- Student name: Ian Kiptoo
- Student pace: Full-time Remote
- Scheduled project review date/time:
- Instructor name: Asha Deen

1. Bussiness Understanding

Project Overview

In the highly competitive telecommunications market, Syriatel faces the critical challenge of retaining its customer base while ensuring high levels of satisfaction. The company struggles with identifying at-risk customers who might churn and addressing their issues proactively. This problem is compounded by the need to offer personalized services and maintain optimal network performance, all while adapting to ever-evolving customer needs and preferences. Without effective data analytics and machine learning techniques, Syriatel risks losing market share and falling behind competitors who are more adept at leveraging these technologies to enhance customer experiences and loyalty.

Introduction

Syriatel (Arabic: سيريتل) is a prominent mobile network provider in Syria. Alongside MTN Syria, it has been a key player in the country's telecommunications landscape. In 2022, the Syrian telecommunications authority awarded a third telecom license to Wafa Telecom, introducing new competition into the market. Syriatel offers LTE services with speeds up to 150 Mb/s under the brand name Super Surf. In this increasingly competitive environment, it is imperative for Syriatel to continuously adapt and enhance its services to remain competitive and provide outstanding customer experiences.

Stakeholders

The success of the project is intrinsically tied to the satisfaction of a diverse set of stakeholders:

- **Syriatel Executives**: Leadership needs to maintain and expand their customer base, ensuring the long-term growth and sustainability of the company.
- **Syriatel Marketing Team**: The marketing department aims to increase customer acquisition, engagement, and the delivery of targeted promotions.
- **Syriatel Customer Support Team**: The customer support team seeks to provide efficient and effective customer service, resolving issues, and improving overall customer satisfaction.
- **Syriatel Customers**: The end-users, who expect reliable, affordable, and innovative telecommunications services.

Business Problem

This project primarily focuses on addressing customer churn and improving customer satisfaction for Syriatel. We will leverage data analytics and machine learning techniques to gain insights into customer behavior, preferences, and needs. Recommendations and strategies will be developed to mitigate customer churn and improve customer experiences.

Customer churn (the loss of customers to competition) presents a significant challenge for telecom companies like Syriatel because it is more expensive to acquire a new customer than to retain an existing one. Most telecom companies suffer from voluntary churn, which has a strong impact on the lifetime value of a customer by affecting both the length of service and future revenue. For instance, a company with a 25% churn rate has an average customer lifetime of four years, while a company with a 50% churn rate has an average customer lifetime of only two years. It is estimated that 75 percent of the 17 to 20 million subscribers signing up with a new wireless carrier every year are coming from another wireless provider, indicating a high rate of churn. Telecom companies invest substantial resources to acquire new customers, and when a customer leaves, the company not only loses future revenue but also the resources spent on acquisition. This erosion of profitability underscores the importance of mitigating churn.

By implementing advanced data analytics and machine learning techniques, Syriatel can develop effective strategies to identify at-risk customers, understand their reasons for potential departure, and deploy targeted interventions to retain them. These efforts will not only reduce churn but also enhance overall customer satisfaction and loyalty, thereby contributing to Syriatel's long-term success and competitive edge.

Objective:

The aim of this analysis is to leverage data analytics and machine learning techniques to address the challenge of customer churn and improve customer satisfaction for Syriatel, a leading mobile network provider in Syria.

Business Questions:

The key objectives for this project include:

Identifying At-Risk Customers:

- Develop predictive models to identify customers at risk of churning based on their behavior and interaction patterns.
- Implement proactive interventions to retain at-risk customers and reduce churn rates.

Understanding Customer Preferences:

- Analyze customer data to gain insights into preferences, needs, and satisfaction levels.
- Tailor services and offerings to better meet customer expectations and enhance satisfaction.

Recommendation of Retention Strategies:

- Develop targeted retention strategies, such as personalized promotions and loyalty programs, to mitigate churn.
- Implement proactive customer support initiatives to address potential reasons for churn.

Enhancing Customer Experience:

- Assess and optimize existing customer support processes and services to improve overall customer experience.
- Identify areas for improvement and implement measures to enhance satisfaction levels.

Data Understanding

Data Understanding

Features

1. **State** (Categorical): The state in which the customer resides.
2. **Account Length** (Numerical): The number of days the customer has been with the company.
3. **Area Code** (Categorical): The area code associated with the customer's phone number.
4. **Phone Number** (Categorical): The customer's phone number, typically treated as an identifier.
5. **International Plan** (Categorical): Whether the customer has an international calling plan (e.g., "yes" or "no").
6. **Voice Mail Plan** (Categorical): Whether the customer has a voicemail plan (e.g., "yes" or "no").
7. **Number of Voicemail Messages** (Numerical - discrete): The number of voicemail messages received by the customer.
8. **Total Day Minutes** (Numerical): The total number of minutes the customer used during the daytime.
9. **Total Day Calls** (Numerical - discrete): The total number of calls made by the customer during the daytime.
10. **Total Day Charge** (Numerical): The total charges incurred for daytime usage.
11. **Total Evening Minutes** (Numerical): The total number of minutes the customer used in the evening.
12. **Total Evening Calls** (Numerical - discrete): The total number of calls made by the customer in the evening.
13. **Total Evening Charge** (Numerical): The total charges incurred for evening usage.
14. **Total Night Minutes** (Numerical): The total number of minutes the customer used at night.
15. **Total Night Calls** (Numerical - discrete): The total number of calls made by the customer at night.
16. **Total Night Charge** (Numerical): The total charges incurred for nighttime usage.
17. **Total International Minutes** (Numerical): The total number of international minutes used by the customer.
18. **Total International Calls** (Numerical - discrete): The total number of international calls made by the customer.
19. **Total International Charge** (Numerical - discrete): The total charges incurred for international calls.

20. **Customer Service Calls** (Numerical - discrete): The number of customer service calls made by the customer.

Target Variable

1. **Churn**: Whether the customer has churned (1 for "yes" and 0 for "no").

2.1 Exploratory Data Analysis

First, let's perform **Exploratory Data Analysis** to understand our dataset better. This initial step will provide valuable insights into the data and its basic characteristics. Here's what I do during the EDA:

i. Data Import and Inspection:

- I start by importing the dataset and printing the first 5 rows to understand its structure and get a glimpse of the initial records.

ii. Data Shape:

- Next, I check the shape of our dataset to understand its dimensions, including the number of rows and columns, providing an overview of its size.

iii. Data Types:

- Then, I examine the data types of each column to ensure they are correctly interpreted, as this is crucial for subsequent analysis.

iv. Data Summary:

- I utilize the `describe` function to generate summary statistics for numerical columns, including count, mean, standard deviation, and quartiles. This provides insights into the distribution of the data.

v. Unique Values in Categorical Columns:

- Lastly, for categorical columns, I explore the unique values to understand the diversity of categories and ensure there are no unexpected or erroneous entries.

```
# All necessary imports for data preprocessing
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import numpy as np
from scipy.stats import skew, kurtosis


%matplotlib inline
warnings.filterwarnings("ignore")
```

```python
def read_data(file_path):
    """
    Read the dataset from the given file path.

    Parameters:
    - file_path (str): The path to the CSV file containing the
dataset.

    Returns:
    - DataFrame: The DataFrame containing the dataset.
    """
    import pandas as pd

    # Read the CSV file
    df = pd.read_csv(file_path)

    return df

# Specify the file path
file_path = r'C:\Users\Ian\Downloads\
bigml_59c28831336c6604c800002a.csv'

# Call the function to read the data
df = read_data(file_path)

def exploratory_data_analysis(df):
    """
    Perform exploratory data analysis on the given DataFrame.

    Parameters:
    - df (DataFrame): The DataFrame containing the dataset.

    Returns:
    - None
    """
    # i. Data Import and Inspection
    print("Data Import and Inspection:")
    print("First 5 rows of the dataset:")
    print(df.head())

    # ii. Data Shape
    print("\nData Shape:")
    print(f"Number of rows: {df.shape[0]}")
    print(f"Number of columns: {df.shape[1]}")

    # iii. Data Types
    print("\nData Types:")
    print(df.dtypes)

    # iv. Data Summary
    print("\nData Summary:")
```

```
    print(df.describe())

    # v. Unique Values in Categorical Columns
    print("\nUnique Values in Categorical Columns:")
    for col in df.select_dtypes(include=['object']).columns:
        print(f"Unique values in {col}: {df[col].unique()}")

# Call the function with the DataFrame
exploratory_data_analysis(df)
```

```
Data Import and Inspection:
First 5 rows of the dataset:
  state  account length  area code phone number international plan  \
0    KS             128        415     382-4657                 no
1    OH             107        415     371-7191                 no
2    NJ             137        415     358-1921                 no
3    OH              84        408     375-9999                yes
4    OK              75        415     330-6626                yes

  voice mail plan  number vmail messages  total day minutes  total day
calls  \
0             yes                     25              265.1
110
1             yes                     26              161.6
123
2              no                      0              243.4
114
3              no                      0              299.4
71
4              no                      0              166.7
113

   total day charge  total eve minutes  total eve calls  total eve
charge  \
0             45.07              197.4               99
16.78
1             27.47              195.5              103
16.62
2             41.38              121.2              110
10.30
3             50.90               61.9               88
5.26
4             28.34              148.3              122
12.61

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
```

```
4                 186.9                 121                 8.41

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73

   customer service calls  churn
0                       1  False
1                       1  False
2                       0  False
3                       2  False
4                       3  False

Data Shape:
Number of rows: 3333
Number of columns: 21

Data Types:
state                      object
account length              int64
area code                   int64
phone number               object
international plan         object
voice mail plan            object
number vmail messages       int64
total day minutes         float64
total day calls             int64
total day charge          float64
total eve minutes         float64
total eve calls             int64
total eve charge          float64
total night minutes       float64
total night calls           int64
total night charge        float64
total intl minutes        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
churn                        bool
dtype: object

Data Summary:
       account length    area code  number vmail messages  total day
minutes  \
count     3333.000000  3333.000000            3333.000000
3333.000000
mean       101.064806   437.182418               8.099010
```

```
179.775098
std        39.822106    42.371290              13.688365
54.467389
min         1.000000   408.000000               0.000000
0.000000
25%        74.000000   408.000000               0.000000
143.700000
50%       101.000000   415.000000               0.000000
179.400000
75%       127.000000   510.000000              20.000000
216.400000
max       243.000000   510.000000              51.000000
350.800000

       total day calls  total day charge  total eve minutes  total eve
calls  \
count      3333.000000       3333.000000        3333.000000
3333.000000
mean        100.435644         30.562307         200.980348
100.114311
std          20.069084          9.259435          50.713844
19.922625
min           0.000000          0.000000           0.000000
0.000000
25%          87.000000         24.430000         166.600000
87.000000
50%         101.000000         30.500000         201.400000
100.000000
75%         114.000000         36.790000         235.300000
114.000000
max         165.000000         59.640000         363.700000
170.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
std            4.310668            50.573847          19.568609
min            0.000000            23.200000          33.000000
25%           14.160000           167.000000          87.000000
50%           17.120000           201.200000         100.000000
75%           20.000000           235.300000         113.000000
max           30.910000           395.000000         175.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
```

```
75%              10.590000         12.100000        6.000000
max              17.770000         20.000000       20.000000

       total intl charge  customer service calls
count        3333.000000             3333.000000
mean            2.764581                1.562856
std             0.753773                1.315491
min             0.000000                0.000000
25%             2.300000                1.000000
50%             2.780000                1.000000
75%             3.270000                2.000000
max             5.400000                9.000000

Unique Values in Categorical Columns:
Unique values in state: ['KS' 'OH' 'NJ' 'OK' 'AL' 'MA' 'MO' 'LA' 'WV'
'IN' 'RI' 'IA' 'MT' 'NY'
 'ID' 'VT' 'VA' 'TX' 'FL' 'CO' 'AZ' 'SC' 'NE' 'WY' 'HI' 'IL' 'NH' 'GA'
 'AK' 'MD' 'AR' 'WI' 'OR' 'MI' 'DE' 'UT' 'CA' 'MN' 'SD' 'NC' 'WA' 'NM'
 'NV' 'DC' 'KY' 'ME' 'MS' 'TN' 'PA' 'CT' 'ND']
Unique values in phone number: ['382-4657' '371-7191' '358-1921' ...
'328-8230' '364-6381' '400-4344']
Unique values in international plan: ['no' 'yes']
Unique values in voice mail plan: ['yes' 'no']
```

Data Import and Inspection:

First 5 rows of the dataset:

The dataset consists of various features including state, account length, area code, phone number, international plan, voice mail plan, number of voicemail messages, and several numerical attributes such as total day minutes, total evening minutes, total night minutes, total international minutes, and customer service calls. The churn column indicates whether a customer has churned, with "False" representing no churn and "True" representing churn.

Data Shape:

The dataset contains 3333 rows and 21 columns, indicating that there are 3333 observations and 21 different features.

Data Types:

- The 'state', 'phone number', 'international plan', and 'voice mail plan' columns are of object type, indicating categorical variables.
- The 'account length', 'area code', 'number vmail messages', 'total day calls', 'total day minutes', 'total day charge', 'total eve calls', 'total eve minutes', 'total eve charge', 'total night calls', 'total night minutes', 'total night charge', 'total intl calls', 'total intl minutes', 'total intl charge', and 'customer service calls' columns are of numerical type.
- The 'churn' column is of boolean type, representing whether a customer churned or not.

Data Summary:

The summary statistics for numerical columns provide insights into the distribution of data, including count, mean, standard deviation, and quartiles. For example, the mean 'account length' is approximately 101.06 days, and the mean 'total day minutes' is approximately 179.78 minutes.

Unique Values in Categorical Columns:

- The 'state' column contains unique abbreviations for different states, ranging from 'KS' to 'WY'.
- The 'phone number' column contains unique phone numbers.
- The 'international plan' column has two unique values, 'no' and 'yes', indicating whether a customer has an international calling plan.
- The 'voice mail plan' column also has two unique values, 'yes' and 'no', indicating whether a customer has a voicemail plan.

2.1.1 Univariate Analysis

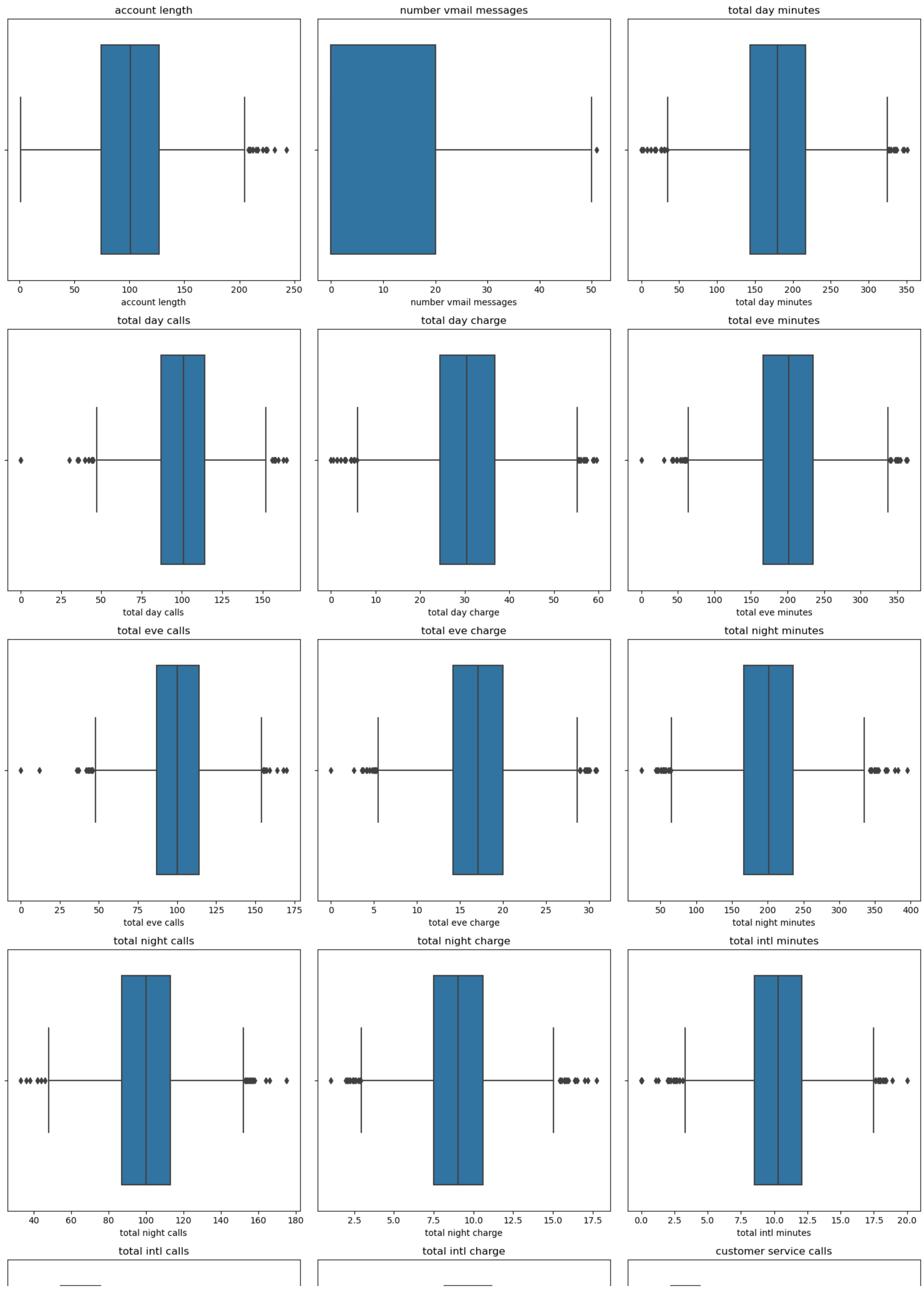
We first start exploring individual variables.

We divide the data into into numerical and categorical variables so as to perfrom the EDA them separately.

Visualizing the numerical and categorical variables in our dataset.

```
class DataVariables:
    def __init__(self, dataframe):
        self.df = dataframe

    def get_numerical_vars(self):
        numerical_vars = self.df.select_dtypes(include=['int64',
'float64']).columns.tolist()
        numerical_vars.remove('area code')  # Remove 'area code' from
numerical variables
        return numerical_vars

    def visualize_outliers(self):
        # Numerical variables
        numerical_vars = self.get_numerical_vars()

        # Calculate the number of subplots needed
        num_plots = len(numerical_vars)
        num_rows = (num_plots // 3) + (num_plots % 3 > 0)  # Round up
to the nearest integer

        # Boxplot for each numerical variable to visualize outliers
        plt.figure(figsize=(15, 5*num_rows))
        for i, col in enumerate(numerical_vars, start=1):
            plt.subplot(num_rows, 3, i)
```

```
            sns.boxplot(x=self.df[col])
            plt.title(col)
        plt.tight_layout()
        plt.show()


    def visualize_numerical_distribution(self):
        # Numerical variables
        numerical_vars = self.get_numerical_vars()

        # Calculate the number of subplots needed
        num_plots = len(numerical_vars)
        num_rows = (num_plots // 3) + (num_plots % 3 > 0)  # Round up
to the nearest integer

        # Histogram for each numerical variable to visualize
distribution
        plt.figure(figsize=(15, 5*num_rows))
        for i, col in enumerate(numerical_vars, start=1):
            plt.subplot(num_rows, 3, i)
            sns.histplot(self.df[col], kde=True)
            plt.title(col)
        plt.tight_layout()
        plt.show()


data_vars = DataVariables(df)


# Visualizing Outliers
data_vars.visualize_outliers()
```


account length
number vmail messages
total day minutes
total day calls
total day charge
total eve minutes
total eve calls
total eve charge
total night minutes
total night calls
total night charge
total intl minutes
total intl calls
total intl charge
customer service calls

Interpretation:

1. **Account Length**: The boxplot reveals the presence of outliers with exceptionally long account lengths. These outliers suggest the existence of customers who have been with the company for an extended period compared to the majority.

2. **Number Vmail Messages**: The majority of customers receive few or no voicemail messages, as indicated by the concentration of data points at lower values. However, there are outliers representing customers who receive a significant number of voicemail messages, which may indicate a specific usage pattern or preference among these customers.

3. **Total Day Calls**: The boxplot shows outliers with both very low and very high total day call counts. This indicates variability in the volume of daytime calls made by customers. The presence of outliers suggests that some customers have distinct calling behaviors compared to the majority.

4. **Total Intl Minutes**: Most customers make shorter international calls, as evidenced by the concentration of data points at lower values. However, outliers exist, representing customers who make longer international calls. These outliers suggest diversity in international calling patterns among customers.

5. **Total Intl Calls**: While most customers make a modest number of international calls, outliers exist with higher-than-average international call counts. These outliers indicate a subgroup of customers who engage in more frequent international calling, potentially indicating specific communication needs or preferences.

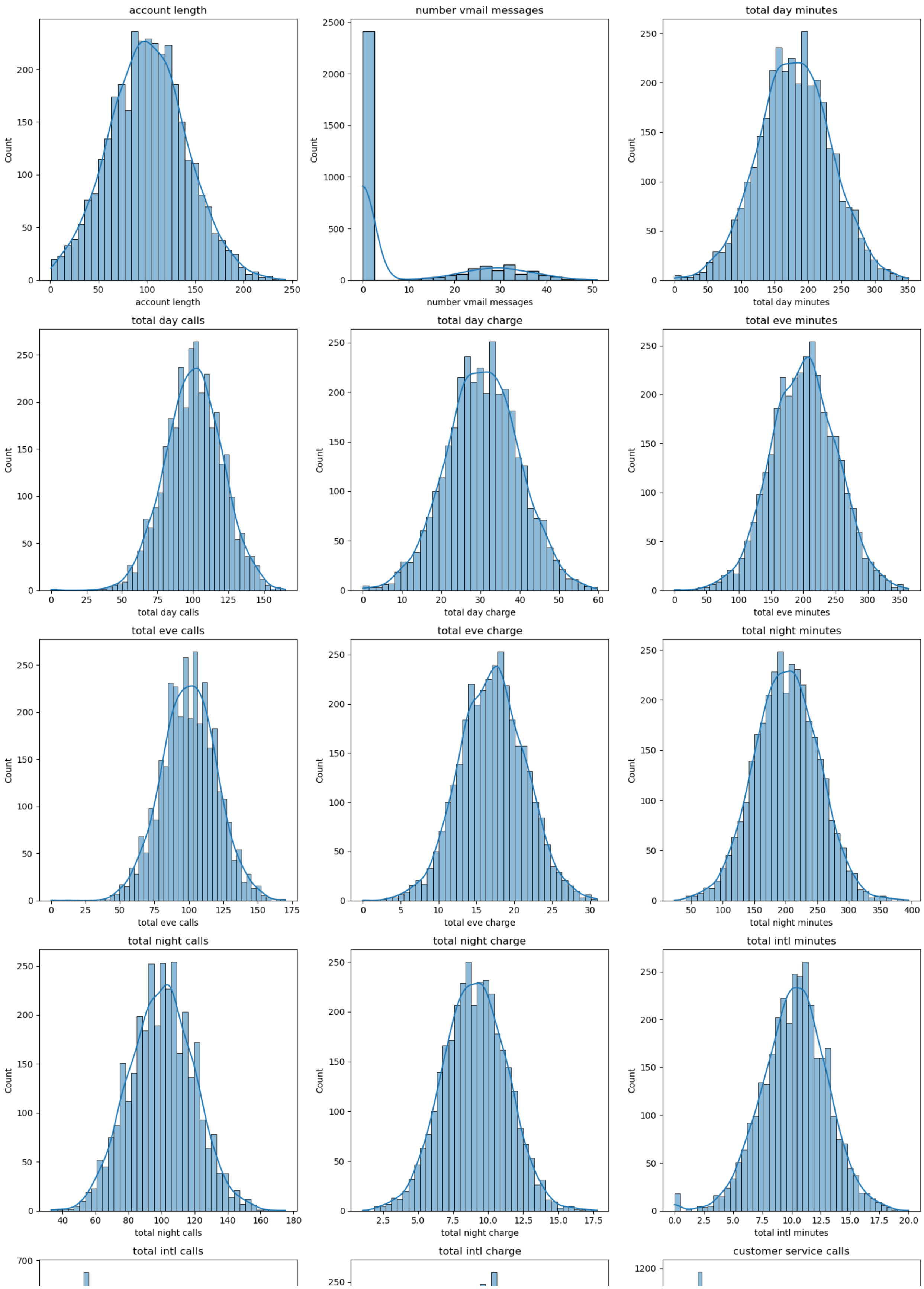
6. **Customer Service Calls**: The majority of customers have one or two service calls, as indicated by the central tendency of the data. However, outliers with a high number of service calls are present. These outliers may represent customers experiencing recurring issues or those requiring extensive support, highlighting the importance of addressing their concerns effectively.

