# Predicting Customer Churn in Telecommunications: A Data-Driven Approach to Enhancing Retention Strategies at SyriaTel ¶

## Business Overview

SyriaTel is a leading telecommunications company providing a range of services including voice, data, and internet to its customers. In the highly competitive telecommunications industry, customer retention is crucial for sustaining revenue and profitability.SyriaTel faces a significant challenge with customer churn—customers discontinuing their services—which impacts its revenue and growth. High churn rates can be costly, leading to lost revenue and increased costs associated with acquiring new customers. To maintain a competitive edge and ensure business stability, SyriaTel needs to effectively manage and reduce churn.

## Stakeholders

SyriaTel: The primary focus of the project is to predict customer churn to reduce costs and improve customer retention.

1. SyriaTel Marketing: Wants to understand why customers are leaving and how to improve retention.
2. SyriaTel Sales: Wants to understand why customers are leaving and how to improve retention.
3. SyriaTel Customer Service: Wants to understand why customers are leaving and how to improve retention.
4. SyriaTel Finance: Wants to understand why customers are leaving and how to improve retention.

## Business Understanding

SyriaTel, a telecommunications company, experiences a significant loss of revenue due to customers who discontinue their services. By accurately predicting which customers are likely to churn, the company can implement targeted retention strategies, improve customer satisfaction, and ultimately reduce the churn rate. Understanding the patterns and factors leading to churn can provide actionable insights for improving customer loyalty and operational efficiency.

## Data Description:

The dataset contains various customer-related attributes, including usage metrics and service plan details. Key variables include:

`State:` The customer's location, represented as a categorical variable.
`Account Length:` Duration of the customer's account in days.
`Area Code:` Numeric representation of the customer's area code.
`International Plan:` Whether the customer has subscribed to an international calling plan.
`Voice Mail Plan:` Subscription status to a voicemail plan.
`Total Day/Eve/Night/Intl Minutes:` Usage minutes during different time segments.
`Total Day/Eve/Night/Intl Calls:` Call counts across different time segments.
`Total Day/Eve/Night/Intl Charge:` Charges accrued in different time segments.
`Customer Service Calls:` Number of calls made to customer service.
`Churn:` The target variable indicating whether the customer has churned (True/False).

## Problem Statement

SyriaTel wants to predict customer churn to proactively address customer retention. The goal is to build a classification model that can accurately predict whether a customer will stop doing business with SyriaTel. This involves identifying the factors contributing to churn and using them to predict future churn events.

## Objective

**Predict Customer Churn:** Develop a model to accurately predict whether a customer will churn based on their features and call metrics.

**Feature Analysis:** Identify key factors that influence customer churn.

**Model Evaluation:** Evaluate model performance using various metrics and refine the model for improved accuracy.

**Steps to achieve this objective:**

Data Exploration: Gain insights into the data by exploring various aspects such as data types, missing values, and summary statistics.

Data Preprocessing: Handle missing values, outliers, and categorical variables appropriately. This may involve imputation, encoding, or scaling the data.

Feature Engineering: Create new features that may help improve the predictive model's performance. This may involve combining existing features, creating interaction terms, or transforming data to better represent the relationships between variables.

Model Selection: Choose an appropriate classification model for predicting customer churn, such as logistic regression, decision trees, or random forests.

Build a Predictive Model: Develop and train a classification model to predict the likelihood of customer churn based on available features.

Identify Key Predictors: Analyze the model to identify which features are most influential in predicting churn.

Evaluate Model Performance: Assess the model using metrics such as accuracy, precision, recall, and F1 score to ensure it meets the required performance standards.

Present Results: Summarize the findings and insights gained from the model, including the most influential features and their impact on customer churn.

Provide Actionable Insights: Offer recommendations to SyriaTel on how to address the factors leading to churn and improve customer retention strategies.

Evaluate Model Performance: Assess the model using metrics such as accuracy, precision, recall, and ROC-AUC to ensure it meets the required performance standards.

In [84]:
```
# Start by importing all the necessary libraries fot our project

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

In a dataframe named "df" load file in the cell below using "pd.read_csv" format

# 1. Data Overview

### 1.1. Load and Inspect the Data

In a dataframe name "df" load "bigml_59c28831336c6604c800002a.csv" file in the cell below using "pd.read_csv" format

In [85]:
```
df = pd.read_csv("Data/bigml_59c28831336c6604c800002a.csv")
df.head()
```

Out[85]:

| | state | account length | area code | phone number | international plan | voice mail plan | number vmail messages | total day minutes | total day calls | total day charge | ... | total eve calls | total eve charge | total night minutes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | KS | 128 | 415 | 382-4657 | no | yes | 25 | 265.1 | 110 | 45.07 | ... | 99 | 16.78 | 244.7 |
| **1** | OH | 107 | 415 | 371-7191 | no | yes | 26 | 161.6 | 123 | 27.47 | ... | 103 | 16.62 | 254.4 |
| **2** | NJ | 137 | 415 | 358-1921 | no | no | 0 | 243.4 | 114 | 41.38 | ... | 110 | 10.30 | 162.6 |
| **3** | OH | 84 | 408 | 375-9999 | yes | no | 0 | 299.4 | 71 | 50.90 | ... | 88 | 5.26 | 196.9 |
| **4** | OK | 75 | 415 | 330-6626 | yes | no | 0 | 166.7 | 113 | 28.34 | ... | 122 | 12.61 | 186.9 |

5 rows × 21 columns

Now lets get familiar with the data we have in our df. This step will include

1. Understanding the dimentionality of our dataset
2. Investigating what type of data it contains, and the data types used to store it
3. Dicovering how missing values are encoded, and how many there are
4. Getting a feel for what information it does and doesn't contain

### 1.2. In the cell below,lets inspect the df columns

In [86]:
```
col_names = df.columns
col_names
```

Out[86]:
```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', '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', 'churn'],
      dtype='object')
```

**1.3. In the cell below,lets inspect the info printout of the dataframe**

In [87]:
```
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
```

The info() printout has provided us with a summary of our dataset, revealing key details about its structure and contents. Here's a brief explanation:

Number of Entries: The dataset contains 3,333 rows, indicating the number of records available for analysis.

Number of Columns: There are 21 columns, which include both features and the target variable (churn).

Data Types:

8 integer columns (int64): These likely represent counts or other discrete values (e.g., account length, number vmail messages).

8 float columns (float64): These are continuous numerical features (e.g., total day minutes, total day charge).

4 object columns (object): These are categorical variables (e.g., state, phone number, international plan).

One column (customer_id): This is a unique identifier for each customer.

1 boolean column (bool): The churn column, indicating whether a customer churned (True) or not (False).

Non-Null Counts: All columns have 3,333 non-null entries, meaning there are no missing values in the dataset.

**1.4. We look for shape of our dataframe**

In [88]:
```
df.shape
```

Out[88]:
```
(3333, 21)
```

The shape (3333, 21) tells us that our dataset contains 3,333 records, with 21 features for each record. This is a key piece of information for understanding the size and complexity of the data we're working with.

**1.5. Summary Statistics**

We now get a summary of numerical features .

In [89]:
```
df.describe()
```

Out[89]:

| | account length | area code | number vmail messages | total day minutes | total day calls | total day charge | total eve minutes | total eve calls | tot c |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 3333.000000 | 3333.000000 | 3333.000000 | 3333.000000 | 3333.000000 | 3333.000000 | 3333.000000 | 3333.000000 | 3333.0 |
| **mean** | 101.064806 | 437.182418 | 8.099010 | 179.775098 | 100.435644 | 30.562307 | 200.980348 | 100.114311 | 17.0 |
| **std** | 39.822106 | 42.371290 | 13.688365 | 54.467389 | 20.069084 | 9.259435 | 50.713844 | 19.922625 | 4.3 |
| **min** | 1.000000 | 408.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **25%** | 74.000000 | 408.000000 | 0.000000 | 143.700000 | 87.000000 | 24.430000 | 166.600000 | 87.000000 | 14.1 |
| **50%** | 101.000000 | 415.000000 | 0.000000 | 179.400000 | 101.000000 | 30.500000 | 201.400000 | 100.000000 | 17.1 |
| **75%** | 127.000000 | 510.000000 | 20.000000 | 216.400000 | 114.000000 | 36.790000 | 235.300000 | 114.000000 | 20.0 |
| **max** | 243.000000 | 510.000000 | 51.000000 | 350.800000 | 165.000000 | 59.640000 | 363.700000 | 170.000000 | 30.9 |

The describe() function provides a summary of the numerical features in the dataset. It includes key statistics such as count, mean, standard deviation, minimum, 25th percentile, 50th percentile (median), 75th percentile, and maximum values. This can help us identify any outliers or skewness in the data.

#### 1.6. Identify Missing Values: Check for missing values using isnull().sum().

In [90]:
```
df.isnull().sum()
```

Out[90]:
```
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
```

It looks like there are no missing values in our dataset.

#### 1.7. Data Types

Ensure that each column has the correct data type. Convert if necessary.

In [91]:
```
df.dtypes
```

Out[91]:
```
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
```

### 1.8. Unique Values

Inspect unique values in categorical columns to ensure there are no anomalies.

In [92]:
```
for column in df.select_dtypes(include=['object']).columns:
    print(f'{column} unique values: {df[column].unique()}')
```

