Project Name - CustomerAnalytics-Predictor

About the Dataset

Features:

UNDERSTAND THE GIVEN VARIABLES

age :- Numeric

job :- Type of Job.

marital :- Martial status.

educational_qual :- Education status.

call_type :- Communication type.

day :- last contact day of the month (numeric).

mon: :- last contact month of year.

dur :- last contact duration, in seconds (numeric).

num_calls :- number of contacts performed during this campaign and for this client

prev_outcome :- outcome of the previous marketing campaign (categorical: "unknown","other","failure","success").

Output variable (desired target) y :- has the client subscribed to the insurance?

Problem Statement

You work for a modern insurance company that uses various outreach strategies to sell term insurance to customers. Among these, telephonic marketing campaigns are still one of the most effective methods for reaching potential clients, but they can be quite costly. Therefore, it's crucial to identify customers who are most likely to convert in advance so that these individuals can be specifically targeted through phone calls. We have historical marketing data from the company, and the task is to develop a machine learning model that predicts whether a client will subscribe to the insurance.

Dataset can be download from Kaggle website. The link is https://www.kaggle.com/datasets/shubhamkalme/customerconversionprediction

```
#Import the required libraries
```

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

#load the dataset
customer_dt = pd.read_csv('CustomerAnalytics.csv')

customer_dt
```

```
       age           job   marital education_qual  call_type  day  mon
dur  \
0       58    management   married       tertiary    unknown    5  may
261
1       44    technician    single      secondary    unknown    5  may
151
2       33  entrepreneur   married      secondary    unknown    5  may
76
3       47   blue-collar   married        unknown    unknown    5  may
92
4       33       unknown    single        unknown    unknown    5  may
198
...    ...           ...       ...            ...        ...  ...  ...
...
45206   51    technician   married       tertiary   cellular   17  nov
977
45207   71       retired  divorced        primary   cellular   17  nov
456
45208   72       retired   married      secondary   cellular   17  nov
1127
45209   57   blue-collar   married      secondary  telephone   17  nov
508
45210   37  entrepreneur   married      secondary   cellular   17  nov
361

       num_calls prev_outcome    y
0              1      unknown   no
1              1      unknown   no
2              1      unknown   no
3              1      unknown   no
4              1      unknown   no
...          ...          ...  ...
45206          3      unknown  yes
45207          2      unknown  yes
45208          5      success  yes
45209          4      unknown   no
45210          2        other   no

[45211 rows x 11 columns]
```

```
customer_dt.isnull().sum()
```

```
age               0
job               0
marital           0
education_qual    0
call_type         0
day               0
mon               0
dur               0
num_calls         0
prev_outcome      0
y                 0
dtype: int64
```

```
customer_dt.shape
```

```
(45211, 11)
```

```
customer_dt.head()
```

```
   age           job  marital education_qual call_type  day  mon  dur  
\
0   58    management  married       tertiary   unknown    5  may  261   

1   44    technician   single      secondary   unknown    5  may  151   

2   33  entrepreneur  married      secondary   unknown    5  may   76   

3   47   blue-collar  married        unknown   unknown    5  may   92   

4   33       unknown   single        unknown   unknown    5  may  198   


   num_calls prev_outcome   y  
0          1      unknown  no  
1          1      unknown  no  
2          1      unknown  no  
3          1      unknown  no  
4          1      unknown  no  
```

```
customer_dt.tail()
```

```
       age          job   marital education_qual  call_type  day  mon  
dur  \
45206   51   technician   married       tertiary   cellular   17  nov  
977   
45207   71      retired  divorced        primary   cellular   17  nov  
456   
45208   72      retired   married      secondary   cellular   17  nov  
1127
```

```
45209   57   blue-collar   married      secondary  telephone   17  nov
508
45210   37  entrepreneur   married      secondary   cellular   17  nov
361

       num_calls prev_outcome    y
45206          3      unknown  yes
45207          2      unknown  yes
45208          5      success  yes
45209          4      unknown   no
45210          2        other   no
```

```
customer_dt.describe()
```

```
                age           day           dur     num_calls
count  45211.000000  45211.000000  45211.000000  45211.000000
mean      40.936210     15.806419    258.163080      2.763841
std       10.618762      8.322476    257.527812      3.098021
min       18.000000      1.000000      0.000000      1.000000
25%       33.000000      8.000000    103.000000      1.000000
50%       39.000000     16.000000    180.000000      2.000000
75%       48.000000     21.000000    319.000000      3.000000
max       95.000000     31.000000   4918.000000     63.000000
```

```
#checking for the data is balanced or not
customer_dt['y'].value_counts()
```

```
y
no     39922
yes     5289
Name: count, dtype: int64
```

```
len(customer_dt)
```

```
45211
```

```
# Calculate the value counts for each class
value_counts = customer_dt['y'].value_counts()

# Calculate the percentage for each class
percentage = value_counts / len(customer_dt) * 100

# Display the percentage
print(percentage)
```

```
y
no     88.30152
yes    11.69848
Name: count, dtype: float64
```

Finding Duplicate values

```
customer_dt.duplicated().sum()
```

```
6
```

```
# We will remove duplicate values

customer_dt = customer_dt.drop_duplicates()

# Again check the how many duplicate values

customer_dt.duplicated().sum()
```

```
0
```

```
customer_dt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 45205 entries, 0 to 45210
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             45205 non-null  int64 
 1   job             45205 non-null  object
 2   marital         45205 non-null  object
 3   education_qual  45205 non-null  object
 4   call_type       45205 non-null  object
 5   day             45205 non-null  int64 
 6   mon             45205 non-null  object
 7   dur             45205 non-null  int64 
 8   num_calls       45205 non-null  int64 
 9   prev_outcome    45205 non-null  object
 10  y               45205 non-null  object
dtypes: int64(4), object(7)
memory usage: 4.1+ MB
```

Unique values of categorical columns of the dataset

```
# Loop through each column in the DataFrame
for column in customer_dt.columns:
    # Check if the column is of object type (categorical)
    if customer_dt[column].dtype == 'object':
        # Print the unique values for the categorical column
        print(f"Unique values in '{column}':
{customer_dt[column].unique()}")
        print("-" * 50)
```

```
Unique values in 'job': ['management' 'technician' 'entrepreneur'
'blue-collar' 'unknown'
 'retired' 'admin.' 'services' 'self-employed' 'unemployed'
'housemaid'
```

```
 'student']
--------------------------------------------------
Unique values in 'marital': ['married' 'single' 'divorced']
--------------------------------------------------
Unique values in 'education_qual': ['tertiary' 'secondary' 'unknown'
'primary']
--------------------------------------------------
Unique values in 'call_type': ['unknown' 'cellular' 'telephone']
--------------------------------------------------
Unique values in 'mon': ['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec'
'jan' 'feb' 'mar' 'apr' 'sep']
--------------------------------------------------
Unique values in 'prev_outcome': ['unknown' 'failure' 'other'
'success']
--------------------------------------------------
Unique values in 'y': ['no' 'yes']
--------------------------------------------------
```

Explore this dataset and replace unknown values

In dataset there are many unknown values in different categorial variables we will check first and remove if it's not too much

```
customer_dt.job.value_counts()
```

```
job
blue-collar      9730
management       9457
technician       7596
admin.           5170
services         4153
retired          2264
self-employed    1579
entrepreneur     1487
unemployed       1303
housemaid        1240
student           938
unknown           288
Name: count, dtype: int64
```

```
len(customer_dt)
```

```
45205
```

So 288 values are unknown in job variable of dataset out of 45205 rows, deletion of 288 rows will not get more impact on dataset .

```
#replacing unknown value as null
customer_dt.loc[customer_dt['job'] == 'unknown', 'job'] = np.nan
```

```
customer_dt.isnull().sum()
```

```
age                 0
job               288
marital             0
education_qual      0
call_type           0
day                 0
mon                 0
dur                 0
num_calls           0
prev_outcome        0
y                   0
dtype: int64
```

```
customer_dt = customer_dt.dropna(subset = ['job'])
```

```
customer_dt.isnull().sum()
```

```
age               0
job               0
marital           0
education_qual    0
call_type         0
day               0
mon               0
dur               0
num_calls         0
prev_outcome      0
y                 0
dtype: int64
```

```
len(customer_dt)
```

```
44917
```

```
customer_dt.education_qual.value_counts()
```

```
education_qual
secondary    23128
tertiary     13260
primary       6799
unknown       1730
Name: count, dtype: int64
```

```
# Calculate the total number of entries in the education_qual column
total_entries = customer_dt['education_qual'].count()

# Calculate the number of 'unknown' entries in the education_qual
column
unknown_count = customer_dt['education_qual'].value_counts()
```

```
['unknown']

# Calculate the percentage of 'unknown' values
unknown_percentage = (unknown_count / total_entries) * 100

# Print the result
print(f"Percentage of 'unknown' in education_qual:
{unknown_percentage:.2f}%")

Percentage of 'unknown' in education_qual: 3.85%
```

So percentage of unknown in education_qual 3.85% so we will remove unknown as it will not effect the dataset .

```
len(customer_dt)

44917

# Remove rows where 'education_qual' is 'unknown'
customer_dt = customer_dt[customer_dt['education_qual'] != 'unknown']

len(customer_dt)

43187

customer_dt.isnull().sum()

age               0
job               0
marital           0
education_qual    0
call_type         0
day               0
mon               0
dur               0
num_calls         0
prev_outcome      0
y                 0
dtype: int64

customer_dt.call_type.value_counts()

call_type
cellular     28210
unknown      12283
telephone     2694
Name: count, dtype: int64

# Calculate the total number of entries in the call_type column
total_entries_cl = customer_dt['call_type'].count()
```

```
# Calculate the number of 'unknown' entries in the call_type column
unknown_count_cl = customer_dt['call_type'].value_counts()['unknown']

# Calculate the percentage of 'unknown' values
unknown_percentage_cl = (unknown_count_cl / total_entries_cl) * 100

# Print the result
print(f"Percentage of 'unknown' in call_type:
{unknown_percentage_cl:.2f}%")
```

```
Percentage of 'unknown' in call_type: 28.44%
```

So percentage of unknown in call_type is 28.44, we will keep as it is .

```
customer_dt.prev_outcome.value_counts()
```

```
prev_outcome
unknown    35280
failure     4709
other       1774
success     1424
Name: count, dtype: int64
```

```
# Calculate the total number of entries in the prev_outcome column
total_entries_pr = customer_dt['prev_outcome'].count()

# Calculate the number of 'unknown' entries in the prev_outcome column
unknown_count_pr = customer_dt['prev_outcome'].value_counts()
['unknown']

# Calculate the percentage of 'unknown' values
unknown_percentage_pr = (unknown_count_pr / total_entries_pr) * 100

# Print the result
print(f"Percentage of 'unknown' in prev_outcome:
{unknown_percentage_pr:.2f}%")
```

```
Percentage of 'unknown' in prev_outcome: 81.69%
```

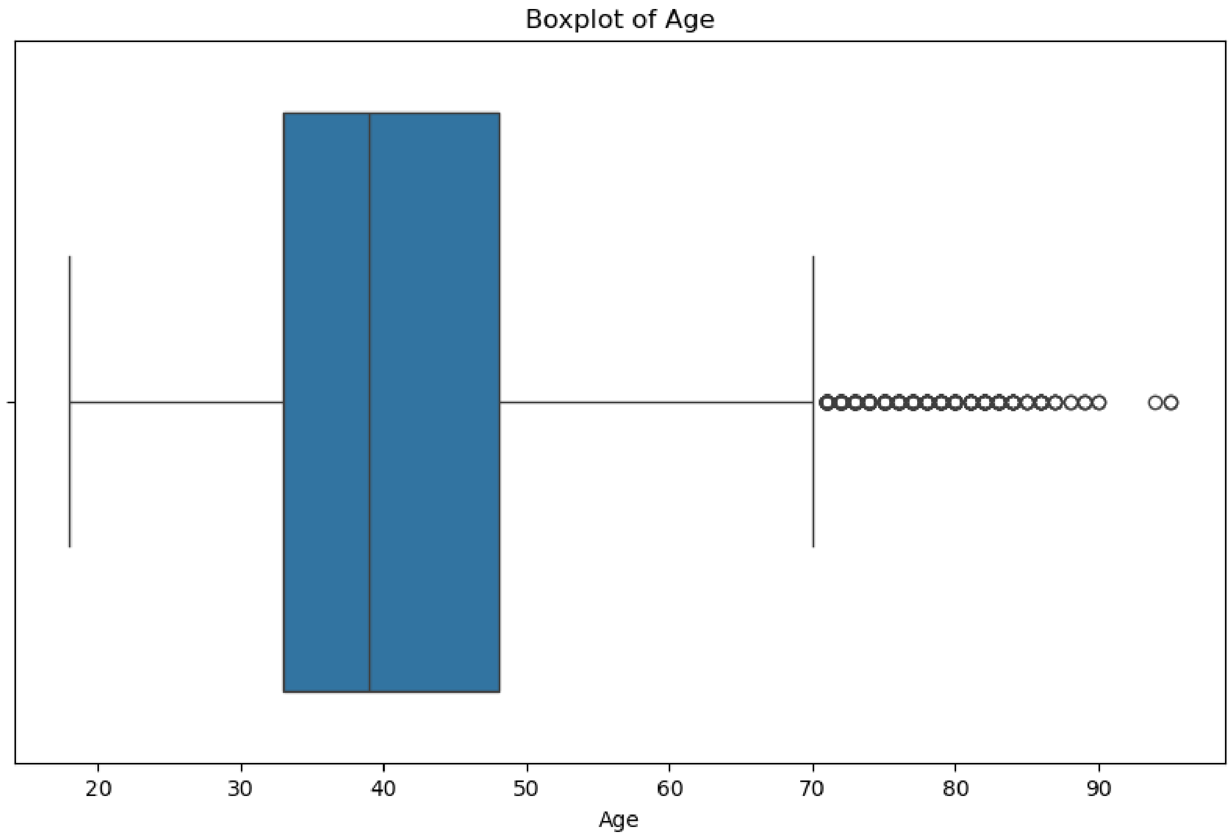
So percentage of unknown in prev_outcome is 81.69, we will keep as it is .

Outlier Detection and Removal

We will check the outliers by plotting box plots and remove by IQR method