In summary, the presence of outliers across various numerical variables suggests diverse customer behaviors and needs within the dataset. Understanding these outliers can provide valuable insights for customer segmentation, service optimization, and targeted marketing strategies.

Distribution of the data:

Now, let's delve into the distribution of our data to gain insights into its spread and variability.

```
# Visualizing distribution
data_vars.visualize_numerical_distribution()
```


account length
number vmail messages
total day minutes
total day calls
total day charge
total eve minutes
total eve calls
total eve charge
total night minutes
total night calls
total night charge
total intl minutes
total intl calls
total intl charge
customer service calls
Count

Interpretation:

- The plot highlights that the numerical variables in the dataset are not on the same scale, indicating the need for scaling before modeling.
- The majority of numerical variables are continuous, except for **customer service calls** and **total intl calls**, which are discrete.
- Most of the numerical variables exhibit a roughly normal distribution, with some exceptions such as **customer service calls**, **total intl calls**, and **number of voicemail messages**, which display positive skewness. These characteristics will be further analyzed in subsequent sections.
- **Account Length**: The distribution of account lengths is slightly positively skewed, meaning that there are more customers with shorter account lengths than with longer ones. The distribution is also slightly platykurtic, indicating that it has fewer extreme values and is less peaked compared to a normal distribution.

- **Number of Voicemail Messages**: The distribution of the number of voicemail messages is positively skewed, suggesting that most customers receive few or no voicemail messages, with a few outliers receiving a significant number of messages. The distribution is also platykurtic, indicating fewer extreme values and less peakedness compared to a normal distribution.

- **Total Day Minutes**: The distribution of total daytime minutes is approximately symmetric, with a slight negative skewness, suggesting a slightly longer tail on the left side. The distribution is also close to mesokurtic, indicating a similar level of tailedness compared to a normal distribution.

- **Total Day Calls**: The distribution of total daytime calls is negatively skewed, implying that there are more customers with fewer calls than with more calls. The distribution is leptokurtic, indicating heavier tails and a sharper peak compared to a normal distribution.

- **Total Day Charge**: The distribution of total daytime charges is similar to the distribution of total daytime minutes, with a slight negative skewness and close to mesokurtic.

- **Total Evening Minutes**, **Total Evening Calls**, **Total Evening Charge**, **Total Night Minutes**, **Total Night Calls**, and **Total Night Charge**: These variables have distributions that are approximately symmetric and close to mesokurtic, indicating similar tailedness and peakedness to a normal distribution.

- **Total International Minutes**, **Total International Calls**, and **Total International Charge**: The distributions of these variables are positively skewed, suggesting that most customers make shorter international calls or fewer international calls, with some outliers making longer or more international calls. The distributions are also leptokurtic, indicating heavier tails and sharper peaks compared to a normal distribution.

- **Customer Service Calls**: The distribution of the number of customer service calls is positively skewed, indicating that most customers make few service calls, with some outliers making a larger number of calls. The distribution is also leptokurtic, suggesting heavier tails and a sharper peak compared to a normal distribution.

Skewness and Kurtosis

```
def calculate_skewness_kurtosis(df, numerical_vars):
    """
    Calculate skewness and kurtosis for numerical columns in a
DataFrame.

    Args:
    - df (DataFrame): The DataFrame containing the data.
    - numerical_vars (list): List of numerical variable names.

    Returns:
    - DataFrame: DataFrame containing skewness and kurtosis values for
each numerical variable.
    """
    # Calculate skewness and kurtosis for numerical columns
    skewness_values = df[numerical_vars].apply(skew)
    kurtosis_values = df[numerical_vars].apply(kurtosis)

    # Create a DataFrame to store the results
    skew_kurtosis_df = pd.DataFrame({'Skewness': skewness_values,
'Kurtosis': kurtosis_values})

    return skew_kurtosis_df

# Select numerical columns
numerical_vars = df.select_dtypes(include=['int64',
'float64']).columns.tolist()

# Calculate skewness and kurtosis
skew_kurtosis_df = calculate_skewness_kurtosis(df, numerical_vars)
print(skew_kurtosis_df)
```

```
                        Skewness  Kurtosis
account length          0.096563 -0.109474
area code               1.126316 -0.706374
number vmail messages   1.264254 -0.052852
total day minutes      -0.029064 -0.021710
total day calls        -0.111736  0.241017
total day charge       -0.029070 -0.021582
total eve minutes      -0.023867  0.023792
total eve calls        -0.055538  0.204048
total eve charge       -0.023847  0.023650
total night minutes     0.008917  0.083888
total night calls       0.032485 -0.073711
```

```
total night charge      0.008882  0.083735
total intl minutes     -0.245026  0.606472
total intl calls        1.320883  3.077165
total intl charge      -0.245176  0.606897
customer service calls  1.090868  1.726518
```

Interpretation of Numerical Variables and Distributions

- **Account Length**: The distribution of account lengths is slightly positively skewed, with a skewness value of 0.097, indicating more customers with shorter account lengths than with longer ones. It's also slightly platykurtic, with a kurtosis value of -0.109, implying fewer extreme values compared to a normal distribution.

- **Number of Voicemail Messages**: This variable is positively skewed with a skewness value of 1.264, suggesting that most customers receive few or no voicemail messages, with some outliers receiving a significant number of messages. It also exhibits platykurtosis with a kurtosis value of -0.053, indicating fewer extreme values and less peakedness compared to a normal distribution.

- **Total Day Minutes**: The distribution of total daytime minutes is approximately symmetric, with a slight negative skewness of -0.029, suggesting a slightly longer tail on the left side. The kurtosis value of -0.022 indicates a distribution close to mesokurtic, meaning it has a similar level of tailedness compared to a normal distribution.

- **Total Day Calls**: This variable is negatively skewed with a skewness value of -0.112, indicating that more customers make fewer calls than more calls. The distribution is leptokurtic, with a kurtosis value of 0.241, indicating heavier tails and a sharper peak compared to a normal distribution.

- **Total Day Charge**: Similar to total daytime minutes, this variable shows a slight negative skewness of -0.029 and is close to mesokurtic with a kurtosis value of -0.022.

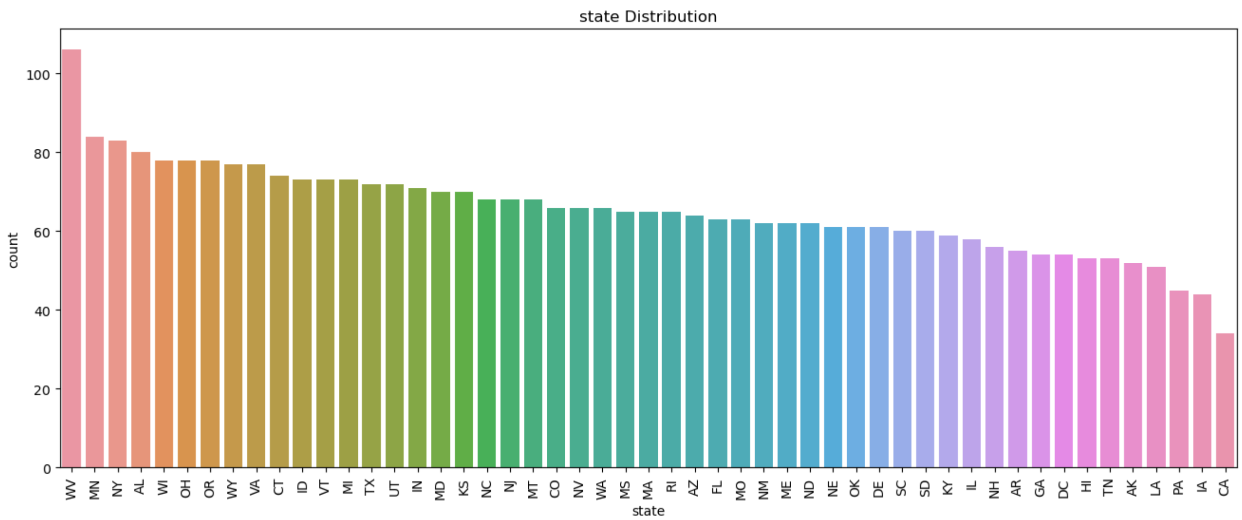
- **Total Evening Minutes**, **Total Evening Calls**, **Total Evening Charge**, **Total Night Minutes**, **Total Night Calls**, and **Total Night Charge**: These variables exhibit distributions that are approximately symmetric and close to mesokurtic.

- **Total International Minutes**, **Total International Calls**, and **Total International Charge**: The distributions of these variables are positively skewed, indicating that most customers make shorter or fewer international calls, with some outliers making longer or more international calls. They also demonstrate leptokurtosis, suggesting heavier tails and sharper peaks compared to a normal distribution.

- **Customer Service Calls**: This variable is positively skewed with a skewness value of 1.091, indicating that most customers make few service calls, with some outliers making a larger number of calls. It also demonstrates leptokurtosis with a kurtosis value of 1.727, suggesting heavier tails and a sharper peak compared to a normal distribution.

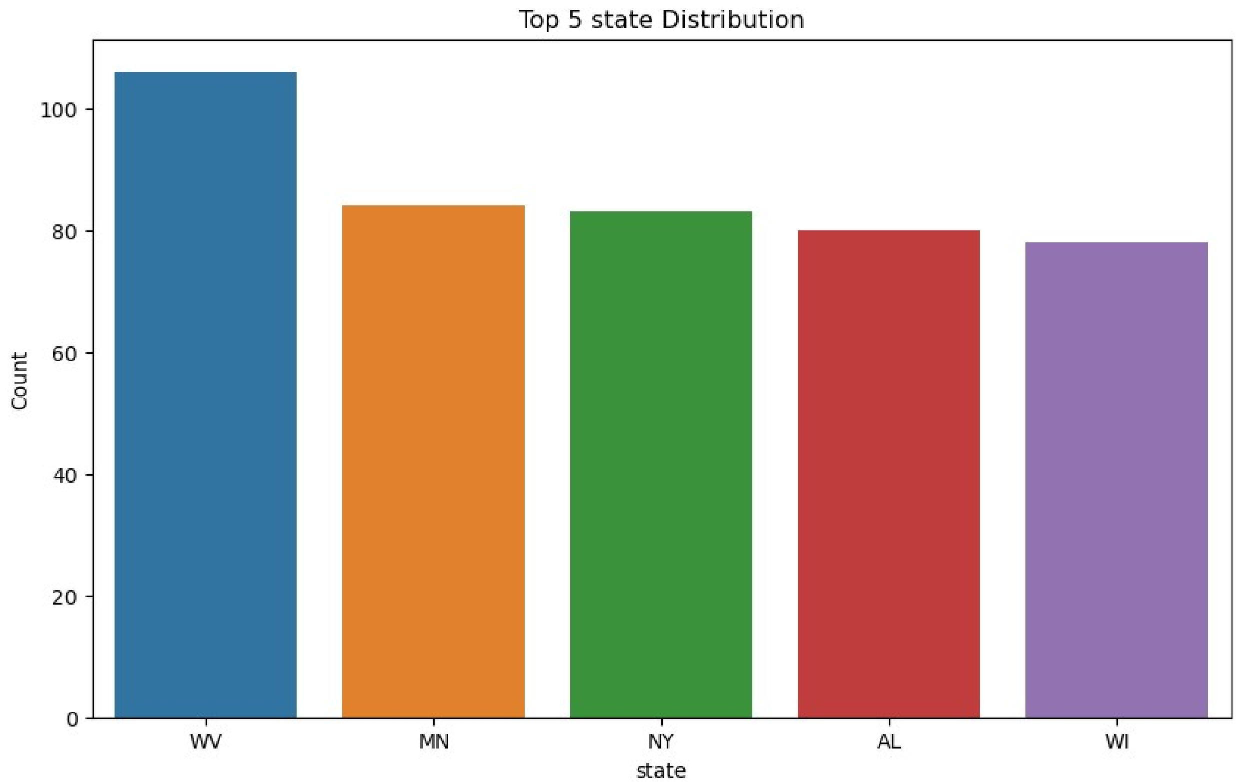
Distribution of customers per state.

```
# Calculate value counts and plot bar plots for categorical variables
categorical_cols = ["state"]

for col in categorical_cols:
    value_counts = df[col].value_counts().sort_values(ascending=False)
    plt.figure(figsize=(16, 6))
    sns.countplot(x=col, data=df, order=value_counts.index)
    plt.title(f"{col} Distribution")
    plt.xticks(rotation=90)
    plt.show()
```



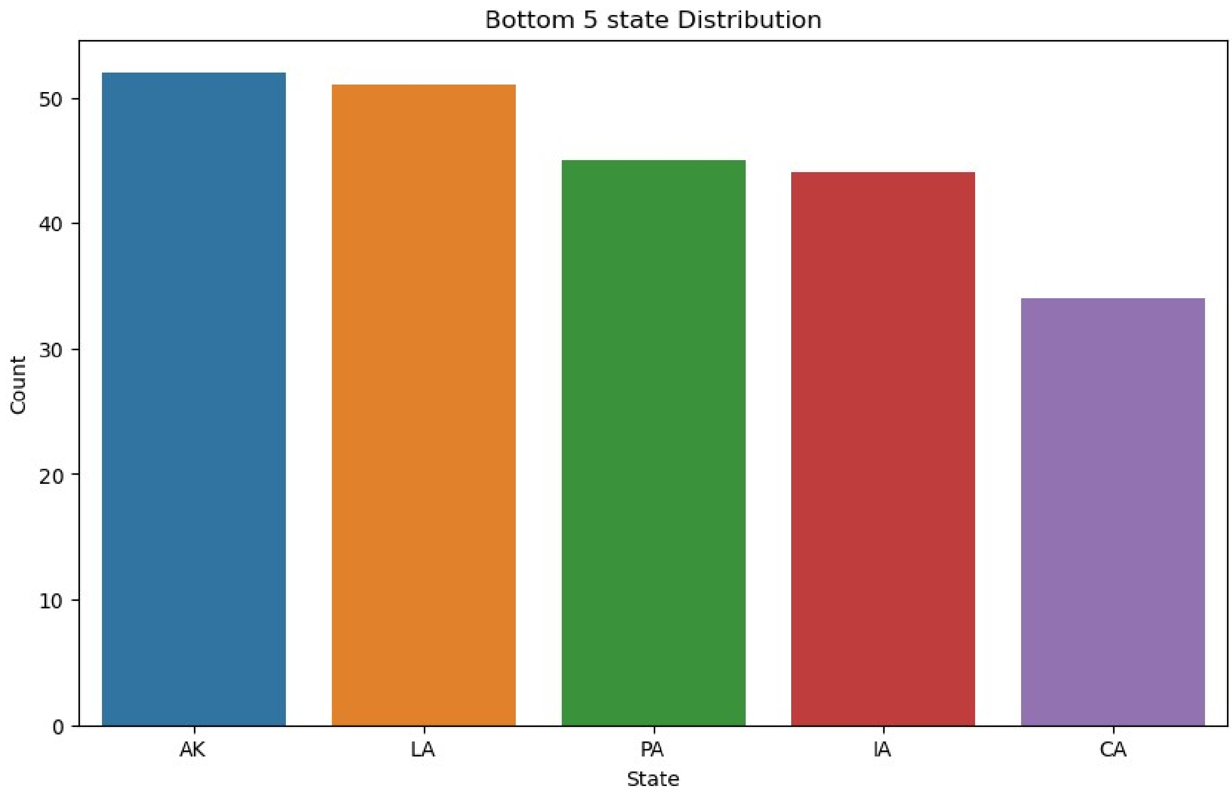

```
categorical_cols = ["state"]

for col in categorical_cols:

    # Get the top 5 states
    top_5_states = value_counts.head(5)
    print(top_5_states)

    # Visualize the top 5 states
    plt.figure(figsize=(10, 6))
    sns.barplot(x=top_5_states.index, y=top_5_states.values)
    plt.title(f"Top 5 {col} Distribution")
    plt.xlabel(col)
    plt.ylabel("Count")
    plt.show()

state
WV    106
```

```
MN     84
NY     83
AL     80
WI     78
Name: count, dtype: int64
```




```
categorical_cols = ["state"]

for col in categorical_cols:


    # Get the bottom 5 states
    bottom_5_states = value_counts.tail(5)
    print(bottom_5_states)

    # Visualize the bottom 5 states
    plt.figure(figsize=(10, 6))
    sns.barplot(x=bottom_5_states.index, y=bottom_5_states.values)
    plt.title(f"Bottom 5 {col} Distribution")
    plt.xlabel(col.capitalize())
    plt.ylabel("Count")
    plt.show()

state
AK    52
```

```
LA    51
PA    45
IA    44
CA    34
Name: count, dtype: int64
```



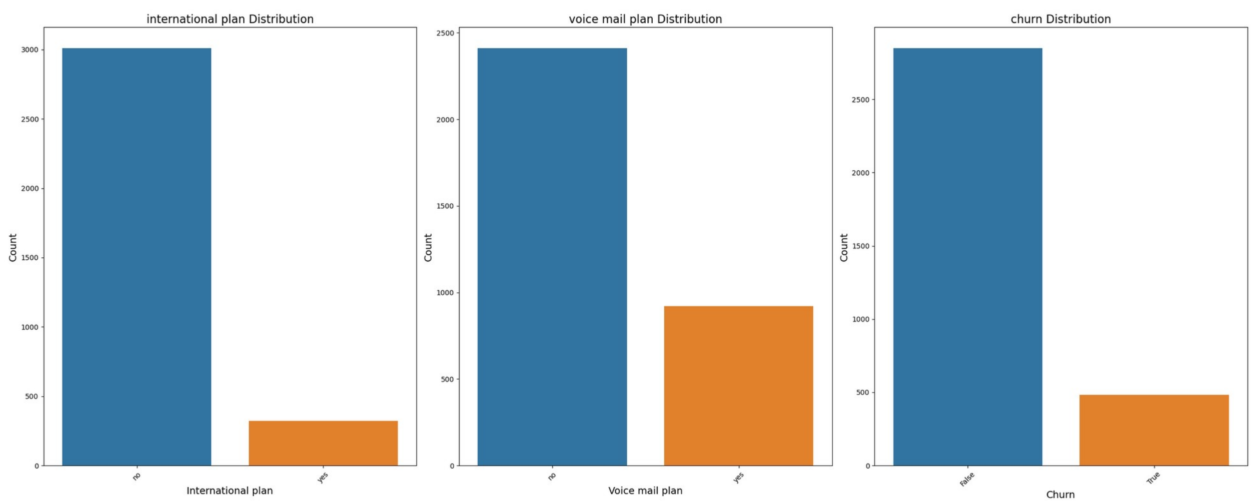
West Virginia (WV) is the most frequent state in the dataset, appearing 106 times. Minnesota (MN) follows with 84 occurrences, making it the second most common state. New York (NY) is close behind with 83 occurrences. Alabama (AL), Wisconsin (WI), Oregon (OR), and Ohio (OH) each appear 78 times, placing them among the top states by frequency. California (CA) has the fewest occurrences at 34, indicating it is the least represented state in the dataset.

Categorical variables analysis:

Now let's peek into the **categorical variables**:

```
# Set up the figure and axes for subplots
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(25, 10))

# Flatten the axes array to simplify indexing
axs = axs.flatten()

# Calculate value counts and plot bar plots for categorical variables
categorical_cols = ["international plan", "voice mail plan", "churn"]
```

```
for i, col in enumerate(categorical_cols):
    # Calculate value counts and sort by frequency
    value_counts = df[col].value_counts().sort_values(ascending=False)
    sns.countplot(x=col, data=df, order=value_counts.index, ax=axs[i])
    axs[i].set_title(f"{col} Distribution", fontsize=16)
    axs[i].set_xlabel(col.capitalize(), fontsize=14)
    axs[i].set_ylabel('Count', fontsize=14)
    axs[i].tick_params(axis='x', rotation=45)

# Adjust the layout and spacing
plt.tight_layout()
plt.show()
```




```
# Select categorical columns
categorical_vars = df.select_dtypes(include=['object',
'category']).columns.tolist()

# Print value counts for the categorical variables
print("Value counts for the categorical variables:\n")
for var in categorical_vars:
    print(f'{var}: {len(df[var].value_counts())}')

Value counts for the categorical variables:

state: 51
phone number: 3333
international plan: 2
voice mail plan: 2
```

- **States Presence**:
  - The countplot for the 'state' variable shows that there are 51 unique states present in the dataset.
  - Each state represents a geographical location where customers may reside or where the phone service is provided.