```
state unique values: ['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']
phone number unique values: ['382-4657' '371-7191' '358-1921' ... '328-8230' '364-6381' '400-434
4']
international plan unique values: ['no' 'yes']
voice mail plan unique values: ['yes' 'no']
```

1. state Column Unique Values: The state column has a variety of state abbreviations, which seems normal.

Action: Convert the state column into numerical format using one-hot encoding. This will create a binary column for each state, allowing the model to utilize this categorical information effectively.

2. phone number Column Unique Values: The phone number column has unique values for each entry.

Action: This column should be dropped because it doesn't provide useful information for predicting churn and might add noise to the model.

3. international plan Column Unique Values: The international plan column has two values: 'no' and 'yes'.

Action: Encode this binary categorical feature using binary encoding (0 and 1). This can be done with label encoding or one-hot encoding.

4. voice mail plan Column Unique Values: The voice mail plan column also has two values: 'yes' and 'no'.

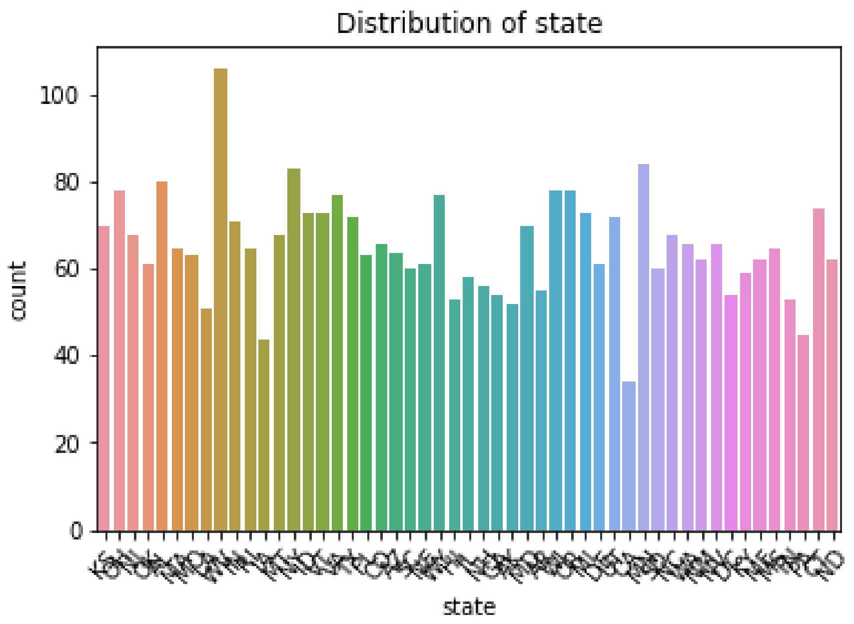
Action: Similar to the international plan, encode this binary categorical feature using binary encoding (0 and 1).

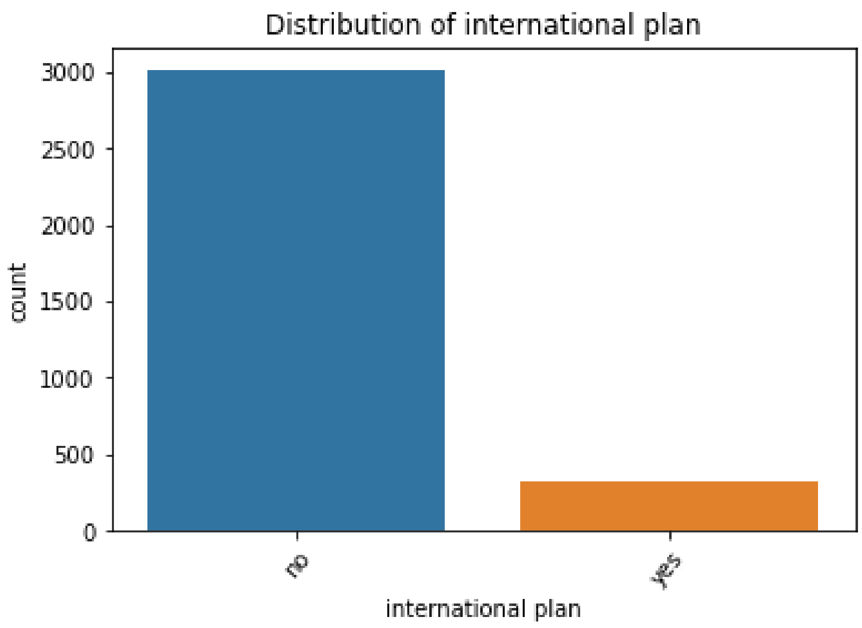
In [93]:
```
# Drop the 'phone number' column as it's not needed
df = df.drop(columns=['phone number'])
```

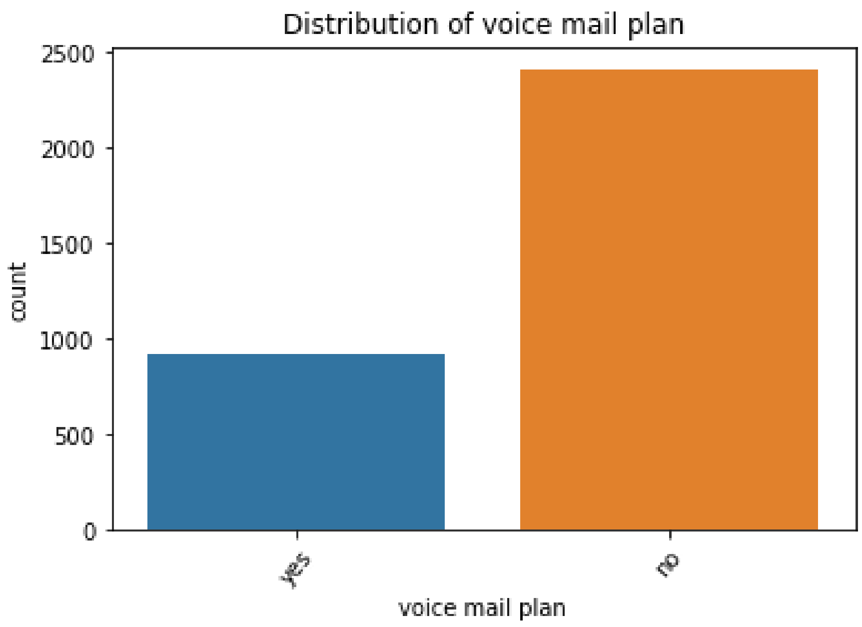
### 1.9. Categorical Features

Use bar plots to show the distribution of categories.

In [94]:
```
for column in df.select_dtypes(include=['object']).columns:
    sns.countplot(data=df, x=column)
    plt.title(f'Distribution of {column}')
    plt.xticks(rotation=50)
    plt.show()
```




## 2. Overview of Categorical Features

Check the distribution of categorical features.

In [95]:
```
# Define categorical features
categorical_features = ['state', 'international plan', 'voice mail plan']

# Count frequency of each category in categorical features
for feature in categorical_features:
    frequency = df[feature].value_counts()
    print(f"Distribution of {feature}:")
    print(frequency)
    print()
```

```
Distribution of state:
WV    106
MN     84
NY     83
AL     80
OH     78
WI     78
OR     78
VA     77
WY     77
CT     74
VT     73
ID     73
MI     73
UT     72
TX     72
IN     71
KS     70
MD     70
MT     68
NJ     68
NC     68
CO     66
WA     66
NV     66
MS     65
RI     65
MA     65
AZ     64
FL     63
MO     63
ND     62
NM     62
ME     62
DE     61
NE     61
OK     61
SC     60
SD     60
KY     59
IL     58
NH     56
AR     55
DC     54
GA     54
TN     53
HI     53
AK     52
LA     51
PA     45
IA     44
CA     34
Name: state, dtype: int64

Distribution of international plan:
no     3010
yes     323
Name: international plan, dtype: int64

Distribution of voice mail plan:
no     2411
yes     922
Name: voice mail plan, dtype: int64
```

In [96]:
```
# print number of labels in International variable

print('International plan contains', len(df['international plan'].unique()), 'labels')
```