```
# Show the boxplot of age
plt.figure(figsize=(10, 6))
sns.boxplot(x=customer_dt['age'])
plt.title('Boxplot of Age')
```

```
plt.xlabel('Age')
plt.show()
```




```
# Calculate the IQR for age
Q1_g = customer_dt['age'].quantile(0.25)
Q3_g = customer_dt['age'].quantile(0.75)
IQR_g = Q3_g - Q1_g

# Determine the lower and upper bounds for outliers
lower_bound_g = Q1_g - 1.5 * IQR_g
upper_bound_g = Q3_g + 1.5 * IQR_g

print(f"Lower Bound of age column: {lower_bound_g}")
print(f"Upper Bound of age column: {upper_bound_g}")

# Identify outliers
outliers_g = customer_dt[(customer_dt['age'] < lower_bound_g) |
(customer_dt['age'] > upper_bound_g)]


# Count the number of outliers
num_outliers_g = outliers_g.shape[0]
print(f"Number of outliers in the 'age' column: {num_outliers_g}")
```

```
Lower Bound of age column: 10.5
Upper Bound of age column: 70.5
Number of outliers in the 'age' column: 434
```

checking after outliers removal in age Column

```
outliers_g
```

```
       age      job   marital education_qual  call_type  day  mon  
dur  \
29158   83  retired   married        primary  telephone    2  feb  
912   
29261   75  retired  divorced        primary   cellular    2  feb  
294   
29263   75  retired   married        primary   cellular    2  feb  
149   
29322   83  retired   married       tertiary   cellular    2  feb  
283   
29865   75  retired  divorced        primary   cellular    4  feb  
136   
...    ...      ...       ...            ...        ...  ...  ...   ..
.   
45163   71  retired   married      secondary   cellular    9  nov  
379   
45191   75  retired  divorced       tertiary   cellular   16  nov  
262   
45204   73  retired   married      secondary   cellular   17  nov  
300   
45207   71  retired  divorced        primary   cellular   17  nov  
456   
45208   72  retired   married      secondary   cellular   17  nov  
1127  

       num_calls prev_outcome    y  
29158          1      unknown   no  
29261          1      unknown   no  
29263          1      unknown   no  
29322          2      unknown   no  
29865          3      unknown  yes  
...          ...          ...  ...  
45163          2      failure   no  
45191          1      failure  yes  
45204          1      failure  yes  
45207          2      unknown  yes  
45208          5      success  yes  

[434 rows x 11 columns]
```

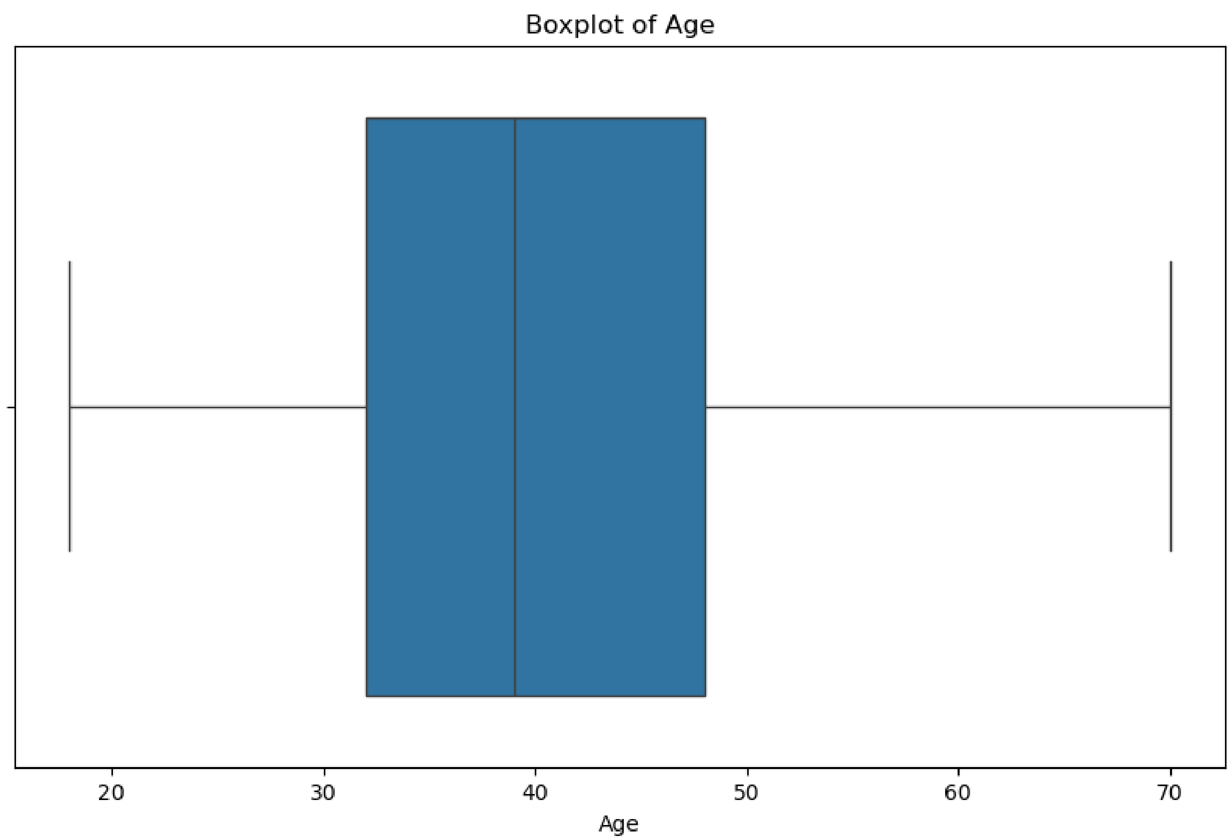
```
customer_dt = customer_dt[(customer_dt['age'] >= lower_bound_g) & 
(customer_dt['age'] <= upper_bound_g)]
```

```
customer_dt.shape
```

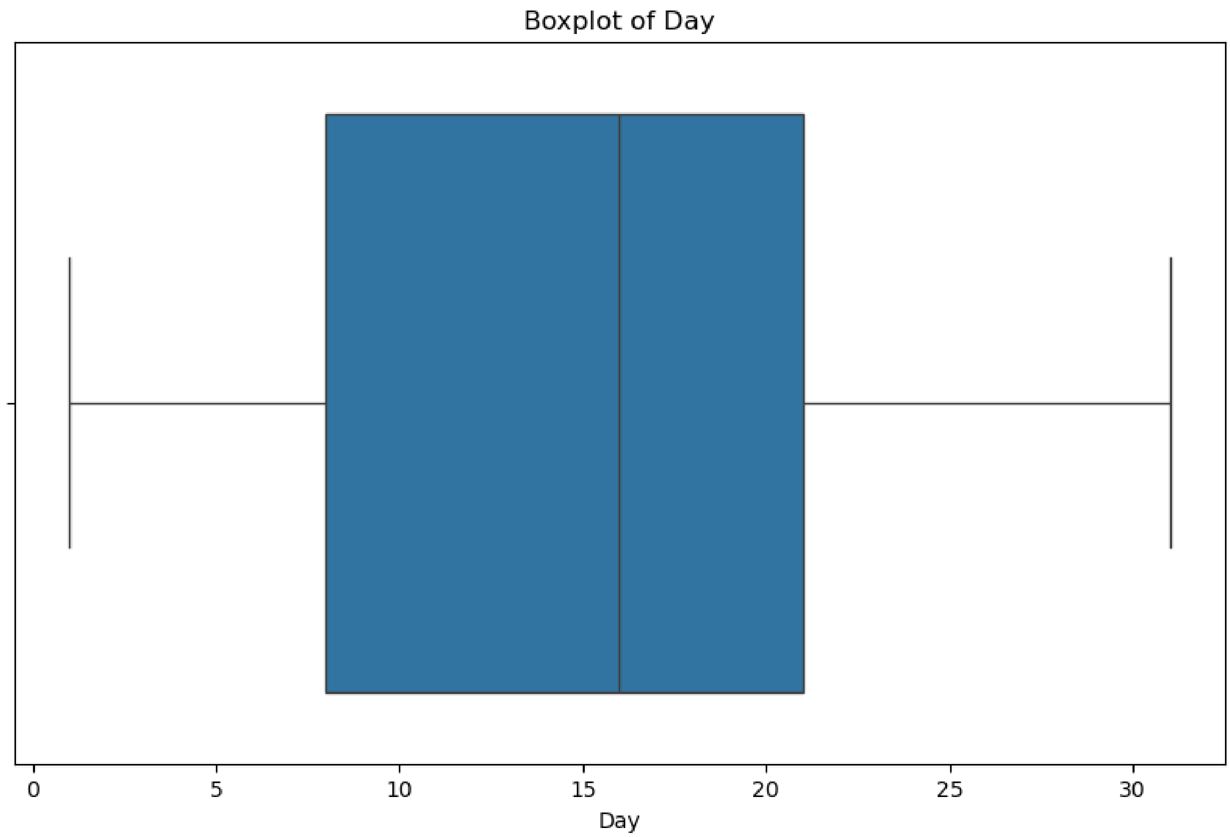
```
(42753, 11)
```

Again check the boxplot of age

```
# Show the boxplot of age
plt.figure(figsize=(10, 6))
sns.boxplot(x=customer_dt['age'])
plt.title('Boxplot of Age')
plt.xlabel('Age')
plt.show()
```

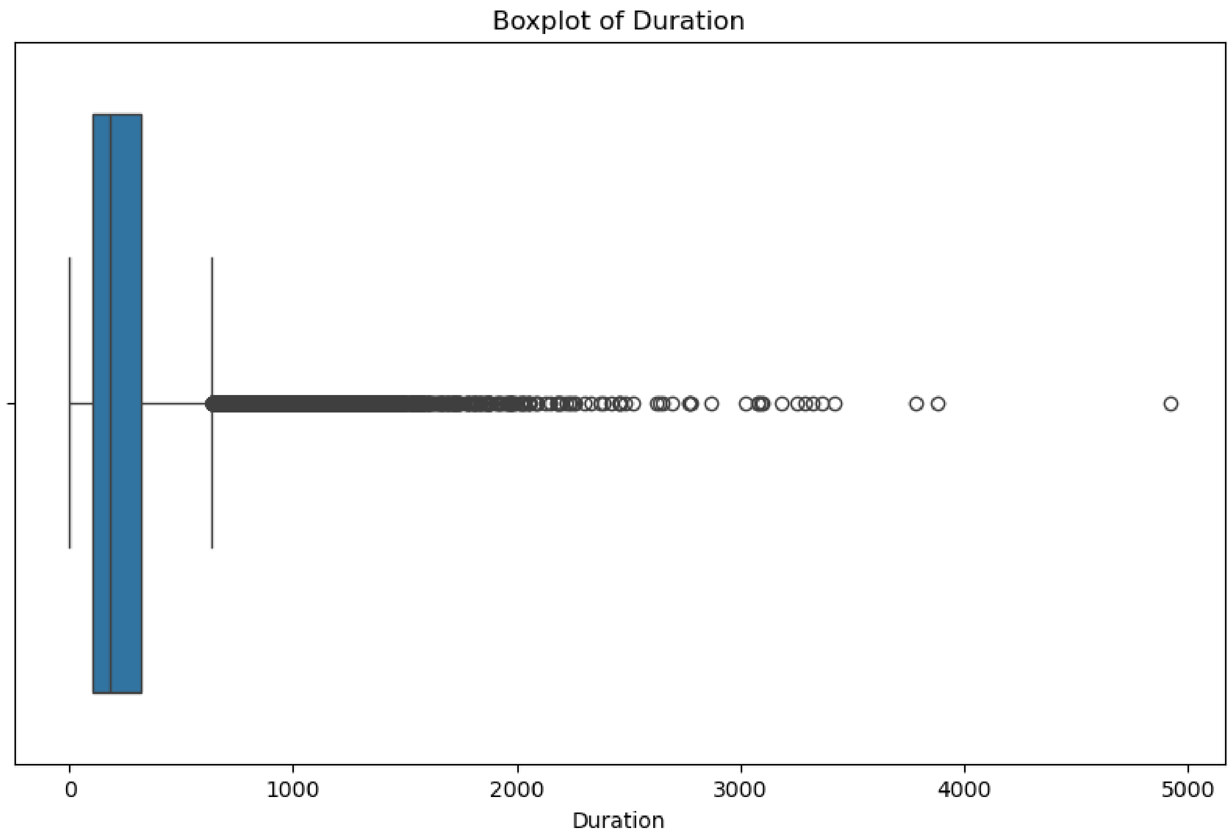



