PRODIGY INFOTECH

Data Science Internship

- Prajwal Singh R

Task-03

> 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.

CUSTOMER PURCHASE PREDICTION

PROJECT DESCRIPTION

In this project, a decision tree classifier is built to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Dataset used is from the UCI Machine Learning Repository, which contains information such as age, job, marital status, education, balance, and various other features about the customers. The goal is to develop a predictive model that can assist marketing efforts by identifying potential customers who are more likely to make a purchase.

BUSINESS UNDERSTANDING

The project is important for businesses, especially in the marketing and sales domain, as it can help in targeting potential customers more effectively. By identifying customers who are likely to make a purchase, businesses can optimize their marketing strategies, allocate resources efficiently, and ultimately increase their conversion rates and revenue.

DATA UNDERSTANDING

The dataset obtained is from UCI Machine Learning Repository website: [Bank Marketing]

The dataset contains the following columns:

`age` : **Age of the customer.**
`job` : **Occupation of the customer.**
`marital` : **Marital status of the customer.**
`education` : **Education level of the customer.**
`default` : **Whether the customer has credit in default (yes/no).**
`balance` : **Average yearly balance in euros.**
`housing` : **Whether the customer has a housing loan (yes/no).**
`loan` : **Whether the customer has a personal loan (yes/no).**
`contact` : **Type of communication used to contact the customer.**
`day` : **Last contact day of the month.**
`month` : **Last contact month of the year.**
`duration` : **Duration of the last contact in seconds.**
`campaign` : **Number of contacts performed during this campaign.**
`pdays` : **Number of days since the customer was last contacted.**
`previous` : **Number of contacts performed before this campaign.**
`poutcome` : **Outcome of the previous marketing campaign.**
`y` : **Whether the customer subscribed to a term deposit (yes/no).**

In [1]:

```
pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in c:\users\lenovo\anaconda3\lib\site-pac
kages (0.12.0)Note: you may need to restart the kernel to use updated packages.

Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\lenovo\anaconda3\lib\site
-packages (from imbalanced-learn) (2.2.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\lenovo\anaconda3\lib\site-packag
es (from imbalanced-learn) (1.21.5)
Requirement already satisfied: scipy>=1.5.0 in c:\users\lenovo\anaconda3\lib\site-package
s (from imbalanced-learn) (1.9.1)
Requirement already satisfied: joblib>=1.1.1 in c:\users\lenovo\anaconda3\lib\site-packag
es (from imbalanced-learn) (1.3.2)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\lenovo\anaconda3\lib\site-
packages (from imbalanced-learn) (1.0.2)
```

In [2]:

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

from sklearn.preprocessing import MinMaxScaler
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, conf
usion_matrix, roc_curve,roc_auc_score,log_loss
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV, StratifiedKFold

import warnings
warnings.filterwarnings("ignore")
```

In [3]:

```
#Initialize the DataUnderstanding class
class DataUnderstanding:
    def __init__(self, df):
        self.df = df
# Get the summary statistics
    def get_summary_statistics(self):
```

```
        summary_stats = self.df.describe()
        return summary_stats
# Get the count of missing values
    def get_missing_values(self):
        missing_values = self.df.isnull().sum()
        return missing_values
# Get the summary of the DataFrame
    def get_info(self):
        info = self.df.info()
        return info
# Get the data types
    def get_dtypes(self):
        dtypes = self.df.dtypes
        return dtypes

    def get_value_counts(self):
        value_counts = {}
        for column in self.df.columns:
            value_counts[column] = self.df[column].value_counts()
        return value_counts
```

In [4]:

```
# load the data
bank = pd.read_csv('D:/Prodigy/Task 3/bank-full.csv', delimiter=';')
bank.head()
```

Out[4]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1

In [5]:

```
# Initialize the DataUnderstanding class
du = DataUnderstanding(bank)
```

In [6]:

```
# Get the summary statistics
du.get_summary_statistics()
```

Out[6]:

	age	balance	day	duration	campaign	pdays	previous
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	40.197828	0.580323
std	10.618762	3044.765829	8.322476	257.527812	3.098021	100.128746	2.303441
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.000000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

In [7]:

```
# get summary of the data
```

```
du.get_info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        45211 non-null  int64 
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64 
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64 
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64 
 12  campaign   45211 non-null  int64 
 13  pdays      45211 non-null  int64 
 14  previous   45211 non-null  int64 
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

The data contains 45211 entries and 17 columns

In [8]:

```
# Get data types
du.get_dtypes()
```

Out[8]:

```
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
y            object
dtype: object
```

DATA PREPARATION

Check for the missing values

In [9]:

```
# Replace the 'unknown' with the NaN for categorical columns
categorical_columns = ['job', 'marital', 'education','contact', 'poutcome', 'month']
bank[categorical_columns]= bank[categorical_columns].replace('unknown', pd.NA)
```

In [10]:

```
# Check for missing values
du.get_missing_values()
```

Out[10]:

```
age              0
job            288
marital          0
education     1857
default          0
balance          0
housing          0
loan             0
contact      13020
day              0
month            0
duration         0
campaign         0
pdays            0
previous         0
poutcome     36959
y                0
dtype: int64
```

dealing with missing values

Job has a few missiing values, So we can drop the rows with missing values

In [11]:

```
# Remove rows with missing ages
bank.dropna(subset=['job'], inplace=True)
```

I will drop both the poutcome column and contact

In [12]:

```
bank = bank.drop(['poutcome', 'contact'], axis=1)
```

We will fill the missing values in education with mode. This will help preserve data and it will have minimum impact on the overall distribution of data

In [13]:

```
bank['education'].fillna(bank['education'].mode()[0], inplace=True)
```

In [14]:

```
bank.isnull().sum()
```

Out[14]:

```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
y            0
dtype: int64
```

In [15]:

```
# get value counts
```

```
# get value counts
du.get_value_counts()
```

Out[15]:

```
{'age': 32    2084
 31    1990
 33    1964
 34    1926
 35    1887
       ...
 93       2
 90       2
 95       2
 88       2
 94       1
 Name: age, Length: 77, dtype: int64,
 'job': blue-collar      9732
 management       9458
 technician       7597
 admin.           5171
 services         4154
 retired          2264
 self-employed    1579
 entrepreneur     1487
 unemployed       1303
 housemaid        1240
 student           938
 Name: job, dtype: int64,
 'marital': married     27011
 single      12722
 divorced     5190
 Name: marital, dtype: int64,
 'education': secondary    23131
 tertiary     13262
 primary       6800
 Name: education, dtype: int64,
 'default': no     44110
 yes      813
 Name: default, dtype: int64,
 'balance':  0        3486
  1         194
  2         155
  4         139
  3         131
           ...
 -923         1
 -1445        1
  10655       1
  4153        1
  16353       1
 Name: balance, Length: 7142, dtype: int64,
 'housing': yes    25104
 no     19819
 Name: housing, dtype: int64,
 'loan': no     37683
 yes     7240
 Name: loan, dtype: int64,
 'contact': cellular     29154
 telephone     2860
 Name: contact, dtype: int64,
 'day': 20    2730
 18    2296
 21    2016
 17    1932
 6     1908
 5     1891
 14    1843
 8     1835
 28    1818
 7     1799
 19    1738
 29    1734
```

```
15    1700
12    1593
13    1581
30    1559
9     1553
11    1460
4     1429
16    1410
2     1286
27    1114
3     1072
26    1025
23     938
22     899
25     834
31     641
10     522
24     447
1      320
Name: day, dtype: int64,
'month': may    13735
jul     6864
aug     6184
jun     5251
nov     3956
apr     2925
feb     2636
jan     1388
oct      727
sep      570
mar      474
dec      213
Name: month, dtype: int64,
'duration': 124     187
90      182
89      176
114     175
122     173
       ...
1833      1
1545      1
1352      1
1342      1
1556      1
Name: duration, Length: 1571, dtype: int64,
'campaign': 1     17437
2     12438
3      5486
4      3502
5      1749
6      1280
7       731
8       534
9       320
10      264
11      200
12      154
13      130
14       92
15       81
16       77
17       69
18       50
19       44
20       43
21       34
22       23
25       22
23       22
24       20
29       16
28       16
```

```
26        13
31        12
27        10
32         9
30         8
33         6
34         5
36         4
35         3
43         3
38         3
37         2
50         2
41         2
46         1
58         1
55         1
63         1
51         1
39         1
44         1
Name: campaign, dtype: int64,
'pdays': -1      36699
 182      165
 92       146
 183      126
 91       123
        ...
 425        1
 578        1
 674        1
 416        1
 530        1
Name: pdays, Length: 558, dtype: int64,
'previous': 0      36699
1       2762
2       2096
3       1139
4        711
5        456
6        275
7        203
8        129
9         92
10        67
11        65
12        44
13        38
15        20
14        19
17        15
16        13
19        11
20         8
23         8
18         6
22         6
24         5
27         5
21         4
29         4
25         4
30         3
38         2
37         2
26         2
28         2
51         1
275        1
58         1
32         1
40         1
```

```
55         1
35         1
41         1
Name: previous, dtype: int64,
'poutcome': failure    4881
other      1838
success    1500
Name: poutcome, dtype: int64,
'y': no     39668
yes     5255
Name: y, dtype: int64}
```

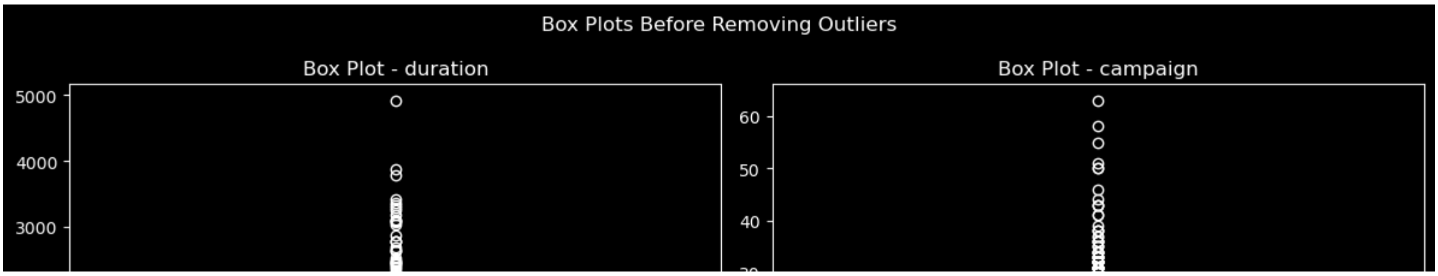
Detecting outliers and removing outliers

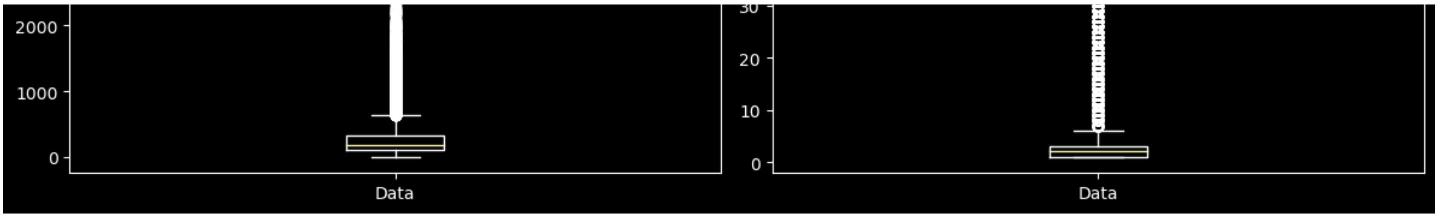
In [16]:

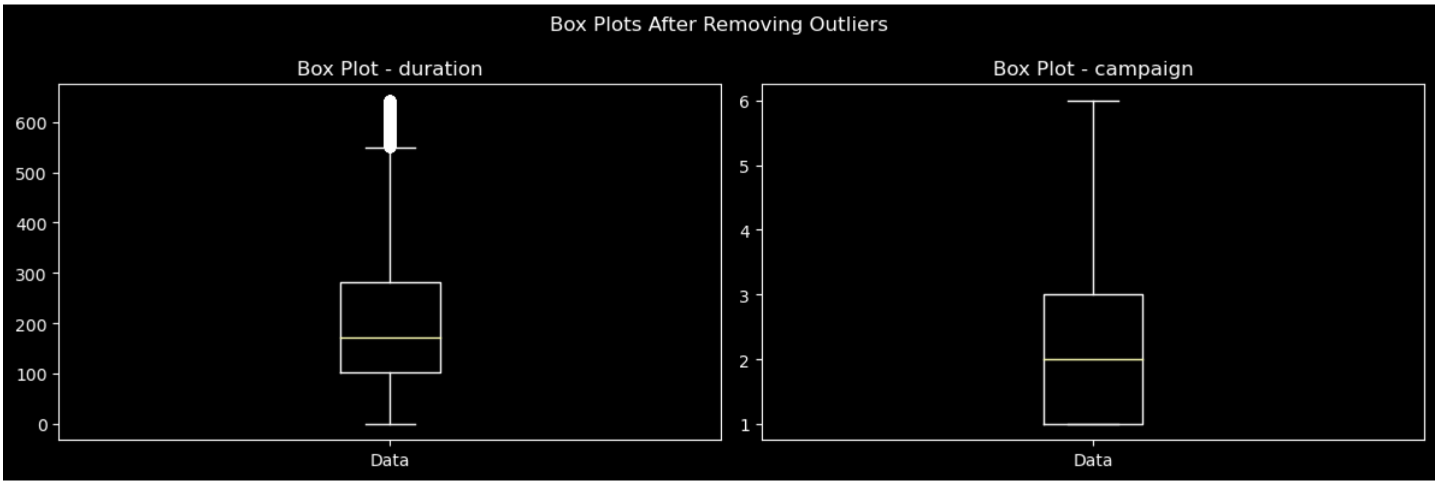
```
# Set the plot style to a dark theme
plt.style.use('dark_background')
```

In [17]:

```
# plot
def plot_boxplots(data, column_names, title):
    plt.figure(figsize=(12, 4))
    for i, column in enumerate(column_names, 1):
        plt.subplot(1, len(column_names), i)
        plt.boxplot(data[column])
        plt.title(f'Box Plot - {column}')
        plt.xticks([1], ['Data'])

    plt.suptitle(title)
    plt.tight_layout()
    plt.show()

# Specify the numeric columns you want to check for outliers
numeric_columns = ['duration', 'campaign']

# Plot box plots before removing outliers
plot_boxplots(bank, numeric_columns, 'Box Plots Before Removing Outliers')

def remove_outliers_iqr(df, column_names):
    outliers_removed = df.copy()
    for column in column_names:
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Detect and remove outliers
        outliers_removed = outliers_removed[(outliers_removed[column] >= lower_bound) &
                                            (outliers_removed[column] <= upper_bound)
]

    return outliers_removed

# Detect and remove outliers
bank = remove_outliers_iqr(bank, numeric_columns)

# Plot box plots after removing outliers
plot_boxplots(bank, numeric_columns, 'Box Plots After Removing Outliers')
```







EXPLORATORY DATA ANALYSIS

Univariate Analysis

Univariate analysis involves examining the distribution of individual variables

Subscription rate

The dependent variable would typically be "y," which represents whether the customer subscribed to a term deposit. This variable indicates the binary outcome of interest: whether a customer made a specific decision or took a specific action, in this case, subscribing to a term deposit or not

In [18]:

```
# count of subscription rate
bank['y'].value_counts(normalize=True)
```

Out[18]:

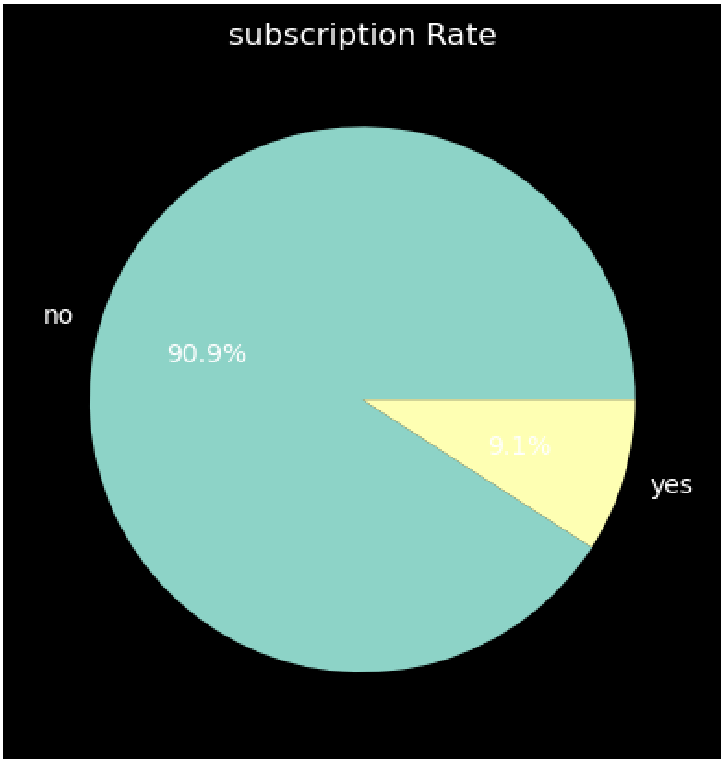
```
no      0.90895
yes     0.09105
Name: y, dtype: float64
```

The distribution of the two classes in the data set is not equal. This causes data imbalance. Data imbalance can cause a model to make false predictions, so it is important to address this issue before modeling.

In [19]:

```
#plotting churn rate
def plot_churn_rate(data):
    #Create a figure
    fig, ax = plt.subplots()

    # Plot the churn rate
    ax.pie(bank['y'].value_counts(), labels=bank['y'].value_counts().index, autopct='%1.
1f%%')

    # Add a title
    ax.set_title('subscription Rate')

    # Show the plot
```

```
    plt.show()
plot_churn_rate(bank['y'])
```

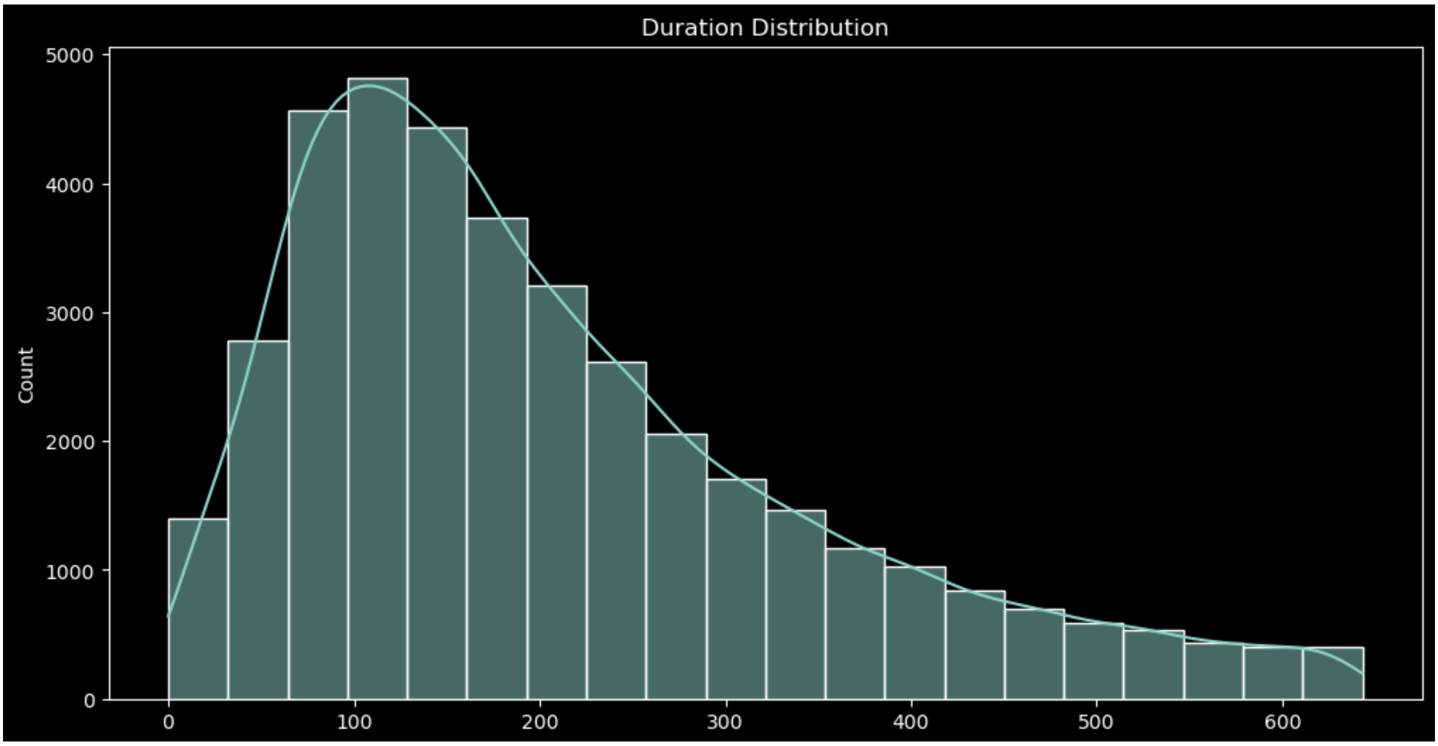


- **Approximately 90.9% of the customers did not subscribe to a term deposit, while the remaining did subscribe.**
- **Knowing that only a small percentage of customers subscribed, marketing campaigns could focus on identifying and targeting specific customer segments that are more likely to subscribe**

Duration Distribution Analysis

In [20]:

```
# plot
plt.figure(figsize=(12, 6))
sns.histplot(bank['duration'], bins=20, kde=True)
plt.title('Duration Distribution')
plt.xlabel('Duration (seconds)')
plt.ylabel('Count')
plt.show()
```