```
International plan contains 2 labels
```

In [97]:
```
# check frequency distribution of values in internatioal plan variable

df['international plan'].value_counts()
```

Out[97]:
```
no     3010
yes     323
Name: international plan, dtype: int64
```

In [98]:
```
# check frequency distribution of values in voice mail plan variable

df['voice mail plan'].value_counts()
```

Out[98]:
```
no     2411
yes     922
Name: voice mail plan, dtype: int64
```

The distribution results for our categorical features are as follows:

1. Distribution of state The state column has a fairly balanced distribution with some states having slightly higher counts:

Most Common: WV (106) MN (84) NY (83) Least Common: CA (34) The distribution seems reasonable, though some states are more common than others. This is normal and reflects the geographical spread of our customer base.

2. Distribution of international plan The distribution for the international plan feature shows:

No: 3010 Yes: 323 This indicates a strong imbalance with a significantly larger proportion of customers not having an international plan.

3. Distribution of voice mail plan The distribution for the voice mail plan feature shows:

No: 2411 Yes: 922 This also indicates a noticeable imbalance, though not as extreme as the international plan.

#### 2.1.Calculate Imbalance Ratios

Compute the ratio of the majority class to the minority class. A high ratio indicates significant imbalance.

In [99]:
```
# Calculate imbalance ratios for each categorical feature
for feature in categorical_features:
    counts = df[feature].value_counts()
    imbalance_ratio = counts.max() / counts.min()
    print(f"Imbalance ratio for {feature}: {imbalance_ratio}")
```

```
Imbalance ratio for state: 3.1176470588235294
Imbalance ratio for international plan: 9.318885448916408
Imbalance ratio for voice mail plan: 2.6149674620390457
```

Imbalance Ratios Interpretation state: 3.12

This ratio suggests a moderate level of imbalance among the states. Some states have significantly more entries compared to others. While not extreme, it's worth considering if certain states are overrepresented or underrepresented.

international plan: 9.32

This indicates a high imbalance between 'yes' and 'no' categories. 'No' is vastly more common than 'yes'. This can impact model performance, as models may become biased towards the majority class.

voice mail plan: 2.61

This ratio indicates a moderate imbalance, with 'no' being more common than 'yes'. While less severe than the international plan, it still suggests that 'no' is more prevalent.

#### 2.2. Churn Distribution

Examining the distribution of the target variable (churn).

In [100]:
```
print(df['churn'].value_counts())
```

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

# 3. Now that we have looked at the categorical features lets look at the

## numerical features

Distribution Plots: Use histograms plots to visualize the distribution of each numeric feature.

**Handling Outliers**

Boxplots: Identify outliers using boxplots.

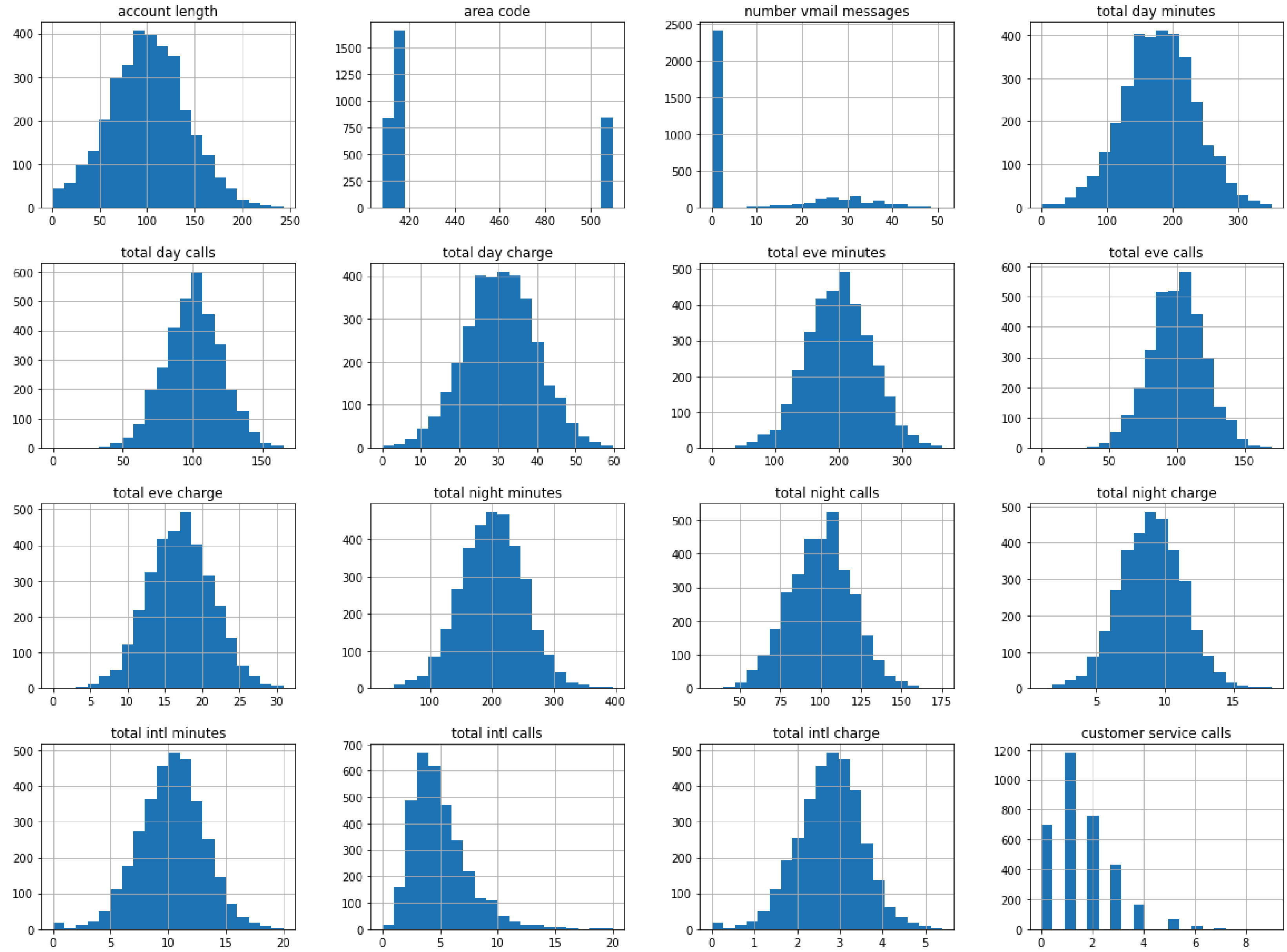
#### 3.1. Define X and y

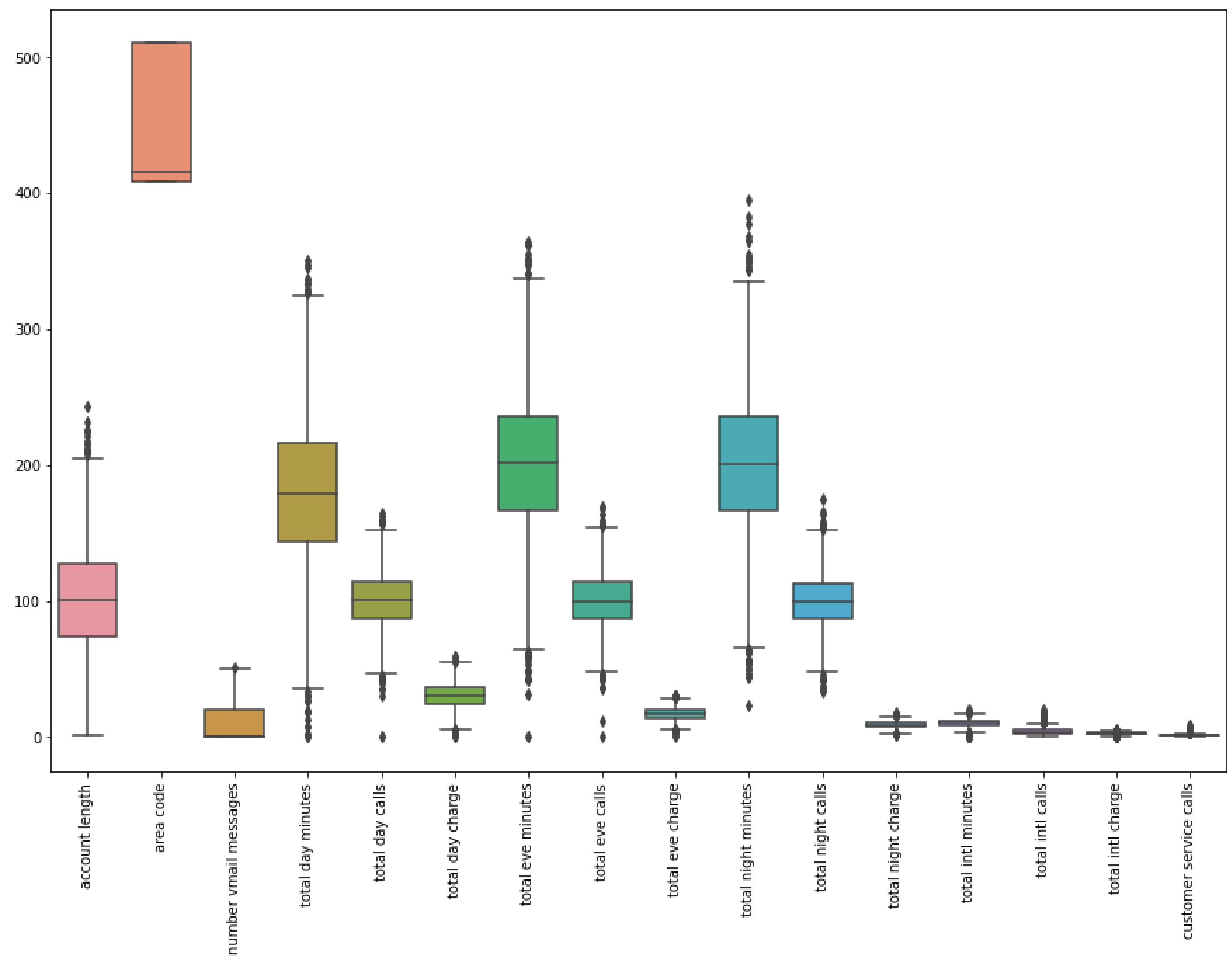
X: This should include all our feature columns (numeric and categorical).

y: This is our target variable (churn).

In [101]:
```
# Features`
X = df.drop(columns=['churn'])
#Target variable (churn)
y = df['churn']
```

In [102]:
```
# Histograms
X.hist(bins=20, figsize=(20, 15))
plt.show()