```
# Show the boxplot of day
plt.figure(figsize=(10, 6))
sns.boxplot(x=customer_dt['day'])
plt.title('Boxplot of Day')
plt.xlabel('Day')
plt.show()
```



So from above graph it's clearly shows that there is no outlier in day column

```
# Show the boxplot of dur
plt.figure(figsize=(10, 6))
sns.boxplot(x=customer_dt['dur'])
plt.title('Boxplot of Duration')
plt.xlabel('Duration')
plt.show()
```




```
# Calculate the IQR for duration
Q1_dur = customer_dt['dur'].quantile(0.25)
Q3_dur = customer_dt['dur'].quantile(0.75)
IQR_dur = Q3_dur - Q1_dur

# Determine the lower and upper bounds for outliers
lower_bound_dur = Q1_dur - 1.5 * IQR_dur
upper_bound_dur = Q3_dur + 1.5 * IQR_dur



# Identify outliers
outliers_dur = customer_dt[(customer_dt['dur'] < lower_bound_dur) |
(customer_dt['dur'] > upper_bound_dur)]


# Count the number of outliers
num_outliers_dur = outliers_dur.shape[0]
print(f"Number of outliers in the 'durarion' column:
{num_outliers_dur}")

Number of outliers in the 'durarion' column: 3093

outliers_dur
```

```
      age          job   marital education_qual call_type  day  mon  
dur  \
37     53   technician   married      secondary   unknown    5  may  
1666   
43     54      retired   married      secondary   unknown    5  may  
1492   
53     42       admin.    single      secondary   unknown    5  may  
787    
59     46     services   married        primary   unknown    5  may  
1778   
61     53   technician  divorced      secondary   unknown    5  may  
812    
...   ...          ...       ...            ...       ...  ...  ...  
...    
45085  25   technician    single      secondary  cellular   22  oct  
716    
45124  27  blue-collar    single        primary  cellular   26  oct  
701    
45199  34  blue-collar    single      secondary  cellular   16  nov  
1166   
45200  38   technician   married      secondary  cellular   16  nov  
1556   
45206  51   technician   married       tertiary  cellular   17  nov  
977    

      num_calls prev_outcome    y  
37            1      unknown   no  
43            1      unknown   no  
53            1      unknown   no  
59            1      unknown   no  
61            1      unknown   no  
...         ...          ...  ...  
45085         3      unknown  yes  
45124         2      unknown  yes  
45199         3        other   no  
45200         4      unknown  yes  
45206         3      unknown  yes  

[3093 rows x 11 columns]
```

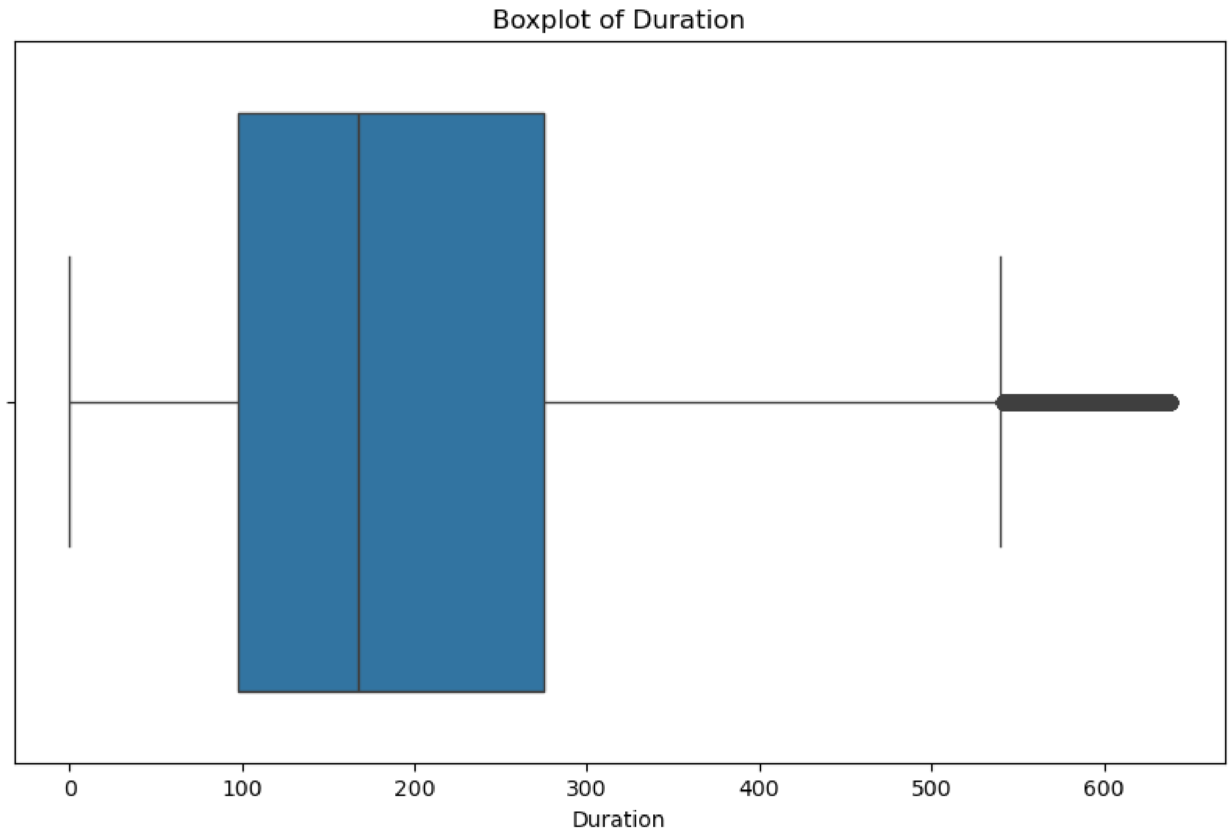
```
customer_dt = customer_dt[(customer_dt['dur'] >= lower_bound_dur) & 
(customer_dt['dur'] <= upper_bound_dur)]
```

```
customer_dt.shape
```

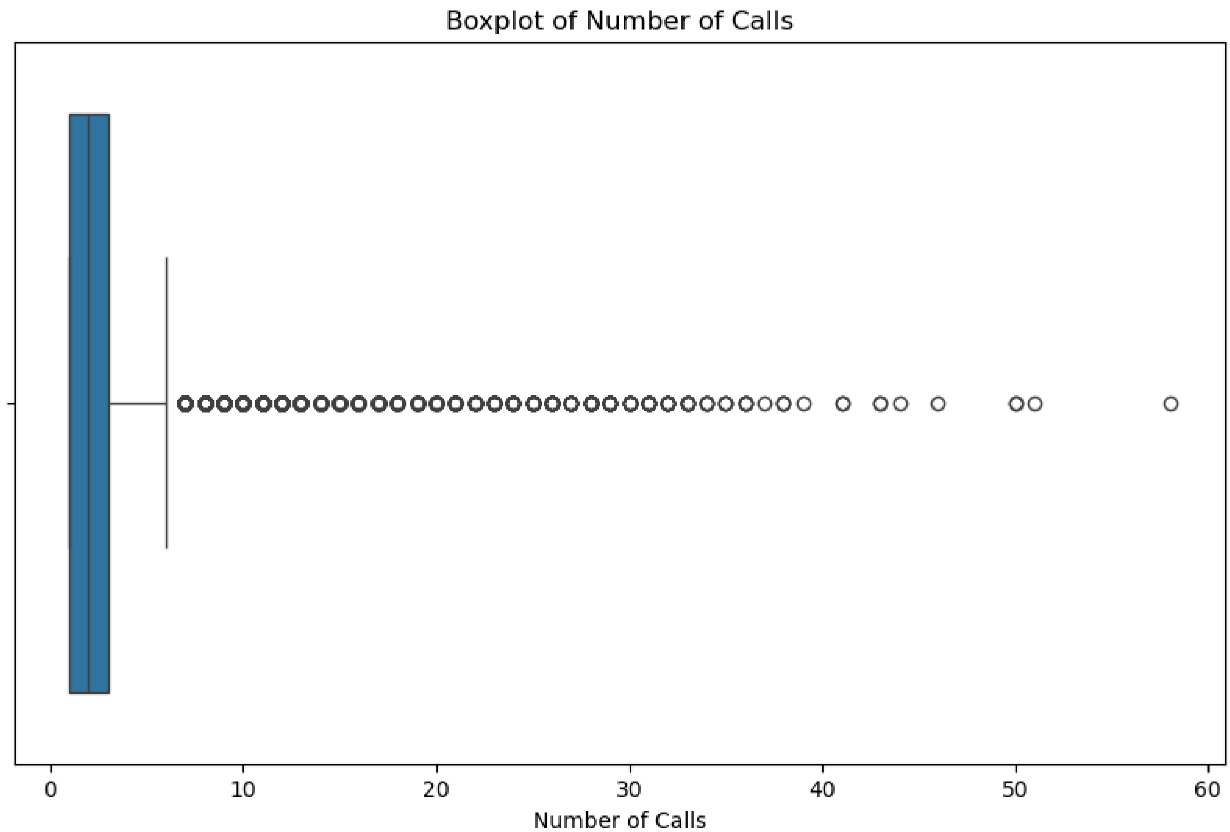
```
(39660, 11)
```

```
# Show the boxplot of dur
plt.figure(figsize=(10, 6))
sns.boxplot(x=customer_dt['dur'])
```

```
plt.title('Boxplot of Duration')
plt.xlabel('Duration')
plt.show()
```




```
# Show the boxplot of dur
plt.figure(figsize=(10, 6))
sns.boxplot(x=customer_dt['num_calls'])
plt.title('Boxplot of Number of Calls')
plt.xlabel('Number of Calls')
plt.show()
```




```python
# Calculate the IQR for age
Q1_cl = customer_dt['num_calls'].quantile(0.25)
Q3_cl = customer_dt['num_calls'].quantile(0.75)
IQR_cl = Q3_cl - Q1_cl

# Determine the lower and upper bounds for outliers
lower_bound_cl = Q1_cl - 1.5 * IQR_cl
upper_bound_cl = Q3_cl + 1.5 * IQR_cl

print(f"Lower Bound of num_calls column: {lower_bound_cl}")
print(f"Upper Bound of num_calls column: {upper_bound_cl}")

# Identify outliers
outliers_cl = customer_dt[(customer_dt['num_calls'] < lower_bound_cl)
| (customer_dt['num_calls'] > upper_bound_cl)]


# Count the number of outliers
num_outliers_cl = outliers_cl.shape[0]
print(f"Number of outliers in the 'age' column: {num_outliers_cl}")
```

```
Lower Bound of num_calls column: -2.0
Upper Bound of num_calls column: 6.0
Number of outliers in the 'age' column: 2720
```