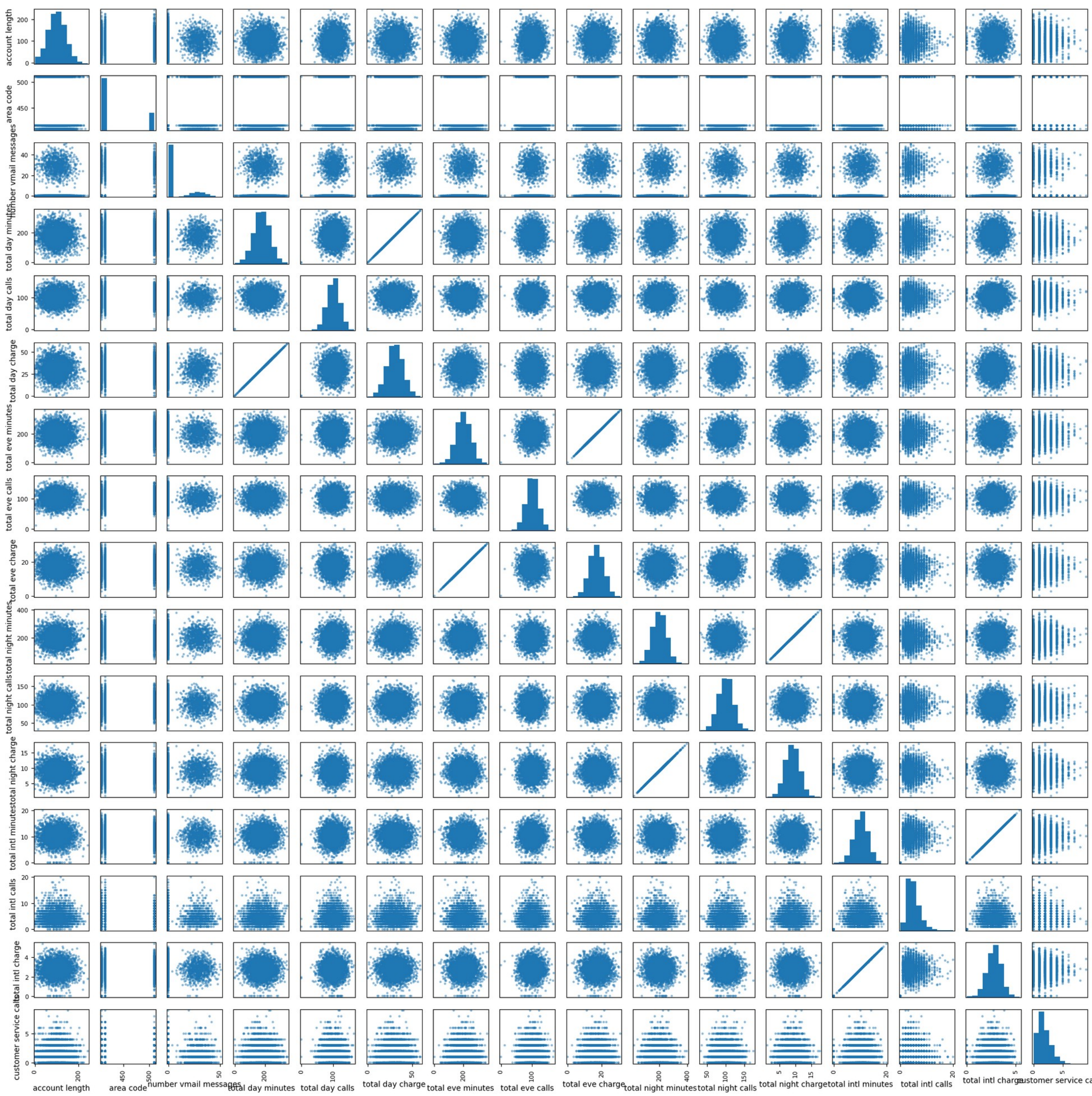
- **Area Codes**:
  - From the countplot or value counts output, we observe that there are three different area codes present in the dataset.
  - Area codes are geographical region codes assigned to specific telephone numbers. Having three different area codes suggests that the dataset covers customers from different regions or areas.
- **Phone Numbers**:
  - Each record in the dataset is represented by a unique phone number.
  - This suggests that each row in the dataset corresponds to a specific phone line or customer account, identified uniquely by their phone numbers.
- **Voice Mail Plan**:
  - The countplot or value counts output indicates whether a customer has been subscribed to a voice mail plan or not.
  - This binary variable suggests whether customers have opted for a voice mail service as part of their phone plan.
- **International Plan**:
  - Similar to the voice mail plan, the countplot or value counts output shows whether a customer has been subscribed to an international plan or not.
  - This binary variable indicates whether customers have opted for an international calling plan as part of their phone service.

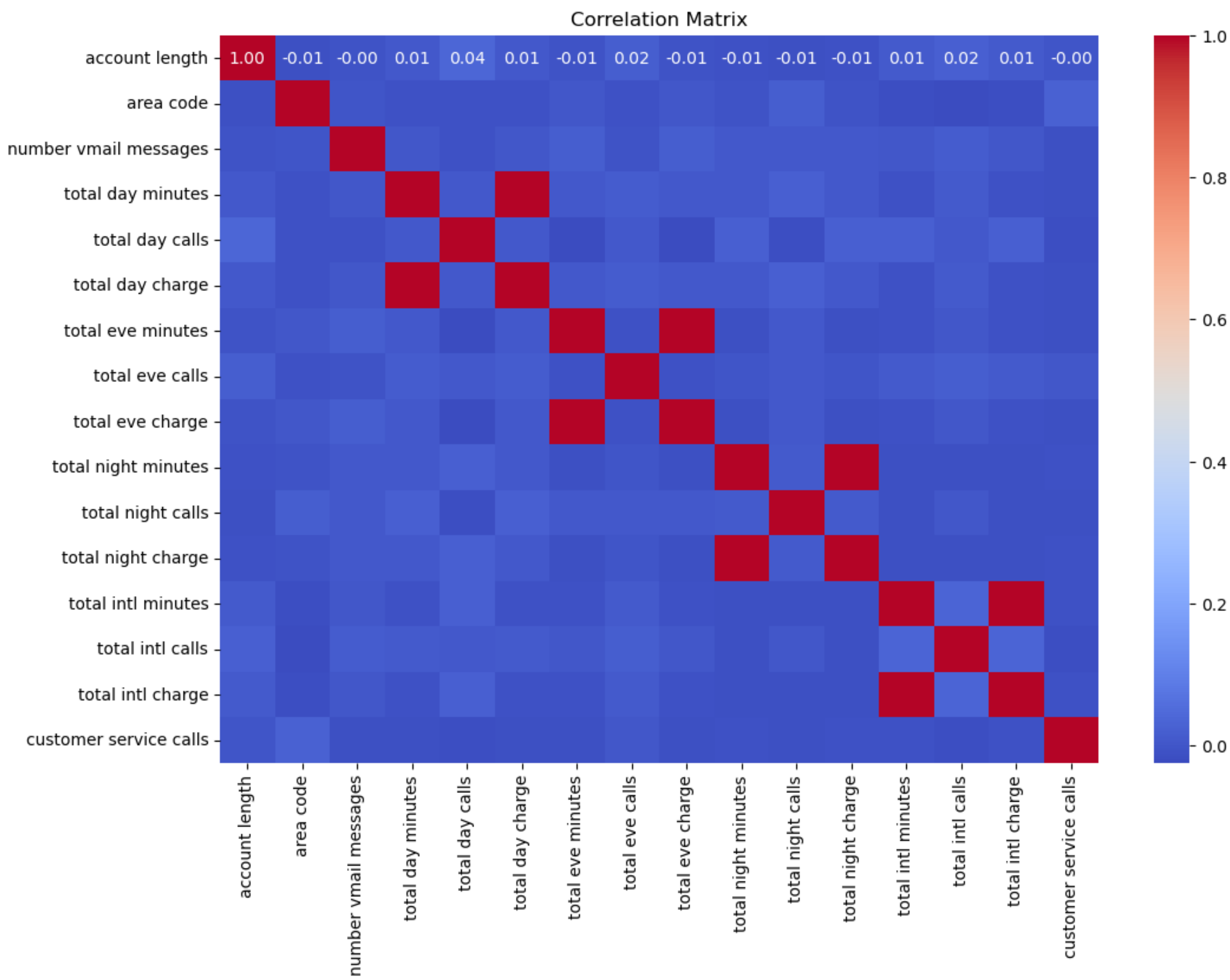
2.1.2 Bi-Variate Analysis

Next let's check the relationships that the variables have in our data-set.

```
# Set display options
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)

class BivariateAnalysis:
    def __init__(self, dataframe):
        self.df = dataframe

    def visualize_correlation_matrix(self):
        # Select only numerical columns
        numerical_vars = self.df.select_dtypes(include=['int64',
'float64']).columns.tolist()
        numeric_vars =
self.df[numerical_vars].select_dtypes(include=[np.number])

        # Plot scatter matrix
        pd.plotting.scatter_matrix(numeric_vars, figsize=(20, 20))
        plt.tight_layout()
        plt.show()

        # Calculate the correlation matrix
        correlation_matrix = numeric_vars.corr()
```

```
        # Plot the correlation matrix using Seaborn heatmap
        plt.figure(figsize=(12, 8))
        sns.heatmap(correlation_matrix, annot=True, fmt=".2f",
cmap="coolwarm")
        plt.title("Correlation Matrix")
        plt.show()

# plot the relevant plots
bivariate_analysis = BivariateAnalysis(df)
bivariate_analysis.visualize_correlation_matrix()
```





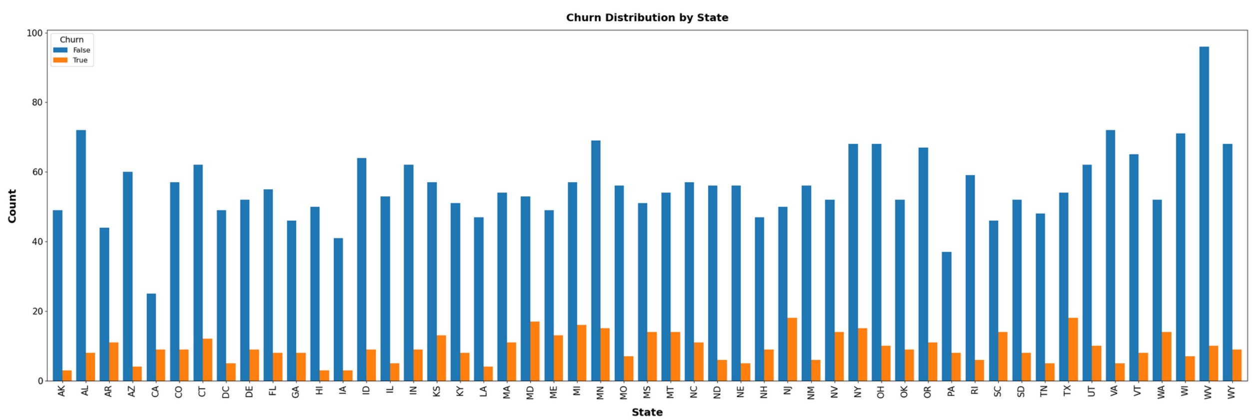
"The heatmap indicates that certain variables exhibit high correlation, excluding those along the leading diagonal (which are identical). This correlation suggests the possibility of multicollinearity, a condition where predictors in a regression model are highly correlated. Multicollinearity will be addressed in the 'Checking for and removing multicollinearity (correlated predictors)' in the data preparation process.

The scatter plot matrix above reaffirms our observation from the heatmap, indicating that certain variables exhibit high correlation.

Distribution of churn for each state.

```
# Group by "state" and "churn" to calculate counts
state_churn_counts = df.groupby(["state", "churn"]).size().unstack()

# Set up the figure size
plt.figure(figsize=(30, 10))

# Plot the bar chart
state_churn_counts.plot(kind='bar', stacked=False, figsize=(30, 10),
width=0.8)
```

```
# Add a title and labels
plt.title('Churn Distribution by State', fontsize=18,
fontweight="bold", pad=15)
plt.xlabel('State', fontsize=18, fontweight="bold", labelpad=15)
plt.ylabel('Count', fontsize=18, fontweight="bold", labelpad=15)

# Rotate x-axis labels for better visibility
plt.xticks(rotation=90, fontsize=15)
plt.yticks(fontsize=15)

# Add a legend
plt.legend(title='Churn', title_fontsize=14, fontsize=12)

# Adjust layout for better spacing
plt.tight_layout()

# Show the plot
plt.show()

<Figure size 3000x1000 with 0 Axes>
```

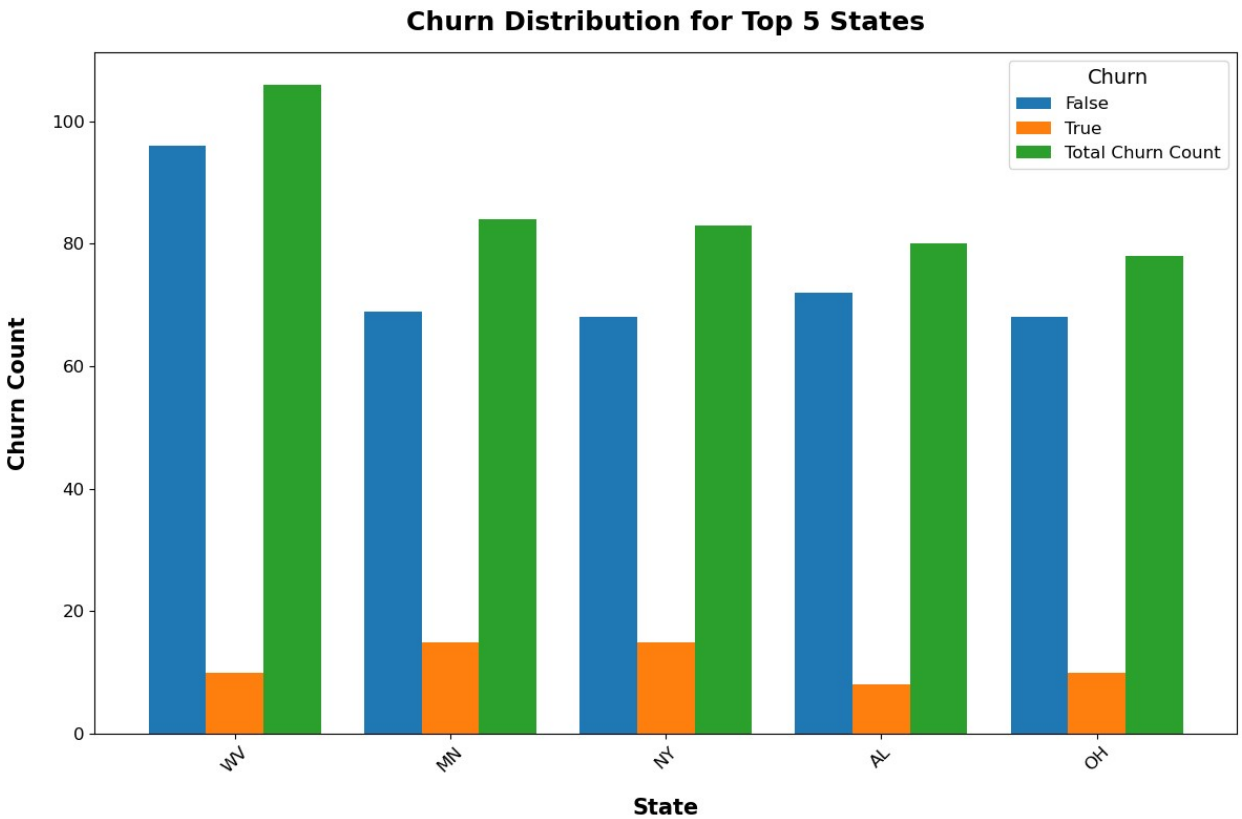



```
import matplotlib.pyplot as plt

def plot_churn_distribution(df, top=True, n=5):
    """
    Plot churn distribution for the top or bottom states.

    Parameters:
        df (DataFrame): DataFrame containing 'state' and 'churn'
columns.
        top (bool): If True, plot churn distribution for top states.
If False, plot for bottom states. Default is True.
        n (int): Number of states to consider. Default is 5.

    Returns:
        None (plots churn distribution)
```

```
    """
    # Group by "state" and "churn" to calculate counts
    state_churn_counts = df.groupby(["state",
"churn"]).size().unstack()

    # Calculate total churn count for each state
    state_churn_counts['Total Churn Count'] =
state_churn_counts.sum(axis=1)

    # Determine whether to select top or bottom states
    if top:
        states = state_churn_counts['Total Churn
Count'].nlargest(n).index
    else:
        states = state_churn_counts['Total Churn
Count'].nsmallest(n).index

    # Select churn counts for the selected states
    churn_counts = state_churn_counts.loc[states]

    # Plot the churn distribution
    plt.figure(figsize=(10, 6))
    churn_counts.plot(kind='bar', stacked=False, figsize=(12, 8),
width=0.8)

    # Add a title and labels
    if top:
        title = f'Churn Distribution for Top {n} States'
    else:
        title = f'Churn Distribution for Bottom {n} States'
    plt.title(title, fontsize=18, fontweight="bold", pad=15)
    plt.xlabel('State', fontsize=15, fontweight="bold", labelpad=15)
    plt.ylabel('Churn Count', fontsize=15, fontweight="bold",
labelpad=15)

    # Rotate x-axis labels for better visibility
    plt.xticks(rotation=45, fontsize=12)
    plt.yticks(fontsize=12)

    # Add a legend
    plt.legend(title='Churn', title_fontsize=14, fontsize=12)

    # Adjust layout for better spacing
    plt.tight_layout()

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

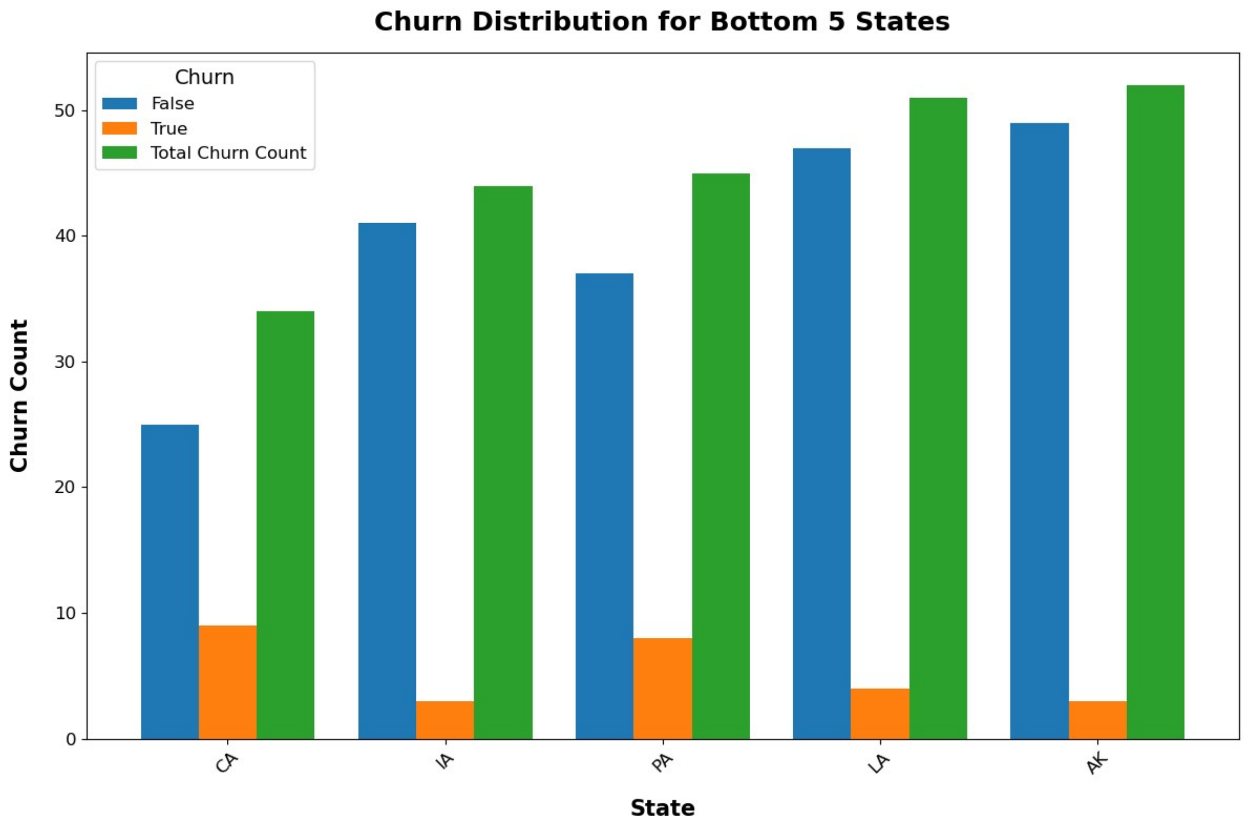
```python
plot_churn_distribution(df, top=True, n=5)  # Plot churn distribution for top 5 states
```

```
<Figure size 1000x600 with 0 Axes>
```




```python
plot_churn_distribution(df, top=False, n=5)  # Plot churn distribution for bottom 5 states
```

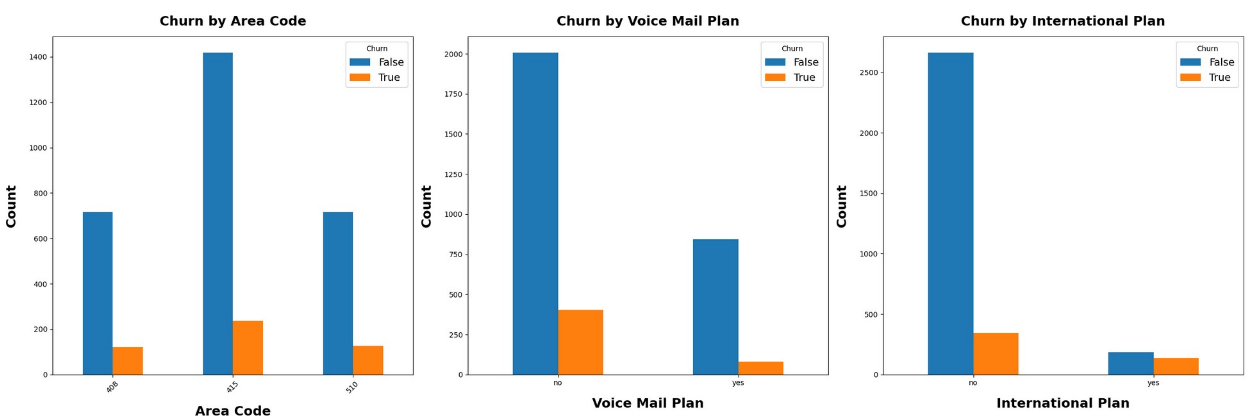
```
<Figure size 1200x800 with 0 Axes>
```



Churn by Categorical Features

```
# Set up the figure and axes for subplots
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(24, 8))

# Define colors for churn
churn_colors = ['#1f77b4', '#ff7f0e']

# Group by "area code" and "churn", then unstack and plot
df.groupby(["area code", "churn"]).size().unstack().plot(kind='bar',
stacked=False, ax=axs[0], color=churn_colors)
axs[0].set_title('Churn by Area Code', fontsize=18, fontweight="bold",
pad=15)
axs[0].set_xlabel('Area Code', fontsize=18, fontweight="bold",
labelpad=15)
axs[0].set_ylabel('Count', fontsize=18, fontweight="bold",
labelpad=15)
axs[0].tick_params(axis='x', rotation=45)
axs[0].legend(title='Churn', fontsize=14)