# Boxplots
plt.figure(figsize=(15, 10))
sns.boxplot(data=X)
plt.xticks(rotation=90)
plt.show()
```




### 3.1.1 Handling the outlier values for the boxplot data structure and skewed distribution

In [103]:
```
# IQR Method
Q1 = X.quantile(0.25)
Q3 = X.quantile(0.75)
IQR = Q3 - Q1

# Define outliers
outliers = (X < (Q1 - 1.5 * IQR)) | (X > (Q3 + 1.5 * IQR))

# Print outliers
print(outliers.sum())  # Count of outliers in each feature
```

```
account length            18
area code                  0
customer service calls   267
international plan         0
number vmail messages      1
state                      0
total day calls           23
total day charge          25
total day minutes         25
total eve calls           20
total eve charge          24
total eve minutes         24
total intl calls          78
total intl charge         49
total intl minutes        46
total night calls         22
total night charge        30
total night minutes       30
voice mail plan            0
dtype: int64
```

In [104]:
```
from scipy.stats import zscore

def handle_normal_outliers(df, columns):
    for column in columns:
        df[f'{column}_zscore'] = zscore(df[column])
        outliers = df[(df[f'{column}_zscore'] > 3) | (df[f'{column}_zscore'] < -3)]
        print(f'{column} has {len(outliers)} outliers.')

        # Optionally remove or cap outliers
        # df = df[(df[f'{column}_zscore'] <= 3) & (df[f'{column}_zscore'] >= -3)]
        # Alternatively, cap outliers:
        # df[column] = df[column].clip(lower=df[column].quantile(0.01), upper=df[column].quantile

    return df.drop([f'{column}_zscore' for column in columns], axis=1)

normal_columns = [
    'account length', '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 charge'
]

df = handle_normal_outliers(df, normal_columns)
```

```
account length has 7 outliers.
total day minutes has 9 outliers.
total day calls has 9 outliers.
total day charge has 9 outliers.
total eve minutes has 9 outliers.
total eve calls has 7 outliers.
total eve charge has 9 outliers.
total night minutes has 11 outliers.
total night calls has 6 outliers.
total night charge has 11 outliers.
total intl minutes has 22 outliers.
total intl charge has 22 outliers.
```

In [105]:
```
from scipy.stats import zscore

class NormalOutlierDetector:
    def __init__(self, dataframe):
        self.dataframe = dataframe

    def find_outliers_zscore(self, column, threshold=3):
        z_scores = zscore(self.dataframe[column])
        lower_fence = self.dataframe[column].mean() - threshold * self.dataframe[column].std()
        upper_fence = self.dataframe[column].mean() + threshold * self.dataframe[column].std()
        print(f'{column} outliers are values < {lower_fence} or > {upper_fence}')
        return lower_fence, upper_fence

# Example Usage
normal_outlier_detector = NormalOutlierDetector(df)

# Replace 'column_name' with your actual column name
for column in normal_columns:
    normal_outlier_detector.find_outliers_zscore(column)
```

```
account length outliers are values < -18.401511305138754 or > 220.53112426643486
total day minutes outliers are values < 16.372929902636827 or > 343.17726511686504
total day calls outliers are values < 40.22839094245375 or > 160.64289618625912
total day charge outliers are values < 2.784003568931574 or > 58.340610892514576
total eve minutes outliers are values < 48.83881475736749 or > 353.12188131223945
total eve calls outliers are values < 40.346435549313796 or > 159.8821873129724
total eve charge outliers are values < 4.151537424704381 or > 30.015543283366426
total night minutes outliers are values < 49.1504961627453 or > 352.59357824469544
total night calls outliers are values < 41.401882732901434 or > 158.81353880925278
total night charge outliers are values < 2.2117064195131624 or > 15.866943445473336
total intl minutes outliers are values < 1.8617750841476894 or > 18.612812374598185
total intl charge outliers are values < 0.5032636201566767 or > 5.025899296134952
```

In [106]:
```
def handle_skewed_outliers(df, columns):
    for column in columns:
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)
        IQR = Q3 - Q1
        outliers = df[(df[column] < (Q1 - 1.5 * IQR)) | (df[column] > (Q3 + 1.5 * IQR))]
        print(f'{column} has {len(outliers)} outliers.')

        # Optionally remove or cap outliers
        # df = df[~((df[column] < (Q1 - 1.5 * IQR)) | (df[column] > (Q3 + 1.5 * IQR)))]
        # Alternatively, cap outliers:
        # df[column] = df[column].clip(lower=(Q1 - 1.5 * IQR), upper=(Q3 + 1.5 * IQR))

    return df

skewed_columns = ['area code', 'number vmail messages', 'total intl calls', 'customer service cal

df = handle_skewed_outliers(df, skewed_columns)
```

```
area code has 0 outliers.
number vmail messages has 1 outliers.
total intl calls has 78 outliers.
customer service calls has 267 outliers.
```

In [107]:
```
class OutlierDetector:
    def __init__(self, dataframe):
        self.dataframe = dataframe

    def find_outliers_iqr(self, column):
        IQR = self.dataframe[column].quantile(0.75) - self.dataframe[column].quantile(0.25)
        lower_fence = self.dataframe[column].quantile(0.25) - (IQR * 3)
        upper_fence = self.dataframe[column].quantile(0.75) + (IQR * 3)
        print(f'{column} outliers are values < {lower_fence} or > {upper_fence}')
        return lower_fence, upper_fence

# Example Usage
outlier_detector = OutlierDetector(df)

# Replace 'column_name' with your actual column name
for column in skewed_columns:
    outlier_detector.find_outliers_iqr(column)
```

```
area code outliers are values < 102.0 or > 816.0
number vmail messages outliers are values < -60.0 or > 80.0
total intl calls outliers are values < -6.0 or > 15.0
customer service calls outliers are values < -2.0 or > 5.0
```

## 4.Declare Feature and target Variable

In [108]:
```
 x = df.drop('churn', axis=1)
y = df['churn'].astype(int)
```

## 5.Data Spliting into separate training and test sets

In [109]:
```
# split X and y into training and testing sets

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

In [110]:
```
# check the shape of X_train and X_test

X_train.shape, X_test.shape
```

Out[110]:
```
((2666, 19), (667, 19))
```

## 6.Feature Scaling

Standardization: Useful if features have different units. It rescales features to have a mean of 0 and a standard deviation of 1. Normalization: Rescales the features to a range of [0, 1], often useful for algorithms like Logistic Regression.

In [111]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Standardization
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X.select_dtypes(include=[float, int]))

# Normalization
normalizer = MinMaxScaler()
X_normalized = normalizer.fit_transform(X.select_dtypes(include=[float, int]))
```

# 7.Feature Engineering

Interactions:I'll Consider creating interaction terms if certain combinations of features could have a significant impact on the target. Polynomial Features:I'll Create polynomial features if non-linear relationships are suspected.

In [112]:
```
from sklearn.preprocessing import PolynomialFeatures

# Polynomial features
poly = PolynomialFeatures(degree=2, interaction_only=True)
X_poly = poly.fit_transform(X.select_dtypes(include=[float, int]))
```

# 8.Feature Selection

Feature Importance: Use models like Random Forest or Logistic Regression with regularization to identify the most important numeric features. Univariate Feature Selection: Use statistical tests to select features that have the strongest relationship with the target variable.

In [113]:
```
from sklearn.feature_selection import SelectKBest, f_classif

# Univariate feature selection
selector = SelectKBest(score_func=f_classif, k='all')
X_selected = selector.fit_transform(X_scaled, y)
print(selector.scores_)
```

```
[146.35078522 146.35065699  28.93257664  28.92644376   4.20149555
   4.20213628  15.58346799  15.59258061]
```

## 9.Combine Preprocessed Features

After scaling and transforming our numeric features, we now combine them with your encoded categorical features before modeling.

In [114]:
```
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