```
outliers_cl
```

```
       age            job  marital education_qual  call_type  day  mon
dur  \
758     59       services  married      secondary    unknown    6  may
250
780     30         admin.  married      secondary    unknown    7  may
172
906     27       services   single      secondary    unknown    7  may
388
1105    43         admin.  married       tertiary    unknown    7  may
244
1386    37         admin.  married        primary    unknown    8  may
161
...    ...            ...      ...            ...        ...  ...  ...
...
44594   34     technician   single       tertiary   cellular   23  aug
220
44666   25     technician   single      secondary   cellular    2  sep
206
44680   27  self-employed   single       tertiary  telephone    3  sep
543
44770   37       services   single       tertiary   cellular   13  sep
323
44886   38     management  married       tertiary   cellular   24  sep
246

       num_calls prev_outcome    y
758            7      unknown   no
780            8      unknown   no
906            7      unknown   no
1105           7      unknown   no
1386           8      unknown   no
...          ...          ...  ...
44594         16        other   no
44666          7        other   no
44680          9      failure   no
44770          9        other  yes
44886         12      failure   no

[2720 rows x 11 columns]
```

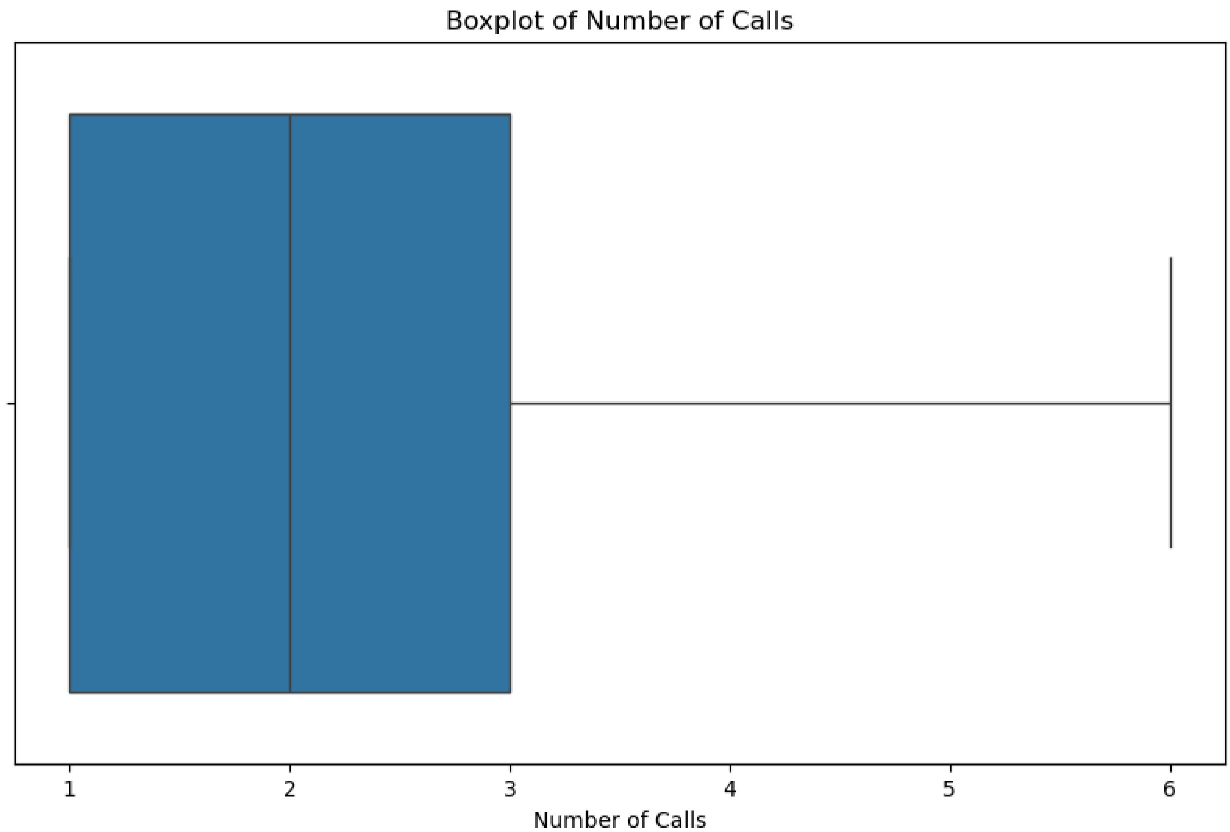
```
customer_dt = customer_dt[(customer_dt['num_calls'] >= lower_bound_cl)
& (customer_dt['num_calls'] <= upper_bound_cl)]
```

```
customer_dt.shape
```

```
(36940, 11)
```

```
# Show the boxplot of dur
plt.figure(figsize=(10, 6))
```

```
sns.boxplot(x=customer_dt['num_calls'])
plt.title('Boxplot of Number of Calls')
plt.xlabel('Number of Calls')
plt.show()
```

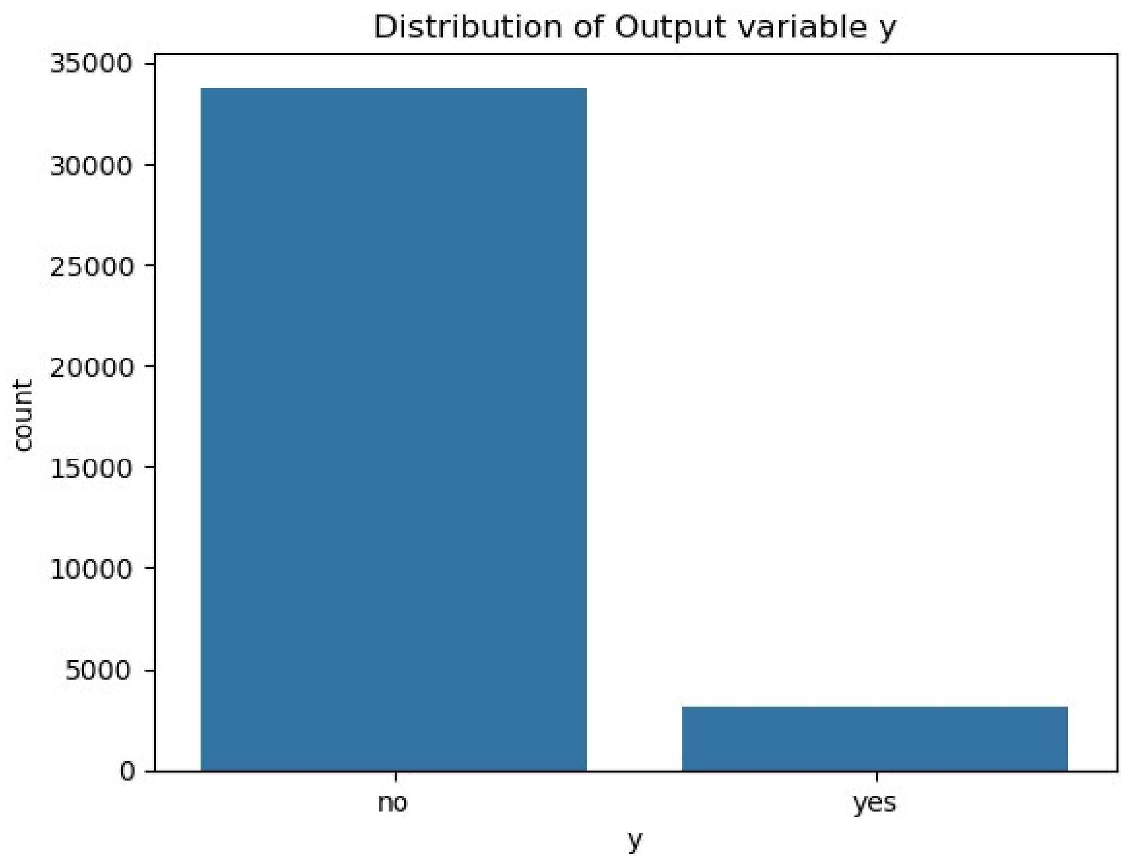


EDA Exploratory data analysis

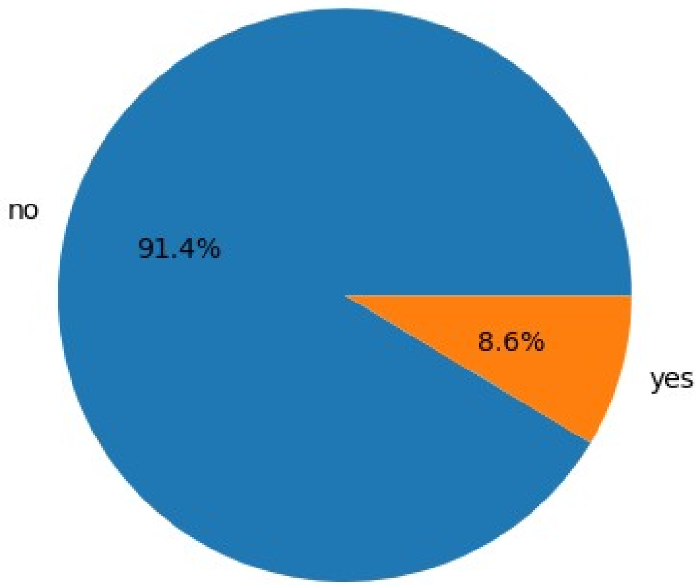
(1) Univariate Analysis

Distribution of Target Variable y

```
sns.countplot(x = 'y', data = customer_dt)
plt.title('Distribution of Output variable y')
plt.show()
```

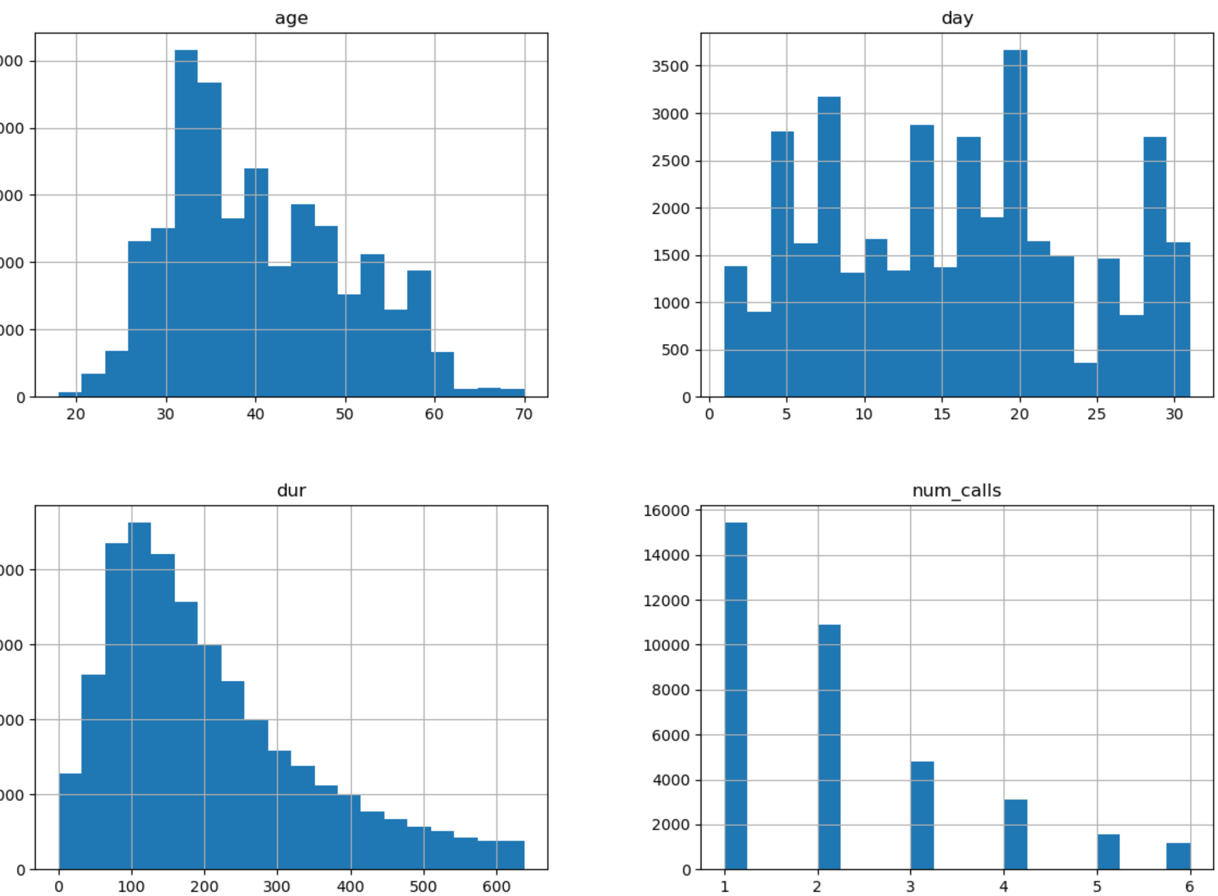


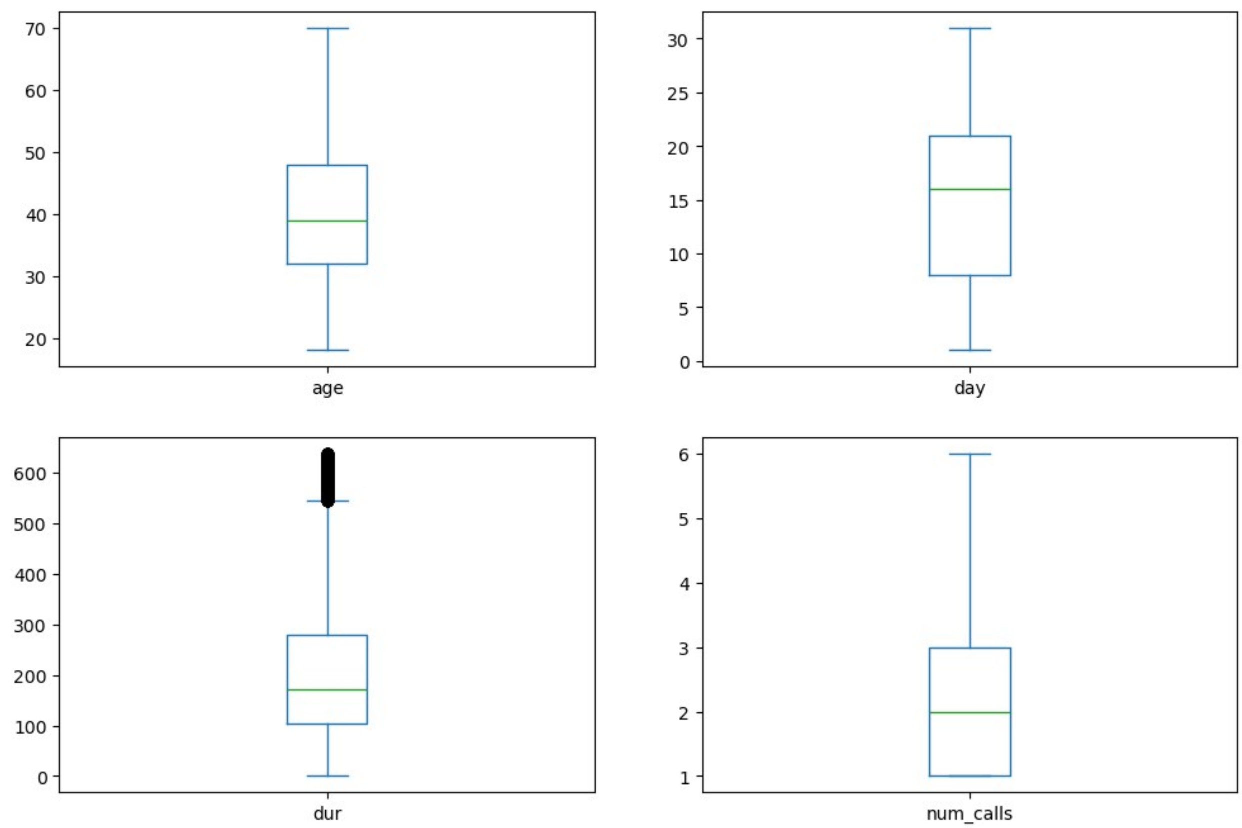