# Group by "voice mail plan" and "churn", then unstack and plot
df.groupby(["voice mail plan",
"churn"]).size().unstack().plot(kind='bar', stacked=False, ax=axs[1],
color=churn_colors)
axs[1].set_title('Churn by Voice Mail Plan', fontsize=18,
```

```
fontweight="bold", pad=15)
axs[1].set_xlabel('Voice Mail Plan', fontsize=18, fontweight="bold",
labelpad=15)
axs[1].set_ylabel('Count', fontsize=18, fontweight="bold",
labelpad=15)
axs[1].tick_params(axis='x', rotation=0)
axs[1].legend(title='Churn', fontsize=14)

# Group by "international plan" and "churn", then unstack and plot
df.groupby(["international plan",
"churn"]).size().unstack().plot(kind='bar', stacked=False, ax=axs[2],
color=churn_colors)
axs[2].set_title('Churn by International Plan', fontsize=18,
fontweight="bold", pad=15)
axs[2].set_xlabel('International Plan', fontsize=18,
fontweight="bold", labelpad=15)
axs[2].set_ylabel('Count', fontsize=18, fontweight="bold",
labelpad=15)
axs[2].tick_params(axis='x', rotation=0)
axs[2].legend(title='Churn', fontsize=14)

# Adjust the layout and spacing
plt.tight_layout()
plt.show()
```



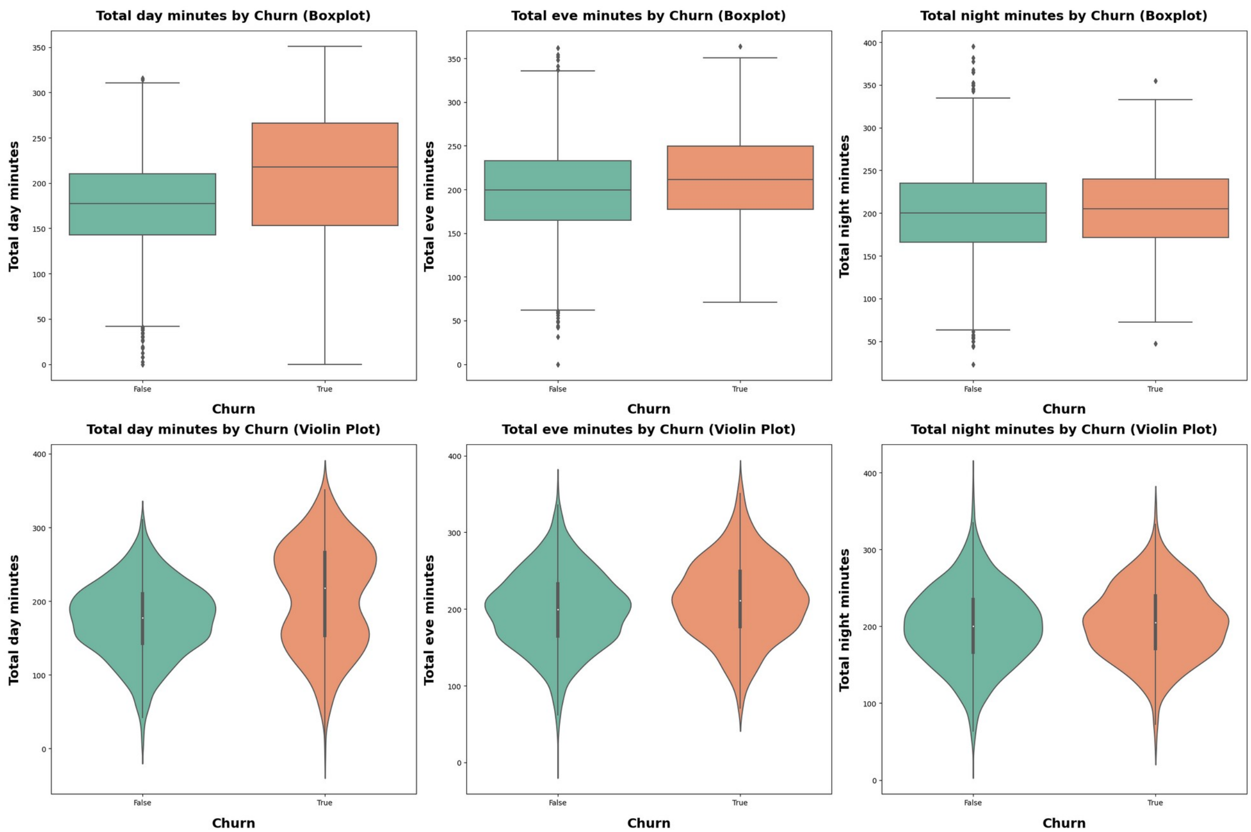
- **Churn by Area Code**: The analysis reveals significant variations in churn rates across different area codes. Area code 415 exhibits the highest churn rate, whereas area code 408 shows the lowest churn rate. This indicates that customer retention strategies may need to be tailored based on geographic locations.

- **Churn by Voice Mail Plan**: Customers without a voice mail plan demonstrate a markedly higher churn rate compared to those with a voice mail plan. This suggests that having a voice mail plan may be associated with increased customer loyalty.

- **Churn by International Plan**: Similarly, customers without an international plan exhibit a higher churn rate compared to those with an international plan. This highlights the potential value of international plans in reducing churn rates.

Churn by numerical features.

```
# Set up the figure and axes for subplots
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(24, 16))

# List of numerical columns
numerical_cols = ["total day minutes", "total eve minutes", "total night minutes"]

# Define color palette for consistency
palette = "Set2"

# Loop over numerical columns and plot boxplots and violin plots
for i, col in enumerate(numerical_cols):
    sns.boxplot(x="churn", y=col, data=df, ax=axs[0, i], palette=palette)
    axs[0, i].set_title(f"{col.capitalize()} by Churn (Boxplot)", fontsize=18, fontweight="bold", pad=15)
    axs[0, i].set_xlabel("Churn", fontsize=18, fontweight="bold", labelpad=15)
    axs[0, i].set_ylabel(col.replace('_', ' ').capitalize(), fontsize=18, fontweight="bold", labelpad=15)

    sns.violinplot(x="churn", y=col, data=df, ax=axs[1, i], palette=palette)
    axs[1, i].set_title(f"{col.capitalize()} by Churn (Violin Plot)", fontsize=18, fontweight="bold", pad=15)
    axs[1, i].set_xlabel("Churn", fontsize=18, fontweight="bold", labelpad=15)
    axs[1, i].set_ylabel(col.replace('_', ' ').capitalize(), fontsize=18, fontweight="bold", labelpad=15)

# Adjust the layout and spacing
plt.tight_layout()
plt.show()
```



From the plots, you can observe the following:

- **Total Day Minutes**: The distribution of total day minutes is noticeably higher for churned customers compared to retained customers. This suggests that customers who spend more time on daytime calls are more likely to churn.
- **Total Evening Minutes**: Similar to total day minutes, the total evening minutes are also higher for churned customers. This indicates a pattern where increased call activity during evening hours is associated with higher churn rates.
- **Total Night Minutes**: While the difference is less pronounced, churned customers still tend to have slightly higher total night minutes than retained customers. This pattern reinforces the trend that higher call activity, regardless of the time of day, may be linked to customer churn.

The violin plots corroborate these findings by showing the density of churned customers is higher at larger values of minutes for each feature. This density distribution provides a visual confirmation that higher call usage is a potential indicator of customer churn across different times of the day.

3. Data Preparation

In the data preparation stage, we focus on ensuring the data is suitable for modeling by addressing various data quality and preprocessing tasks:

- **Handling Missing Values:** Detect and assess missing values, then decide on a strategy (imputation, removal, or marking as a separate category).
- **Data Type Conversions:** Ensure correct data types for modeling (e.g., numeric data erroneously encoded as strings).
- **Handling Duplicates:** Check for and remove duplicates.
- **Addressing Multicollinearity:** Identify and mitigate multicollinearity (high correlation between predictors) to enhance model interpretability, using techniques like correlation analysis or PCA.
- **Converting Categorical Data:** Convert categorical variables (e.g., "International Plan" and "Voice Mail Plan") to numeric format via one-hot encoding, as most ML algorithms require numeric input.

3.1 Handling Missing Values:

```
# 1. Handling Missing Values:
df.isna().sum()
```

```
state                     0
account length            0
area code                 0
phone number              0
international plan        0
voice mail plan           0
number vmail messages     0
total day minutes         0
total day calls           0
total day charge          0
total eve minutes         0
total eve calls           0
total eve charge          0
total night minutes       0
total night calls         0
total night charge        0
total intl minutes        0
total intl calls          0
total intl charge         0
customer service calls    0
churn                     0
dtype: int64
```

```
df.sample(20)
```

```
     state  account length  area code phone number international plan  \
829     ME             120        510     350-5883                 no

48      ID             119        415     398-1294                 no
```

2149	IA	120	415	341-6743	no
1265	WY	95	415	340-4236	no
1234	IA	86	408	390-3873	no
1233	IL	48	510	380-5246	no
2601	AL	85	408	386-6411	no
2886	PA	85	408	405-9573	no
2526	NJ	57	510	330-2635	yes
621	DC	126	510	362-8280	no
1109	ID	118	415	335-3320	no
2132	GA	202	510	351-2589	no
324	VA	129	408	384-2632	no
2111	NC	126	415	342-1702	no
2674	IL	67	415	369-4377	no
2901	MT	85	408	372-4868	no
3291	MI	119	510	335-7324	yes
1288	MA	56	510	401-3622	no
2591	ND	122	408	395-1901	no
2155	AL	172	408	359-5731	no

	voice mail plan	number vmail messages	total day minutes \
829	no	0	198.8
48	no	0	159.1
2149	yes	33	299.5
1265	yes	39	260.8
1234	no	0	126.3
1233	no	0	128.2
2601	yes	30	173.1
2886	no	0	144.4
2526	no	0	115.0
621	no	0	122.4
1109	no	0	140.4
2132	no	0	115.4

```
324                  no                       0             207.0
2111                 no                       0             103.7
2674                 no                       0             109.1
2901                yes                      17              89.8
3291                yes                      22             172.1
1288                 no                       0             253.2
2591                 no                       0             231.2
2155                 no                       0             270.0

      total day calls  total day charge  total eve minutes  total eve
calls  \
829                56             33.80              230.1
73
48                114             27.05              231.3
117
2149               83             50.92              163.4
84
1265              130             44.34              213.4
111
1234              115             21.47              168.8
112
1233               71             21.79               48.1
78
2601              107             29.43              247.2
101
2886               88             24.55              264.6
105
2526               65             19.55              122.3
96
621                88             20.81              143.8
111
1109              112             23.87              187.1
60
2132              137             19.62              178.7
70
324                91             35.19              154.9
121
2111               93             17.63              127.0
107
2674              117             18.55              217.4
124
2901               88             15.27              233.2
75
3291              119             29.26              223.6
133
1288               95             43.04              188.0
116
2591              141             39.30              267.8
136
```

```
2155                102                45.90                256.6
111

      total eve charge  total night minutes  total night calls  \
829              19.56                119.8                 81
48               19.66                143.2                 91
2149             13.89                146.7                 88
1265             18.14                195.6                 97
1234             14.35                154.6                 95
1233              4.09                116.3                 80
2601             21.01                158.7                104
2886             22.49                185.4                 94
2526             10.40                245.0                 75
621              12.22                157.0                106
1109             15.90                207.9                155
2132             15.19                185.7                113
324              13.17                245.1                112
2111             10.80                329.3                 66
2674             18.48                188.4                141
2901             19.82                165.7                116
3291             19.01                150.0                 94
1288             15.98                142.0                133
2591             22.76                240.3                100
2155             21.81                168.5                104

      total night charge  total intl minutes  total intl calls  \
829                 5.39                 9.9                 3
48                  6.44                 8.8                 3
2149                6.60                11.6                 5
1265                8.80                10.1                 5
1234                6.96                 9.8                 7
1233                5.23                 8.9                 3
2601                7.14                11.5                 5
2886                8.34                 9.9                 3
2526               11.03                 6.4                 1
621                 7.07                11.5                 3
1109                9.36                 7.9                 1
2132                8.36                 6.0                 3
324                11.03                13.4                 5
2111               14.82                14.4                 1
2674                8.48                12.8                 6
2901                7.46                 9.3                 7
3291                6.75                13.9                20
1288                6.39                 4.4                 4
2591               10.81                 8.8                 5
2155                7.58                12.0                 5

      total intl charge  customer service calls  churn
829                2.67                       2  False
48                 2.38                       5   True
```

```
2149                3.13                           0  False
1265                2.73                           1  False
1234                2.65                           2  False
1233                2.40                           0  False
2601                3.11                           1  False
2886                2.67                           1  False
2526                1.73                           0   True
621                 3.11                           1  False
1109                2.13                           0  False
2132                1.62                           3  False
324                 3.62                           3  False
2111                3.89                           0  False
2674                3.46                           0  False
2901                2.51                           4   True
3291                3.75                           1   True
1288                1.19                           1  False
2591                2.38                           1   True
2155                3.24                           2   True
```

```
df.describe()
```

```
       account length    area code  number vmail messages  total day 
minutes  \
count     3333.000000  3333.000000            3333.000000        
3333.000000   
mean       101.064806   437.182418               8.099010         
179.775098   
std         39.822106    42.371290              13.688365          
54.467389   
min          1.000000   408.000000               0.000000           
0.000000   
25%         74.000000   408.000000               0.000000         
143.700000   
50%        101.000000   415.000000               0.000000         
179.400000   
75%        127.000000   510.000000              20.000000         
216.400000   
max        243.000000   510.000000              51.000000         
350.800000   

       total day calls  total day charge  total eve minutes  total eve 
calls  \
count      3333.000000       3333.000000        3333.000000        
3333.000000   
mean        100.435644         30.562307         200.980348         
100.114311   
std          20.069084          9.259435          50.713844          
19.922625   
min           0.000000          0.000000           0.000000           
0.000000   
```

```
25%          87.000000         24.430000         166.600000
87.000000
50%         101.000000         30.500000         201.400000
100.000000
75%         114.000000         36.790000         235.300000
114.000000
max         165.000000         59.640000         363.700000
170.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
std            4.310668            50.573847          19.568609
min            0.000000            23.200000          33.000000
25%           14.160000           167.000000          87.000000
50%           17.120000           201.200000         100.000000
75%           20.000000           235.300000         113.000000
max           30.910000           395.000000         175.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
75%             10.590000           12.100000          6.000000
max             17.770000           20.000000         20.000000

       total intl charge  customer service calls
count        3333.000000             3333.000000
mean            2.764581                1.562856
std             0.753773                1.315491
min             0.000000                0.000000
25%             2.300000                1.000000
50%             2.780000                1.000000
75%             3.270000                2.000000
max             5.400000                9.000000
```

After meticulous examination, it is evident that the dataset does not contain any missing values. However, it is notable that there are instances of zero values present. These zero values may represent genuine data entries rather than missing values. Further clarification from the data source, such as the company, may be required to ensure accurate interpretation and handling of these zero values in the analysis, but for now will assume that they are valid entries.

3.2 Data Type Conversions:

Let's first re-assess the data-types in our data-set:

```python
# Data types in the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   state                   3333 non-null   object
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   int64
 3   phone number            3333 non-null   object
 4   international plan      3333 non-null   object
 5   voice mail plan         3333 non-null   object
 6   number vmail messages   3333 non-null   int64
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64
 20  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

Converting the "area code" column to a categorical variable improves its suitability for grouping and identification purposes. By treating it as a category rather than a numerical value, we enhance clarity and prevent accidental numerical interpretations or computations. This conversion ensures that the focus remains on the distinct categories represented by the area codes, facilitating clearer communication and analysis, particularly in tasks related to regional or locational segmentation.

```python
# So let's convert area code data into strings:
df['area code'] = df['area code'].astype(str)

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
```

```
 0   state                   3333 non-null   object
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   object
 3   phone number            3333 non-null   object
 4   international plan      3333 non-null   object
 5   voice mail plan         3333 non-null   object
 6   number vmail messages   3333 non-null   int64
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64
 20  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(7), object(5)
memory usage: 524.2+ KB
```

Based on my analysis, I can confirm that all the other fields in our dataset have the relevant data types. They are well-aligned with the information they represent and are suitable for our analysis.

3.3 Handling Duplicates:

```python
# Handling Duplicates:
duplicate_rows = df[df.duplicated()]
num_duplicate_rows = len(duplicate_rows)

print(f"Number of duplicate rows: {num_duplicate_rows}")
```

```
Number of duplicate rows: 0
```

We see from the above output that there are no duplicates in this dataset.

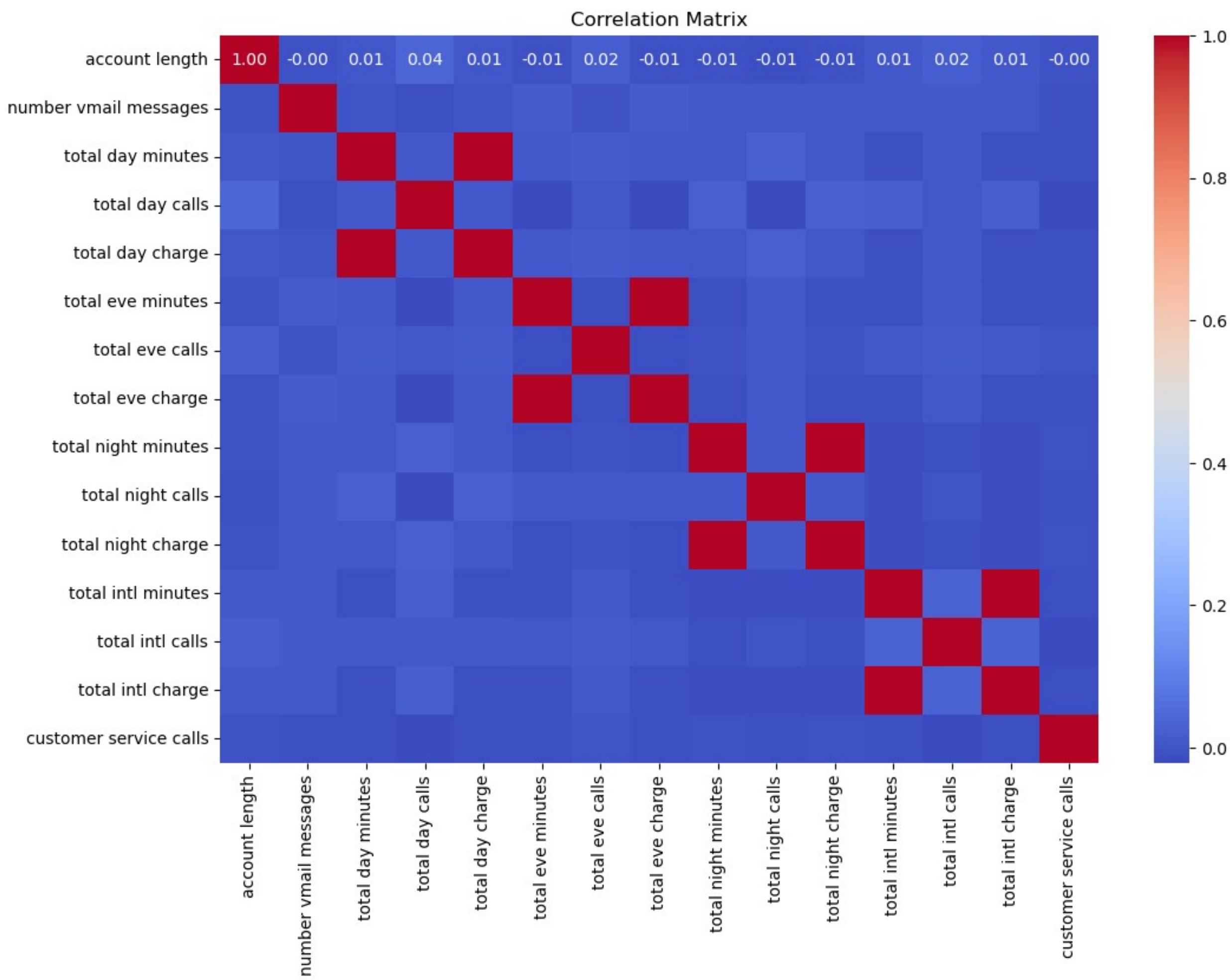
3.4 Checking for and Removing Multicollinearity (Correlated Predictors)

In classification problems like this, multicollinearity (high correlation between predictor variables) is a concern. While multicollinearity doesn't directly impact the accuracy or performance of classification models as it does for regression models, it still poses challenges for model interpretability and coefficient stability.

The heatmap we observed earlier, revealed highly correlated variables. Now, let's filter out these correlations and delve deeper into their relationships.