# Assume `categorical_features` are the columns that need encoding
categorical_features = ['state', 'international plan', 'voice mail plan']
numeric_features = X.select_dtypes(include=[float, int]).columns.tolist()

# OneHotEncode categorical features and combine with scaled numeric features
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_features),  # or use your preferred scaler
        ('cat', OneHotEncoder(), categorical_features)])

# Preprocessing pipeline
X_processed = preprocessor.fit_transform(X)

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_processed, y, test_size=0.3, random_state=4
```

# 10. Modeling

## 10.1. Logistic Regression

In [118]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score

# Logistic Regression model
log_reg = LogisticRegression(class_weight='balanced', random_state=42)
log_reg.fit(X_train, y_train)

# Predictions
y_pred = log_reg.predict(X_test)
y_prob = log_reg.predict_proba(X_test)[:, 1]

# Evaluation
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
print("AUC-ROC Score:", roc_auc_score(y_test, y_prob))
```

```
[[630 227]
 [ 53  90]]
              precision    recall  f1-score   support

           0       0.92      0.74      0.82       857
           1       0.28      0.63      0.39       143

    accuracy                           0.72      1000
   macro avg       0.60      0.68      0.60      1000
weighted avg       0.83      0.72      0.76      1000

AUC-ROC Score: 0.7300144429666017
```

### Interpretation

Class 0 Performance (Non-churn):

The model performs well with class 0, achieving high precision (0.92) and a decent recall (0.74). This means the model is good at correctly identifying non-churn cases, but it sometimes misclassifies churn cases as non-churn (as indicated by the recall of 0.74).

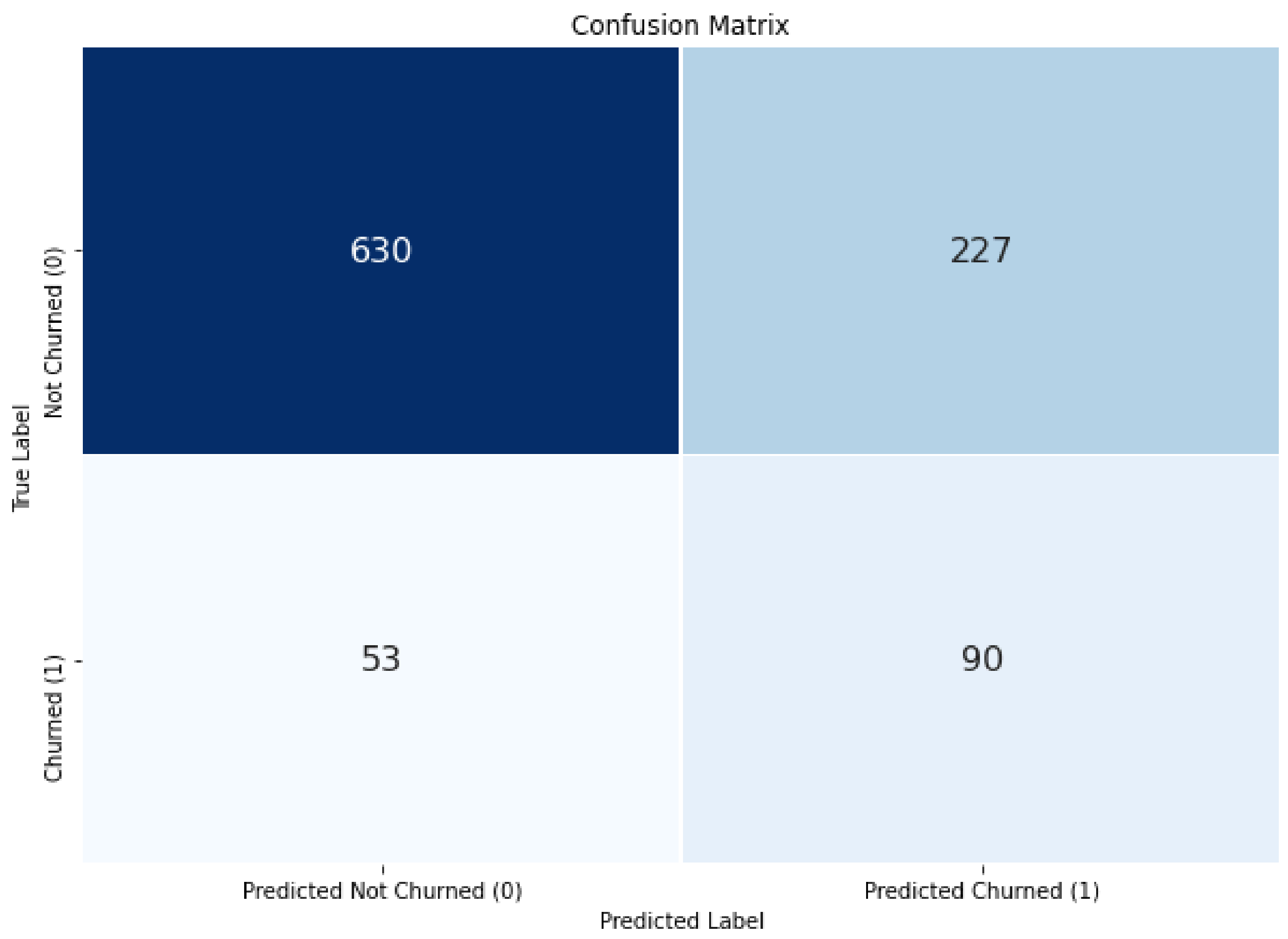
Class 1 Performance (Churn):

The model struggles with class 1 (churn), with a low precision of 0.28, meaning many non-churn cases are misclassified as churn. However, the recall is 0.63, meaning the model correctly identifies 63% of the actual churn cases. The F1-score of 0.39 reflects the balance between precision and recall for this class, indicating room for improvement.

AUC-ROC Score

AUC-ROC Score: 0.730. The AUC-ROC score is the area under the ROC curve and is a measure of the model's ability to distinguish between the positive class (churn) and the negative class (non-churn). A score of 0.73 indicates a good level of separability between the two classes, though there is room for improvement.

In [116]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Define the confusion matrix values
conf_matrix = [[630, 227],
               [53, 90]]

# Create a DataFrame for better visualization
conf_matrix_df = pd.DataFrame(conf_matrix, index=['Not Churned (0)', 'Churned (1)'],
                              columns=['Predicted Not Churned (0)', 'Predicted Churned (1)'])

# Plot the confusion matrix
plt.figure(figsize=(10, 7))
sns.heatmap(conf_matrix_df, annot=True, fmt='d', cmap='Blues', cbar=False,
            annot_kws={"size": 16}, linewidths=0.5)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```




#### 10.1.1.Confusion Matrix Interpretation:

True Negatives (TN): 630

Customers correctly predicted as Not Churned.

False Positives (FP): 227

Customers incorrectly predicted as Churned when they actually did not churn.