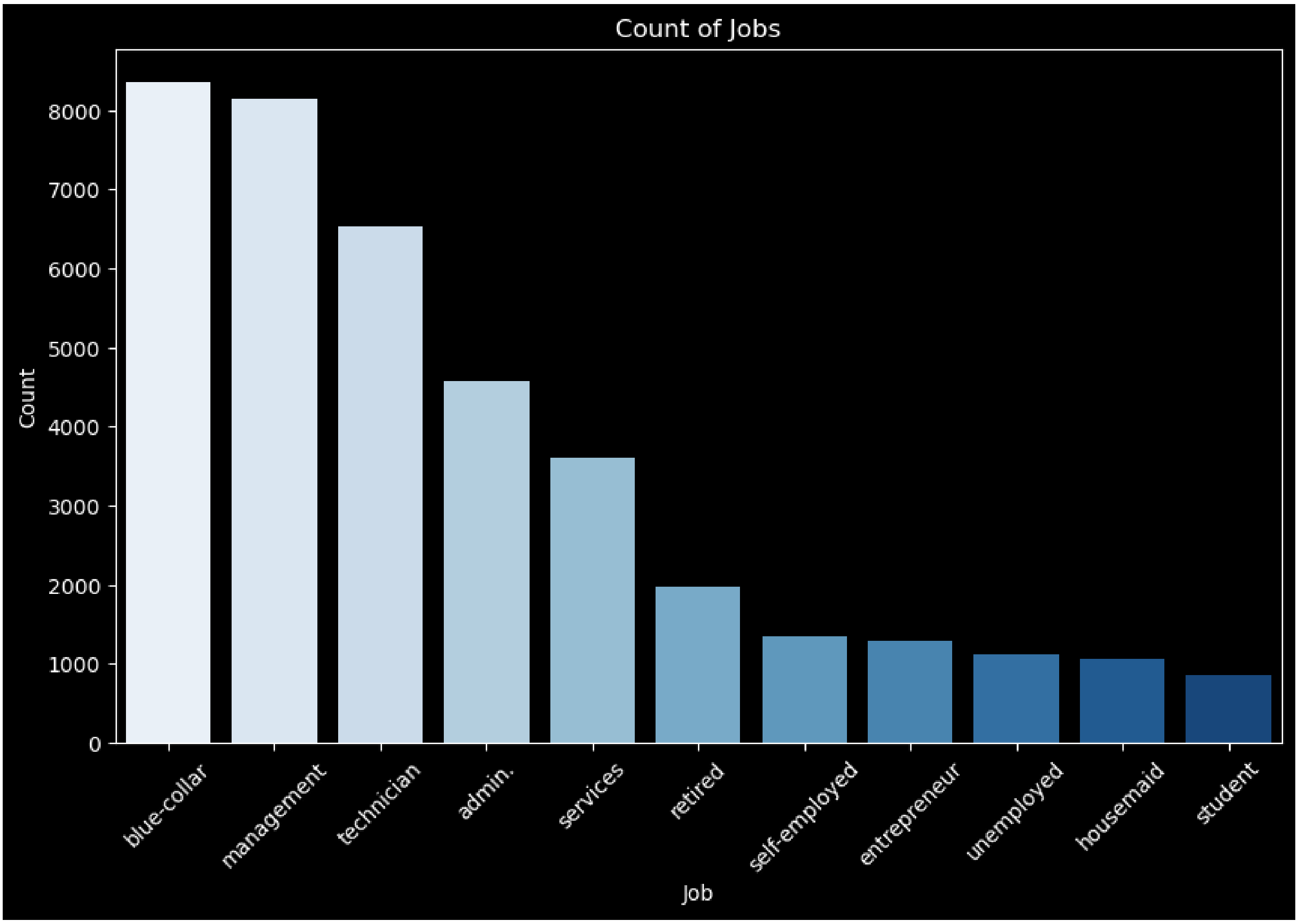


- **Right-Skewed Distribution: The duration distribution is right-skewed, indicating that most customer interactions have shorter durations, with a few exceptionally long durations.**
- **Peak at Short Durations: The peak of the distribution is at shorter call durations, suggesting that the majority of customer interactions are relatively brief.**
- **Long Call Durations: There are significant outliers on the right side, representing a minority of customer interactions with very long call durations.**
- **Potential Significance: Longer call durations may indicate more in-depth conversations, potentially related to successful subscription outcomes. It's worth exploring whether longer durations correlate with higher subscription rates.**
- **Based on this distribution, it may be beneficial to tailor communication strategies for shorter and longer call durations. Shorter calls could focus on concise messaging, while longer calls might involve more detailed discussions.**

Job Analysis

In [21]:

```
# Define a color palette with shades of blue
blue_palette = sns.color_palette("Blues", n_colors=len(bank['job'].unique()))
# plot
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='job', order=bank['job'].value_counts().index, palette=blue_p
alette)
plt.title('Count of Jobs')
plt.xlabel('Job')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



- **Most Common Jobs: The most common jobs among customers include "blue-collar," "management," "technician," and "admin"**

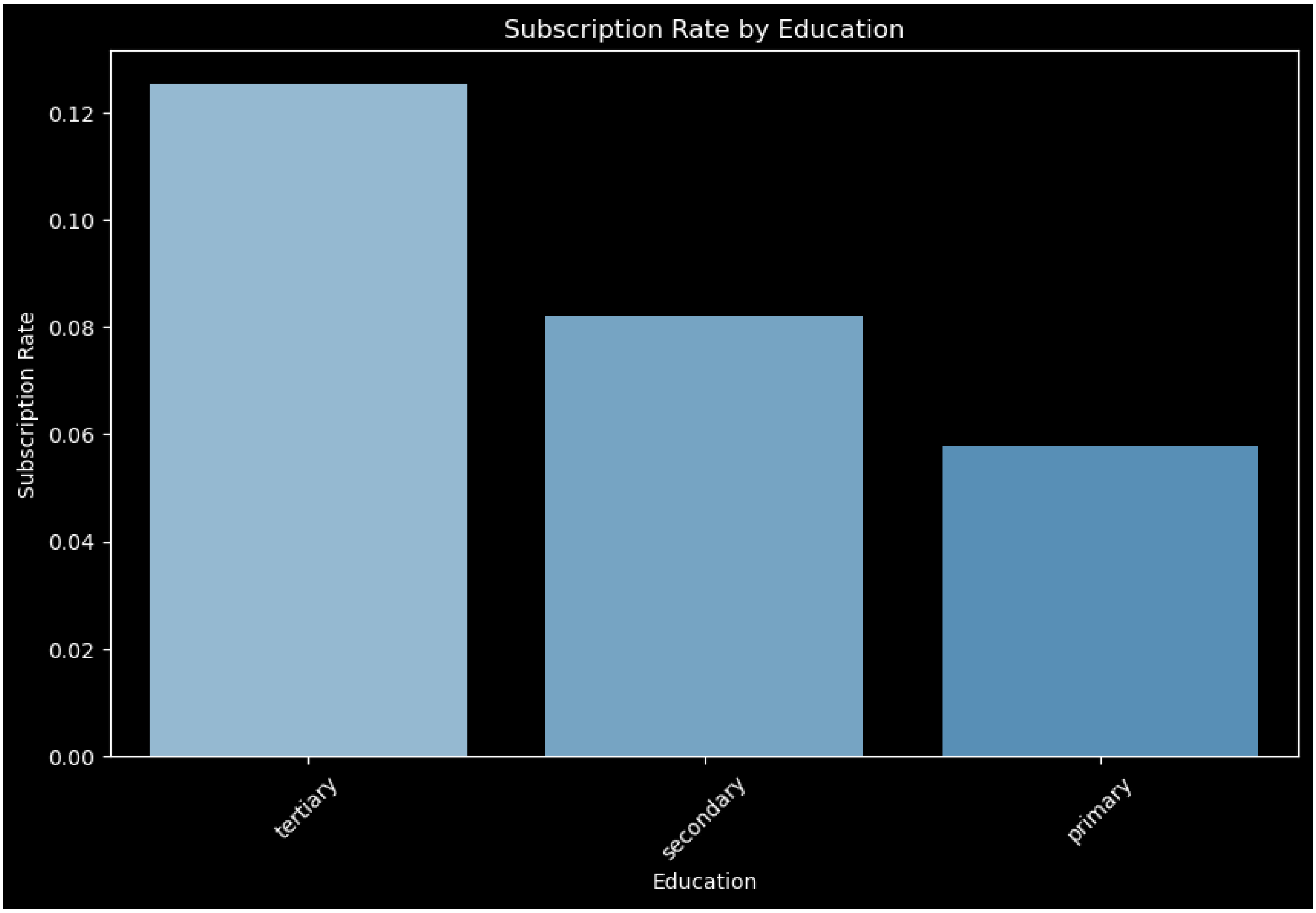
- **Imbalanced Job Categories: Some job categories are imbalanced, with a significantly larger number of customers in certain occupations compared to others.**
- **Marketing strategies can be tailored based on job categories. For instance, promotions or messaging can be customized to appeal to specific professional groups.**

Bivariate Analysis

Subscription Rate by Education

In [22]:

```
# Define a custom color palette with darker shades of blue
custom_palette = sns.color_palette("Blues_d")
# Pivot table to examine the relationship between education and subscription (y)
pivot_table = bank.pivot_table(index='education', columns='y', values='age', aggfunc='co
unt', fill_value=0)
pivot_table['subscription_rate'] = pivot_table['yes'] / (pivot_table['yes'] + pivot_tabl
e['no'])

# Bar plot to visualize subscription rate by education
plt.figure(figsize=(10, 6))
sns.barplot(data=pivot_table, x=pivot_table.index, y='subscription_rate', order=pivot_ta
ble.sort_values(by='subscription_rate', ascending=False).index, palette=custom_palette)
plt.title('Subscription Rate by Education')
plt.xlabel('Education')
plt.ylabel('Subscription Rate')
plt.xticks(rotation=45)
plt.show()
```



- **Customers with a "tertiary" education have the highest subscription rate, indicating that individuals with higher education levels are more likely to subscribe to the term deposit**
- **Followed by those with "secondary" education status.**
- **In contrast, customers with a "primary" education level have the lowest subscription rate.This group may require more targeted and persuasive marketing efforts to increase their subscription rates.**

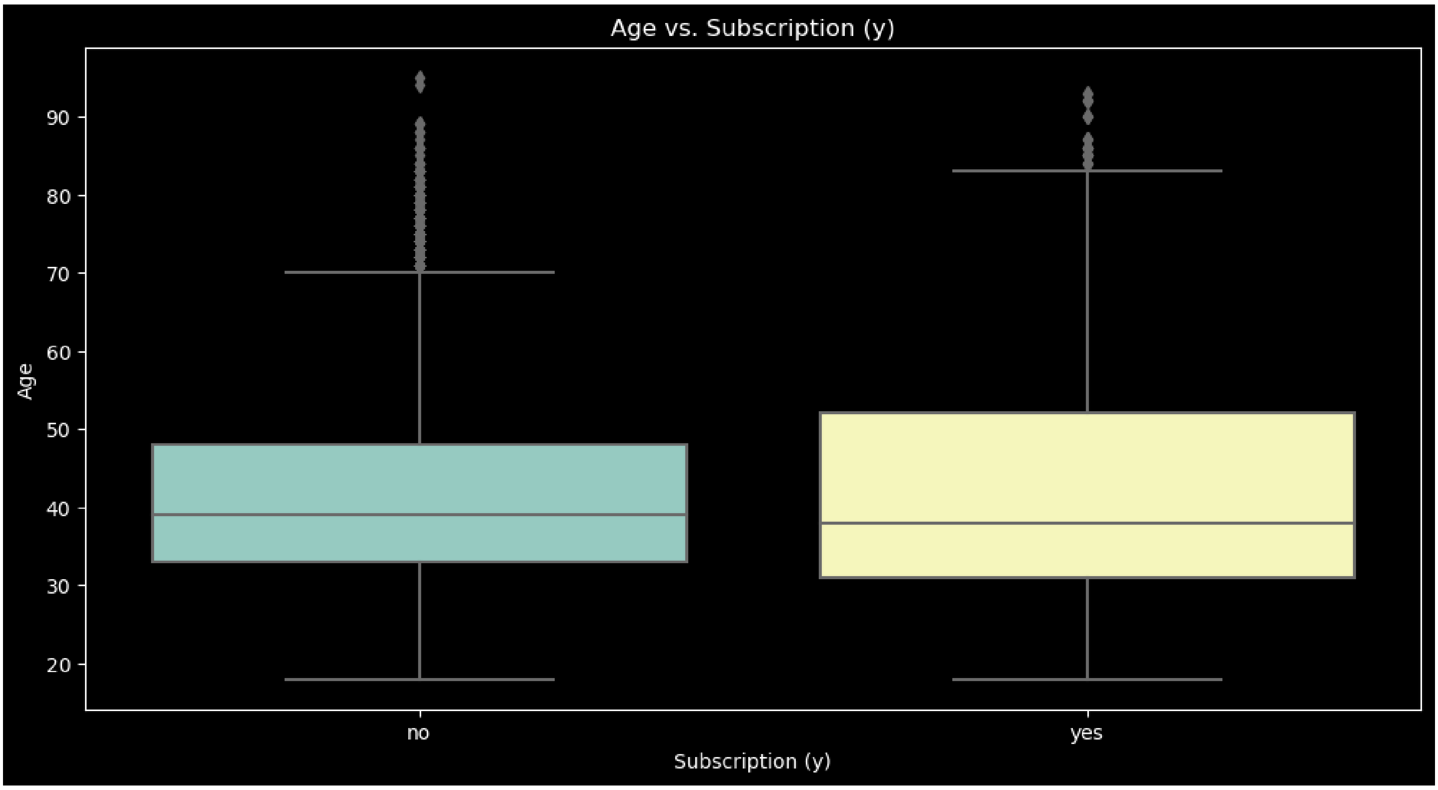
require more targeted and persuasive marketing efforts to increase their subscription rates

- To improve subscription rates, marketing strategies could be adjusted to target customers with higher education levels more effectively. Tailoring campaigns or promotions to appeal to customers with "tertiary" education might be a successful approach

Age vs. Subscription (y)

In [23]:

```
# Bivariate analysis with respect to the target variable ("y")
plt.figure(figsize=(12, 6))
sns.boxplot(data=bank, x='y', y='age')
plt.title('Age vs. Subscription (y)')
plt.xlabel('Subscription (y)')
plt.ylabel('Age')
plt.show()
```

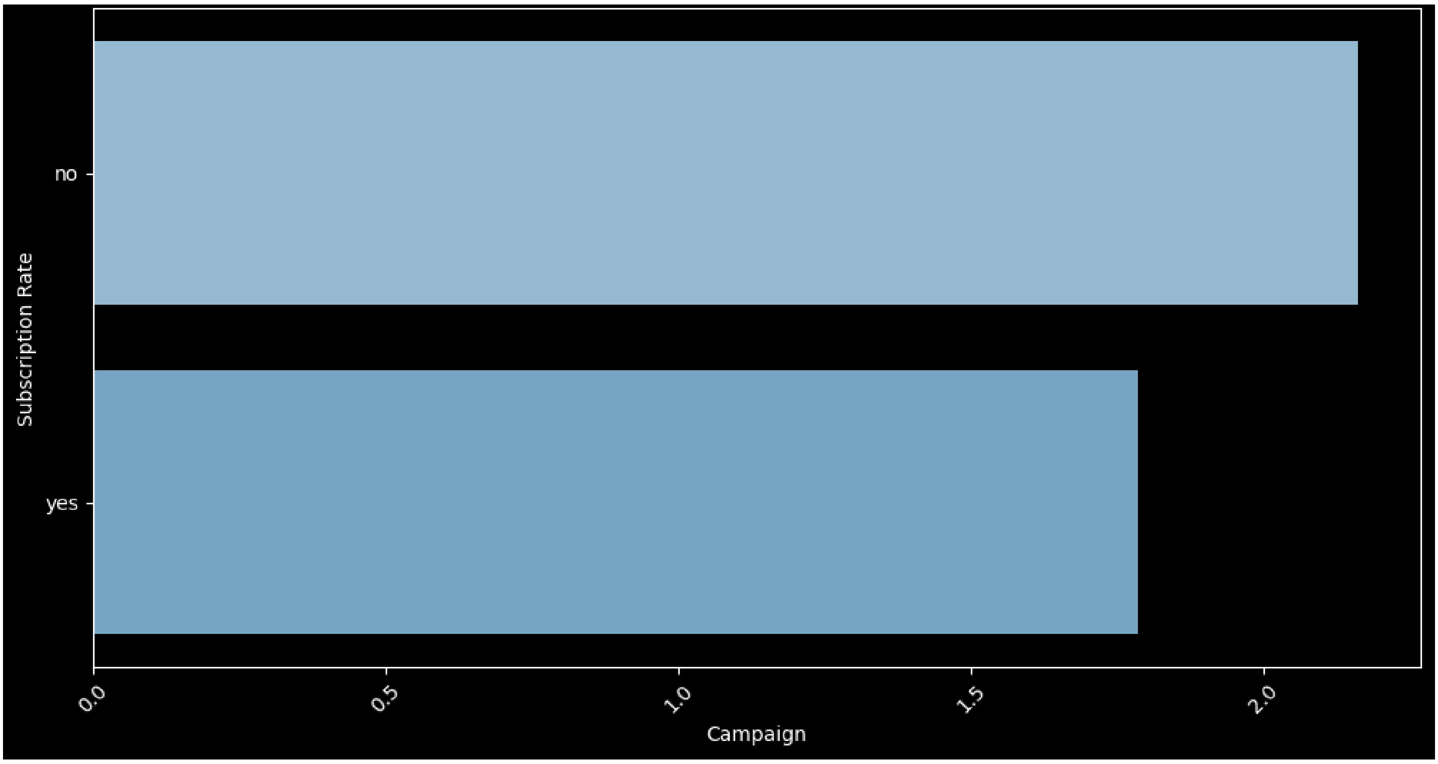


- Customers who subscribed to the term deposit ("yes") tend to have a slightly higher median age compared to those who did not subscribe ("no").
- The age distribution for both "yes" and "no" categories has some overlap. However, there are more outliers (individual points outside the whiskers) in the "yes" category, suggesting that there might be a greater variation in age among customers who subscribed.
- Age alone may not be the sole determinant of subscription behavior, but it appears to have some influence. Older customers might be slightly more inclined to subscribe, while younger customers might have a broader range of subscription behaviors.

Subscription by Campaign

In [24]:

```
# plot
plt.figure(figsize=(12, 6))
sns.barplot(data=bank, x='campaign', y='y', ci=None, palette=custom_palette)
plt.title('Subscription by Campaign')
plt.xlabel('Campaign')
plt.ylabel('Subscription Rate')
plt.xticks(rotation=45)
plt.show()
```



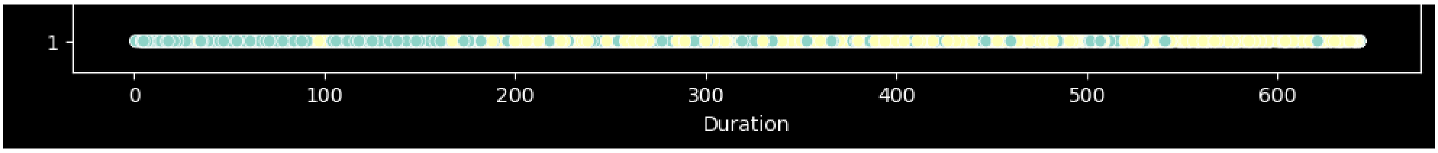
- Decreasing Subscription Rate: As the number of campaign contacts increases, the subscription rate tends to decrease. This suggests that repeatedly contacting a customer during a campaign may have diminishing returns and could potentially be seen as intrusive
- To improve subscription rates, marketers should consider optimizing their campaign strategies. Instead of increasing the number of contacts, they could concentrate on tailoring their messages and interactions to be more compelling and relevant to the custome

Multivariate Analysis

Scatter Plot of Duration vs. Campaign Colored by Subscription

In [25]:

```
# plot
plt.figure(figsize=(12, 6))
sns.scatterplot(data=bank, x='duration', y='campaign', hue='y')
plt.title('Scatter Plot of Duration vs. Campaign Colored by Subscription (y)')
plt.xlabel('Duration')
plt.ylabel('Campaign')
plt.show()
```



- The plot shows a general trend where longer "Duration" of the last contact tends to be associated with a lower "Campaign" number. In other words, customers who subscribed to the term deposit ("y" = yes) tend to have shorter campaign interactions (fewer contacts) and longer last contact durations
- The plot indicates that a marketing strategy that focuses on shorter and more effective interactions during the last contact may be more successful in achieving subscriptions. It's essential to identify and target customers within the subscriber cluster
- Too many campaign contacts with short durations may not be as effective in achieving subscriptions

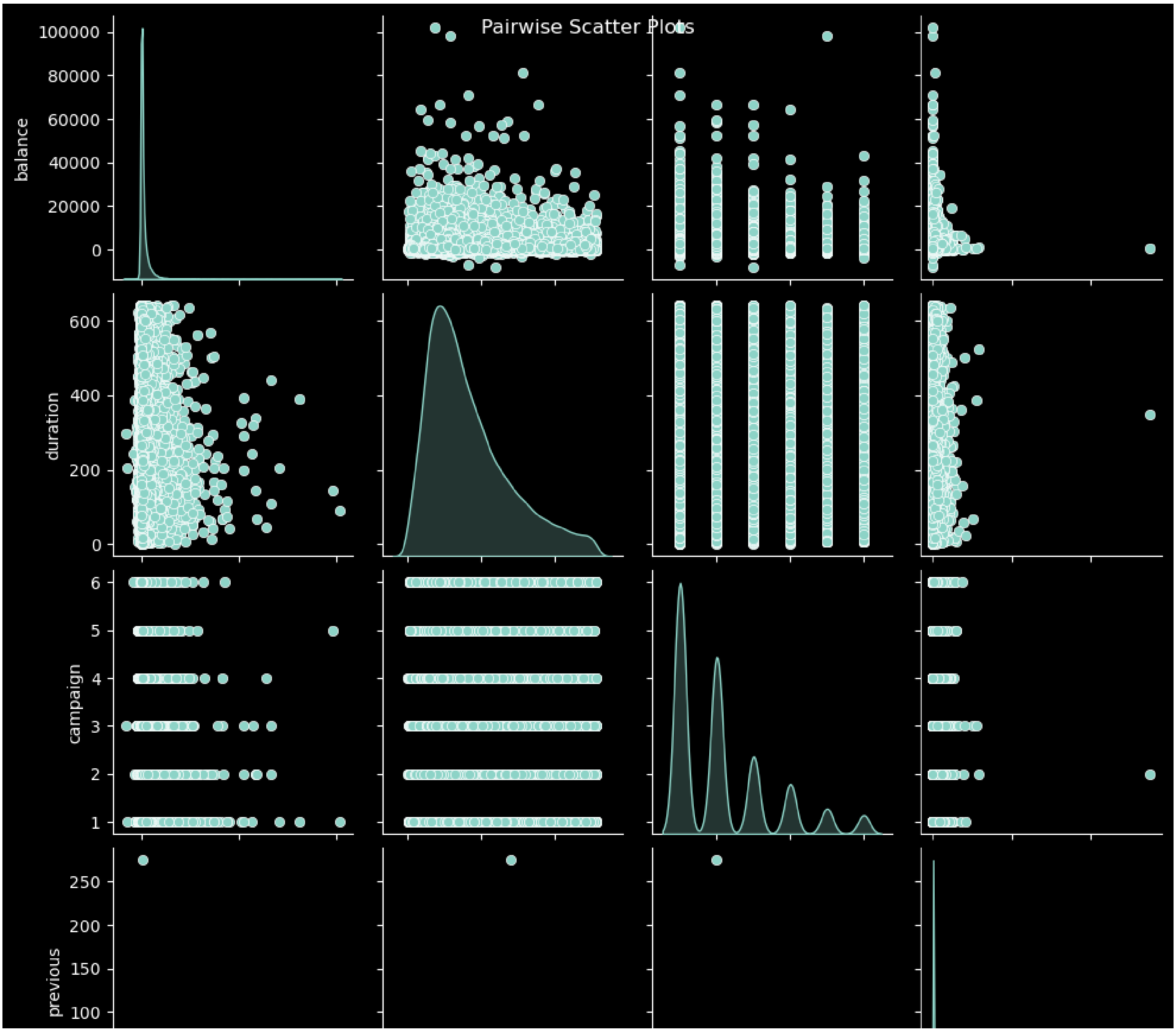
Pairwise Scatter Plots

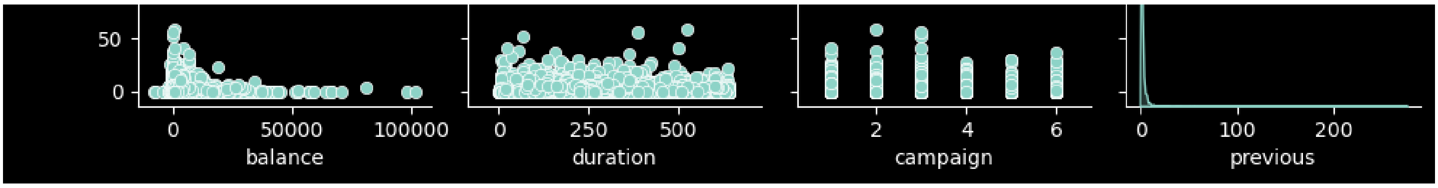
In [26]:

```
# Select the numerical columns for the plot
columns = ['balance', 'duration', 'campaign', 'previous']
```

In [27]:

```
# Pairwise scatter plots for numerical variables
sns.pairplot(data=bank[columns], diag_kind='kde')
plt.suptitle('Pairwise Scatter Plots')
plt.show()
```





- **Balance vs. Duration: No strong relationship observed. Balance alone doesn't predict contact duration.**
- **Balance vs. Campaign: No clear link between balance and campaign contacts.**
- **Balance vs. Previous: Balance isn't a reliable indicator of prior campaign interactions.**
- **Duration vs. Campaign: Longer contact durations are linked to fewer campaign contacts.**
- **Duration vs. Previous: No strong correlation between duration and prior campaign contacts.**
- **Balance and duration alone don't predict campaign success.**

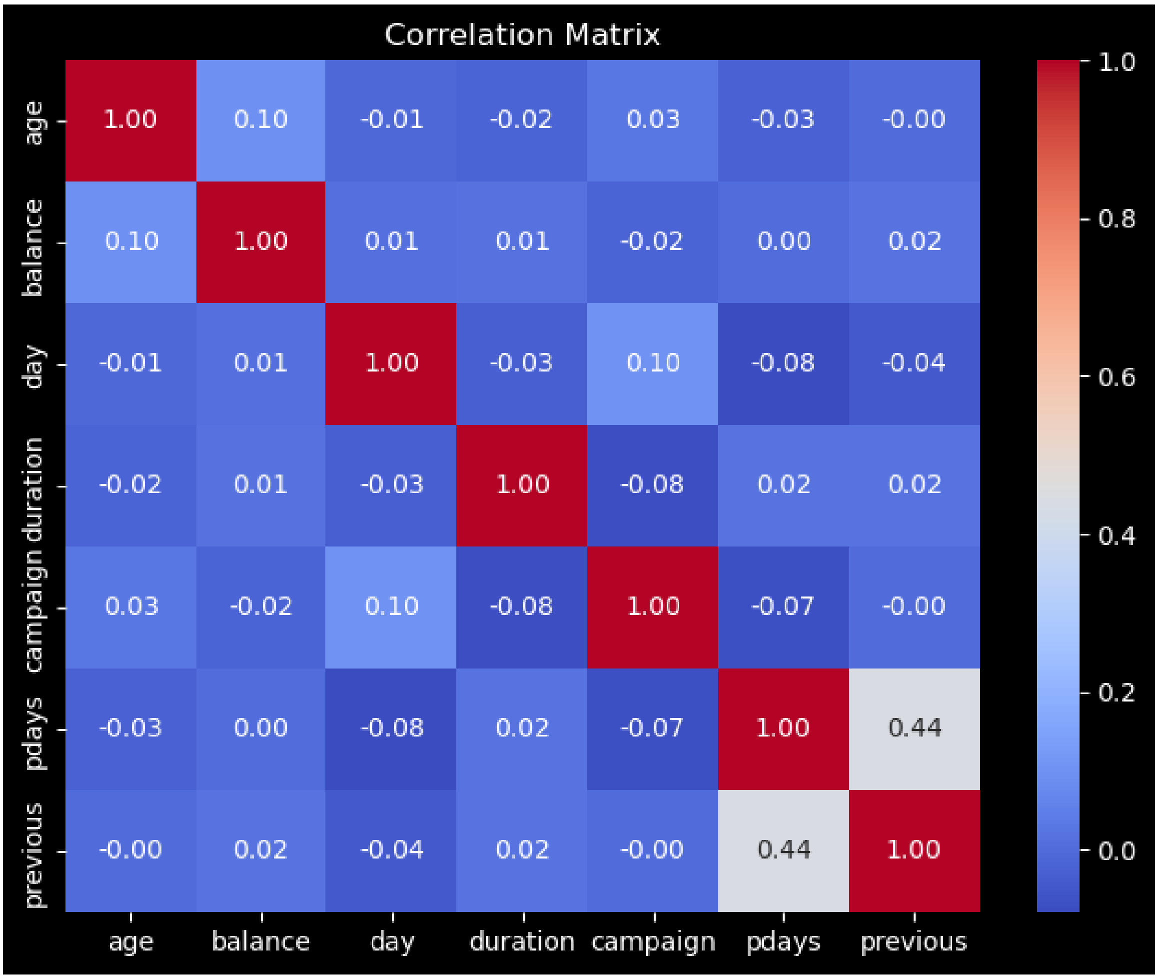
Correlation matrix

In [28]:

```
# Select numerical columns for correlation
numerical_columns = ['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous
']
```

In [29]:

```
# Correlation matrix for numerical variables
correlation_matrix = bank[numerical_columns].corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



- **Duration and Previous Contacts: Positive correlation, indicating longer past conversations may lead to more prior interactions.**
- **Duration and Campaign: Negative correlation, implying longer conversations may result in fewer follow-up contacts during the same campaign.**

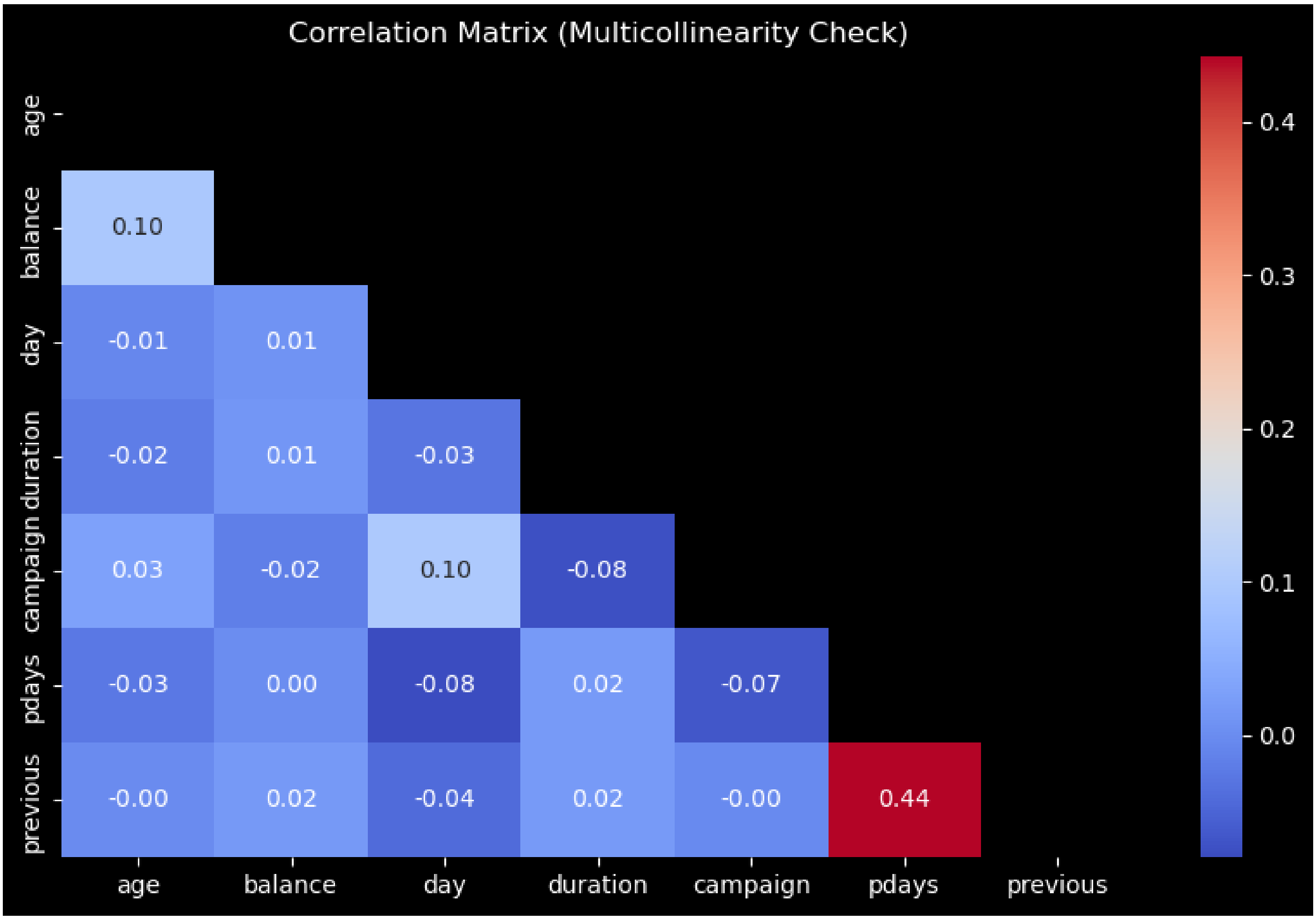
- **Previous Contacts and Campaign: Mild positive correlation, suggesting customers with more prior interactions tend to have more contacts in the current campaign.**
- **Pdays and Previous Contacts: Weak negative correlation, hinting that customers contacted more in the past tend to have shorter intervals between contacts.**

DATA PREPROCESSING

Check for multicollinearity

In [30]:

```
# Calculate the correlation matrix
correlation_matrix = bank[numerical_columns].corr()

# Create a mask for the upper triangle of the correlation matrix
mask = np.triu(np.ones_like(correlation_matrix, dtype=bool))

# Set up the matplotlib figure
plt.figure(figsize=(10, 6))

# Generate a heatmap of the correlation matrix
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", mask=mask)

# Set plot title
plt.title('Correlation Matrix (Multicollinearity Check)')

# Show the plot
plt.show()
```



The variables are not highly correlated with each other hence no multicollinearity

Convert Column y to numeric(0s and 1s)

The y feature need to be binary encoded to be used in the classification problem

In [31]:

```
# Convert binary categorical columns to numeric (yes/no to 1/0)
bank['y'] = bank['y'].map({'no': 0, 'yes': 1})
```

In [32]:

```
# display values in y
bank.y.unique()
```

Out[32]:

```
array([0, 1], dtype=int64)
```

Assign the variables

assigning target variable to y for prediction and the rest of the Features to independebt variable X

In [33]:

```
# Assign the data to X and y
y = bank['y']
X = bank.drop(columns=['y'], axis=1)
```

In [34]:

```
X.head()
```

Out[34]:

	age	job	marital	education	default	balance	housing	loan	day	month	duration	campaign	pdays	previous
0	58	management	married	tertiary	no	2143	yes	no	5	may	261	1	-1	0
1	44	technician	single	secondary	no	29	yes	no	5	may	151	1	-1	0
2	33	entrepreneur	married	secondary	no	2	yes	yes	5	may	76	1	-1	0
3	47	blue-collar	married	secondary	no	1506	yes	no	5	may	92	1	-1	0
5	35	management	married	tertiary	no	231	yes	no	5	may	139	1	-1	0

One-hot encode the categorical features

One-hot encoding converts categorical variables into binary vectors, where each category becomes a separate binary feature.This is necessary step in order to build a classification model

In [35]:

```
categorical_columns = ['job', 'marital', 'education', 'month', 'housing', 'loan', 'defau
lt']
```

In [36]:

```
# Onehotencode
ohe = OneHotEncoder(sparse=False)
X_categorical_encoded = ohe.fit_transform(X[categorical_columns])
# Retrieve feature names for the encoded columns
feature_names = []
for i, col in enumerate(categorical_columns):
    categories = ohe.categories_[i]
    for category in categories:
        feature_names.append(f"{col}_{category}")
# Create a DataFrame for the encoded features
X_categorical_encoded_df = pd.DataFrame(X_categorical_encoded, columns=feature_names)
```

```
X_categorical_encoded_df
```

Out[36]:

	job_admin.	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services	job_stu
0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	
38842	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
38843	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
38844	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
38845	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	
38846	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	

38847 rows × 35 columns

Scaling the numerical features

Scaling the numerical features is an essential preprocessing step before applying SMOTE (Synthetic Minority Over-sampling Technique) to address class imbalance in the dependent variable. Scaling ensures that numerical features are in the same range, making them directly comparable. This is crucial because SMOTE generates synthetic samples to balance the classes, and we want these synthetic samples to be consistent with the original data. Scaling prevents the introduction of unnecessary bias by ensuring that both original and synthetic samples exist within the same scaled range. Therefore, scaling is recommended before utilizing SMOTE to create a balanced dataset for modeling.