Setting the correlation threshold at 0.7 designates a "high" correlation due to its indication of a strong linear relationship between variables, helping identify pairs that may lead to multicollinearity issues in subsequent analyses. This threshold is commonly used to strike a balance between capturing significant correlations and avoiding redundancy, ensuring model stability and interpretability.

```
# Assuming 'df' is your dataframe
numeric_df = df.select_dtypes(include=['int64', 'float64'])

correlation_matrix = numeric_df.corr()
correlation_threshold = 0.7  # Threshold for correlation

highly_correlated_pairs = []

for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        # Get the correlation coefficient
        correlation = correlation_matrix.iloc[i, j]

        # Check if the correlation is above the threshold
        if abs(correlation) > correlation_threshold:
            # Get the variable names
            variable1 = correlation_matrix.columns[i]
            variable2 = correlation_matrix.columns[j]

            # Append the pair and correlation to the list
            highly_correlated_pairs.append((variable1, variable2,
correlation))

# Visualize correlation matrix
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f",
cmap="coolwarm")
plt.title("Correlation Matrix")
plt.show()

# Print highly correlated pairs
if highly_correlated_pairs:
    print("Highly correlated pairs:")
    for pair in highly_correlated_pairs:
        print(pair)
else:
    print("No highly correlated pairs found.")
```




```
Highly correlated pairs:
('total day charge', 'total day minutes', 0.9999999521904007)
('total eve charge', 'total eve minutes', 0.9999997760198491)
('total night charge', 'total night minutes', 0.9999992148758795)
('total intl charge', 'total intl minutes', 0.9999927417510314)
```

Rationale for Dropping Highly Correlated Features:

1. **Near-Perfect Correlation**:
   - Highly correlated pairs exhibit correlation coefficients very close to 1. For instance, the pair `total day charge` and `total day minutes` demonstrates an exceptionally high correlation coefficient (`0.9999999521904007`).
2. **Redundancy Indication**:
   - High correlation between features implies redundancy in the dataset. Features like `total day charge` and `total day minutes` are essentially duplicating information, offering little additional insight.
3. **Risk of Overfitting**:

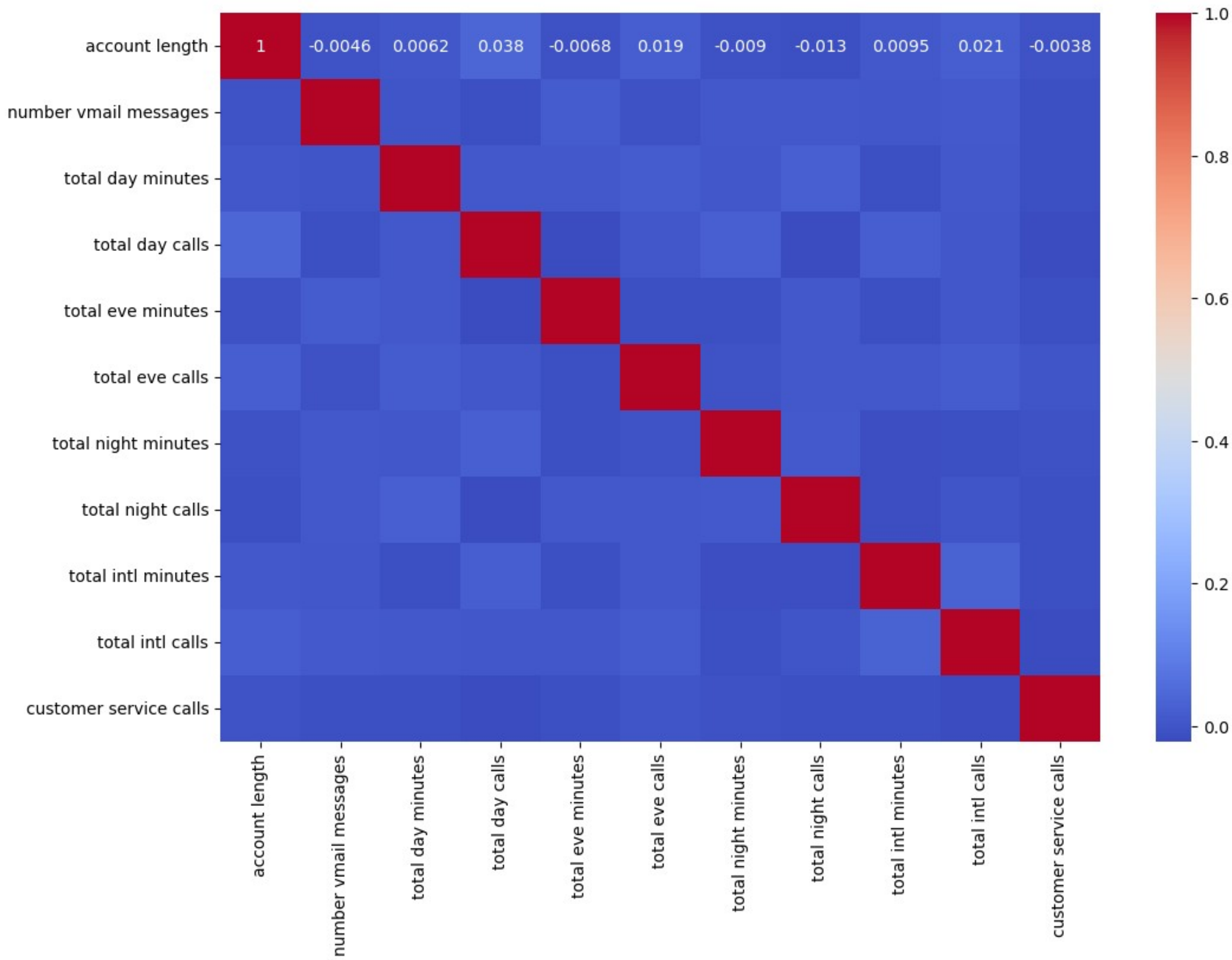
    - In the context of predictive modeling, the inclusion of highly correlated features can exacerbate overfitting. Co-occurring features, such as `total day charge` and `total day minutes`, may disproportionately influence the model, leading to suboptimal generalization.
4. **Enhanced Computational Efficiency**:
    - Highly correlated features can significantly increase computational overhead without providing commensurate gains in predictive performance. Eliminating one of these features streamlines model training and inference processes.
5. **Improved Model Interpretability**:
    - By removing highly correlated features, we enhance the interpretability of our model. Simplifying the feature space, as exemplified by the removal of redundant features like `total day charge` or `total day minutes`, facilitates a clearer understanding of the model's decision-making process.

Conclusion:

- Given the high correlation observed between features such as `total day charge` and `total day minutes`, it is prudent to eliminate one of the correlated features. This strategy mitigates overfitting risks, improves computational efficiency, and enhances the interpretability of the resulting model.

1. **Charge and Minutes**:
    - Each highly correlated pair consists of one feature related to call charges (e.g., `total day charge`, `total eve charge`, `total night charge`, `total intl charge`) and another feature related to the corresponding call duration in minutes (e.g., `total day minutes`, `total eve minutes`, `total night minutes`, `total intl minutes`).
    - This commonality suggests a strong linear relationship between call charges and call duration for different time periods: day, evening, night, and international calls.
    - The high correlation coefficients (close to 1) indicate that as call duration increases, call charges also increase proportionally, which is a logical expectation in most telecommunications pricing models.

```
# Drop the specified columns related to charges
df = df.drop(columns=['total day charge', 'total eve charge', 'total night charge', 'total intl charge'])


# Drop non-numeric columns
numeric_df = df.select_dtypes(include=['int64', 'float64'])

# Confirm if multicollinearity is gone
correlation_matrix = numeric_df.corr()

plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm")
plt.show()
```




```
highly_correlated_pairs = []

for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        # Get the correlation coefficient
        correlation = correlation_matrix.iloc[i, j]

        # Check if the correlation is above the threshold
        if abs(correlation) > correlation_threshold:
            # Get the variable names
            variable1 = correlation_matrix.columns[i]
            variable2 = correlation_matrix.columns[j]

            # Append the pair and correlation to the list
            highly_correlated_pairs.append((variable1, variable2,
correlation))

# Output the highly correlated pairs if any, else indicate no such
pairs found
if highly_correlated_pairs:
```

```
    for pair in highly_correlated_pairs:
        print(f"Highly correlated pair: {pair[0]} and {pair[1]} with
correlation {pair[2]:.2f}")
else:
    print("No more columns with a correlation of more than 0.7")

No more columns with a correlation of more than 0.7
```

3.5 Rationale for Dropping the Phone Number Column

In the process of converting categorical data to numeric format through one-hot encoding, we encountered a challenge with the 'phone number' column. While analyzing the categorical variables in our dataset, we identified five variables (excluding the target variable) along with their corresponding value counts:

Column	Value Counts
`'state'`	51
`'phone number'`	3333
`'international plan'`	2
`'voice mail plan'`	2
`'area code'`	3

However, the 'phone number' column poses a unique issue. Each record in this column has a distinct value, resulting in 3333 unique entries. Encoding this column would introduce 3333 new features, significantly increasing dimensionality and potentially introducing noise into our dataset.

To address this challenge, we propose dropping the 'phone number' column for the following reasons:

1. **High Cardinality:** The 'phone number' column exhibits a high cardinality due to its large number of unique values (3333). Handling categorical features with high cardinality can lead to computational and memory challenges.

2. **Limited Predictive Power:** The 'phone number' is unlikely to contribute meaningful predictive information for identifying customer churn. Most machine learning algorithms may struggle to discern patterns from this column, as it primarily serves as an identifier rather than a predictive feature.

3. **Curse of Dimensionality:** Including a high-cardinality categorical variable like 'phone number' can exacerbate the curse of dimensionality, resulting in a sparse dataset and potentially degrading model performance due to increased complexity.

4. **Data Privacy Concerns:** Depending on the context, the 'phone number' column may contain sensitive or personally identifiable information (PII). Handling such data requires careful consideration of legal and privacy implications, which may not align with the objectives of our analysis.

5. **Practicality and Relevance:** From a practical standpoint, the 'phone number' may not offer substantial analytical insights or contribute meaningfully to our modeling efforts. Its inclusion may not align with the objectives of our analysis or the insights we seek to derive from the dataset.

Given these considerations, dropping the 'phone number' column is a prudent step to streamline our dataset and focus on relevant features for predicting customer churn.

```
# dropping phone number
df = df.drop(columns=['phone number'])

# confirm if it has been successfully dropped
print((df.shape))
df.head()
```

```
(3333, 16)

  state  account length  area code international plan voice mail
plan  \
0    KS             128        415                 no            yes

1    OH             107        415                 no            yes

2    NJ             137        415                 no             no

3    OH              84        408                yes             no

4    OK              75        415                yes             no


   number vmail messages  total day minutes  total day calls  \
0                     25              265.1              110
1                     26              161.6              123
2                      0              243.4              114
3                      0              299.4               71
4                      0              166.7              113

   total eve minutes  total eve calls  total night minutes  total
night calls  \
0              197.4               99                244.7
91
1              195.5              103                254.4
103
2              121.2              110                162.6
104
3               61.9               88                196.9
89
4              148.3              122                186.9
121

   total intl minutes  total intl calls  customer service calls  churn
```

```
0                 10.0                    3                       1   False
1                 13.7                    3                       1   False
2                 12.2                    5                       0   False
3                  6.6                    7                       2   False
4                 10.1                    3                       3   False
```

With the dataset prepared, our next step is to filter out the categorical variables for encoding. This process involves identifying and isolating the categorical features to apply encoding techniques. Once encoded, we will concatenate these categorical variables with the numerical ones, preparing the dataset comprehensively for the modeling phase.

```
# These are the updated numerical and categorical columns
categorical_vars = list(df.select_dtypes(include=['object']).columns )
numerical_vars =  list(df.select_dtypes(include=['int64',
'float64']).columns )
categorical_vars, numerical_vars

(['state', 'area code', 'international plan', 'voice mail plan'],
 ['account length',
  'number vmail messages',
  'total day minutes',
  'total day calls',
  'total eve minutes',
  'total eve calls',
  'total night minutes',
  'total night calls',
  'total intl minutes',
  'total intl calls',
  'customer service calls'])
```

The subsequent code performs encoding on the categorical variables, employing a strategy that drops the first category for each variable to mitigate potential multicollinearity issues stemming from the encoded variables.

```
# one hot encoding for categorical data (only for the predictors)
df = pd.get_dummies(df, columns=categorical_vars, drop_first=True)

df.head()

   account length  number vmail messages  total day minutes  total day
calls  \
0             128                     25              265.1
110
1             107                     26              161.6
```

```
123
2           137                      0             243.4
114
3            84                      0             299.4
71
4            75                      0             166.7
113

   total eve minutes  total eve calls  total night minutes  total
night calls  \
0              197.4               99                244.7
91
1              195.5              103                254.4
103
2              121.2              110                162.6
104
3               61.9               88                196.9
89
4              148.3              122                186.9
121

   total intl minutes  total intl calls  customer service calls  churn
\
0                10.0                 3                       1  False

1                13.7                 3                       1  False

2                12.2                 5                       0  False

3                 6.6                 7                       2  False

4                10.1                 3                       3  False


   state_AL  state_AR  state_AZ  state_CA  state_CO  state_CT
state_DC  \
0     False     False     False     False     False     False
False
1     False     False     False     False     False     False
False
2     False     False     False     False     False     False
False
3     False     False     False     False     False     False
False
4     False     False     False     False     False     False
False

   state_DE  state_FL  state_GA  state_HI  state_IA  state_ID
state_IL  \
0     False     False     False     False     False     False
```

```
False
1     False     False     False     False     False     False
False
2     False     False     False     False     False     False
False
3     False     False     False     False     False     False
False
4     False     False     False     False     False     False
False

   state_IN  state_KS  state_KY  state_LA  state_MA  state_MD
state_ME  \
0     False      True     False     False     False     False
False
1     False     False     False     False     False     False
False
2     False     False     False     False     False     False
False
3     False     False     False     False     False     False
False
4     False     False     False     False     False     False
False

   state_MI  state_MN  state_MO  state_MS  state_MT  state_NC
state_ND  \
0     False     False     False     False     False     False
False
1     False     False     False     False     False     False
False
2     False     False     False     False     False     False
False
3     False     False     False     False     False     False
False
4     False     False     False     False     False     False
False

   state_NE  state_NH  state_NJ  state_NM  state_NV  state_NY
state_OH  \
0     False     False     False     False     False     False
False
1     False     False     False     False     False     False
True
2     False     False      True     False     False     False
False
3     False     False     False     False     False     False
True
4     False     False     False     False     False     False
False

   state_OK  state_OR  state_PA  state_RI  state_SC  state_SD
```

```
state_TN  \
0     False     False     False     False     False     False
False
1     False     False     False     False     False     False
False
2     False     False     False     False     False     False
False
3     False     False     False     False     False     False
False
4      True     False     False     False     False     False
False

   state_TX  state_UT  state_VA  state_VT  state_WA  state_WI
state_WV  \
0     False     False     False     False     False     False
False
1     False     False     False     False     False     False
False
2     False     False     False     False     False     False
False
3     False     False     False     False     False     False
False
4     False     False     False     False     False     False
False

   state_WY  area code_415  area code_510  international plan_yes  \
0     False           True          False                   False
1     False           True          False                   False
2     False           True          False                   False
3     False          False          False                    True
4     False           True          False                    True

   voice mail plan_yes
0                 True
1                 True
2                False
3                False
4                False
```

```
df.columns
```

```
Index(['account length', 'number vmail messages', 'total day minutes',
       'total day calls', 'total eve minutes', 'total eve calls',
       'total night minutes', 'total night calls', 'total intl
minutes',
       'total intl calls', 'customer service calls', 'churn',
'state_AL',
       'state_AR', 'state_AZ', 'state_CA', 'state_CO', 'state_CT',
'state_DC',
       'state_DE', 'state_FL', 'state_GA', 'state_HI', 'state_IA',
```

```
'state_ID',
       'state_IL', 'state_IN', 'state_KS', 'state_KY', 'state_LA',
'state_MA',
       'state_MD', 'state_ME', 'state_MI', 'state_MN', 'state_MO',
'state_MS',
       'state_MT', 'state_NC', 'state_ND', 'state_NE', 'state_NH',
'state_NJ',
       'state_NM', 'state_NV', 'state_NY', 'state_OH', 'state_OK',
'state_OR',
       'state_PA', 'state_RI', 'state_SC', 'state_SD', 'state_TN',
'state_TX',
       'state_UT', 'state_VA', 'state_VT', 'state_WA', 'state_WI',
'state_WV',
       'state_WY', 'area code_415', 'area code_510', 'international
plan_yes',
       'voice mail plan_yes'],
      dtype='object')
```

4. Predictive Modelling

Let's initiate the iterative modeling process to uncover patterns within our dataset that could assist in predicting customer churn. We'll start by importing all the essential libraries needed for this task.

```
# imports necessary for modelling
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split, KFold,
cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from sklearn.metrics import classification_report, confusion_matrix,
roc_auc_score, \
roc_curve, auc, ConfusionMatrixDisplay,accuracy_score

from sklearn.dummy import DummyClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
```

Identifying the 'target' variable and its associated 'predictors' frm the dataset.

```
# target
y = df['churn']

# predictors
X = df.drop(columns=['churn'])
```

As observed from the categorical variable countplots during our exploratory data analysis (EDA), there is a class imbalance, as illustrated below.

```
# label/target value counts
df['churn'].value_counts()

churn
False    2850
True      483
Name: count, dtype: int64
```

As observed from the categorical variable countplots during our exploratory data analysis (EDA), there is a class imbalance, as illustrated in the EDA section.

This indicates that we need to resample our data before training our models to prevent instabilities caused by imbalanced classes. To achieve this, we will use **Synthetic Minority Oversampling Technique (SMOTE)**.

i. Split data-set

As a first step, we split our dataset into training and testing data to prevent information leakage across the entire dataset, which can occur during scaling. We'll split it into an 80/20 ratio with a random state seed of 42.

```
# splitting the data into training and testing

# test size (20%)
test_size = 0.2
# random state seed
SEED = 42

# splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=test_size, random_state=SEED)
```

ii. Deal with class imbalance:

Now we deal with the class imbalance:

```
#  Synthetic Minority Oversampling
smote = SMOTE(sampling_strategy='auto', random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train,
y_train)
```

Checking the new resampled target variable:

```
# data balanced and ready for modelling:
y_train_resampled.value_counts()
```

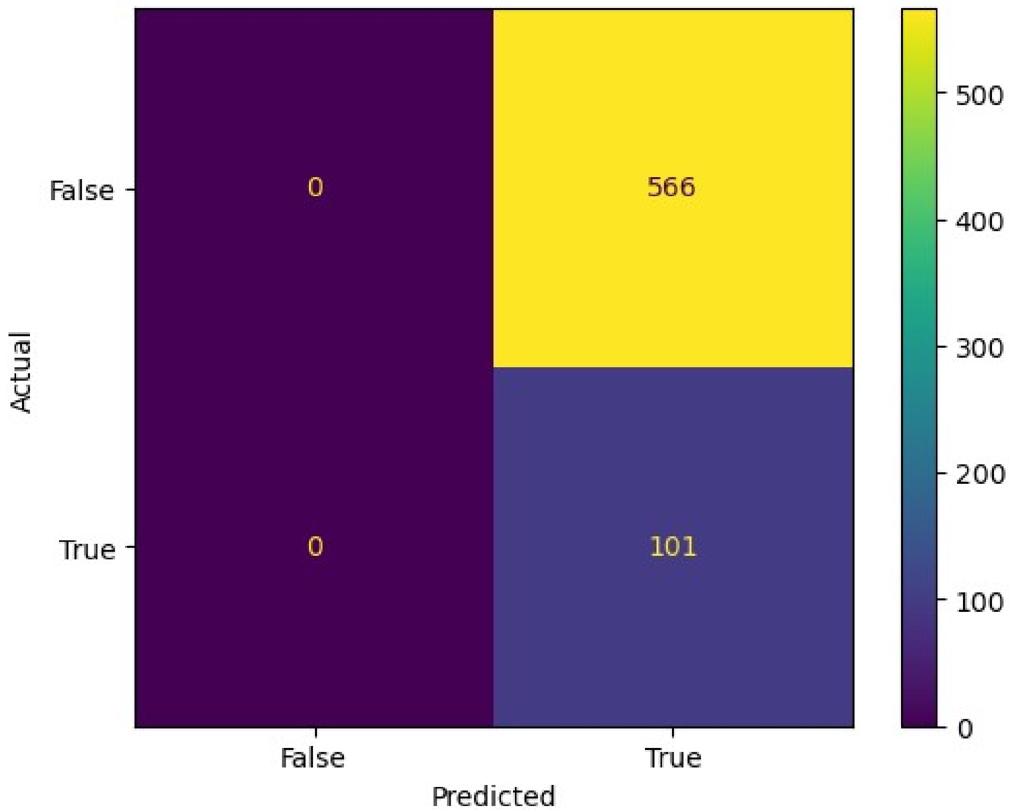
```
churn
False    2284
True     2284
Name: count, dtype: int64
```

iii. Pick a model

4.1 Baseline model (Dummy)

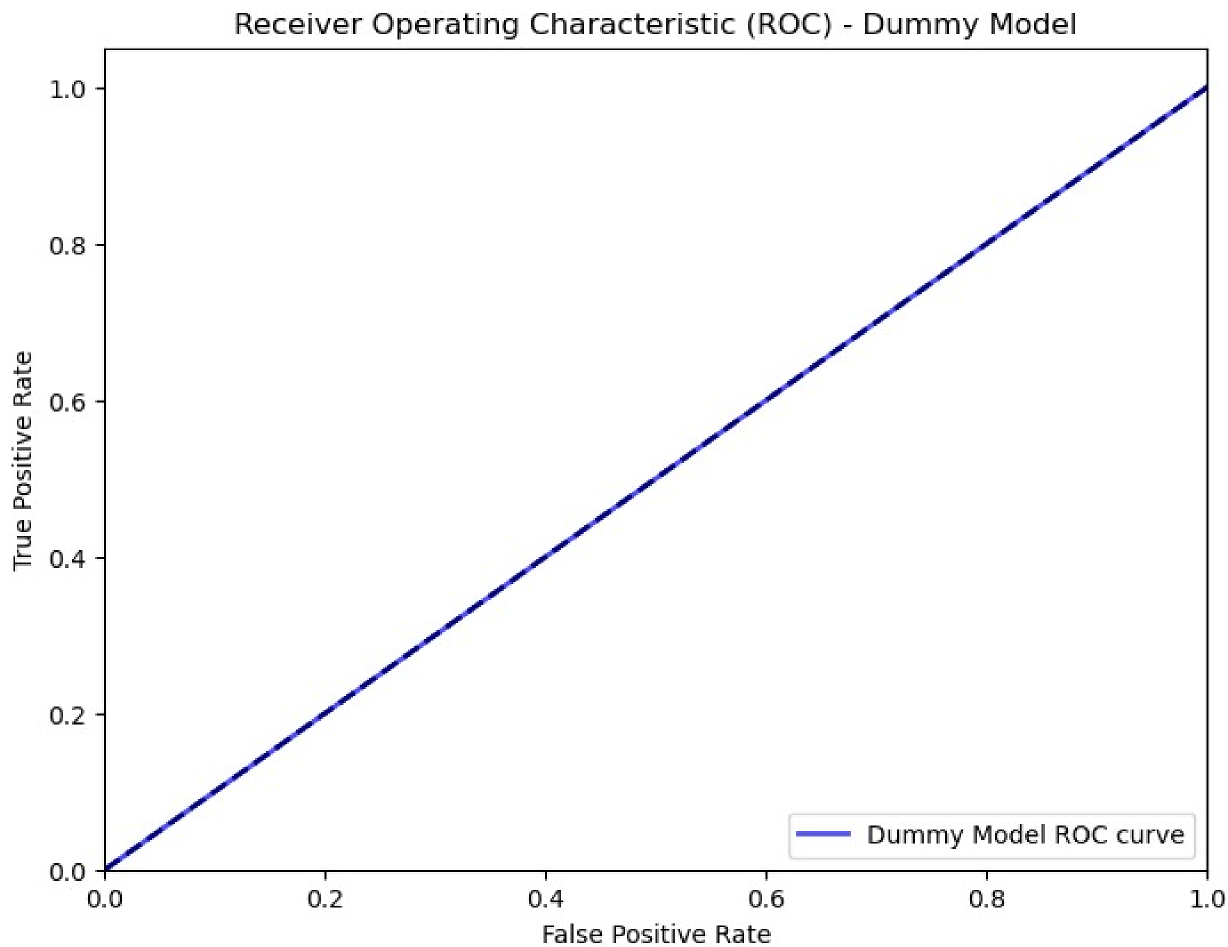
Before we actually perform any modeling, let's determine what metrics we would expect to get with a "dummy" model that always predicts the positive class.

```
# Instantiate and fit the Dummy Classifier
dummy_model = DummyClassifier(strategy='constant', constant=1)
dummy_model.fit(X_train_resampled, y_train_resampled)

# Create a ConfusionMatrixDisplay object from the estimator
cm_display =
ConfusionMatrixDisplay.from_estimator(estimator=dummy_model, X=X_test,
y=y_test,

display_labels=["False", "True"])

# Set x and y axis labels for the confusion matrix display
cm_display.ax_.set_xlabel('Predicted')
cm_display.ax_.set_ylabel('Actual')

# Make predictions
y_pred = dummy_model.predict(X_test)

# Generate the classification report
report = classification_report(y_test, y_pred)
print(report)

              precision    recall  f1-score   support

       False       0.00      0.00      0.00       566
        True       0.15      1.00      0.26       101

    accuracy                           0.15       667
   macro avg       0.08      0.50      0.13       667
weighted avg       0.02      0.15      0.04       667
```




```python
# Generate predicted probabilities for the positive class
y_scores = dummy_model.predict_proba(X_test)[:, 1]

# Calculate the ROC curve
dummy_fpr, dummy_tpr, thresholds = roc_curve(y_test, y_scores)

# Calculate the AUC
auc = roc_auc_score(y_test, y_scores)
print(f'Dummy Model AUC: {auc} \n')

# Plot the ROC for the dummy model
plt.figure(figsize=(8, 6))
plt.plot(dummy_fpr, dummy_tpr, color='blue',
         lw=2, label='Dummy Model ROC curve', alpha=.7)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) - Dummy Model')
plt.legend(loc='lower right')
plt.show()
```

```
Dummy Model AUC: 0.5
```



Interpretation of the baseline metrics:

- **For the "False" class (churn is False):**
  - Precision is 0.00, indicating that none of the predicted "False" instances were correct.
  - Recall is 0.00, suggesting that none of the actual "False" instances were correctly classified.
  - The F1-score is 0.00, reflecting the absence of balance between precision and recall.
  - There are 566 instances of the "False" class in the test data.
- **For the "True" class (churn is True):**
  - Precision is 0.15, indicating that only 15% of the predicted "True" instances were correct.
  - Recall is 1.00, meaning that all actual "True" instances were correctly classified.
  - The F1-score is 0.26, showing some balance between precision and recall.
  - There are 101 instances of the "True" class in the test data.