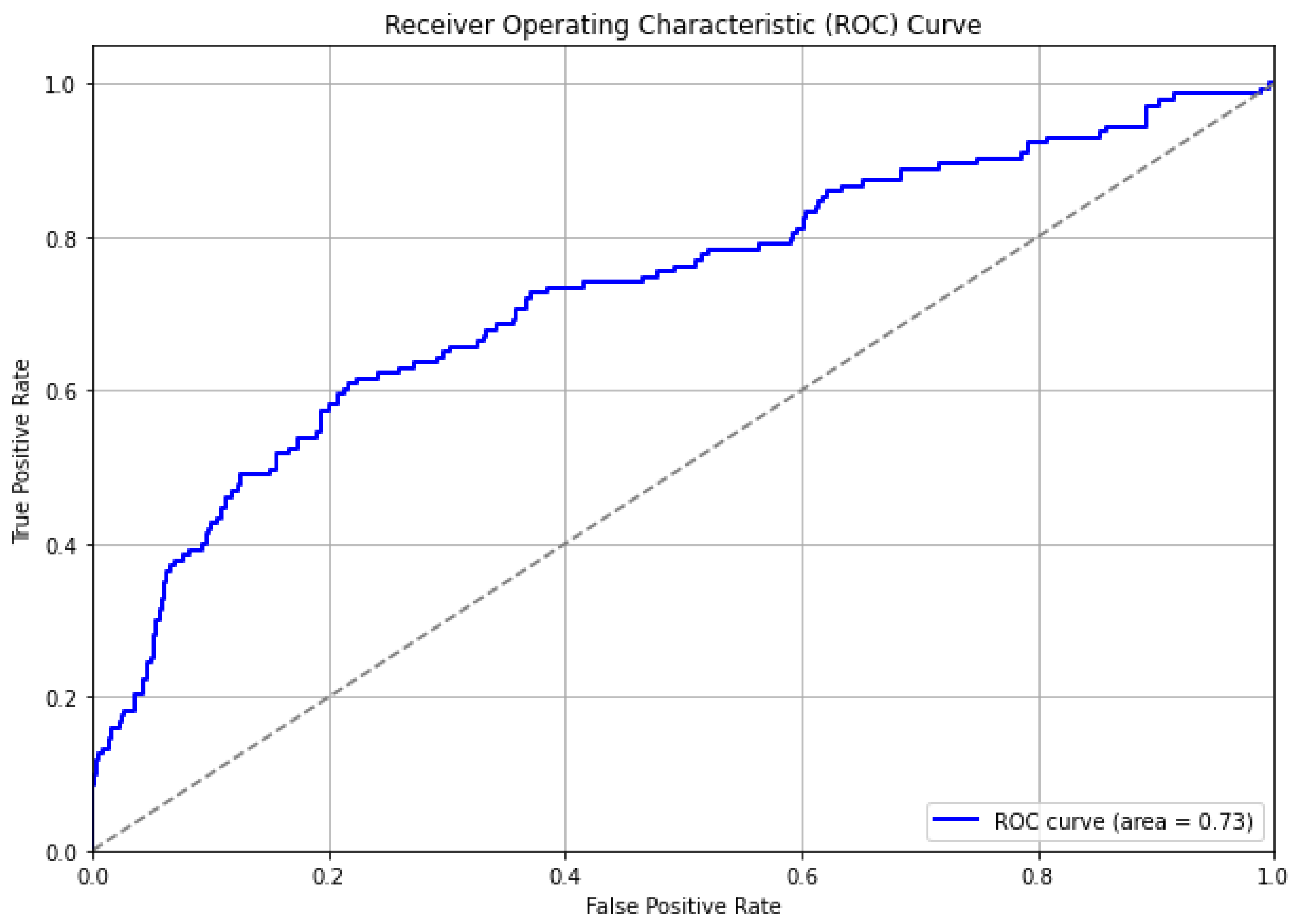
False Negatives (FN): 53

Customers incorrectly predicted as Not Churned when they actually did churn.

True Positives (TP): 90

Customers correctly predicted as Churned.

In [119]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc


# Compute ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)  # Calculate the AUC score

# Plot ROC curve
plt.figure(figsize=(10, 7))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')  # Diagonal line for random classifier
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) Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```




**Key observations from the plot:**

The ROC curve (blue line) rises above the diagonal line (which represents a random classifier with no predictive power).

The area under the curve (AUC) is approximately 0.83, which indicates that the model has a good ability to distinguish between the two classes.

## 10.2.Random Forest Classifier

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier

# Initialize and train the model
rf_clf = RandomForestClassifier(random_state=42)
rf_clf.fit(X_train, y_train)

# Make predictions
rf_y_pred = rf_clf.predict(X_test)

# Evaluate the model
print(confusion_matrix(y_test, rf_y_pred))
print(classification_report(y_test, rf_y_pred))
```

```
[[853   4]
 [ 86  57]]
              precision    recall  f1-score   support

           0       0.91      1.00      0.95       857
           1       0.93      0.40      0.56       143

    accuracy                           0.91      1000
   macro avg       0.92      0.70      0.75      1000
weighted avg       0.91      0.91      0.89      1000
```

## Breakdown:

True Negatives (TN): 853

The number of customers correctly predicted as not churned. False Positives (FP): 4

The number of customers incorrectly predicted as churned when they actually did not churn. False Negatives (FN): 86

The number of customers incorrectly predicted as not churned when they actually did churn. True Positives (TP): 57

The number of customers correctly predicted as churned. Classification Report For Not Churned (Class 0) Precision: 0.91

Among the customers predicted to not churn, 91% were correctly predicted. This shows that when the model predicts a customer will stay, it's highly accurate. Recall: 1.00

Among all actual non-churned customers, the model identified 100% correctly. This perfect recall means that the model is excellent at identifying customers who do not churn. F1-Score: 0.95

The harmonic mean of precision and recall, reflecting a strong performance in predicting non-churned customers. For Churned (Class 1) Precision: 0.93

Among the customers predicted to churn, 93% actually churned. This high precision means that when the model predicts churn, it's very accurate. Recall: 0.40

Among all actual churned customers, only 40% were correctly identified. This lower recall suggests that the model misses a significant portion of churned customers. F1-Score: 0.56

The harmonic mean of precision and recall for churned customers. An F1-score of 0.56 indicates that while precision is high, the model struggles with recall for churned customers. Overall Metrics Accuracy: 0.91

The proportion of correctly predicted instances (both churned and not churned) out of all predictions. The accuracy of 91% shows that the model performs well overall. Macro Average:

Precision: 0.92 Recall: 0.70 F1-Score: 0.75 These metrics average the performance across both classes without considering the imbalance in class distribution. They show that the model performs well in precision but has a moderate recall. Weighted Average:

Precision: 0.91 Recall: 0.91 F1-Score: 0.89 These metrics account for the imbalance in class frequencies, providing a more balanced view of the model's performance across classes. Summary Based on Churn Performance for Not Churned (Class 0):

The model performs excellently in predicting customers who will not churn, with high precision and perfect recall. This indicates strong performance in identifying customers who will stay. Performance for Churned (Class 1):

The model is less effective at identifying churned customers. Despite high precision, the recall is low, meaning many churned customers are missed. This suggests a need for improvement in capturing all churned customers. Overall Model Performance:

The model achieves high overall accuracy (91%) and good precision but has room for improvement in recall, especially for the churned class.#

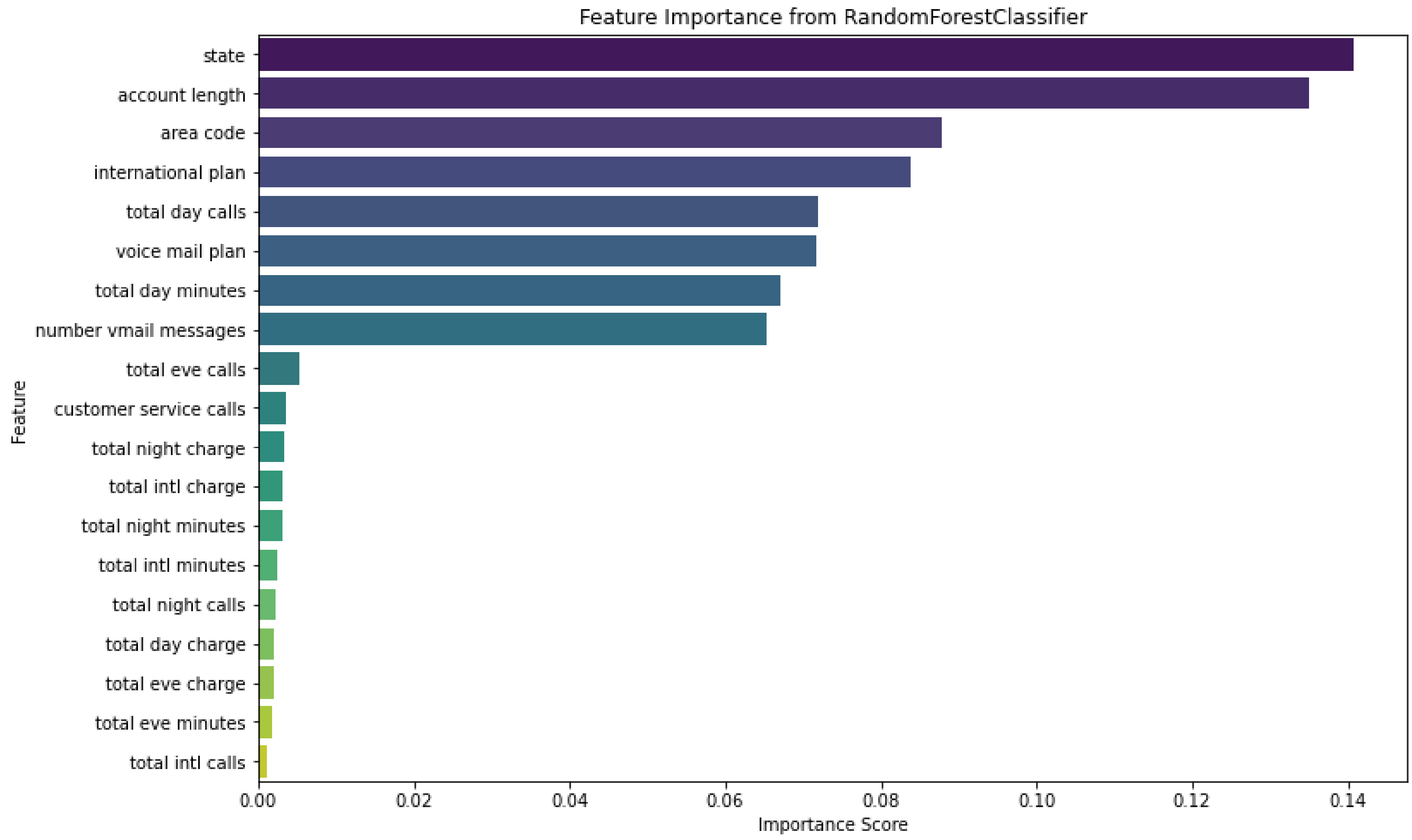
#### 10.2.1 Feature Importance

Analyze Feature Importance

Check feature importance from the Random Forest model.

In [129]:
```
# Extract feature importances
importances = rf_clf.feature_importances_