```
y = customer_dt['y'].value_counts()
plt.pie(y.values,
        labels=y.index,
        autopct='%1.1f%%')
plt.show()
```



Numerical Features Distribution

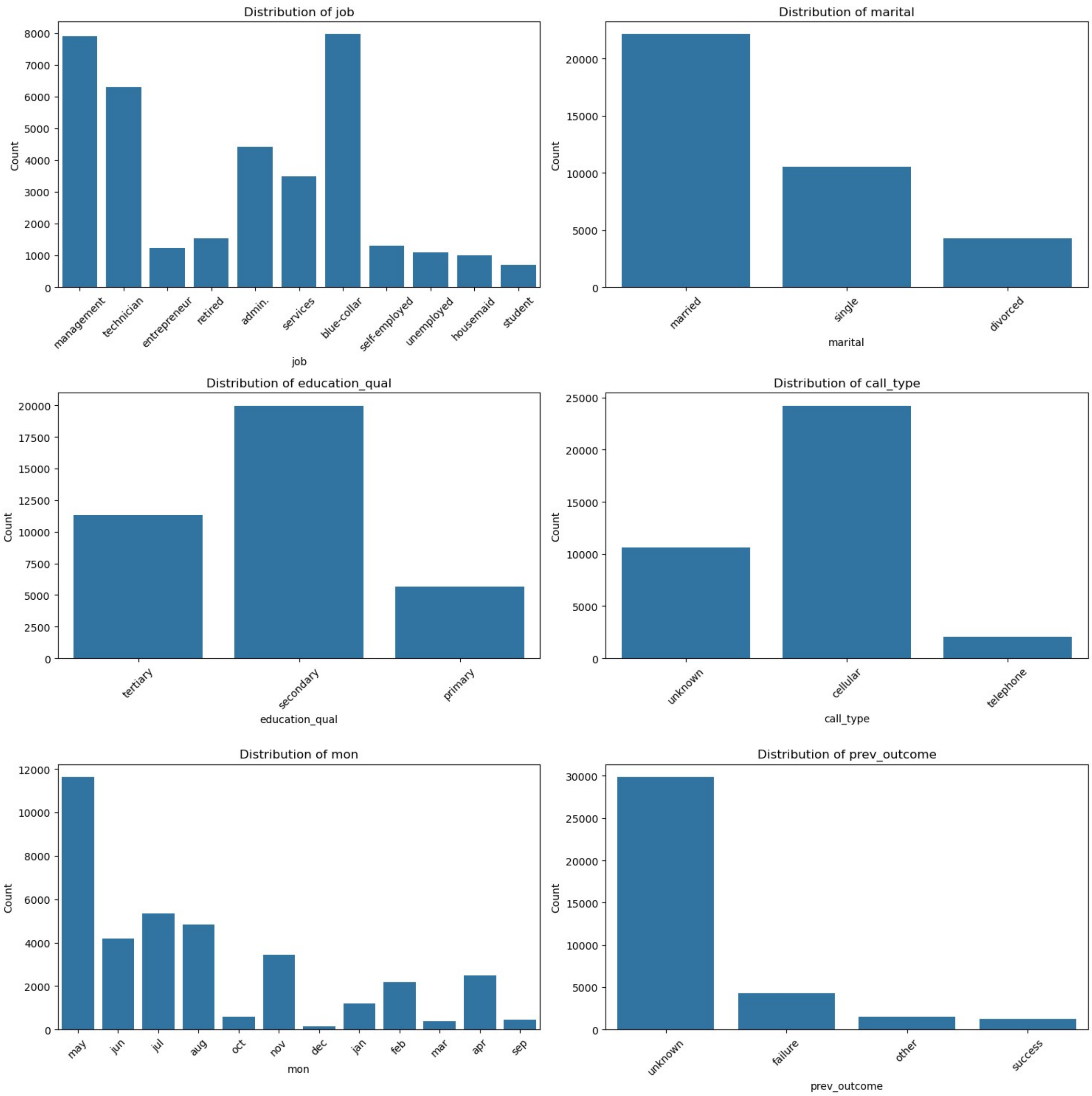
```
# Plot histograms for numerical features
customer_dt.hist(bins=20, figsize=(14,10))
plt.show()

# Boxplot for numerical features
customer_dt[['age', 'day', 'dur', 'num_calls']].plot(kind='box',
subplots=True, layout=(2,2), figsize=(12,8))
plt.show()
```


age
0
1000
2000
3000
4000
5000
20
30
40
50
60
70
day
0
500
1000
1500
2000
2500
3000
3500
0
5
10
15
20
25
30
dur
0
1000
2000
3000
4000
0
100
200
300
400
500
600
num_calls
0
2000
4000
6000
8000
10000
12000
14000
16000
1
2
3
4
5
6



Categorical features Distribution

```
# List of categorical features
categorical_features = ['job', 'marital', 'education_qual',
'call_type', 'mon', 'prev_outcome']

# Set up a 3x2 grid for plotting
fig, axes = plt.subplots(3, 2, figsize=(15, 15))

# Flatten the axes array for easy iteration
axes = axes.flatten()

# Loop through the categorical features and create count plots
for i, column in enumerate(categorical_features):
    sns.countplot(x=column, data=customer_dt, ax=axes[i])
    axes[i].set_title(f'Distribution of {column}')
    axes[i].set_ylabel('Count')
    axes[i].set_xlabel(column)
    axes[i].tick_params(axis='x', rotation=45)

# Adjust layout for better spacing
plt.tight_layout()
plt.show()
```

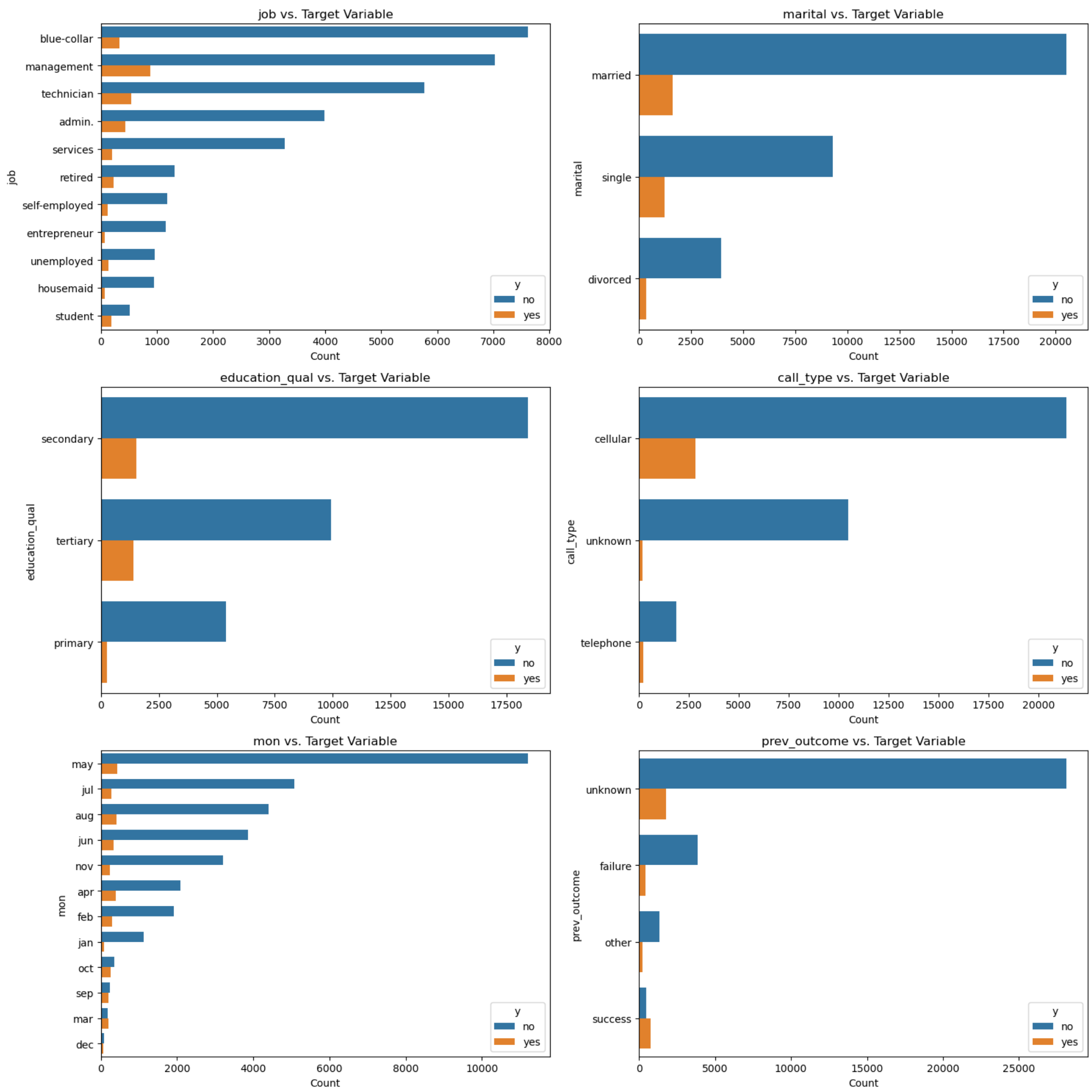


(2) Bivariate Analysis

Categorical features vs Target (Outcome)

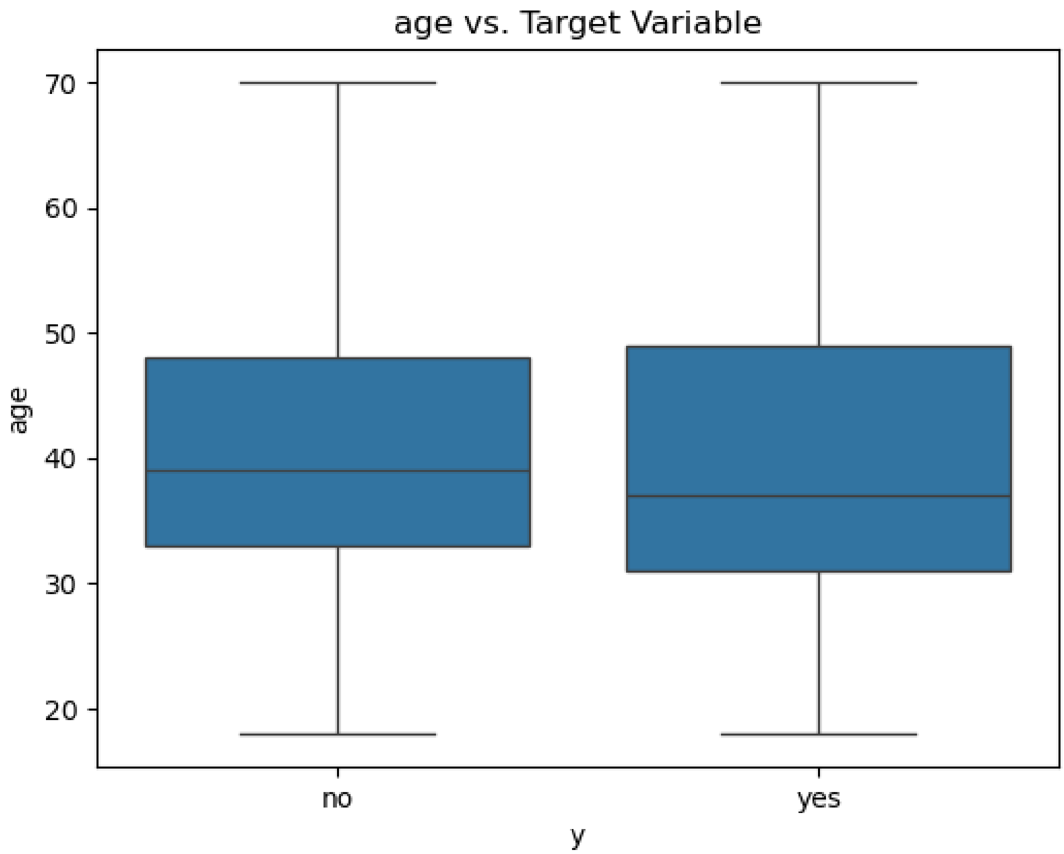
```
# List of categorical features to plot
categorical_features = ['job', 'marital', 'education_qual',
'call_type', 'mon', 'prev_outcome']