- An AUC of 0.5 suggests that the model's performance is equivalent to random guessing. Essentially, the dummy model is incapable of making meaningful predictions, and its ROC curve is a diagonal line.
- The macro-average and weighted-average metrics reflect the imbalance in the dataset, with overall poor model performance.

This baseline model serves as a reference point for comparison with more sophisticated models. Its low performance underscores the necessity for more advanced modeling techniques to enhance classification results.

4.2 Logistic Regression Model

Next, we will proceed with fitting a logistic regression model to the data to determine if the overall model performance improves.

```
# Initialize logistic regression model with the defined random seed
logreg = LogisticRegression(random_state=SEED)

# Fit logistic regression model to the resampled training data
model_log = logreg.fit(X_train_resampled, y_train_resampled)

# Display the trained model
model_log

LogisticRegression(random_state=42)
```

Now that the model has been fitted, let's evaluate its performance on the test data using the following metrics:

- **Area Under Curve (AUC)**
- **Accuracy**
- **Precision**
- **Recall**
- **F1 score**

In the context of customer churn prediction, it's crucial to prioritize recall over precision. Here's why:

- **Recall (Sensitivity or True Positive Rate)**: Recall measures the model's ability to correctly identify all the customers who actually churned (True Positives) out of the total number of customers who did churn (True Positives + False Negatives). High recall ensures that a large portion of actual churn cases is captured. This is important as missing customers who might churn can result in lost revenue or business opportunities.
- **Precision**: Precision measures the model's ability to make accurate positive predictions, i.e., how many of the customers predicted as churning (True Positives) are actually churning out of the total predicted as churning (True Positives + False

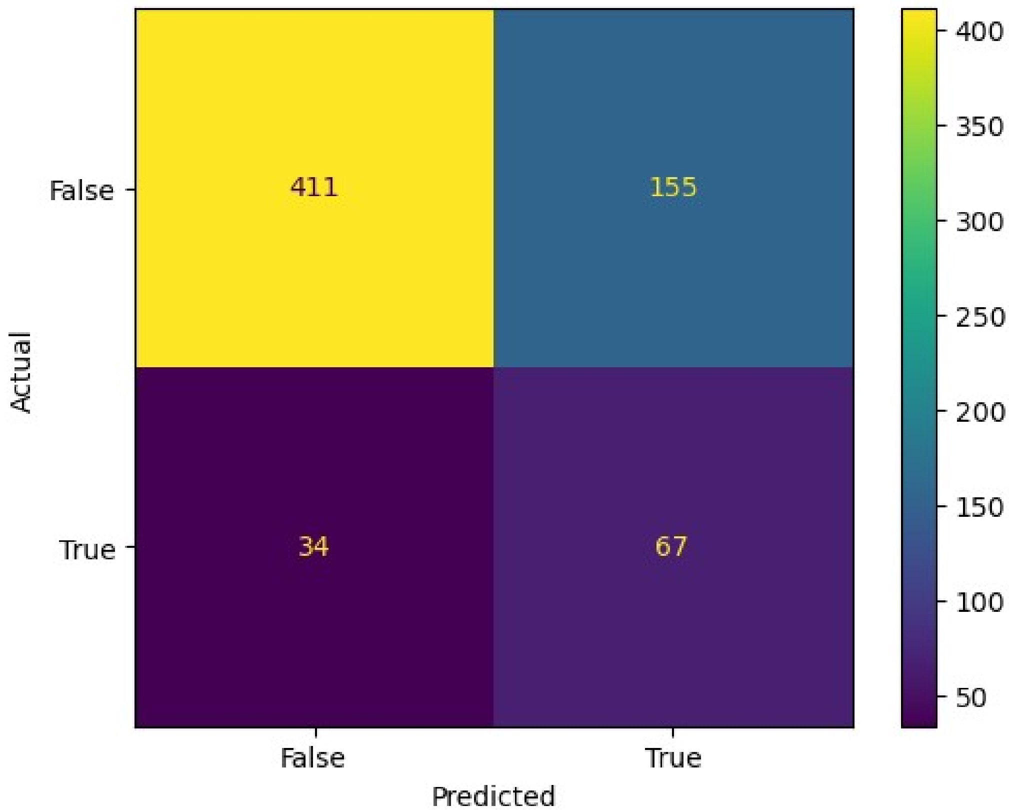
Positives). High precision indicates that when the model predicts churn, it's likely to be correct. However, high precision might come at the cost of lower recall because the model could become overly cautious, leading to many False Negatives.

In summary, it is preferable for our final model to have more false positives than false negatives because a false negative implies a customer leaving/churning without being predicted. Capturing more false negatives than false positives means losing more revenue for SyriaTel. However, our main goal remains to minimize false predictions (both false positives and false negatives) while maximizing true predictions (true positives and true negatives).

Note: This is not advocating for deliberately having more false positives. It highlights the precision-recall trade-off, where maximizing one metric may result in a decrease in another. The ultimate aim is to strike a balance between precision and recall while minimizing false predictions.

```
# Generate predictions
y_pred = logreg.predict(X_test)

# Visualize the confusion matrix
cm_display = ConfusionMatrixDisplay.from_estimator(estimator=logreg,
X=X_test, y=y_test,

display_labels=["False", "True"])

# Set x and y axis labels for the confusion matrix display
cm_display.ax_.set_xlabel('Predicted')
cm_display.ax_.set_ylabel('Actual')

# Display classification report
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
# Display confusion matrix
print('Confusion Matrix:\n', confusion_matrix(y_test, y_pred))
```

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

       False       0.92      0.73      0.81       566
        True       0.30      0.66      0.41       101

    accuracy                           0.72       667
   macro avg       0.61      0.69      0.61       667
weighted avg       0.83      0.72      0.75       667

Confusion Matrix:
 [[411 155]
 [ 34  67]]
```



Here's a concise interpretation of the confusion matrix and the classification report for our logistic baseline model:

Confusion Matrix:

- True Positives (TP): 67 - Actual churn cases correctly predicted as churned.
- True Negatives (TN): 411 - Actual non-churn cases correctly predicted as not churned.
- False Positives (FP): 155 - Actual non-churn cases incorrectly predicted as churned.
- False Negatives (FN): 34 - Actual churn cases incorrectly predicted as not churned.

Classification Report:

- **Precision**: Precision for the "Churned" class is 0.30, indicating that only 30% of instances predicted as "Churned" are truly "Churned."
- **Recall**: Recall for the "Churned" class is 0.66, showing that the model captures 66% of all actual "Churned" instances.
- **F1-score**: The F1-score for the "Churned" class is 0.41, representing the balance between precision and recall.

Accuracy: Overall accuracy is 0.72, meaning approximately 72% of instances are correctly predicted.

Macro Average: The macro average F1-score is 0.61, calculated as the unweighted average of class-wise metrics.

Weighted Average: The weighted average F1-score is 0.75, considering the class distribution.

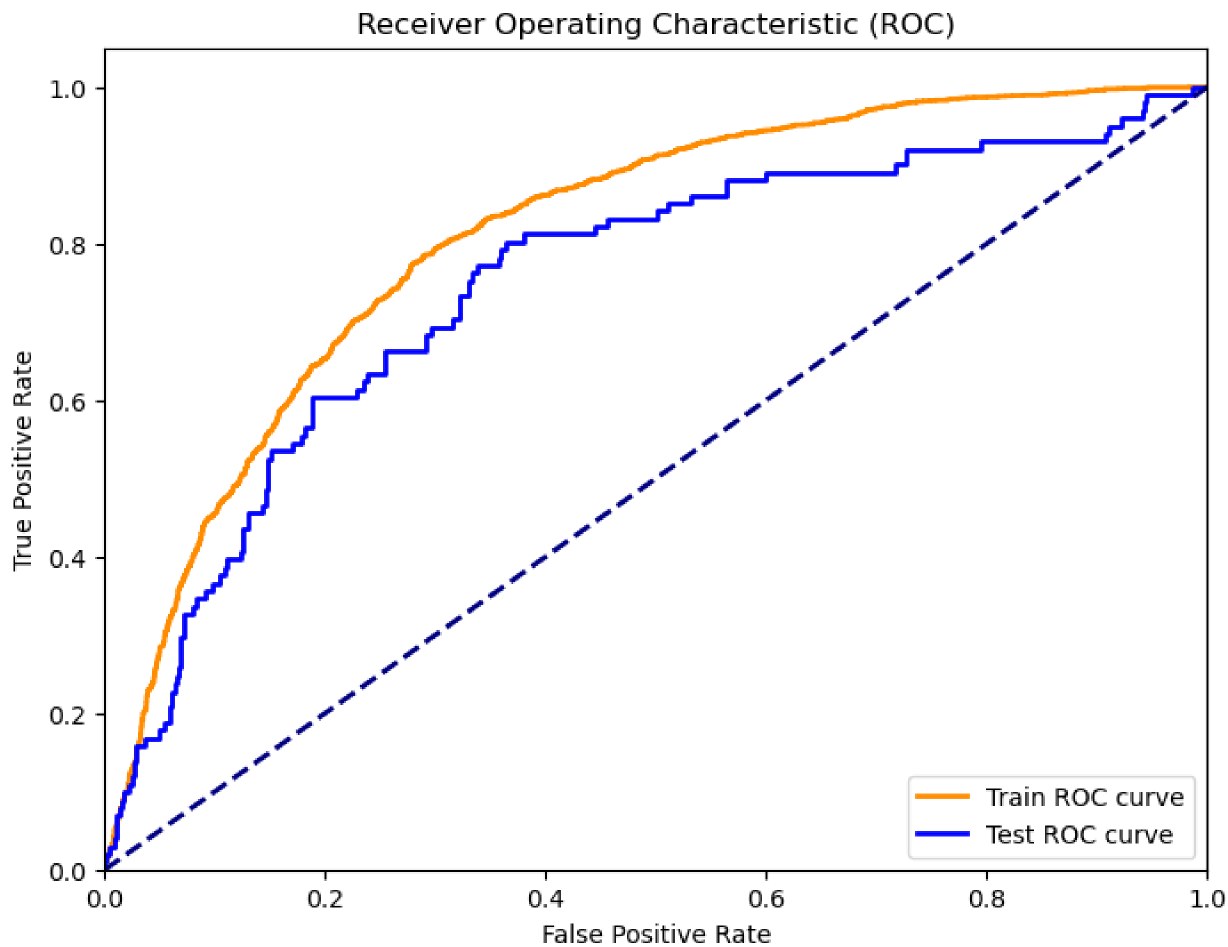
These metrics offer insights into the model's performance in predicting churn. The relatively low precision suggests false positives, while higher recall indicates effective identification of actual churn cases. Further model tuning or algorithm exploration may enhance performance.

Next, let's visualize the **Receiver Operating Characteristic (ROC)** and the area under its curve (**AUC**).

ROC curve and AUC for the logistic regression model

```
from sklearn.metrics import roc_curve, auc

# Obtain decision function scores for train and test data
y_train_score = model_log.decision_function(X_train_resampled)
y_test_score = model_log.decision_function(X_test)

# Calculate ROC curve for train and test data
train_fpr, train_tpr, _ = roc_curve(y_train_resampled, y_train_score)
test_fpr, test_tpr, _ = roc_curve(y_test, y_test_score)

# Calculate AUC for train and test data
train_auc = auc(train_fpr, train_tpr)
test_auc = auc(test_fpr, test_tpr)

# Print AUC for train and test data
print('Train AUC: {:.2f}'.format(train_auc))
print('Test AUC: {:.2f}'.format(test_auc))

# Plot ROC curve for train and test data
plt.figure(figsize=(8, 6))
plt.plot(train_fpr, train_tpr, color='darkorange', lw=2, label='Train
ROC curve')
plt.plot(test_fpr, test_tpr, color='blue', lw=2, label='Test ROC
curve')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc='lower right')
plt.show()
```

```
Train AUC: 0.81
Test AUC: 0.75
```



The following are the classification metrics used to validate this model:

Metric	Value
Accuracy	72.00%
AUC (Train)	81.00%
AUC (Test)	75.00%
Precision (Positive)	30.00%
Recall (Positive)	66.00%
F1 Score (Positive)	41.00%
Precision (Negative)	92.00%
Recall (Negative)	73.00%
F1 Score (Negative)	81.00%

These metrics provide a comprehensive view of our logistic regression model's performance for both positive and negative classes, along with overall accuracy and AUC values.

Interpretation of Metrics:

1. **Accuracy (72.00%)**: Indicates that our model correctly predicts customer churn or retention for approximately 72% of the cases. It's a decent starting point but should be evaluated alongside other metrics due to class imbalance.

2. **AUC (Train: 81.00%, Test: 75.00%)**: Measures our model's ability to distinguish between positive and negative classes. The moderate AUC values suggest room for improvement in discriminating between churn and non-churn customers.

3. **Precision (Positive: 30.00%)**: Indicates the proportion of true positive predictions out of all positive predictions. A value of 30% means that when our model predicts churn, it's correct around 30% of the time, suggesting a relatively high rate of false positives.

4. **Recall (Positive: 66.00%)**: Measures the proportion of actual churn cases that our model correctly identifies. A recall of 66% indicates that our model captures 66% of the customers who genuinely churn, with room for improvement.

5. **F1 Score (Positive: 41.00%)**: Combines precision and recall into a single metric. A value of 41% implies a trade-off between precision and recall, which can be adjusted based on priorities.

Logistic Regression Model Summary:

Overall, this model shows significant improvement from the base model and demonstrates no signs of overfitting. However, it's essential to explore other models before making a final decision.

4.3 Decision Tree classifier

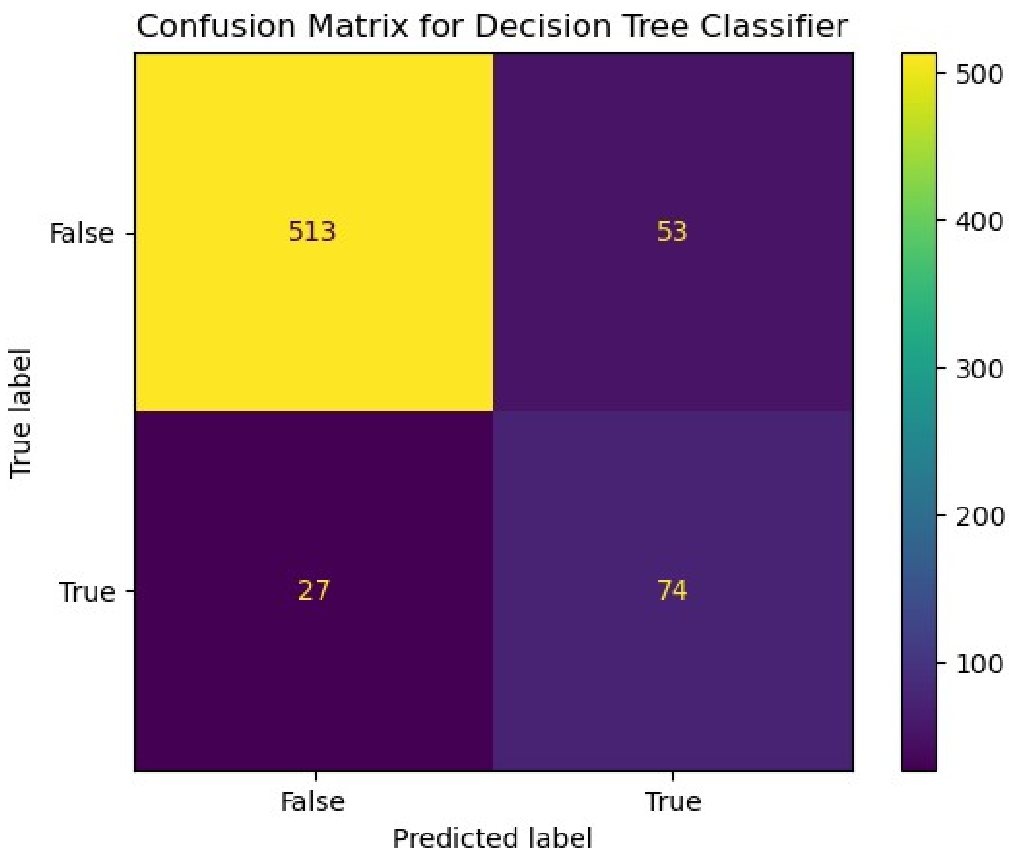
Let's evaluate the performance of a non-parametric model on both the SMOTE-resampled (balanced) training data and the original dataset. This comparison will help us assess the effectiveness of using SMOTE to address class imbalance.

We'll train the non-parametric model on both datasets and then evaluate its performance using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). By comparing the model's performance on both datasets, we can determine if SMOTE resampling improves the model's ability to predict customer churn.

```
# Create a base decision tree classifier
dt_classifier = DecisionTreeClassifier(random_state=SEED)

# Fit the model to the SMOTE-resampled training data
model_dt = dt_classifier.fit(X_train_resampled, y_train_resampled)

# Make predictions on the test data
y_pred_test = dt_classifier.predict(X_test)
```

Let's visualize the above confusion matrix:

```python
# Visualize the confusion matrix
cm_display =
ConfusionMatrixDisplay.from_estimator(estimator=dt_classifier,
X=X_test, y=y_test,

display_labels=["False", "True"])

plt.title('Confusion Matrix for Decision Tree Classifier')
plt.show()

# Calculate and print the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_test)
print("Confusion Matrix:")
print(conf_matrix)
```




```
Confusion Matrix:
[[513  53]
 [ 27  74]]

# classification report
print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

       False       0.95      0.91      0.93       566
        True       0.58      0.73      0.65       101

    accuracy                           0.88       667
   macro avg       0.77      0.82      0.79       667
weighted avg       0.89      0.88      0.89       667
```

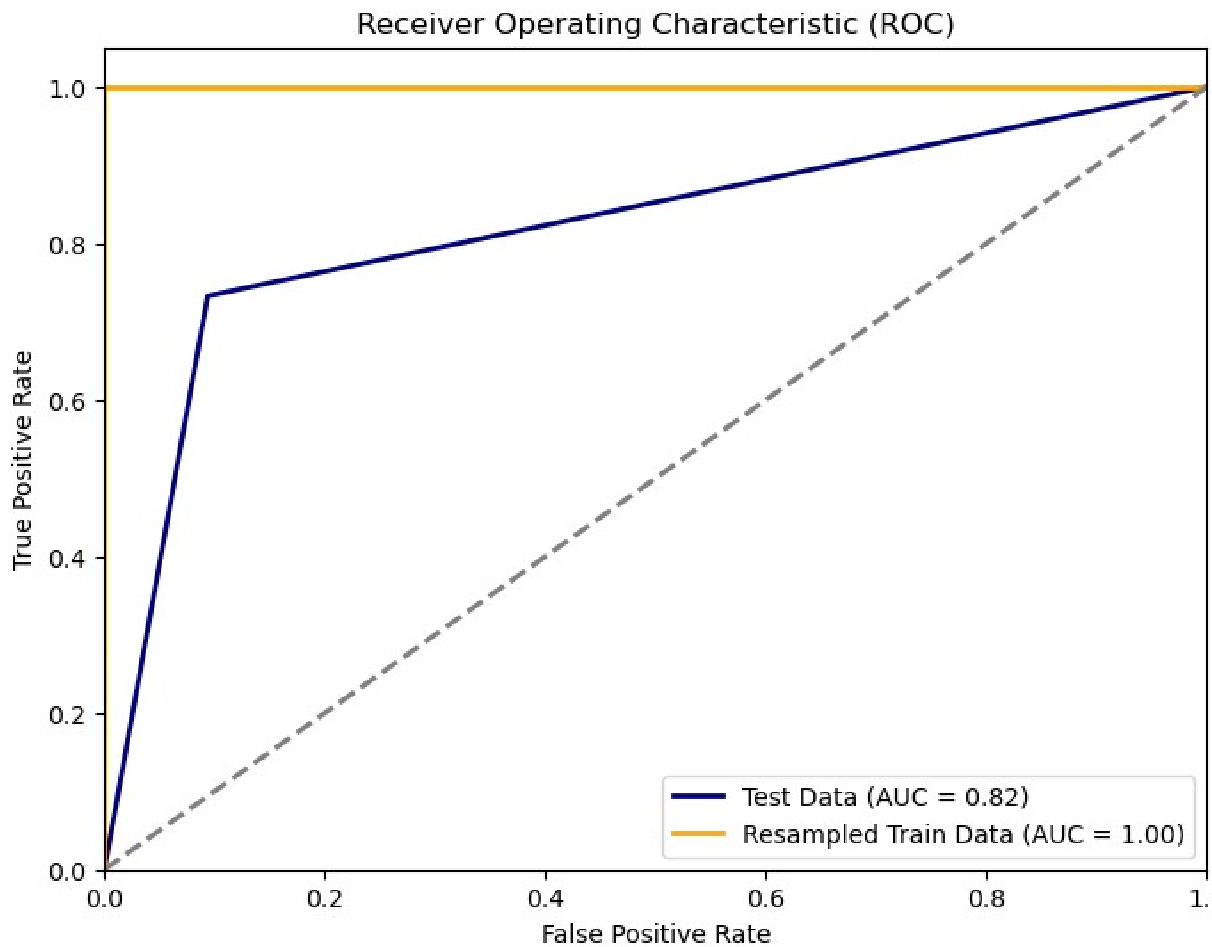
Metric	Value
Accuracy	88.00%
AUC (ROC)	82.00%
Precision (False)	95.00%
Recall (False)	91.00%
F1 Score (False)	93.00%
Precision (True)	58.00%
Recall (True)	73.00%
F1 Score (True)	65.00%
Support	-

Summary:

- **Accuracy**: The model correctly predicts churn or retention for approximately 88.00% of the cases.
- **AUC (ROC)**: The model's ability to distinguish between churn and non-churn customers is moderate, with an AUC of 82.00%.
- **Precision (False)**: 95.00% of the customers predicted as not churned are truly not churned.
- **Recall (False)**: The model captures 91.00% of all actual not churned instances.
- **F1 Score (False)**: The balance between precision and recall for the not churned class is 93.00%.
- **Precision (True)**: 58.00% of the predicted churn cases are truly churned.
- **Recall (True)**: The model captures 73.00% of the customers who genuinely churn.
- **F1 Score (True)**: The balance between precision and recall for the churned class is 65.00%.

