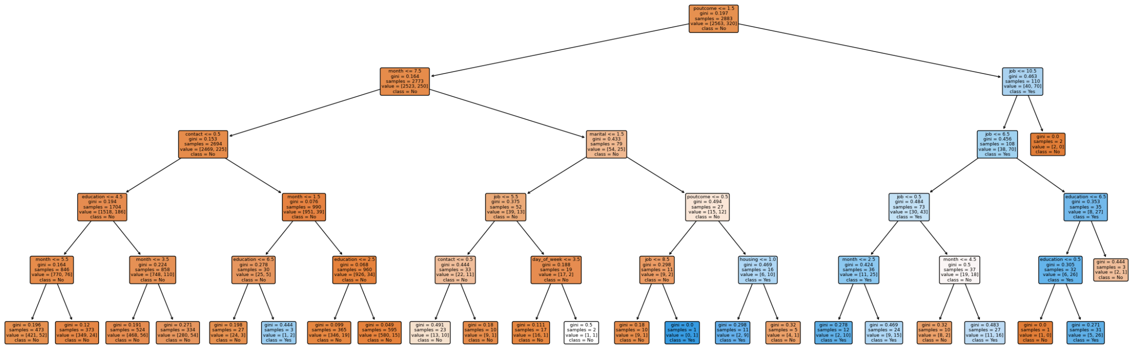
```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, classification_report, accura

dt = DecisionTreeClassifier(criterion='gini', max_depth=5, min_samples_spli
dt.fit(X_train, y_train)

# Predictions
y_pred_train = dt.predict(X_train)
y_pred_test = dt.predict(X_test)

# Scores
print("Training Accuracy:", accuracy_score(y_train, y_pred_train))
print("Testing Accuracy:", accuracy_score(y_test, y_pred_test))

# Confusion Matrix
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_test))
print("Classification Report:\n", classification_report(y_test, y_pred_test
```

```
Training Accuracy: 0.9060006937218176
Testing Accuracy: 0.8988673139158576
Confusion Matrix:
 [[1092   13]
 [ 112   19]]
Classification Report:
               precision    recall  f1-score   support

           0       0.91      0.99      0.95      1105
           1       0.59      0.15      0.23       131

    accuracy                           0.90      1236
   macro avg       0.75      0.57      0.59      1236
weighted avg       0.87      0.90      0.87      1236
```

Visualize the Decision Tree

In [47]:

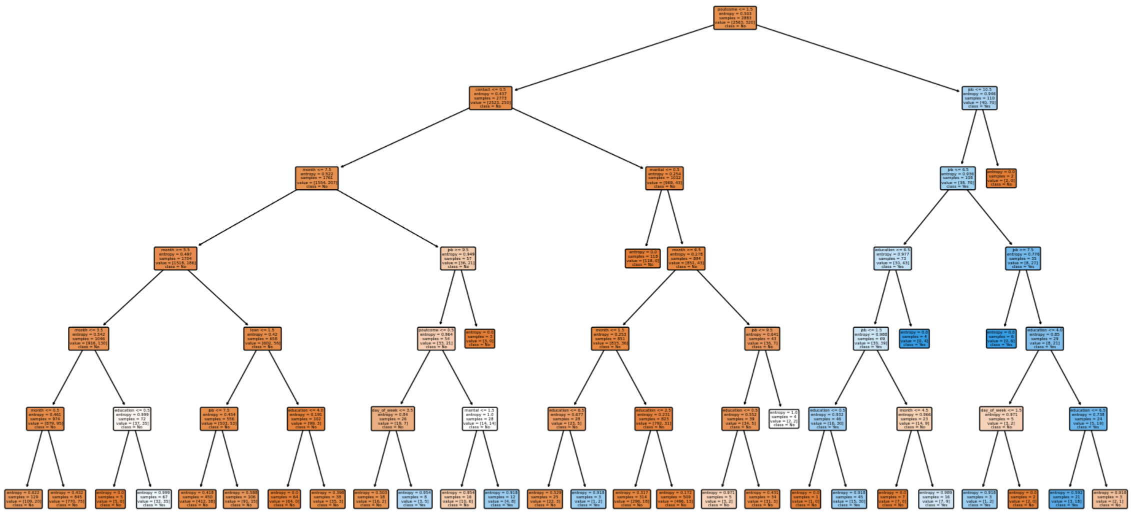
```
from sklearn.tree import plot_tree

fn = X_train.columns
cn = ['No', 'Yes']



plt.figure(figsize=(30, 10))
plot_tree(dt, feature_names=fn, class_names=cn, filled=True, rounded=True)
plt.show()
```



Decision Tree with Specific Parameters

In [48]:
```
# Initialize Decision Tree with specific parameters
dt1 = DecisionTreeClassifier(criterion='entropy', max_depth=6, min_samples_
dt1.fit(X_train, y_train)

# Predict on the test set
y_pred1 = dt1.predict(X_test)

# Updated Scores
print("Training Accuracy:", dt1.score(X_train, y_train))
print("Testing Accuracy:", dt1.score(X_test, y_test))


# Calculate accuracy
accuracy1 = accuracy_score(y_test, y_pred1)
print(f"Accuracy with specific parameters: {accuracy1}")

# Confusion Matrix
conf_matrix1 = confusion_matrix(y_test, y_pred1)
print(f"Confusion Matrix with specific parameters:\n {conf_matrix1}")


# Updated Tree Plot
plt.figure(figsize=(20, 10))
plot_tree(dt1, feature_names=fn, class_names=cn, filled=True, rounded=True)
plt.show()
```

```
Training Accuracy: 0.9073881373569199
Testing Accuracy: 0.8940129449838188
Accuracy with specific parameters: 0.8940129449838188
Confusion Matrix with specific parameters:
 [[1072   33]
 [  98   33]]
```



Conclusion

- The Decision Tree Classifier successfully predicts customer purchase behavior with a significant accuracy rate.
- The model provides interpretable insights into key factors influencing customer decisions, such as contact duration, marital status, and education level.
- Businesses can leverage these insights to develop focused marketing strategies and improve decision-making processes.
- The project highlights the power of machine learning in deriving actionable insights from data and emphasizes the importance of continuous evaluation and tuning for optimal performance.