# Set up a 3x2 grid for plotting
fig, axes = plt.subplots(3, 2, figsize=(15, 15))

# Flatten the axes array for easy iteration
axes = axes.flatten()
```

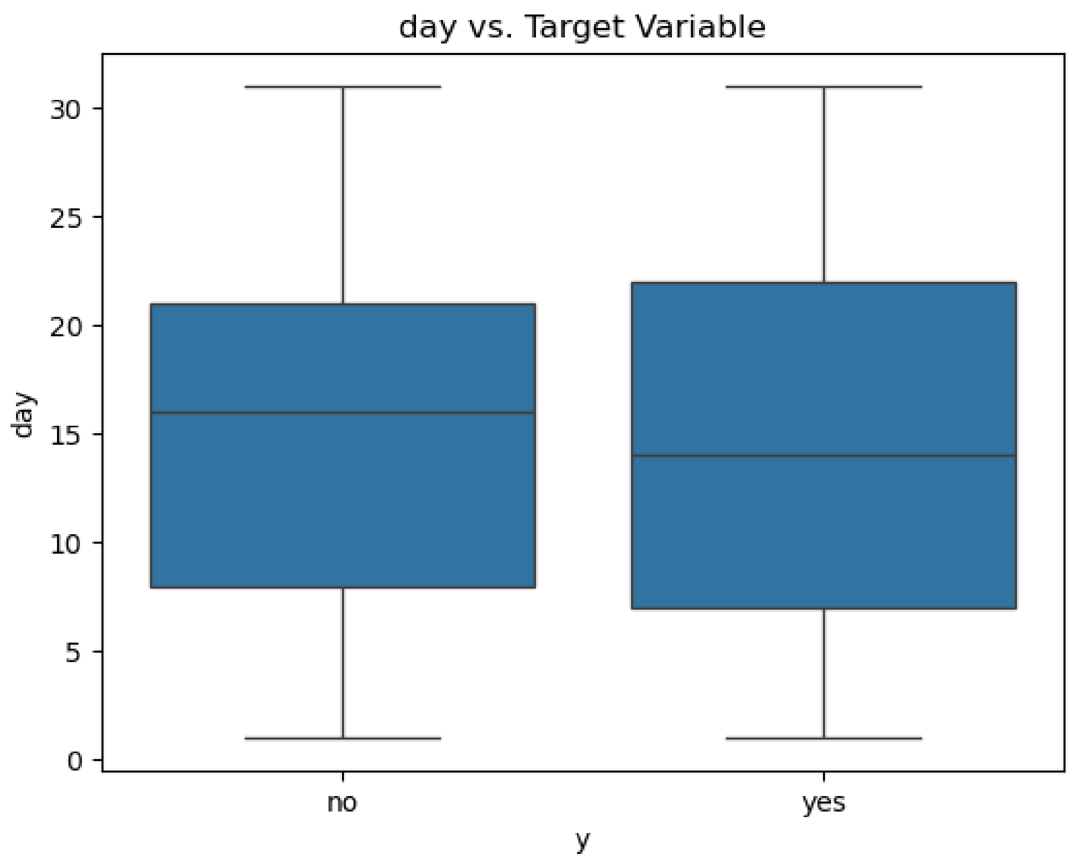
```
# Loop through the categorical features and create count plots
for i, column in enumerate(categorical_features):
    sns.countplot(y=column, hue='y', data=customer_dt,
order=customer_dt[column].value_counts().index, ax=axes[i])
    axes[i].set_title(f'{column} vs. Target Variable')
    axes[i].set_xlabel('Count')
    axes[i].set_ylabel(column)

# Adjust layout for better spacing
plt.tight_layout()
plt.show()
```

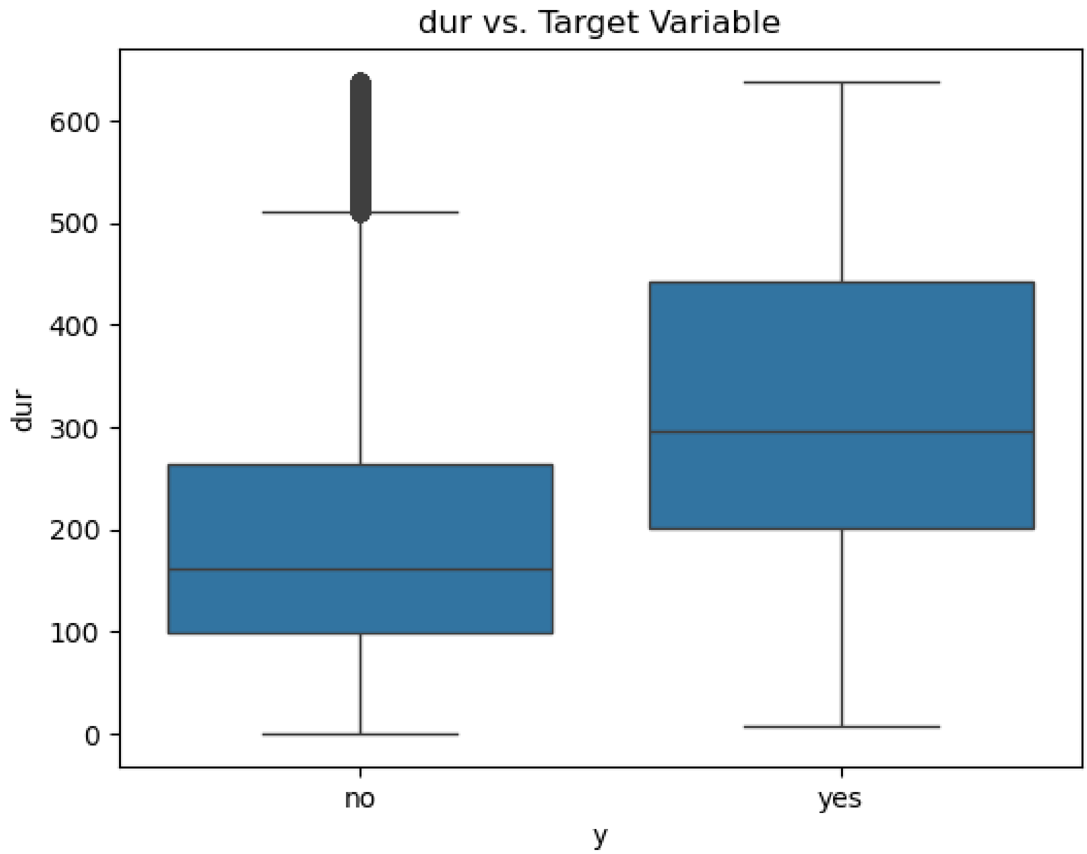


Numeric features vs Target (Outcome)

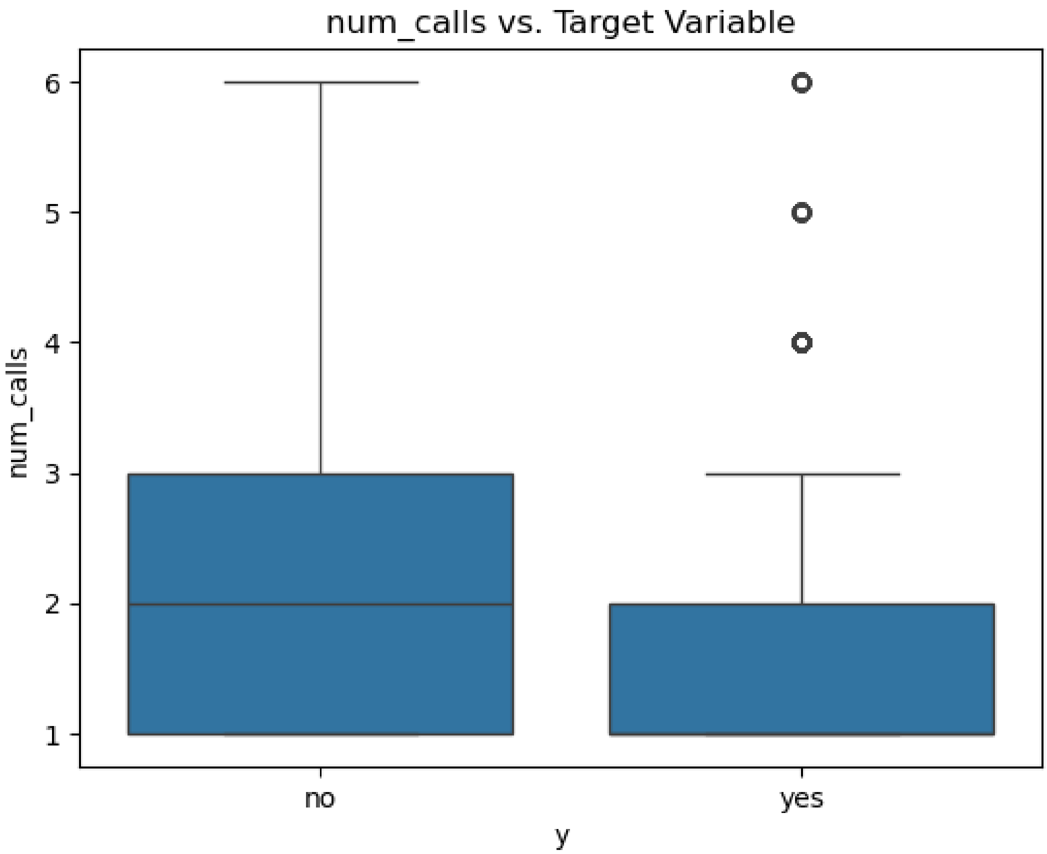
```
# Boxplot to see the relationship between numerical features and target variable
for column in ['age', 'day', 'dur', 'num_calls']:
    sns.boxplot(x='y', y=column, data=customer_dt)
    plt.title(f'{column} vs. Target Variable')
    plt.show()
```




day vs. Target Variable
day
30
25
20
15
10
5
0
no
yes
y

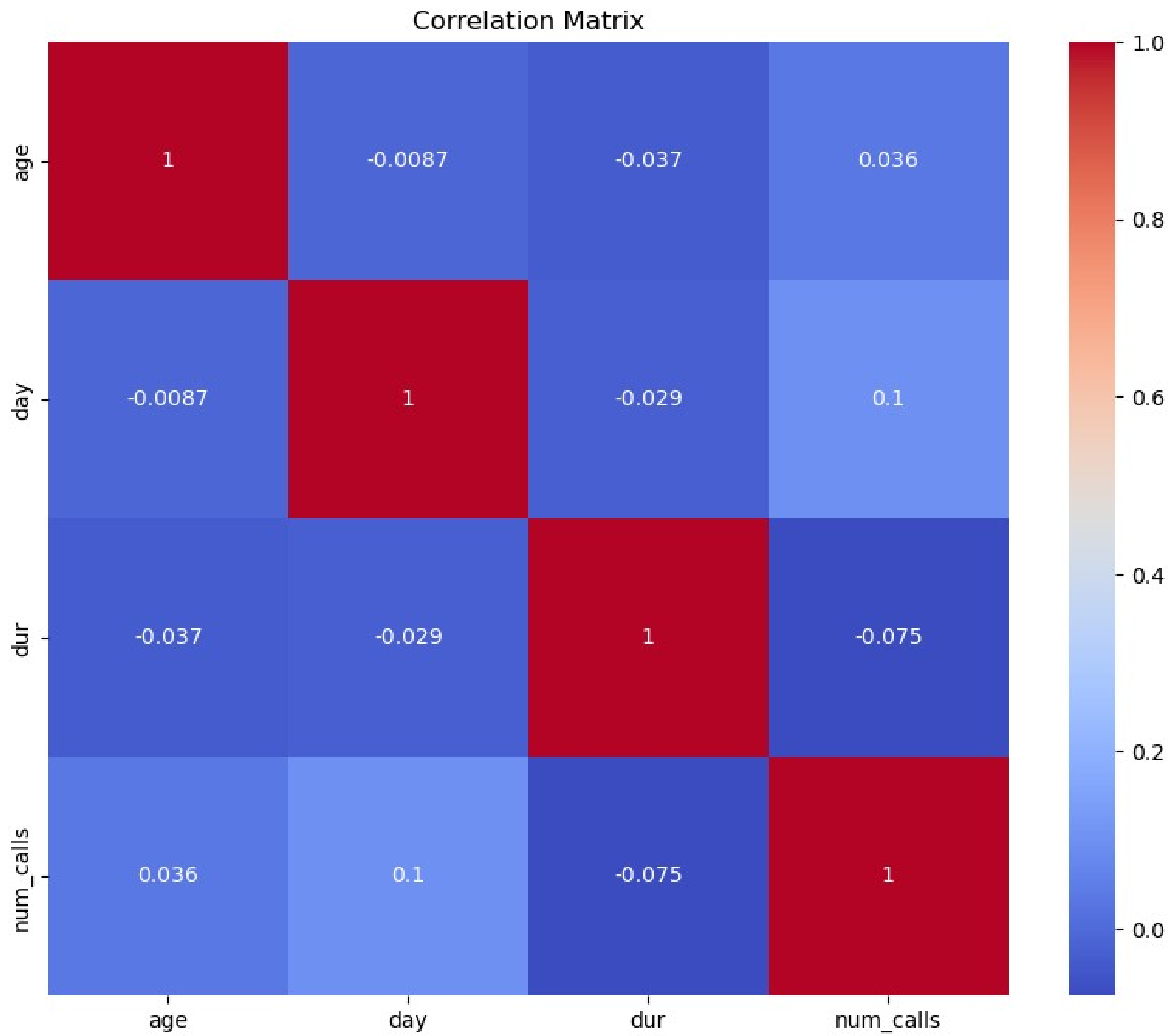


dur vs. Target Variable
600
500
400
300
200
100
0
dur
no
yes
y



Correlation Analysis