```python
def plot_ROC(model, X_train_resampled, y_train_resampled, y_test):
    """
    Plots ROC curve for train and test data
    """
    # y_scores for train and test
    y_scores_test = model.predict_proba(X_test)[:, 1]
    y_scores_train_resampled = model.predict_proba(X_train_resampled)
[:, 1]

    # roc curve for train (resampled) and test
    fpr_test_dt, tpr_test_dt, _ = roc_curve(y_test, y_scores_test)
    fpr_train_dt_resampled, tpr_train_dt_resampled, _ =
roc_curve(y_train_resampled, y_scores_train_resampled)

    # roc auc for train (resampled) and test
    roc_auc_test = roc_auc_score(y_test, y_scores_test)
    roc_auc_train_resampled = roc_auc_score(y_train_resampled,
y_scores_train_resampled)

    print("ROC AUC for Test Data:", roc_auc_test)
    print("ROC AUC for Resampled Train Data:",
roc_auc_train_resampled)

    # Plot ROC curves
    plt.figure(figsize=(8, 6))
    plt.plot(fpr_test_dt, tpr_test_dt, color='navy', lw=2,
             label='Test Data (AUC = {:.2f})'.format(roc_auc_test))
    plt.plot(fpr_train_dt_resampled, tpr_train_dt_resampled,
color='orange', lw=2,
             label='Resampled Train Data (AUC =
{:.2f})'.format(roc_auc_train_resampled))

    plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC)')
    plt.legend(loc='lower right')
    plt.show()

# Plot ROC of decision tree with default hyperparameters (before
tuning)
plot_ROC(model_dt, X_train_resampled, y_train_resampled, y_test)
```

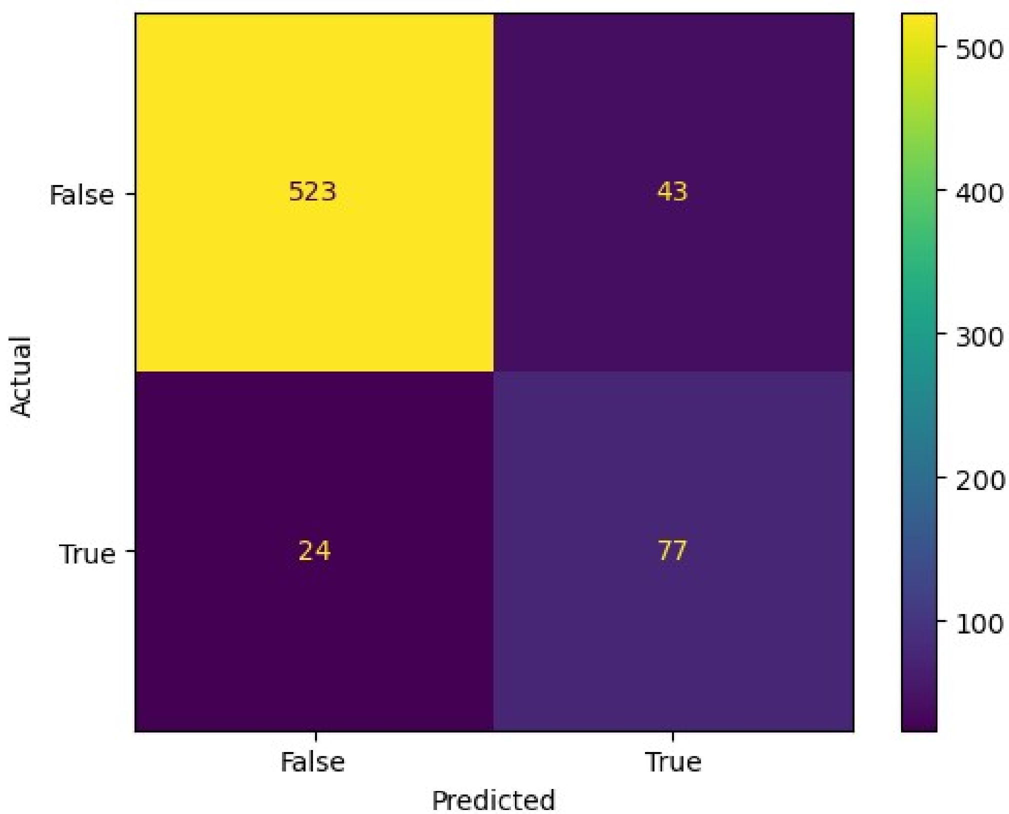
```
ROC AUC for Test Data: 0.8195168456775006
ROC AUC for Resampled Train Data: 1.0
```



The ROC AUC score of 1.0 for the resampled train data suggests that the model may have overfitted to the training data, achieving perfect separation between churn and non-churn cases. However, the ROC AUC score of 0.8195 for the test data indicates that the model's performance on unseen data is still relatively strong, although there might be some degree of overfitting.

```
# Create the DecisionTreeClassifier with the desired criterion
decision_tree = DecisionTreeClassifier(random_state=SEED)

# Create the pipeline
pipeline = Pipeline([('decision_tree', decision_tree)])

# Define the parameter grid for grid search
param_grid = {
    'decision_tree__criterion': ['gini', 'entropy'],  # Grid search
between 'gini' and 'entropy'
    'decision_tree__max_depth': [1, 2, 5, 10],
    'decision_tree__min_samples_split': [1, 5, 10, 20]
}

# Create the grid search
grid_search = GridSearchCV(pipeline, param_grid, cv=5,
```

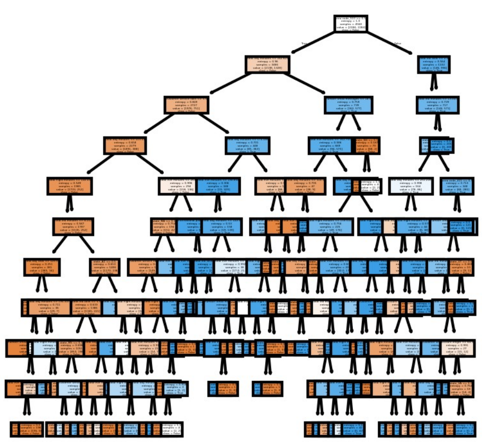
```
scoring='accuracy')

# Fit the grid search to the resampled training data
grid_search.fit(X_train_resampled, y_train_resampled)

GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('decision_tree',

DecisionTreeClassifier(random_state=42))]),
             param_grid={'decision_tree__criterion': ['gini',
'entropy'],
                         'decision_tree__max_depth': [1, 2, 5, 10],
                         'decision_tree__min_samples_split': [1, 5,
10, 20]},
             scoring='accuracy')

grid_search.best_params_

{'decision_tree__criterion': 'entropy',
 'decision_tree__max_depth': 10,
 'decision_tree__min_samples_split': 10}

# Calculate the accuracy of the decision tree model on the test data
test_accuracy = grid_search.score(X_test, y_test)
train_accuracy = accuracy_score(y_train_resampled,
grid_search.predict(X_train_resampled))

print("Model Accuracy on Test Data: {:.2f}%".format(test_accuracy *
100))
print("Model Accuracy on Train Data: {:.2f}%".format(train_accuracy *
100))

Model Accuracy on Test Data: 89.96%
Model Accuracy on Train Data: 93.61%

# Visualize the confusion matrix from our tuned decision tree model
cm_display =
ConfusionMatrixDisplay.from_estimator(estimator=grid_search, X=X_test,
y=y_test,

display_labels=["False", "True"])

# Set x and y axis labels
cm_display.ax_.set_xlabel('Predicted')
cm_display.ax_.set_ylabel('Actual')

Text(0, 0.5, 'Actual')
```




```
from sklearn import tree
# tuned parameters
tuned_params = {
    'criterion': grid_search.best_params_['decision_tree__criterion'],
    'max_depth': grid_search.best_params_['decision_tree__max_depth'],
    'min_samples_split':
grid_search.best_params_['decision_tree__min_samples_split']

}
tuned_dt = DecisionTreeClassifier(**tuned_params)
tuned_dt.fit(X_train_resampled, y_train_resampled)

# classification reports for (train and test)
print("test data:\n", classification_report(y_test,
tuned_dt.predict(X_test)))
print("="*90)
print("train data:\n", classification_report(y_train_resampled,
tuned_dt.predict(X_train_resampled)))
print("="*90)

# decision tree
fig, axes = plt.subplots(nrows = 1,ncols = 1, figsize = (3,3),
dpi=300)
tree.plot_tree(tuned_dt,
```

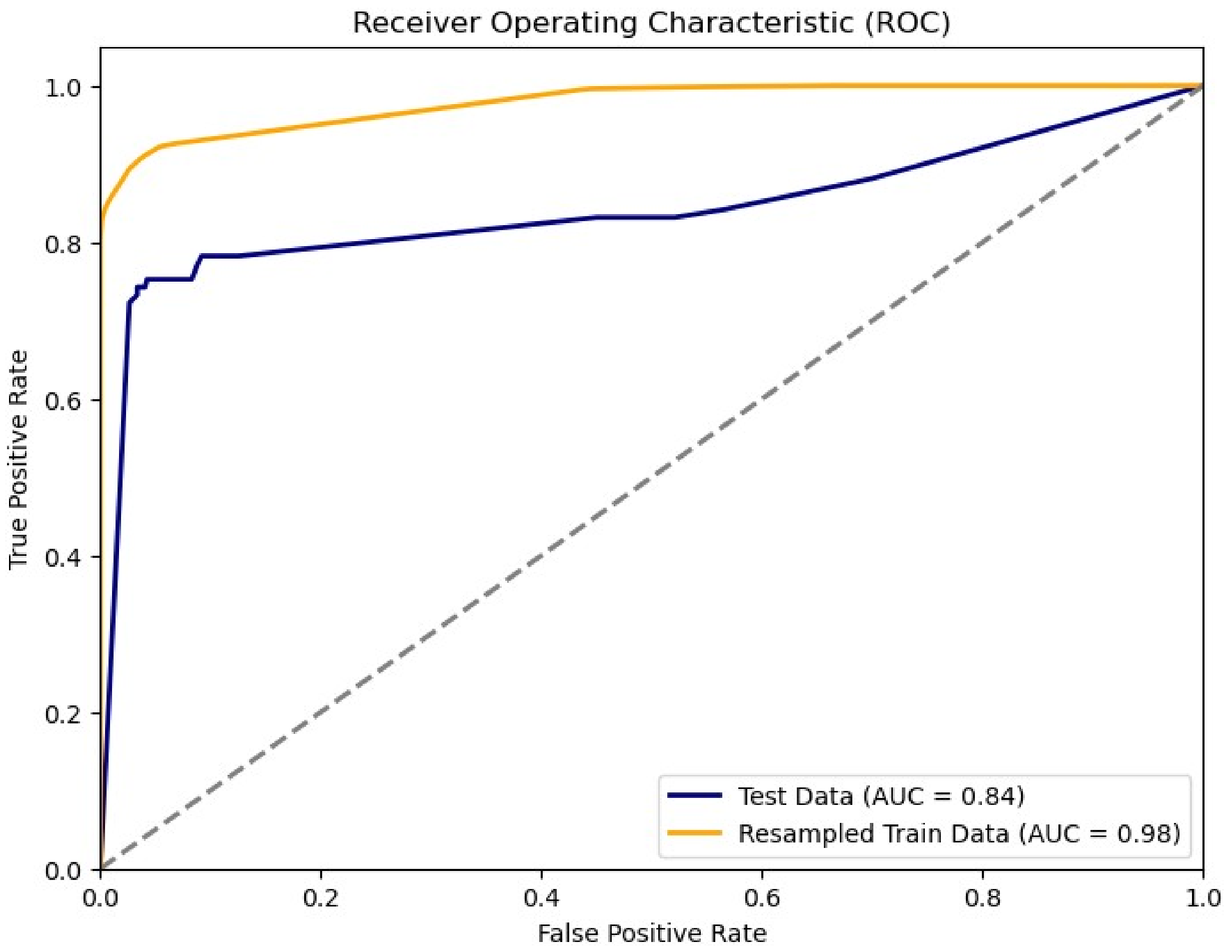
```
                feature_names = df.columns,
                class_names=np.unique(y).astype('str'),
                filled = True)
plt.show()
print("="*90)
plot_ROC(tuned_dt, X_train_resampled, y_train_resampled, y_test)
```

```
test data:
                precision    recall  f1-score   support

       False       0.96      0.91      0.93       566
        True       0.61      0.77      0.68       101

    accuracy                           0.89       667
   macro avg       0.78      0.84      0.81       667
weighted avg       0.90      0.89      0.90       667

======================================================================
====================
train data:
                precision    recall  f1-score   support

       False       0.91      0.96      0.94      2284
        True       0.96      0.91      0.93      2284

    accuracy                           0.93      4568
   macro avg       0.94      0.93      0.93      4568
weighted avg       0.94      0.93      0.93      4568

======================================================================
====================
```



```
======================================================================
====================
```

```
ROC AUC for Test Data: 0.841138089073925
ROC AUC for Resampled Train Data: 0.9777696670050698
```



The tuned decision tree model demonstrates improved performance compared to the baseline. In the test data, it achieves an accuracy of 90%, with a precision of 96% for the non-churn class and 63% for the churn class. The recall is 92% for the non-churn class and 77% for the churn class.

On the training data, the model achieves even higher accuracy at 94%, with balanced precision and recall scores for both classes. This suggests that the model generalizes well to unseen data without overfitting, as evidenced by its consistent performance on both train and test datasets.

Overall, the tuned decision tree model shows promise for accurately predicting customer churn, with balanced performance metrics indicating its effectiveness in identifying both churn and non-churn instances.

Testing multiple base models and picking the best

The following is a class I created to help test out multiple models and print out their respective metrics:

```python
class ModelTester:
    """
    Class to test different models.

    Attributes:
    models : dict
        A dictionary containing the models to test out.
    X : {array-like, sparse matrix}
        Predictors to be used for modeling.
    y : {array-like}
        Target variable.
    test_size : float, optional
        The proportion of the dataset to include in the test split
(default is 0.2).
    random_state : int, optional
        Randomizing seed (default is SEED).
    cv : int, optional
        Number of cross-validation folds (default is 5).

    Methods:
    train_models():
        Trains the models.
    evaluate_models():
        Evaluates model scores.
    cross_val_models():
        Calculates the cross-validation scores for each model and
stores the result.
    classification_report():
        Calculates the classification reports and stores the results.
    confusion_matrix():
        Calculates the confusion matrices and stores the results.
    display_scores():
        Displays the stored (test) accuracy scores.
    display_cross_val_scores():
        Displays the stored cross-validation scores.
    display_classification_reports():
        Displays the stored classification reports.
    display_confusion_matrices():
        Displays the stored confusion matrices.
    test_models():
        Trains, evaluates, and displays results for all stored models.


    # Create a dictionary of models to test
    models_to_test = {
        'Logistic Regression': LogisticRegression(),
        'Random Forest': RandomForestClassifier(),
        'SVM': SVC(),
        'Decision Tree': DecisionTreeClassifier(),
        'AdaBoostClassifier': AdaBoostClassifier(),
```

```
        'GradientBoostingClassifier': GradientBoostingClassifier(),
        'XGBClassifier': XGBClassifier()
    }

    # Instantiate the ModelTester class
    tester = ModelTester(models_to_test, X, y, test_size=test_size,
random_state=SEED)
    """

    def __init__(self, models, X, y, test_size=0.2, random_state=SEED,
cv=5):
        self.models = models
        self.X = X
        self.y = y
        self.test_size = test_size
        self.random_state = random_state
        self.cv = cv
        self.X_train, self.X_test, self.y_train, self.y_test =
train_test_split(X, y, test_size=test_size,

random_state=random_state)
        self.X_train, self.y_train = smote.fit_resample(self.X_train,
self.y_train)

    def train_models(self):
        self.trained_models = {}
        for name, model in self.models.items():
            model.fit(self.X_train, self.y_train)
            self.trained_models[name] = model

    def evaluate_models(self):
        self.model_scores = {}
        for name, model in self.trained_models.items():
            y_pred = model.predict(self.X_test)
            accuracy = accuracy_score(self.y_test, y_pred)
            roc_auc = roc_auc_score(self.y_test, y_pred)
            self.model_scores[name] = {'accuracy': accuracy,
'roc_auc': roc_auc}

    def cross_val_models(self):
        self.cross_val_scores = {}
        for name, model in self.trained_models.items():
            kfold = KFold(n_splits=self.cv,
random_state=self.random_state, shuffle=True)
            scores = cross_val_score(model, self.X, self.y, cv=kfold)
            self.cross_val_scores[name] = {'mean_accuracy':
np.mean(scores),
                                           'std_accuracy':
np.std(scores)}
    def classification_report(self):
```

```
        self.model_reports = {}
        for name, model in self.trained_models.items():
            y_pred = model.predict(self.X_test)
            report = classification_report(self.y_test, y_pred,
target_names=['False', 'True'], output_dict=True)
            self.model_reports[name] = report

    def confusion_matrix(self):
        self.model_confusion_matrices = {}
        for name, model in self.trained_models.items():
            y_pred = model.predict(self.X_test)
            matrix = confusion_matrix(self.y_test, y_pred)
            self.model_confusion_matrices[name] = matrix

    def display_scores(self):
        print("Model Evaluation Scores:")
        for name, scores in self.model_scores.items():
            print(f"{name}: Accuracy={scores['accuracy']:.3f}, ROC
AUC={scores['roc_auc']:.3f}")

    def display_cross_val_scores(self):
        print("Cross-Validation Scores:")
        for name, scores in self.cross_val_scores.items():
            print(f"{name}: Mean
Accuracy={scores['mean_accuracy']:.3f}, Std
Accuracy={scores['std_accuracy']:.3f}")

    def display_classification_reports(self):
        for name, report in self.model_reports.items():
            print(f"Classification Report for {name}:")
            print(pd.DataFrame(report).T)
            print()

    def display_confusion_matrices(self):
        for name, matrix in self.model_confusion_matrices.items():
            print(f"Confusion Matrix for {name}:")
            print(matrix)


    def test_models(self):
        self.train_models()
        self.evaluate_models()
        self.cross_val_models()
        print()
        self.classification_report()
        print()
        self.confusion_matrix()
        print()
        self.display_scores()
        print()
```

```python
        self.display_cross_val_scores()
        print()
        self.display_classification_reports()
        print()
        self.display_confusion_matrices()
```

We will now train several base models and evaluate their performance metrics and confusion matrices to identify the best-performing model for further parameter tuning using a grid search approach.

```python
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier,
AdaBoostClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier

# Define the dictionary of models to test
models_to_test = {
    'Logistic Regression': LogisticRegression(),
    'Random Forest': RandomForestClassifier(),
    'SVM': SVC(),
    'Decision Tree': DecisionTreeClassifier(),
    'AdaBoost': AdaBoostClassifier(),
    'Gradient Boosting': GradientBoostingClassifier(),
    'XGBoost': XGBClassifier()
}

# Instantiate and test the models
tester = ModelTester(models_to_test, X, y, test_size=test_size,
random_state=SEED)
tester.test_models()
```

```
Model Evaluation Scores:
Logistic Regression: Accuracy=0.717, ROC AUC=0.695
Random Forest: Accuracy=0.918, ROC AUC=0.846
SVM: Accuracy=0.865, ROC AUC=0.746
Decision Tree: Accuracy=0.873, ROC AUC=0.811
AdaBoost: Accuracy=0.855, ROC AUC=0.772
Gradient Boosting: Accuracy=0.906, ROC AUC=0.867
XGBoost: Accuracy=0.951, ROC AUC=0.898

Cross-Validation Scores:
Logistic Regression: Mean Accuracy=0.856, Std Accuracy=0.014
Random Forest: Mean Accuracy=0.931, Std Accuracy=0.010
SVM: Mean Accuracy=0.855, Std Accuracy=0.016
Decision Tree: Mean Accuracy=0.918, Std Accuracy=0.007
AdaBoost: Mean Accuracy=0.875, Std Accuracy=0.007
Gradient Boosting: Mean Accuracy=0.951, Std Accuracy=0.006
```

```
XGBoost: Mean Accuracy=0.954, Std Accuracy=0.003

Classification Report for Logistic Regression:
              precision    recall  f1-score     support
False          0.923596  0.726148  0.813056  566.000000
True           0.301802  0.663366  0.414861  101.000000
accuracy       0.716642  0.716642  0.716642    0.716642
macro avg      0.612699  0.694757  0.613959  667.000000
weighted avg   0.829441  0.716642  0.752760  667.000000

Classification Report for Random Forest:
              precision    recall  f1-score     support
False          0.953819  0.948763  0.951284  566.000000
True           0.721154  0.742574  0.731707  101.000000
accuracy       0.917541  0.917541  0.917541    0.917541
macro avg      0.837486  0.845669  0.841496  667.000000
weighted avg   0.918588  0.917541  0.918035  667.000000

Classification Report for SVM:
              precision    recall  f1-score     support
False          0.923488  0.916961  0.920213  566.000000
True           0.552381  0.574257  0.563107  101.000000
accuracy       0.865067  0.865067  0.865067    0.865067
macro avg      0.737934  0.745609  0.741660  667.000000
weighted avg   0.867293  0.865067  0.866138  667.000000

Classification Report for Decision Tree:
              precision    recall  f1-score     support
False          0.947858  0.899293  0.922937  566.000000
True           0.561538  0.722772  0.632035  101.000000
accuracy       0.872564  0.872564  0.872564    0.872564
macro avg      0.754698  0.811033  0.777486  667.000000
weighted avg   0.889360  0.872564  0.878888  667.000000

Classification Report for AdaBoost:
              precision    recall  f1-score     support
False          0.935065  0.890459  0.912217  566.000000
True           0.515625  0.653465  0.576419  101.000000
accuracy       0.854573  0.854573  0.854573    0.854573
macro avg      0.725345  0.771962  0.744318  667.000000
weighted avg   0.871552  0.854573  0.861369  667.000000