# Define feature names based on your initial dataset
feature_names = [
    'state',
    'account length',
    'area code',
    'international plan',
    'voice mail plan',
    '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'
]

# Adjust lengths if they don't match
if len(feature_names) > len(importances):
    feature_names = feature_names[:len(importances)]
elif len(importances) > len(feature_names):
    importances = importances[:len(feature_names)]

# Create DataFrame for feature importances
feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': importances})
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

# Display the DataFrame
print("\nFeature Importance DataFrame:")
print(feature_importance_df)

# Visualization
plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df, palette='viridis')
plt.title('Feature Importance from RandomForestClassifier')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.show()
```

```
Feature Importance DataFrame:
                   Feature  Importance
0                    state    0.140654
1           account length    0.135059
2                area code    0.087748
3       international plan    0.083961
7          total day calls    0.071853
4          voice mail plan    0.071775
6        total day minutes    0.067029
5    number vmail messages    0.065312
10         total eve calls    0.005283
18  customer service calls    0.003610
14      total night charge    0.003338
17       total intl charge    0.003115
12     total night minutes    0.003087
15      total intl minutes    0.002460
13       total night calls    0.002188
8         total day charge    0.002128
11        total eve charge    0.002076
9        total eve minutes    0.001799
16        total intl calls    0.001098
```




## Top Features:

**State (0.140654):** This feature has the highest importance, indicating that the customer's state is a strong predictor of churn in this model.

**Account length (0.135059):** The length of time a customer has had their account also plays a significant role in predicting churn.

**Area code (0.087748): The area code of the customer's phone number is another important factor.**

**International plan (0.083961):** Whether a customer has an international plan impacts the likelihood of churn.

**Total day calls (0.071853):** The total number of day calls made by the customer is another significant feature.

**Voice mail plan (0.071775):** Whether a customer has a voicemail plan also affects the churn prediction.

## Less Important Features:

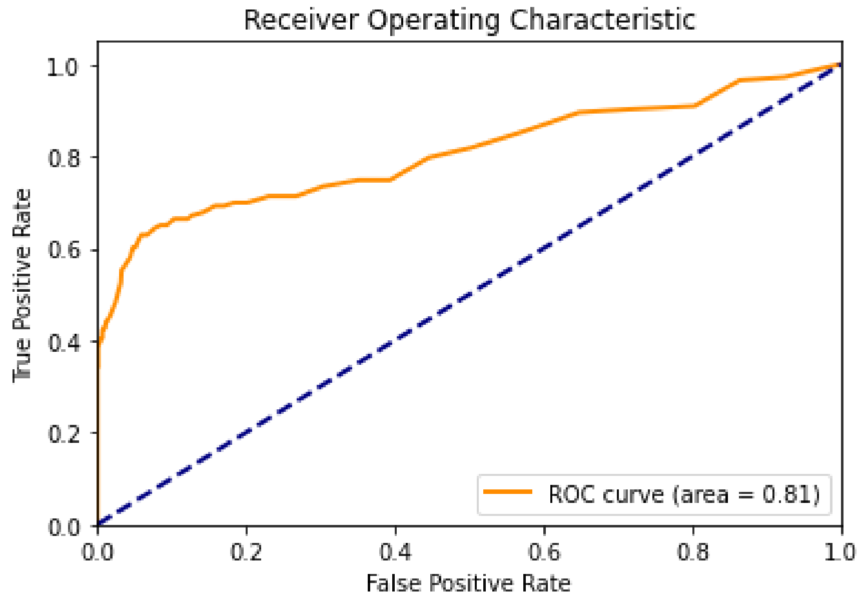
Total international calls (0.001098), Total evening minutes (0.001799), and other low-importance features contribute little to the model's decisions and may have a minimal impact on the churn prediction.

## Interpretation:

Features like state, account length, and area code are major drivers of the model’s predictions. These could be due to regional differences in service quality, competition, or customer behavior.

International and voice mail plans likely influence customer satisfaction and their decision to stay with or leave the service.

In [ ]:
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Get the probability scores
y_probs = rf_clf.predict_proba(X_test)[:, 1]

# Compute ROC curve and AUC
fpr, tpr, _ = roc_curve(y_test, y_probs)
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
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')
plt.legend(loc='lower right')
plt.show()
```




In [ ]:
```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(class_weight='balanced', random_state=42)
```

In [ ]:
```
# Assuming X_train and y_train are our training data and labels
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
```

Out[170]:
```
RandomForestClassifier(random_state=42)
```

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

In [ ]:
```
# Predict probabilities for the test set
y_probs = model.predict_proba(X_test)[:, 1]
```

In [ ]:
```
from sklearn.metrics import roc_curve

# Predict probabilities
y_probs = model.predict_proba(X_test)[:, 1]

# Find the optimal threshold
fpr, tpr, thresholds = roc_curve(y_test, y_probs)
optimal_idx = np.argmax(tpr - fpr)
optimal_threshold = thresholds[optimal_idx]
optimal_threshold
```

Out[172]:
```
0.28
```

A threshold of 0.28 in the context of random forest means we're classifying a sample as positive (e.g., class 1) if the model predicts a probability of at least 28% for that class. This approach can be useful in scenarios where missing a positive case (e.g., a customer likely to churn) is more costly than falsely predicting a negative case as positive.

# 10.3.Decision Tree

In [ ]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score

# Decision Tree model
dt = DecisionTreeClassifier(class_weight='balanced', random_state=1)
dt.fit(X_train, y_train)

# Predictions
y_pred = dt.predict(X_test)
y_prob = dt.predict_proba(X_test)[:, 1]

# Evaluation
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
print("AUC-ROC Score:", roc_auc_score(y_test, y_prob))
```

```
[[765  92]
 [ 68  75]]
              precision    recall  f1-score   support

           0       0.92      0.89      0.91       857
           1       0.45      0.52      0.48       143

    accuracy                           0.84      1000
   macro avg       0.68      0.71      0.69      1000
weighted avg       0.85      0.84      0.85      1000

AUC-ROC Score: 0.708562149635662
```

**Interpretation**:

Precision for False is 0.92, meaning that when the model predicts False, it’s correct 92% of the time. For True, the precision is 0.45, indicating the model is correct 45% of the time when it predicts True.

Recall for False is 0.89, meaning the model identifies 89% of the actual False cases. For True, the recall is 0.52, indicating the model identifies 52% of the actual True cases.

F1-score is the harmonic mean of precision and recall. For False, it’s 0.91 and for True, it’s 0.48. The F1-score is useful for balancing precision and recall.

Accuracy is 0.84, which is the proportion of correctly classified instances.

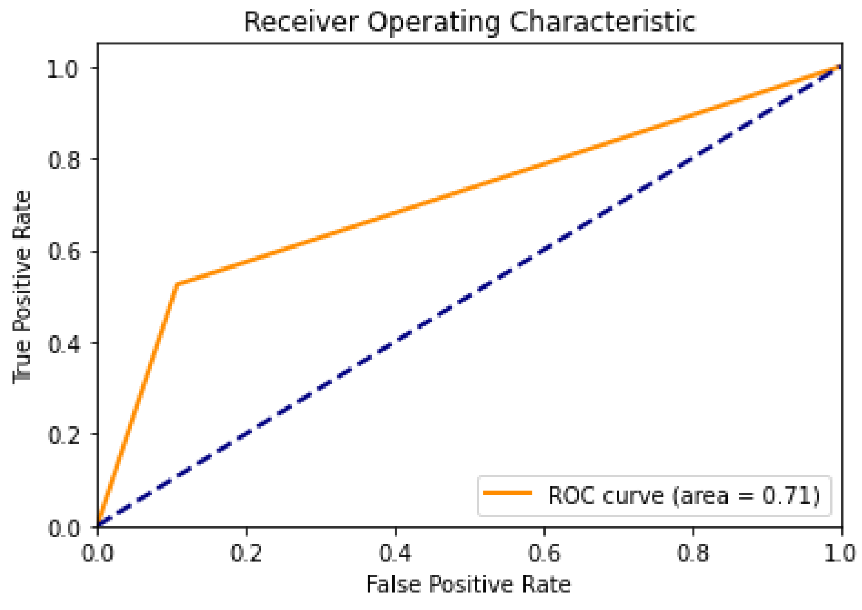
Macro average gives equal weight to each class, regardless of support, and it averages precision, recall, and F1-score.

Weighted average takes into account the support of each class, averaging the metrics by the number of true instances in each class.

AUC-ROC Score of 0.71 indicates how well the model distinguishes between the classes, with 1 being perfect discrimination and 0.5 being no discrimination.

Overall, your model performs well in classifying False cases but struggles more with True cases. Depending on your use case, you might need to adjust the model to improve its performance on the minority class (True). Consider techniques like oversampling, undersampling, or adjusting the decision threshold.

In [ ]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, roc_auc_score

# ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
auc_score = roc_auc_score(y_test, y_prob)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = {:.2f})'.format(auc_score))
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')
plt.legend(loc="lower right")
plt.show()
```