```
# Select only numeric columns
numeric_cols = customer_dt.select_dtypes(include=['int64', 'float64'])

# Compute the correlation matrix
corr_matrix = numeric_cols.corr()

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



Encoding and Train test splitting

```
# Label encode the targer variable Y

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
customer_dt['y'] = le.fit_transform(customer_dt['y'])

customer_dt['y']

0        0
1        0
2        0
5        0
6        0
        ..
45202    1
```

```
45203    1
45205    1
45209    0
45210    0
Name: y, Length: 36940, dtype: int32

X = customer_dt.drop(columns = ['y'])
y = customer_dt['y']

#Split data into training and testing
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2 , random_state = 42)

# List the columns that need to be transformed
ordinal_features = ['education_qual']
nominal_features = ['job', 'marital', 'call_type', 'mon',
'prev_outcome']

# Define the transformers
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder,
StandardScaler
preprocessor = ColumnTransformer(
    transformers=[
        ('ord', OrdinalEncoder(categories=[['primary', 'secondary',
'tertiary']]), ordinal_features),
        ('nom', OneHotEncoder(drop='first', sparse_output=False),
nominal_features)
    ],
    remainder='passthrough'  # This will leave the numeric features as
they are
)

# Apply the ColumnTransformer to the training data
X_train_processed = preprocessor.fit_transform(X_train)
X_test_processed = preprocessor.transform(X_test)

scaler = StandardScaler()

# Identify where numeric columns start after transformation
# The ordinal encoding adds 1 column, and one-hot encoding adds
columns equal to the number of unique values in the nominal features
minus one for each.
ordinal_columns = 1  # Only 1 ordinal feature 'education_qual'
onehot_columns = sum(len(preprocessor.transformers_[1]
[1].categories_[i]) - 1 for i in
range(len(preprocessor.transformers_[1][1].categories_)))

num_start = ordinal_columns + onehot_columns
```

```
# Scale only the numeric features
X_train_scaled_numeric = scaler.fit_transform(X_train_processed[:,
num_start:])
X_test_scaled_numeric = scaler.transform(X_test_processed[:,
num_start:])

# Combine scaled numeric features with encoded categorical features
X_train_final = np.hstack((X_train_processed[:, :num_start],
X_train_scaled_numeric))
X_test_final = np.hstack((X_test_processed[:, :num_start],
X_test_scaled_numeric))
```

Apply Logistic Regression model

```
from sklearn.linear_model import LogisticRegression

# Step 6: Train the Logistic Regression model
modelLg = LogisticRegression()
modelLg.fit(X_train_final, y_train)
```

```
LogisticRegression()
```

```
# Predict on the test data
y_predLg = modelLg.predict(X_test_final)

#  Evaluate the model
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
accuracy = accuracy_score(y_test, y_predLg)
print(f'Accuracy: {accuracy:.2f}')
```

```
Accuracy: 0.93
```

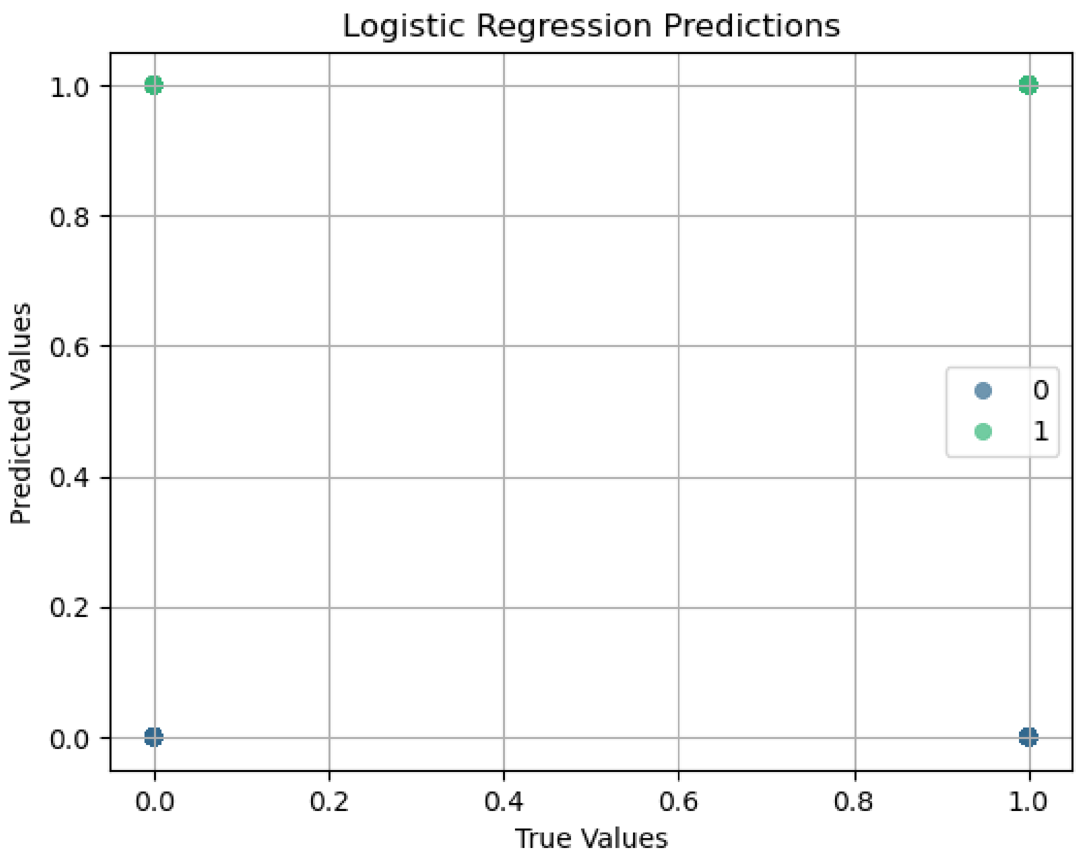
```
conf_matrix = confusion_matrix(y_test, y_predLg)
print('Confusion Matrix:')
print(conf_matrix)
```

```
Confusion Matrix:
[[6692   94]
 [ 441  161]]
```

```
class_report = classification_report(y_test, y_predLg)
print('Classification Report:')
print(class_report)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.99      0.96      6786
           1       0.63      0.27      0.38       602
```

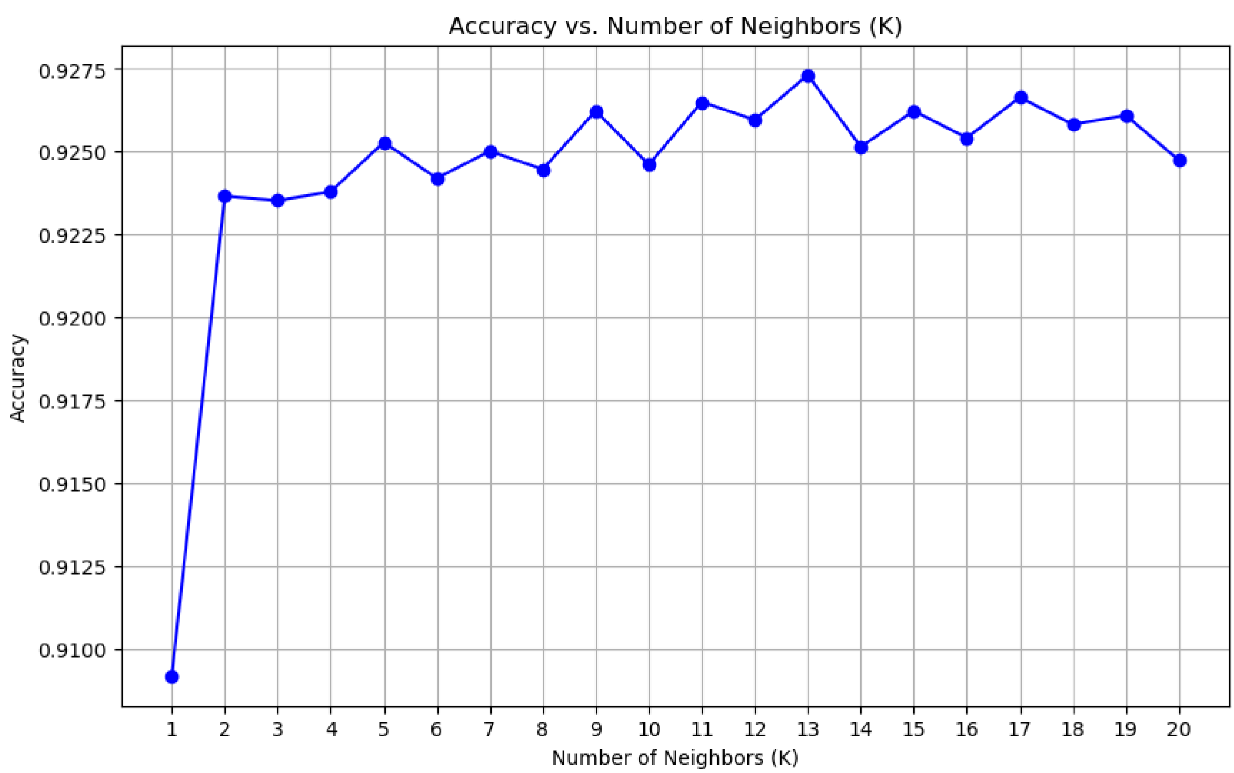
```
    accuracy                           0.93      7388
   macro avg       0.78      0.63      0.67      7388
weighted avg       0.91      0.93      0.91      7388


# Logistic Regression Predictions

sns.scatterplot(x=y_test, y=y_predLg, hue=y_predLg, palette='viridis',
alpha=0.7, edgecolor=None)
plt.title('Logistic Regression Predictions')
plt.xlabel('True Values')
plt.ylabel('Predicted Values')
plt.grid(True)
```