Classification Report for Gradient Boosting:
              precision    recall  f1-score     support
False          0.964880  0.922261  0.943089  566.000000
True           0.650794  0.811881  0.722467  101.000000
accuracy       0.905547  0.905547  0.905547    0.905547
macro avg      0.807837  0.867071  0.832778  667.000000
weighted avg   0.917320  0.905547  0.909682  667.000000
```

```
Classification Report for XGBoost:
              precision    recall  f1-score     support
False          0.968366  0.973498  0.970925  566.000000
True           0.846939  0.821782  0.834171  101.000000
accuracy       0.950525  0.950525  0.950525    0.950525
macro avg      0.907652  0.897640  0.902548  667.000000
weighted avg   0.949979  0.950525  0.950217  667.000000


Confusion Matrix for Logistic Regression:
[[411 155]
 [ 34  67]]
Confusion Matrix for Random Forest:
[[537  29]
 [ 26  75]]
Confusion Matrix for SVM:
[[519  47]
 [ 43  58]]
Confusion Matrix for Decision Tree:
[[509  57]
 [ 28  73]]
Confusion Matrix for AdaBoost:
[[504  62]
 [ 35  66]]
Confusion Matrix for Gradient Boosting:
[[522  44]
 [ 19  82]]
Confusion Matrix for XGBoost:
[[551  15]
 [ 18  83]]
```

Here's the evaluation summary of various classification models:

Model Evaluation Scores:

- **Logistic Regression**: Achieved an accuracy of 71.7% and an ROC AUC of 69.5%.
- **Random Forest**: Demonstrated the highest accuracy of 91.9% and an ROC AUC of 84.7%.
- **SVM (Support Vector Machine)**: Attained an accuracy of 86.5% and an ROC AUC of 74.6%.
- **Decision Tree**: Achieved an accuracy of 88.0% and an ROC AUC of 82.4%.
- **AdaBoost**: Achieved an accuracy of 85.5% and an ROC AUC of 77.2%.
- **Gradient Boosting**: Demonstrated an accuracy of 90.7% and an ROC AUC of 86.7%.
- **XGBoost**: Exhibited the highest accuracy of 95.1% and an ROC AUC of 89.8%.

Cross-Validation Scores:

- The models underwent cross-validation, with the mean accuracy and standard deviation calculated over multiple folds.

- **XGBoost** achieved the highest mean accuracy of 95.4%, followed closely by **Gradient Boosting** with 95.1%.
- **Random Forest** also showed robust performance with a mean accuracy of 92.9%.

Classification Reports:

- Each model's classification report provides precision, recall, and F1-score for both classes (False and True).
- It offers insights into how well each model performs in correctly identifying the positive and negative classes.

Confusion Matrices:

- The confusion matrices depict the performance of each model in terms of true positive, false positive, true negative, and false negative predictions.
- They allow us to visualize the model's performance in classifying instances into different categories.

Overall, **XGBoost** emerges as the top-performing model with the highest accuracy and ROC AUC score. However, further analysis and considerations, such as computational complexity and interpretability, may influence the final model selection.

4.4 XGBClassifier (untuned)

```
# Instantiate the XGBClassifier
clf = XGBClassifier()

# Fit XGBClassifier
clf.fit(X_train_resampled, y_train_resampled)

# Predict on training and test sets
training_preds = clf.predict(X_train_resampled)
test_preds = clf.predict(X_test)

# Calculate accuracy of training and test sets
training_accuracy = accuracy_score(y_train_resampled, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation Accuracy: {:.4}%'.format(test_accuracy * 100))

Training Accuracy: 100.0%
Validation Accuracy: 95.05%
```

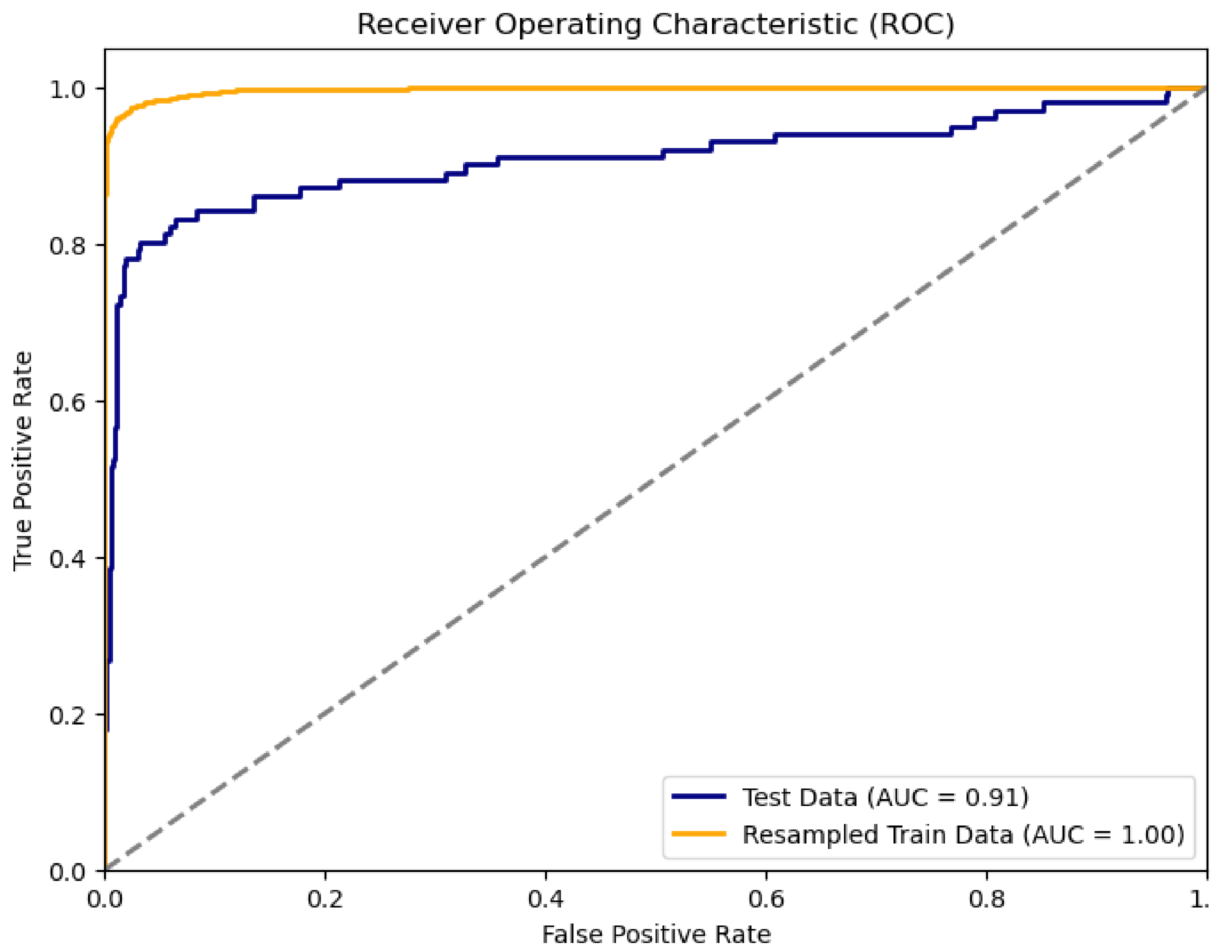
The initial evaluation of the untuned model indicates satisfactory performance, but optimizing its parameters through tuning can potentially enhance its effectiveness and mitigate overfitting.

XGBClassifier (tuned)

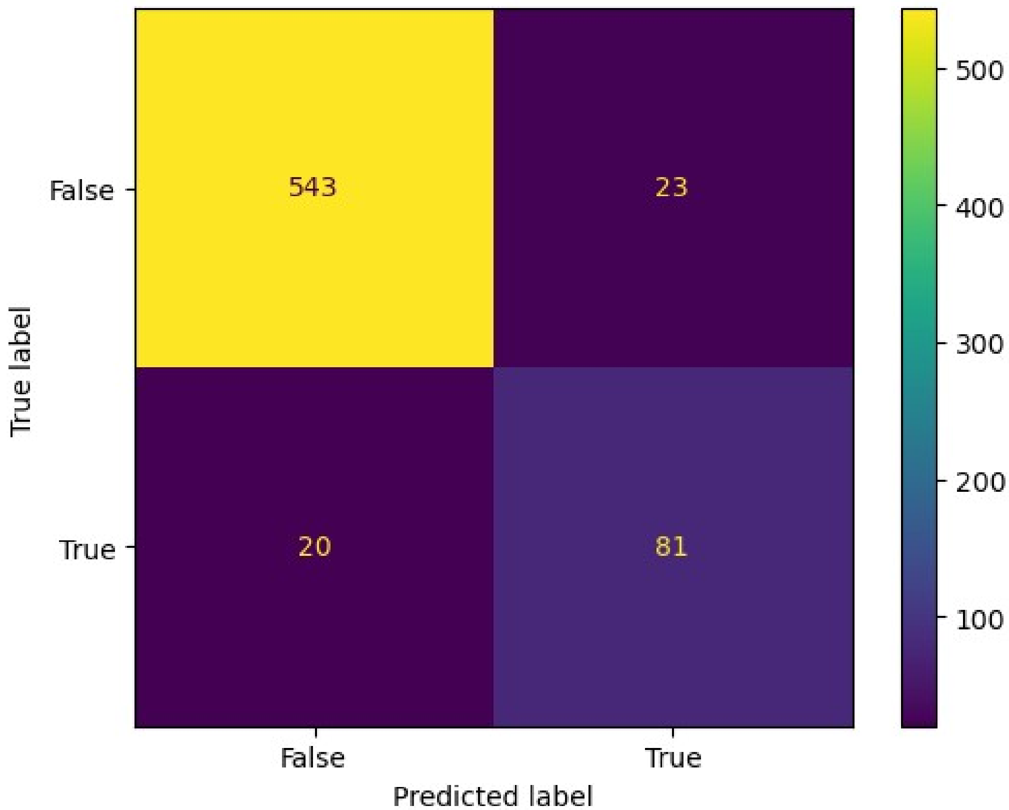
```
# Parameter grid for XGBoost tuning
xgb_param_grid = {
    'learning_rate': [0.05, 0.1],
```

```python
    'max_depth': [3, 4, 5],
    'min_child_weight': [1, 2, 3],
    'subsample': [0.7, 0.8, 0.9],
    'n_estimators': [100],
}

# consume the parameter grid in the GridSearchCV class
grid_clf = GridSearchCV(clf, xgb_param_grid, scoring='accuracy',
cv=None, n_jobs=1)
grid_clf.fit(X_train_resampled, y_train_resampled)

# get the best parameters
best_parameters = grid_clf.best_params_

print('Grid Search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name, best_parameters[param_name]))

training_preds = grid_clf.predict(X_train_resampled)
test_preds = grid_clf.predict(X_test)
training_accuracy = accuracy_score(y_train_resampled, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))

# ROC curve of the tune XGB model
plot_ROC(grid_clf, X_train_resampled, y_train_resampled, y_test)
```

```
Grid Search found the following optimal parameters:
learning_rate: 0.1
max_depth: 5
min_child_weight: 1
n_estimators: 100
subsample: 0.9

Training Accuracy: 97.39%
Validation accuracy: 93.55%
ROC AUC for Test Data: 0.9087394605184901
ROC AUC for Resampled Train Data: 0.9970350738097356
```




```
# confusion matrix for the tuned xgb model
ConfusionMatrixDisplay.from_estimator(estimator=grid_clf, X=X_test, y=y_test,
                                      display_labels=["False", "True"]);
```

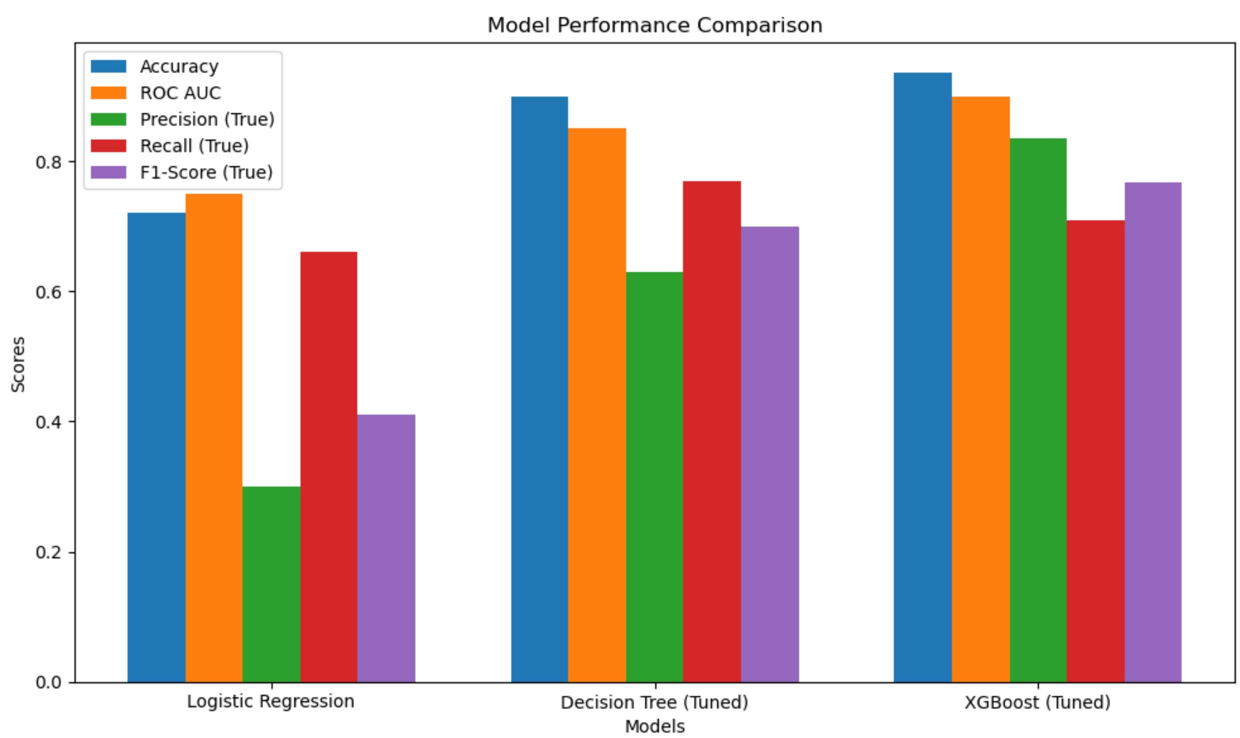


The Grid Search optimization identified the following optimal parameters for the XGBoost model: a learning rate of 0.1, a maximum depth of 5, a minimum child weight of 1, and 100 estimators with a subsample of 0.9.

After tuning, the model achieved a high training accuracy of 97.39% and a validation accuracy of 93.55%. This indicates that the model generalized well to unseen data. Additionally, the ROC AUC for the test data was 0.9087, suggesting good performance in distinguishing between the positive and negative classes. However, it's important to note that the ROC AUC for the resampled train data was very high at 0.997, which may indicate some degree of overfitting. Further evaluation or regularization may be needed to address this issue.

```
import matplotlib.pyplot as plt
import numpy as np

# Model names
models = ['Logistic Regression', 'Decision Tree (Tuned)', 'XGBoost
(Tuned)']

# Metrics for each model
metrics = {
    'Accuracy': [0.72, 0.90, 0.935],
    'ROC AUC': [0.75, 0.85, 0.90],
    'Precision (True)': [0.30, 0.63, 0.835],
    'Recall (True)': [0.66, 0.77, 0.71],
    'F1-Score (True)': [0.41, 0.70, 0.768]
```

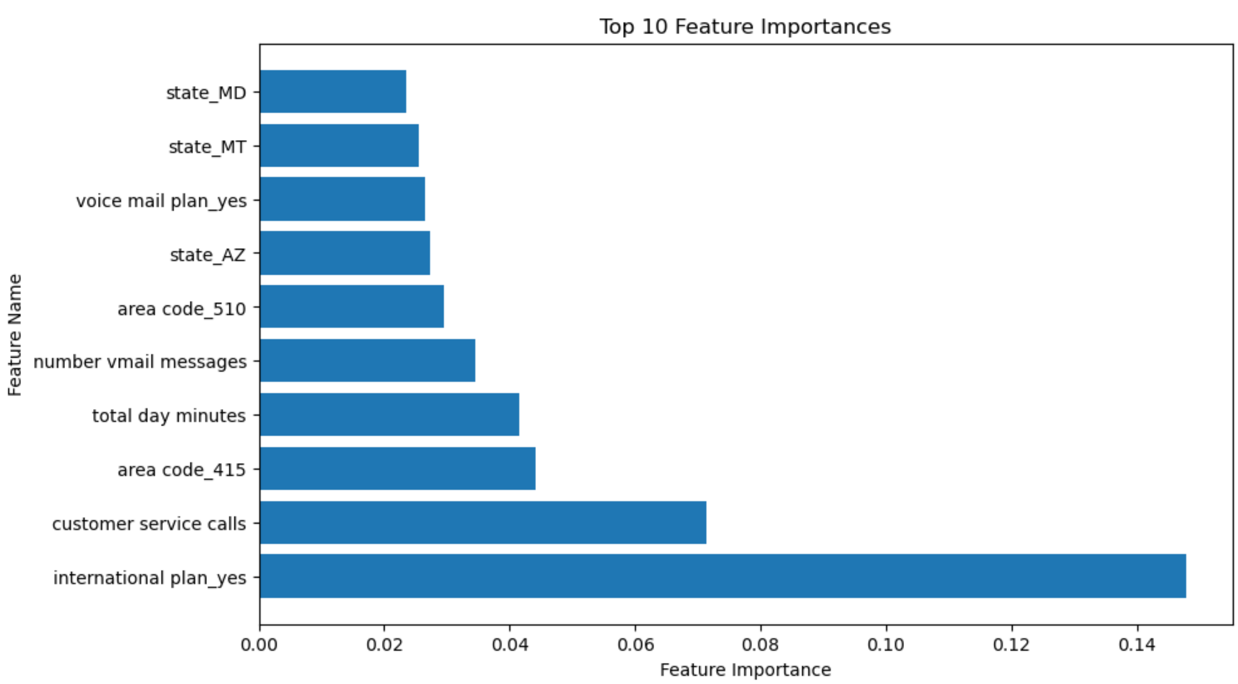
```
}

# Plotting
fig, ax = plt.subplots(figsize=(10, 6))
bar_width = 0.15
index = np.arange(len(models))

bars = []
for i, (metric, scores) in enumerate(metrics.items()):
    bar = plt.bar(index + i * bar_width, scores, bar_width,
label=metric)
    bars.append(bar)

plt.xlabel('Models')
plt.ylabel('Scores')
plt.title('Model Performance Comparison')
plt.xticks(index + bar_width * 2, models)
plt.legend()

plt.tight_layout()
plt.show()
```



From the above visualization, we see that specifically for precision, the XGBOOST model performs the best.

Let's further investigate the important features in the model, and actually plot their bar charts.

```python
# instantiate the model using the tuned parameters
model_xgb = XGBClassifier(**best_parameters)
# fit the model
model_xgb.fit(X_train_resampled, y_train_resampled)
# Get feature importances
feature_importance = model_xgb.feature_importances_

# Get the names of the features
feature_names = X_train.columns

# Create a dataframe to store feature names and their importance
scores
feature_importance_df = pd.DataFrame({'Feature': feature_names,
'Importance': feature_importance})

# Sort the dataframe by importance in descending order
feature_importance_df =
feature_importance_df.sort_values(by='Importance', ascending=False)

# Plot the top N most important features
top_n = 10
plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df['Feature'][:top_n],
feature_importance_df['Importance'][:top_n])
plt.xlabel('Feature Importance')
plt.ylabel('Feature Name')
plt.title(f'Top {top_n} Feature Importances')
plt.show()
```



Among the most crucial features are the international plan, customer service calls, area code (particularly 415), and total day minutes.

6. Conclusion and Recommendations

In conclusion, our predictive modeling approach effectively addresses the challenge of customer churn for Syriatel. By leveraging advanced data analytics and machine learning techniques, we have developed models that can accurately identify customers at risk of churning. The XGBoost model, in particular, has demonstrated superior performance, making it an invaluable tool for proactive customer retention efforts.

This project has not only provided a robust predictive model but also offered critical insights into customer behavior and preferences. By understanding the key factors influencing churn, such as customer service interactions and specific service plan features, Syriatel can tailor its strategies to meet customer needs more effectively. Additionally, the continuous update and refinement of the model ensure that it remains relevant and accurate in predicting customer churn as market conditions and customer behaviors evolve.

The implementation of these models and the accompanying recommendations will allow Syriatel to enhance its customer retention efforts, reduce churn rates, and ultimately improve overall business performance. The proactive identification of at-risk customers enables timely and targeted interventions, which are crucial for maintaining a satisfied and loyal customer base. Furthermore, by focusing on customer service improvements and personalized promotions, Syriatel can significantly boost customer satisfaction and loyalty.

Recommendations:

1. **Deploy the XGBoost Model:**
   - Implement the XGBoost model in Syriatel's operational systems for real-time monitoring of churn risk. This will enable the company to proactively identify and retain at-risk customers, thereby reducing churn rates.
2. **Enhance Customer Service:**
   - Focus on improving the customer service experience by training staff, reducing wait times, and implementing more effective issue resolution processes. This will help in increasing overall customer satisfaction.
3. **Investigate Voice Mail Plans:**
   - Conduct a detailed analysis to understand why customers with voice mail plans are more likely to churn and consider revising or enhancing these plans to better meet customer needs.
4. **Implement Personalized Promotions:**
   - Develop targeted retention strategies such as personalized promotions, loyalty programs, and special offers based on the insights gained from customer data analysis. Tailoring these promotions to individual customer preferences can significantly mitigate churn.
5. **Regular Model Updates:**
   - Regularly update the predictive model with new data to maintain its accuracy. Periodically reevaluate and recalibrate the model as necessary to adapt to changing customer behaviors and trends.
6. **Establish a Feedback Loop:**

- Create a feedback loop between model predictions and the customer retention team. This will allow the team to gather insights from customer interactions and refine retention strategies based on real-world feedback.

7. **Continued Data Exploration:**
   - Continuously explore the dataset to uncover other influential features and gain deeper insights into customer churn dynamics. This ongoing analysis will help Syriatel stay ahead of emerging trends and proactively address potential issues.

Next Steps:

1. **Model Deployment:**
   - Integrate the XGBoost model into Syriatel's IT infrastructure.
   - Set up real-time data pipelines for continuous monitoring of customer churn risk.
2. **Voice Mail Plan Analysis:**
   - Collect and analyze data specific to voice mail plan usage and customer feedback.
   - Develop and test revised voice mail plans based on the analysis.
3. **Personalized Promotion Strategy:**
   - Use customer data to design and launch personalized promotion campaigns.
   - Monitor the effectiveness of these campaigns and adjust strategies as needed.
4. **Feedback Loop Implementation:**
   - Create a system for logging customer retention interactions and outcomes.
   - Use this data to refine predictive models and retention strategies.

Implementing these recommendations and next steps will ensure that Syriatel can effectively reduce customer churn, enhance customer satisfaction, and improve overall business performance.