In [37]:

```
# Select the numerical columns to be scaled
numerical_columns = ['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous
']

# Create a StandardScaler object
scaler = MinMaxScaler()
X_numeric_scaled = scaler.fit_transform(X[numerical_columns])

# Create a DataFrame for the scaled features
X_numeric_scaled_df = pd.DataFrame(X_numeric_scaled, columns=numerical_columns)
```

In [38]:

```
X_numeric_scaled_df.head()
```

Out[38]:

	age	balance	day	duration	campaign	pdays	previous
0	0.519481	0.092259	0.133333	0.405910	0.0	0.0	0.0
1	0.337662	0.073067	0.133333	0.234837	0.0	0.0	0.0
2	0.194805	0.072822	0.133333	0.118196	0.0	0.0	0.0
3	0.376623	0.086476	0.133333	0.143079	0.0	0.0	0.0
4	0.220779	0.074901	0.133333	0.216174	0.0	0.0	0.0

In [39]:

```
# combine the scaled columns and onehotencoded columns
X_final = pd.concat([X_numeric_scaled_df, X_categorical_encoded_df, ], axis=1)
X_final
```

Out[39]:

	age	balance	day	duration	campaign	pdays	previous	job_admin.	job_blue-collar	job_entrepreneur	...	mc
0	0.519481	0.092259	0.133333	0.405910	0.0	0.000000	0.000000	0.0	0.0	0.0	...	
1	0.337662	0.073067	0.133333	0.234837	0.0	0.000000	0.000000	0.0	0.0	0.0	...	
2	0.194805	0.072822	0.133333	0.118196	0.0	0.000000	0.000000	0.0	0.0	1.0	...	
3	0.376623	0.086476	0.133333	0.143079	0.0	0.000000	0.000000	0.0	1.0	0.0	...	
4	0.220779	0.074901	0.133333	0.216174	0.0	0.000000	0.000000	0.0	0.0	0.0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
38842	0.714286	0.098678	0.533333	0.466563	0.0	0.047018	0.029091	0.0	0.0	0.0	...	
38843	0.090909	0.077388	0.533333	0.600311	0.2	0.000000	0.000000	0.0	0.0	0.0	...	
38844	0.688312	0.088501	0.533333	0.709176	0.2	0.000000	0.000000	0.0	0.0	0.0	...	
38845	0.506494	0.078868	0.533333	0.790047	0.6	0.000000	0.000000	0.0	1.0	0.0	...	
38846	0.246753	0.099777	0.533333	0.561431	0.2	0.216743	0.040000	0.0	0.0	1.0	...	

38847 rows × 42 columns

Train-Test Split

Split the dataset into training and testing sets to evaluate model performance.This will help in preventing overfitting, tuning hyperparameters, refining features, and avoiding data leakage.It also helps to ensure that the models generalize well to new, unseen data and can make accurate predictions in real-world scenarios.

I will split the data in 80% training and 20% testing data

In [40]:

```
# Perform train test split using sci kit learn train_test_split
X_train , X_test, y_train, y_test = train_test_split(X_final, y, test_size =0.2, random_
state=1)
```

SMOTE

Synthetic Minority Over-sampling Technique is used to handle imbalanced distribution of the target variable

In [41]:

```
y.value_counts()
```

Out[41]:

```
0    35310
1     3537
Name: y, dtype: int64
```

I will use smote to resolve the imbalance in the target variable above where 1 has very few samples compared to 0.

In [42]:

```
# instantiate SMOTE
```

```
sm = SMOTE(random_state=1)
# fit sm on the training data
X_train_resampled, y_train_resampled = sm.fit_resample(X_train, y_train)
# print training data set before over sampling
print('Before resampling, the shape of X_train: {}'.format(X_train.shape))
print('Before resampling, the shape of y_train: {}'.format(y_train.shape))
# print training data set after over sampling
print('After resampling, the shape of X_train_resampled: {}'.format(X_train_resampled.sha
pe))
print('After resampling, the shape of y_train_resampled: {}'.format(y_train_resampled.sha
pe))
y_train_resampled.value_counts()
```

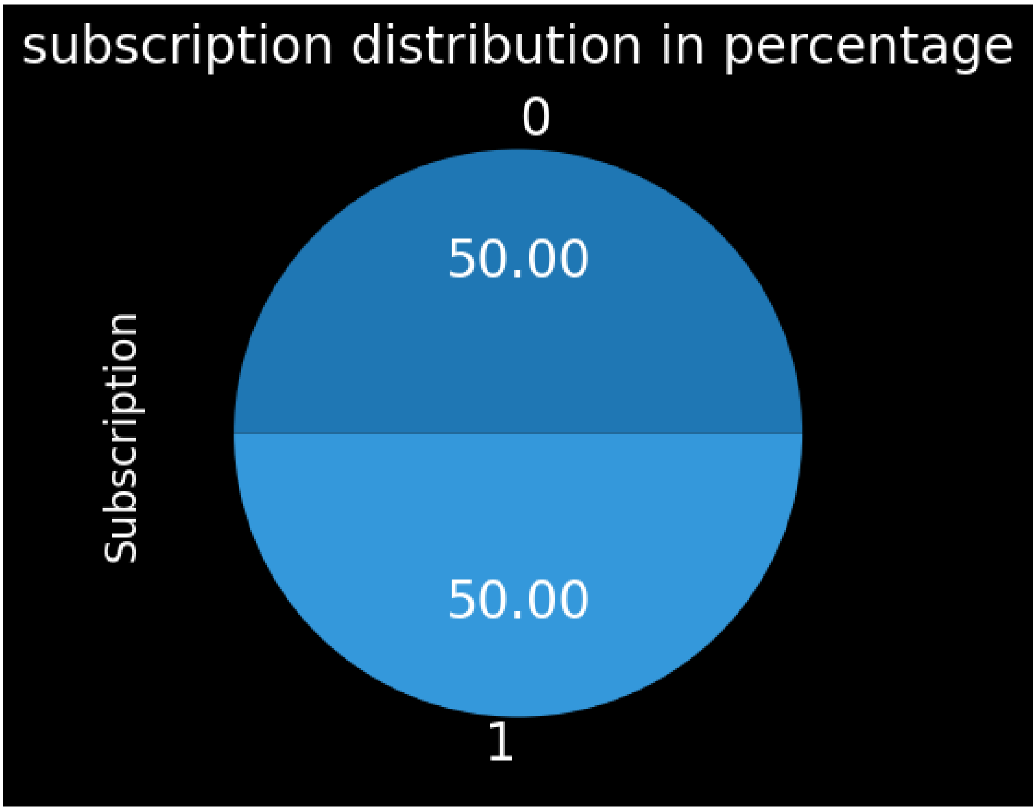
```
Before resampling, the shape of X_train: (31077, 42)
Before resampling, the shape of y_train: (31077,)
After resampling, the shape of X_train_resampled: (56422, 42)
After resampling, the shape of y_train_resampled: (56422,)
```

Out[42]:

```
0    28211
1    28211
Name: y, dtype: int64
```

In [43]:

```
# pie chart showing distribution of target variable
fig, ax = plt.subplots(figsize=(10, 5))
#plot pie chart
y_train_resampled.value_counts().plot(kind='pie', autopct='%.2f', textprops={'fontsize':
20}, colors=['#1f77b4', '#3498db'], ax=ax)
# plot labels
ax.set_ylabel('Subscription', fontsize=16)
ax.set_title('subscription distribution in percentage', fontsize=20);
```



The training data is balanced

MODELING

Baseline Model - Decision Tree Classifier

A Decision Tree Classifier is a supervised machine learning algorithm used for both classification and regression

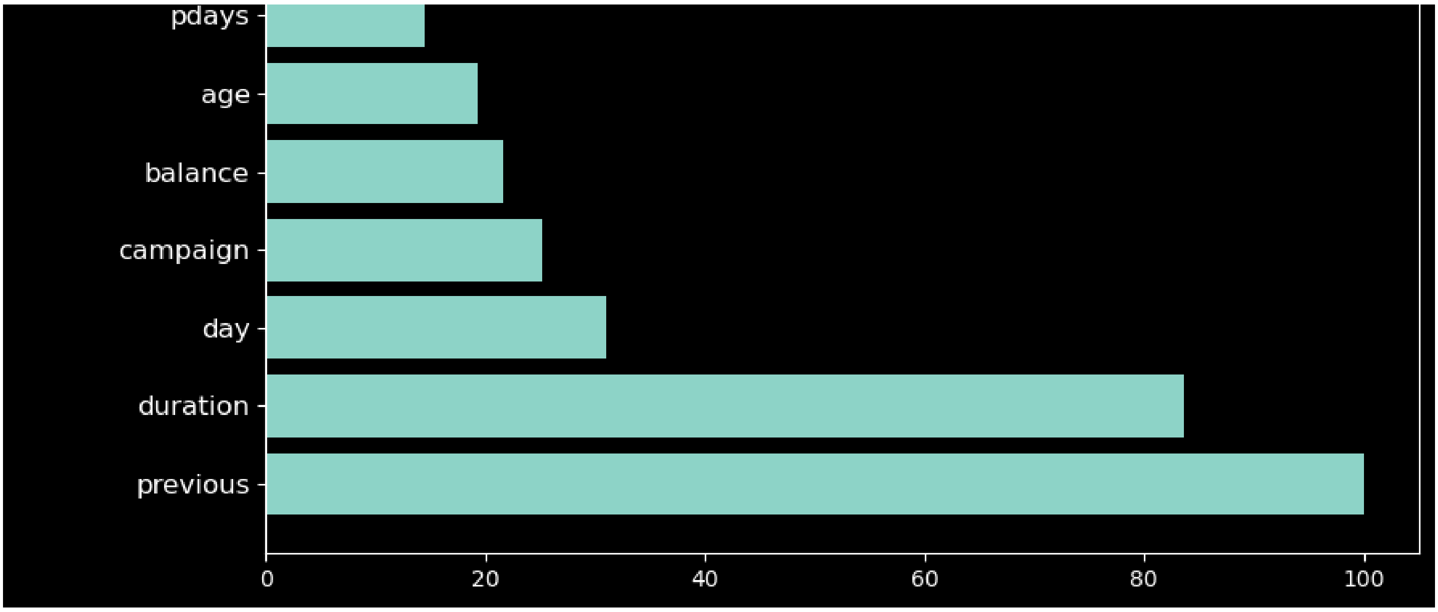
A Decision Tree Classifier is a supervised machine learning algorithm used for both classification and regression tasks. It is a type of predictive modeling tool that is widely used in various fields, including data mining, finance, and healthcare, due to its simplicity and interpretability. Decision Trees are especially valuable when you need to make decisions based on data and want to understand the reasoning behind those decisions
The Decision Tree Classifier was selected for its interpretability, ability to handle mixed data types, and capacity to capture complex relationships in customer data. It not only predicts customer purchases accurately but also provides valuable insights for guiding marketing strategies

In [44]:

```
# Instantiate the model
dt_classifier = DecisionTreeClassifier(random_state=1)

# fit the model on the training data
dt_classifier.fit(X_train_resampled, y_train_resampled)

# predict on the test data
y_test_pred_dt = dt_classifier.predict(X_test)

# predict on the training data
y_train_pred_dt = dt_classifier.predict(X_train_resampled)
```

In [45]:

```
# function to plot
def plot_top_feature_importance_tree(feature_importance, feature_names, top_n=10, model_n
ame=None):
    # Sort feature importances and select the top N
    sorted_idx = np.argsort(feature_importance)[::-1][:top_n]
    pos = np.arange(sorted_idx.shape[0]) + 0.5

    # Create a figure and axis
    fig, ax = plt.subplots(figsize=(9, 6))

    # Create a horizontal bar chart
    ax.barh(pos, feature_importance[sorted_idx], align='center')
    ax.set_title(f"Top {top_n} Relative Feature Importance for {model_name}", fontsize=1
3, fontweight='bold')
    ax.set_yticks(pos)
    ax.set_yticklabels(np.array(feature_names)[sorted_idx], fontsize=12)

    # Adjust layout and display the chart
    plt.tight_layout()
    plt.show()

# Calculate the feature importances
feature_importance_tree = dt_classifier.feature_importances_

# Select top 10 features
top_n = 10  # Change this number to select a different number of top features
top_feature_importance_tree = 100.0 * (feature_importance_tree / feature_importance_tree.
max())[:top_n]

# Get the names of the features
feature_names_tree = X_train_resampled.columns.tolist()

# Plot the top feature importance
plot_top_feature_importance_tree(top_feature_importance_tree, feature_names_tree, top_n=t
op_n, model_name='Decision Tree Classifier')
```