Apply K-Nearest Neighbour (KNN)

```
from sklearn.neighbors import KNeighborsClassifier

# Initialize a list to store accuracy scores for each value of
n_neighbors
accuracy_scores = []

# Manually try different values of n_neighbors
```

```
for k in range(1, 21):  # Trying values from 1 to 20
    knn_model = KNeighborsClassifier(n_neighbors=k)
    knn_model.fit(X_train_final, y_train)  # Train the model
    y_pred = knn_model.predict(X_test_final)  # Predict on the test
set
    accuracy = accuracy_score(y_test, y_pred)  # Calculate accuracy
    accuracy_scores.append(accuracy)  # Store the accuracy

# Plot the accuracy scores
plt.figure(figsize=(10, 6))
plt.plot(range(1, 21), accuracy_scores, marker='o', linestyle='-',
color='b')
plt.title('Accuracy vs. Number of Neighbors (K)')
plt.xlabel('Number of Neighbors (K)')
plt.ylabel('Accuracy')
plt.xticks(range(1, 21))
plt.grid(True)
plt.show()

# Identify the best k
best_k = accuracy_scores.index(max(accuracy_scores)) + 1
best_accuracy = max(accuracy_scores)

print(f'Best number of neighbors: {best_k}')
print(f'Best accuracy: {best_accuracy:.4f}')
```



```
Best number of neighbors: 13
Best accuracy: 0.9273
```

Apply DecisionTreeClassifier

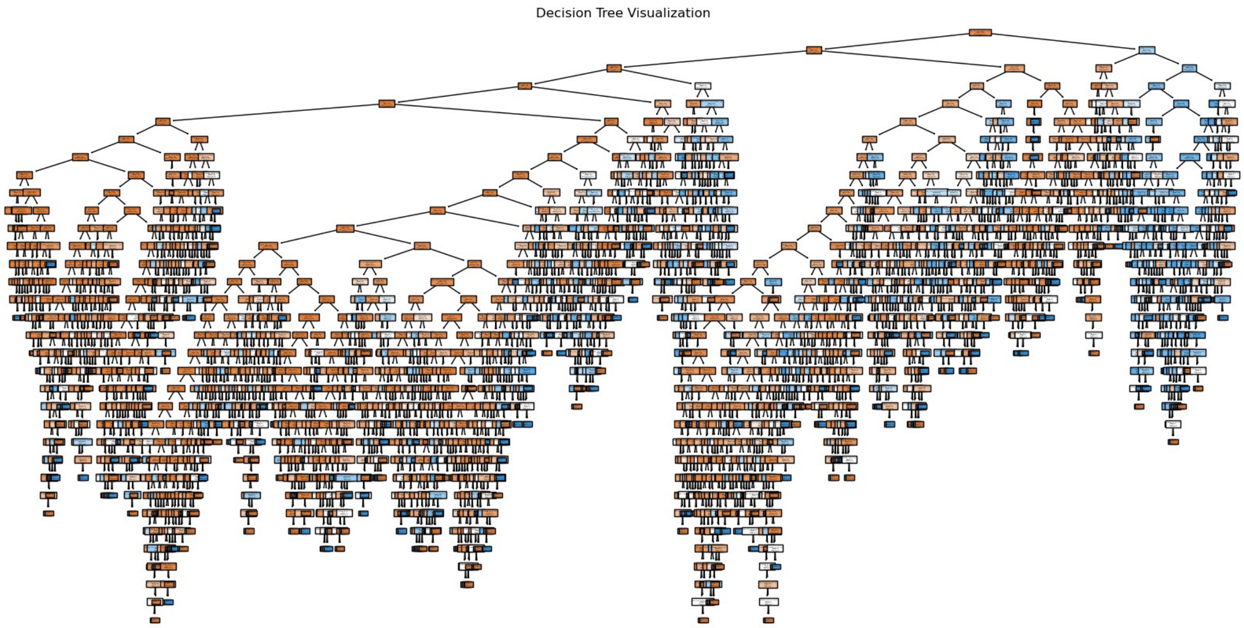
```python
from sklearn.tree import DecisionTreeClassifier, plot_tree

# Initialize and train the Decision Tree model
decision_tree_model = DecisionTreeClassifier(random_state=42)
decision_tree_model.fit(X_train_final, y_train)

# Make predictions on the test set
y_pred_tree = decision_tree_model.predict(X_test_final)

# Evaluate the model
accuracy_tree = accuracy_score(y_test, y_pred_tree)
print(f'Accuracy of Decision Tree: {accuracy_tree:.4f}')
```

```
Accuracy of Decision Tree: 0.9004
```

```python
# Create confusion matrix
conf_matrix_tree = confusion_matrix(y_test, y_pred_tree)

conf_matrix_tree
```

```
array([[6386,  400],
       [ 336,  266]], dtype=int64)
```

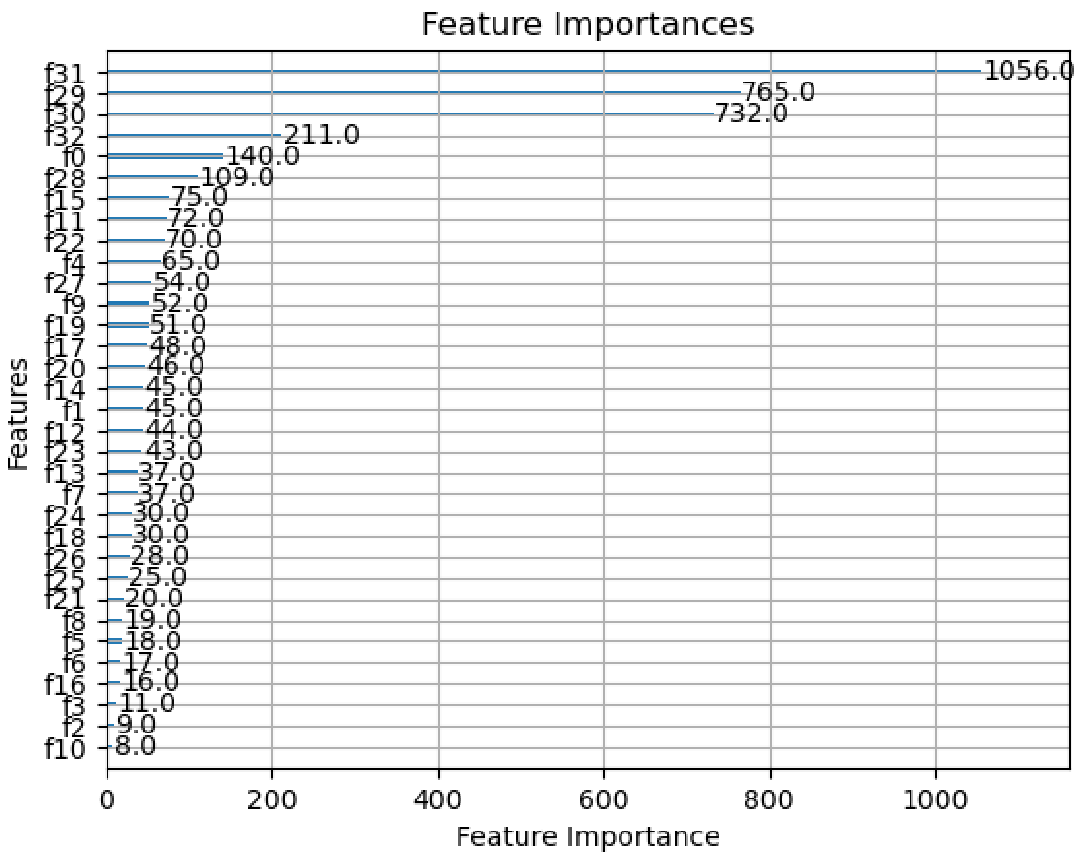
```python
# Plot decision tree
plt.figure(figsize=(20, 10))
plot_tree(decision_tree_model,
feature_names=preprocessor.get_feature_names_out(), class_names=['no',
'yes'], filled=True)
plt.title('Decision Tree Visualization')
plt.show()
```



Apply XG Boost

```
import xgboost as xgb

# Initialize and train the XGBoost model
xgb_model = xgb.XGBClassifier(eval_metric='logloss',  random_state=42)
xgb_model.fit(X_train_final, y_train)

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None,
early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None,
max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None,
max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None,
n_estimators=None,
              n_jobs=None, num_parallel_tree=None,
random_state=42, ...)

# Make predictions on the test set
y_pred_xgb = xgb_model.predict(X_test_final)

# Evaluate the model
accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
print(f'Accuracy of XGBoost: {accuracy_xgb:.4f}')
```

```
Accuracy of XGBoost: 0.9285

# Plot feature importances
plt.figure(figsize=(12, 8))
xgb.plot_importance(xgb_model, importance_type='weight',
title='Feature Importances', xlabel='Feature Importance',
ylabel='Features')
plt.show()

<Figure size 1200x800 with 0 Axes>
```



Apply Random Forest

```
from sklearn.ensemble import RandomForestClassifier

# Initialize and train the Random Forest model
random_forest_model = RandomForestClassifier(n_estimators=100,
random_state=42)
random_forest_model.fit(X_train_final, y_train)

# Make predictions on the test set
y_pred_rf = random_forest_model.predict(X_test_final)
```

```python
# Evaluate the model
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print(f'Accuracy of Random Forest: {accuracy_rf:.4f}')
```

```
Accuracy of Random Forest: 0.9327
```

Now Compare all 5 Models

```python
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, classification_report
# Evaluate models
metrics = {
    'Model': ['Logistic Regression', 'KNN', 'Decision Tree', 'Random
Forest', 'XGBoost'],
    'Accuracy': [
        accuracy_score(y_test, y_predLg),
        accuracy_score(y_test, y_pred),
        accuracy_score(y_test, y_pred_tree),
        accuracy_score(y_test, y_pred_rf),
        accuracy_score(y_test, y_pred_xgb),
    ],
    'Precision': [
        precision_score(y_test, y_predLg, pos_label= 1),
        precision_score(y_test, y_pred, pos_label=1),
        precision_score(y_test, y_pred_tree, pos_label=1),
        precision_score(y_test, y_pred_rf, pos_label=1),
        precision_score(y_test, y_pred_xgb, pos_label=1),
    ],
    'Recall': [
        recall_score(y_test, y_predLg, pos_label=1),
        recall_score(y_test, y_pred, pos_label=1),
        recall_score(y_test, y_pred_tree, pos_label=1),
        recall_score(y_test, y_pred_rf, pos_label=1),
        recall_score(y_test, y_pred_xgb, pos_label=1),
    ],
    'F1 Score': [
        f1_score(y_test, y_predLg, pos_label=1),
        f1_score(y_test, y_pred, pos_label=1),
        f1_score(y_test, y_pred_tree, pos_label=1),
        f1_score(y_test, y_pred_rf, pos_label=1),
        f1_score(y_test, y_pred_xgb, pos_label=1),
    ]
}


# Create DataFrame for better visualization
metrics_df = pd.DataFrame(metrics)

# Display metrics
print(metrics_df)
```

```python
# Plot metrics for comparison
metrics_df.set_index('Model').plot(kind='bar', figsize=(14, 8))
plt.title('Model Comparison')
plt.ylabel('Score')
plt.xlabel('Model')
plt.xticks(rotation=45)
plt.legend(loc='best')
plt.show()
```

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.927585	0.631373	0.267442	0.375729
1	KNN	0.924743	0.755556	0.112957	0.196532
2	Decision Tree	0.900379	0.399399	0.441860	0.419558
3	Random Forest	0.932729	0.673267	0.338870	0.450829
4	XGBoost	0.928533	0.586449	0.416944	0.487379