Most important features

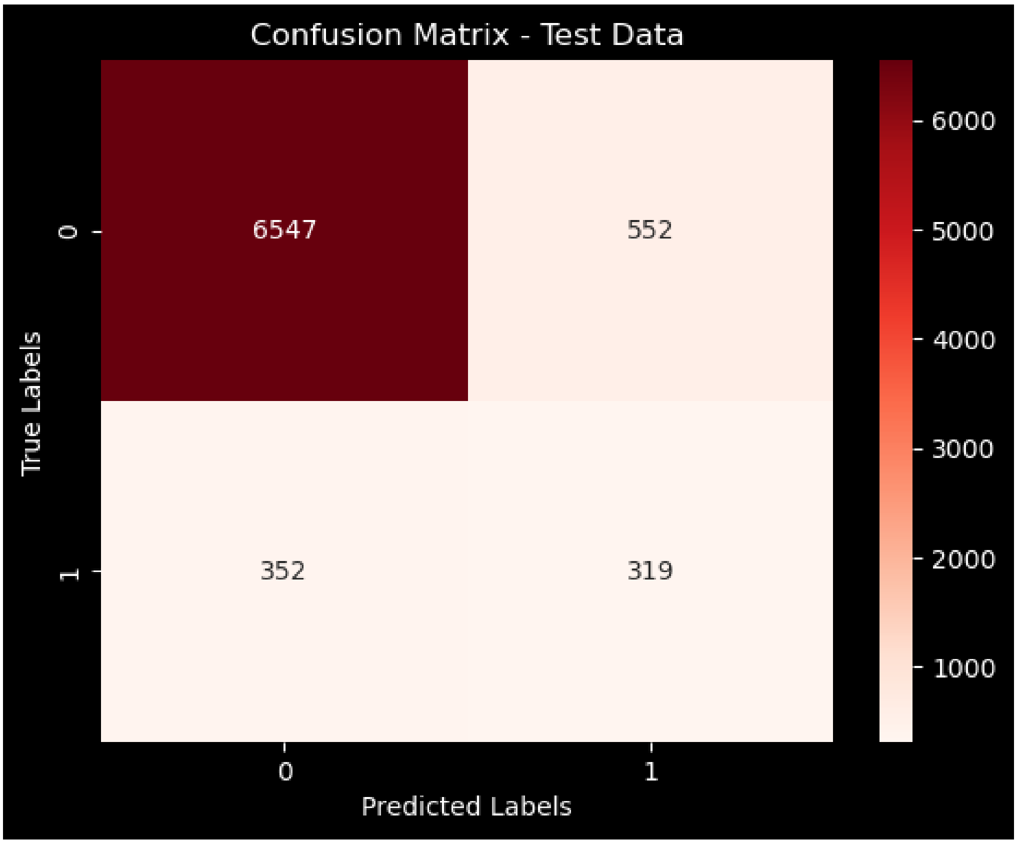
- **previous**
- **duration**
- **day**

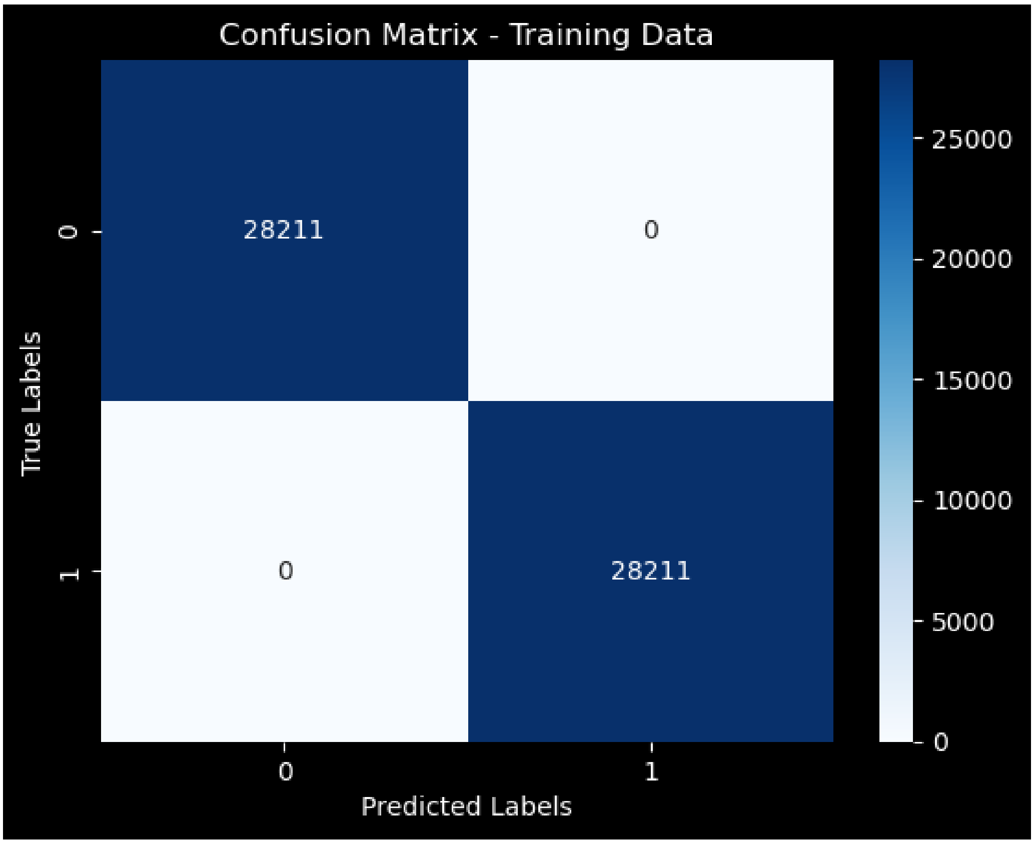
Baseline Model Evaluation

In [46]:

```
def evaluate_model(model, X_train, y_train, X_test, y_test):
    # Predict the labels for the training and test data
    y_train_pred = model.predict(X_train)
    y_test_pred = model.predict(X_test)

    # Calculate the evaluation metrics for training data
    train_accuracy = accuracy_score(y_train, y_train_pred)
    train_precision = precision_score(y_train, y_train_pred)
    train_recall = recall_score(y_train, y_train_pred)
    train_f1 = f1_score(y_train, y_train_pred)
    train_cm = confusion_matrix(y_train, y_train_pred)

    # Calculate the evaluation metrics for test data
    test_accuracy = accuracy_score(y_test, y_test_pred)
    test_precision = precision_score(y_test, y_test_pred)
    test_recall = recall_score(y_test, y_test_pred)
    test_f1 = f1_score(y_test, y_test_pred)
    test_cm = confusion_matrix(y_test, y_test_pred)

    # Plot the confusion matrix for test data
    sns.heatmap(test_cm, annot=True, fmt="d", cmap="Reds")
    plt.title("Confusion Matrix - Test Data")
    plt.xlabel("Predicted Labels")
    plt.ylabel("True Labels")
    plt.show()

    # Plot the confusion matrix for training data
    sns.heatmap(train_cm, annot=True, fmt="d", cmap="Blues")
    plt.title("Confusion Matrix - Training Data")
    plt.xlabel("Predicted Labels")
    plt.ylabel("True Labels")
    plt.show()

    # Print the evaluation metrics for training data
    print("Training Data:")
    print("Accuracy:", train_accuracy)
    print("Precision:", train_precision)
    print("Recall:", train_recall)
```

```
    print("F1-score:", train_f1)

    # Print the evaluation metrics for test data
    print("\nTest Data:")
    print("Accuracy:", test_accuracy)
    print("Precision:", test_precision)
    print("Recall:", test_recall)
    print("F1-score:", test_f1)
evaluate_model(dt_classifier, X_train_resampled, y_train_resampled, X_test, y_test)
```






```
Training Data:
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1-score: 1.0

Test Data:
```

```
Test Data:
Accuracy: 0.8836550836550836
Precision: 0.36624569460390355
Recall: 0.47540983606557374
F1-score: 0.41374837872892345
```

The model achieves perfect performance on the training data, possibly indicating overfitting. On the test data, it demonstrates good accuracy but lower precision, recall, and F1-score, suggesting the need for refinement and tuning to strike a better balance between precision and recall

In [47]:

```
# Make predictions on the test data
y_pred_proba2 = dt_classifier.predict_proba(X_test)

# Compute the log loss
logloss = log_loss(y_test, y_pred_proba2)

print('Log Loss:', logloss)
```

```
Log Loss: 4.018411050321656
```

Second Model - Hyperparameter tuning of Decision Tree Classifier

The Parameters of the decision tree can be tuned for the model's better performance in predicting the target class

In [50]:

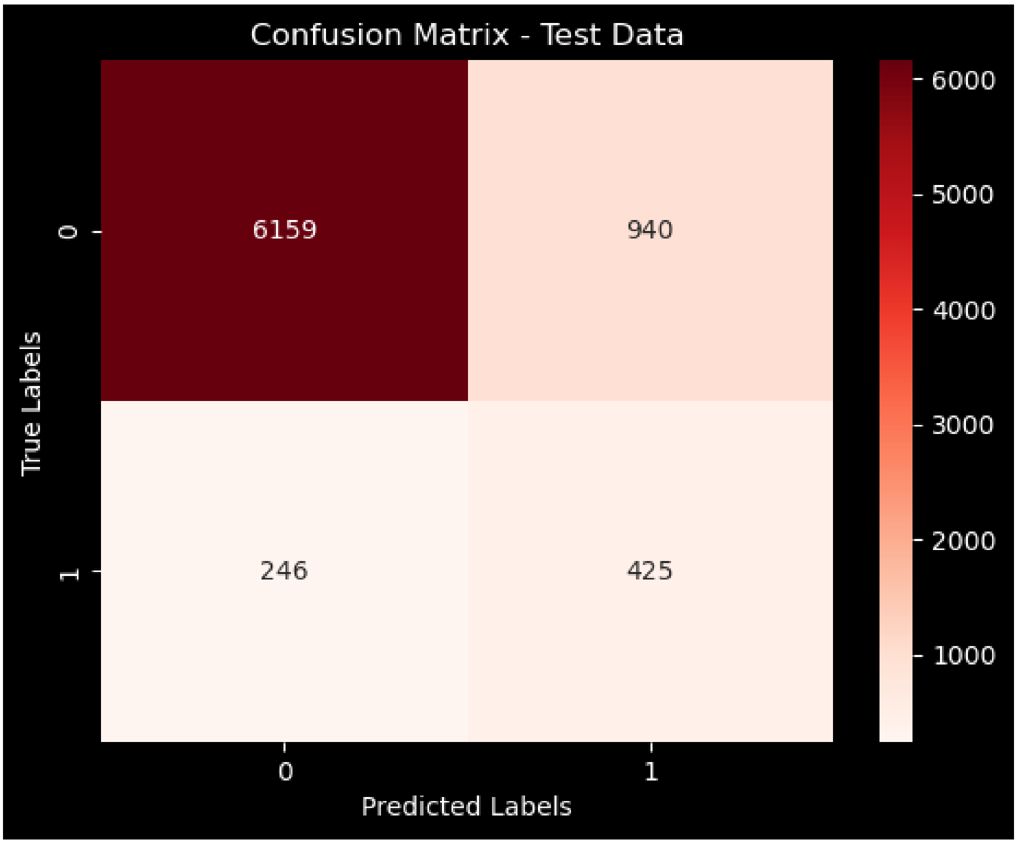
```
# Define the cross-validation strategy
cv = StratifiedKFold(n_splits=10, shuffle=True, random_state=1)

# Define the hyperparameters to tune for the Decision Tree Classifier
param_grid_dt = {
    'dt__max_depth': [None, 1, 2],   # Reduce max_depth to prevent overfitting
    'dt__min_samples_split': [35, 17, 30],   # Increase min_samples_split to limit splitt
ing
    'dt__min_samples_leaf': [28, 40, 29, 30],   # Increase min_samples_leaf to control le
af nodes
    'dt__criterion': ['gini', 'entropy'],
    'dt__max_features': ['sqrt', 5, 7], # Further reduce max_features
    'dt__min_impurity_decrease': [0.0, 0.1],
}

# Create a new pipeline with the Decision Tree classifier
pipe_dt = Pipeline([('dt', DecisionTreeClassifier(random_state=1))])

# Perform grid search cross-validation
grid_search_dt = GridSearchCV(pipe_dt, param_grid_dt, cv=cv, scoring='accuracy', n_jobs=
-1)

# Fit the training data
grid_search_dt.fit(X_train_resampled, y_train_resampled)

# Print the best hyperparameters and best score
print("Best Hyperparameters (Decision Tree): ", grid_search_dt.best_params_)
print("Best Score (Decision Tree): ", grid_search_dt.best_score_)

# Cross-validation scores
cv_scores_dt = grid_search_dt.cv_results_['mean_test_score']
# Calculate and print the mean cross-validation accuracy
mean_cv_accuracy_dt = cv_scores_dt.mean()
print("Mean CV Accuracy (Decision Tree):", mean_cv_accuracy_dt)
```

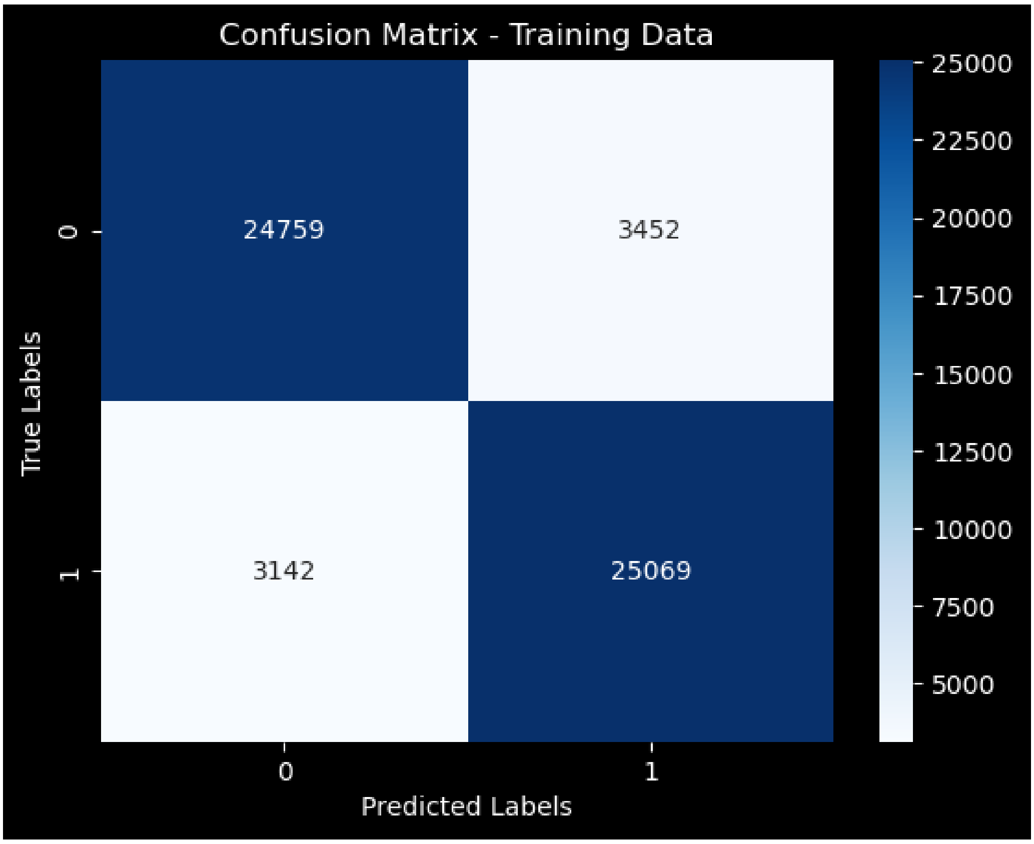
```
Best Hyperparameters (Decision Tree):  {'dt__criterion': 'entropy', 'dt__max_depth': None
, 'dt__max_features': 7, 'dt__min_impurity_decrease': 0.0, 'dt__min_samples_leaf': 28, 'd
t__min_samples_split': 35}
Best Score (Decision Tree):  0.8723547030847539
Mean CV Accuracy (Decision Tree): 0.5963219990331621
```

Model Evaluation

In [51]:

```
evaluate_model(grid_search_dt.best_estimator_, X_train_resampled, y_train_resampled, X_te
st, y_test)
```






```
Training Data:
Accuracy: 0.8831306937010386
Precision: 0.8789663756530276
Recall: 0.8886250044308958
F1-score: 0.8837693012761757

Test Data:
```

```
Accuracy: 0.8473616473616473
Precision: 0.31135531135531136
Recall: 0.6333830104321908
F1-score: 0.4174852652259332
```

The tuned model maintains a high level of performance on both training and test data, indicating better generalization. The tuned model achieves a better balance between precision and recall, making it more suitable for real-world applications
The tuned model performs better than the baseline model because it provides a more balanced trade-off between different evaluation metrics and is less likely to overfit to the training data

In [52]:

```
# Make predictions on the test data
y_pred_proba2 = grid_search_dt.best_estimator_.predict_proba(X_test)

# Compute the log loss
logloss = log_loss(y_test, y_pred_proba2)

print('Log Loss:', logloss)
```

```
Log Loss: 0.5642157056897168
```

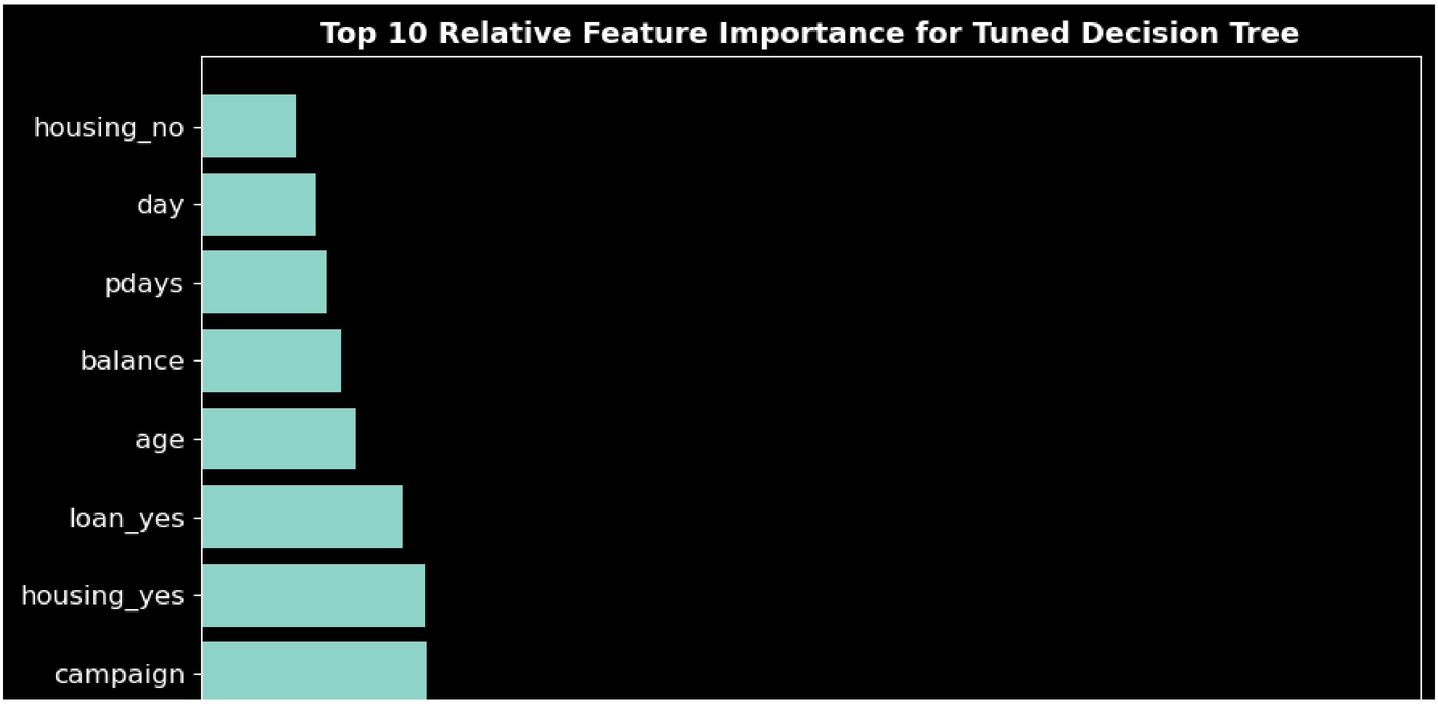
The log loss of the tuned model (0.5) is significantly lower than that of the baseline model (4.0). This indicates that the tuned model provides much better probability estimates and is more confident in its predictions compared to the baseline model

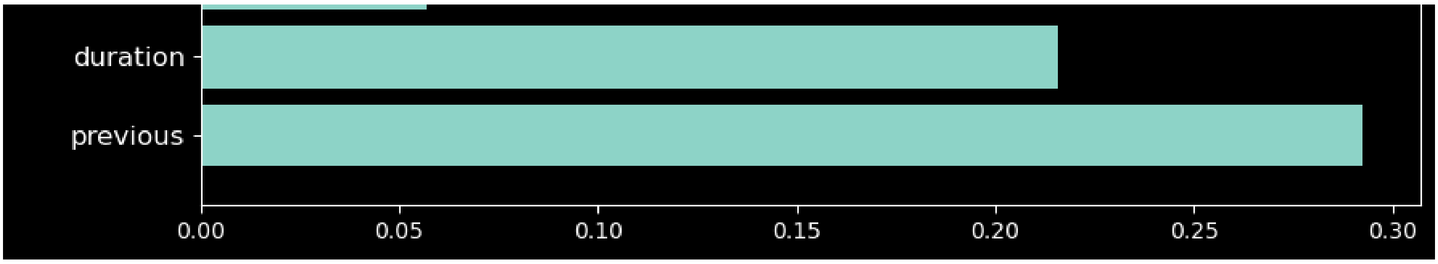
This will be the model used for the prediction as it has high accuracy, lower log loss and does not overfit compared to the baseline model.

Most important Features

In [54]:

```
# Get the trained Decision Tree model from the pipeline
dt_model = grid_search_dt.best_estimator_.named_steps['dt']

# Get the feature importances from the Decision Tree model
feature_importance_dt = dt_model.feature_importances_
# Get the names of the features
feature_names_dt = X_final.columns.tolist()

# Plot the top feature importances using the plot_top_feature_importance_tree function
plot_top_feature_importance_tree(feature_importance_dt, feature_names_dt, top_n=10, mode
l_name='Tuned Decision Tree')
```





The factors which have the most significant impact on whether a customer subscribes to a term deposit are:

- Previous Contacts (previous): High importance. Customers contacted more in the past are more likely to subscribe, emphasizing the value of building relationships.
- Duration of Last Contact (duration): High importance. Longer conversations during the last contact increase subscription likelihood, indicating higher customer interest.
- Number of Contacts in the Current Campaign (CAMPAIGN): The number of contacts made during the current campaign is the third most important feature. However, it has a negative influence on subscription. This suggests that bombarding customers with too many contacts during a single campaign may be counterproductive. A more targeted approach with fewer contacts might be more effective.

RECOMMENDATIONS

These recommendations can help optimize the marketing strategy to increase subscription rates for the term deposit service.The recommendation is driven from the most significant features and the Exploratory data analysis.

- Leverage Previous Contacts: Focus marketing efforts on customers who have been contacted before, as they are more likely to subscribe. Build on these existing relationships to increase conversions.
- Engage in Longer Conversations: Encourage customer interactions with longer and more engaging conversations during contact. This can be achieved by providing valuable information and addressing their needs
- Be cautious about over-contacting customers during a single campaign. Instead, adopt a more balanced and targeted approach to avoid overwhelming potential subscribers
- It may be beneficial to tailor communication strategies for shorter and longer call durations. Shorter calls could focus on concise messaging, while longer calls might involve more detailed discussions
- Marketing strategies can be tailored based on job categories. For instance, promotions or messaging can be customized to appeal to specific professional groups.
- To improve subscription rates, marketing strategies could be adjusted to target customers with higher education levels more effectively. Tailoring campaigns or promotions to appeal to customers with "tertiary" education might be a successful approach
- marketing strategy that focuses on shorter and more effective interactions during the last contact may be more successful in achieving subscriptions. It's essential to identify and target customers within the subscriber cluster
- To improve subscription rates, marketers should consider optimizing their campaign strategies. Instead of increasing the number of contacts, they could concentrate on tailoring their messages and interactions to be more compelling and relevant to the custome

NEXT STEPS

- Feature Engineering: Enhance dataset features for better model performance
- Model Selection and Evaluation: Experiment with various models, assess performance using metrics like accuracy and precision
- Deployment: Prepare for practical use, possibly through a web app or API

Thank you!