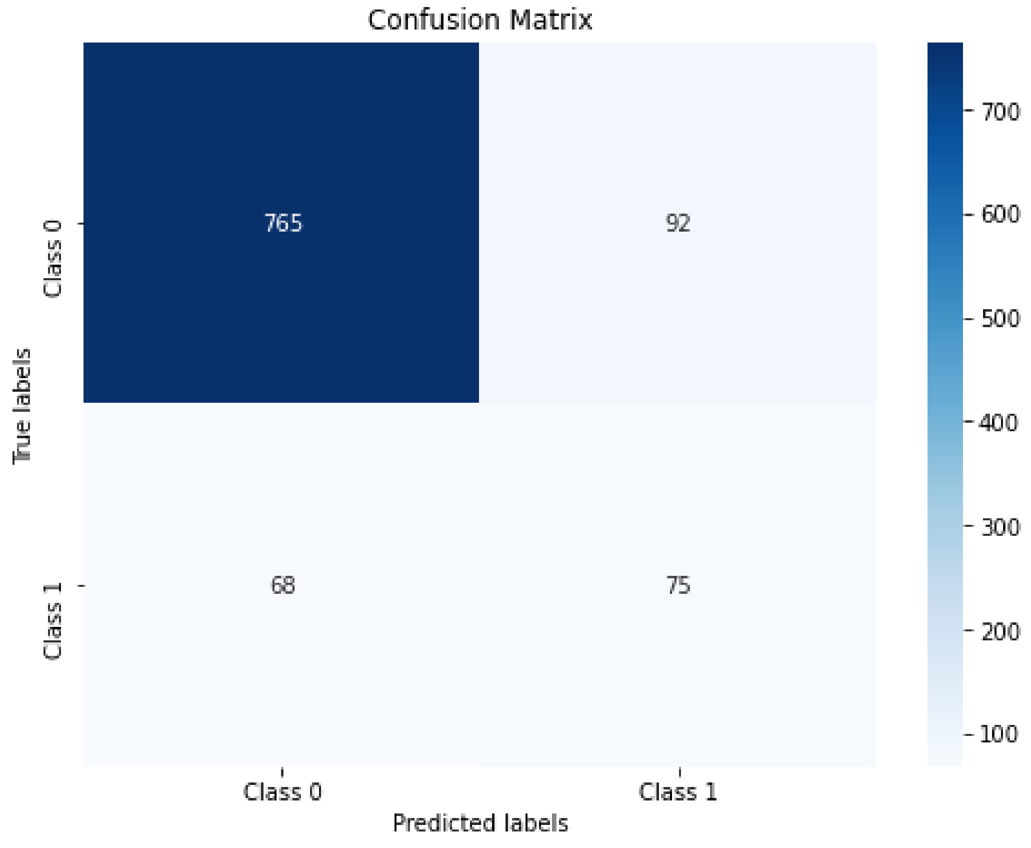



**Interpretation:**

AUC = 0.71: This value indicates that the model has a moderate ability to distinguish between the positive and negative classes. An AUC of 0.71 suggests that, on average, the model has a 71% chance of ranking a randomly chosen positive instance higher than a randomly chosen negative one.

ROC Curve Shape: The shape of the curve appears to be less smooth and more angular, which might suggest a smaller or more imbalanced dataset, or it could indicate that the model's predictions are less certain or the classification boundaries are not well-defined.

In [ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Class 0', 'Class 1'], yticklabel
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()
```




**10.3.1.Model Tuning and Visualization** Hyperparameter Tuning

Decision Trees have several hyperparameters that you can tune to improve model performance, such as max_depth, min_samples_split, and min_samples_leaf.

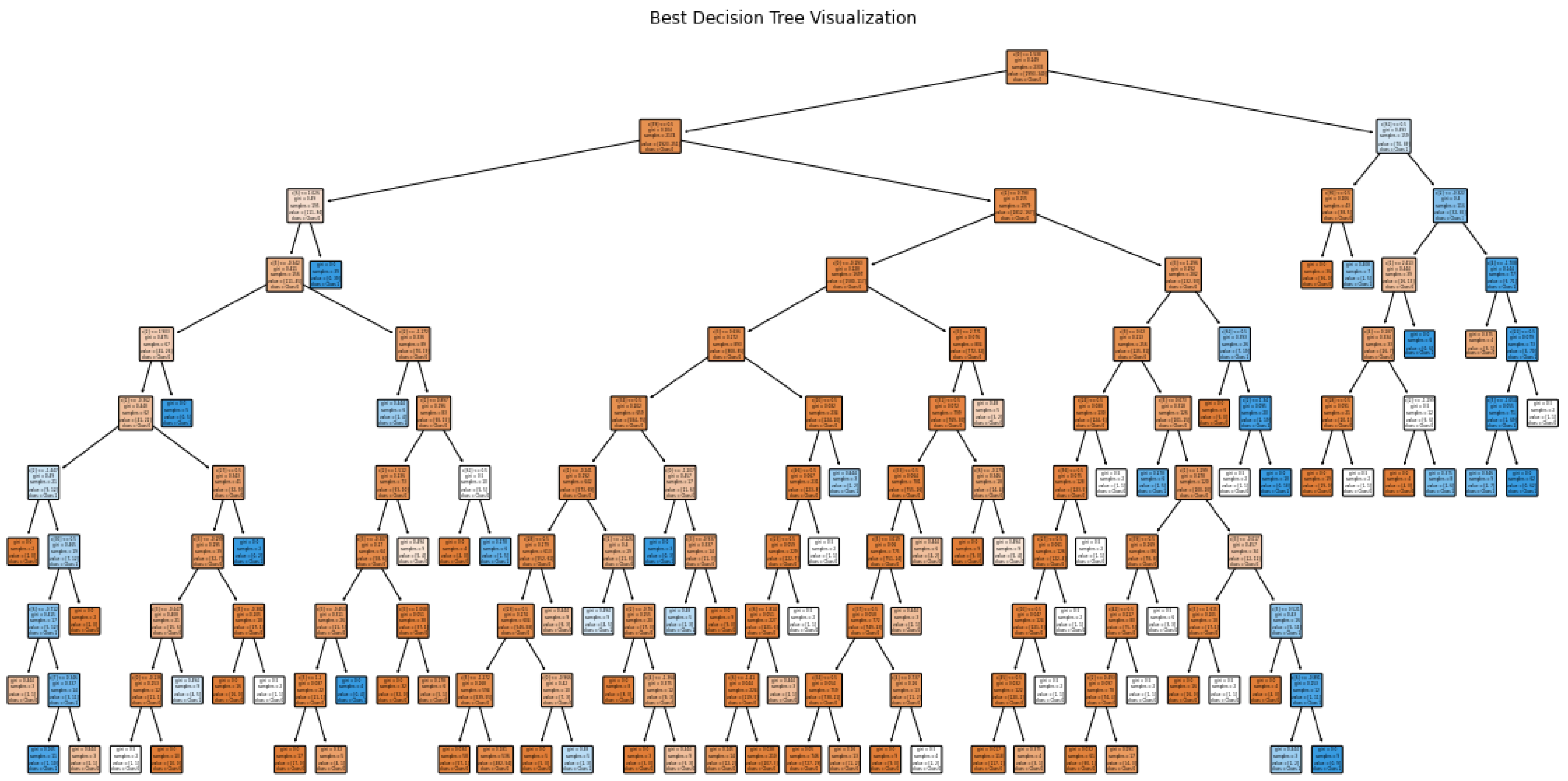
In [ ]:
```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid
param_grid = {
    'max_depth': [None, 10, 20, 30, 40, 50],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Initialize GridSearchCV
grid_search = GridSearchCV(DecisionTreeClassifier(random_state=42), param_grid, cv=5, scoring='ac

# Fit GridSearchCV
grid_search.fit(X_train, y_train)

# Best parameters
print("Best parameters:", grid_search.best_params_)

# Best model
best_dt_classifier = grid_search.best_estimator_

# Make predictions with the best model
best_dt_y_pred = best_dt_classifier.predict(X_test)

# Evaluate the best model
print(confusion_matrix(y_test, best_dt_y_pred))
print(classification_report(y_test, best_dt_y_pred))
```

```
Best parameters: {'max_depth': 10, 'min_samples_leaf': 2, 'min_samples_split': 10}
[[815  42]
 [ 73  70]]
              precision    recall  f1-score   support

           0       0.92      0.95      0.93       857
           1       0.62      0.49      0.55       143

    accuracy                           0.89      1000
   macro avg       0.77      0.72      0.74      1000
weighted avg       0.88      0.89      0.88      1000
```

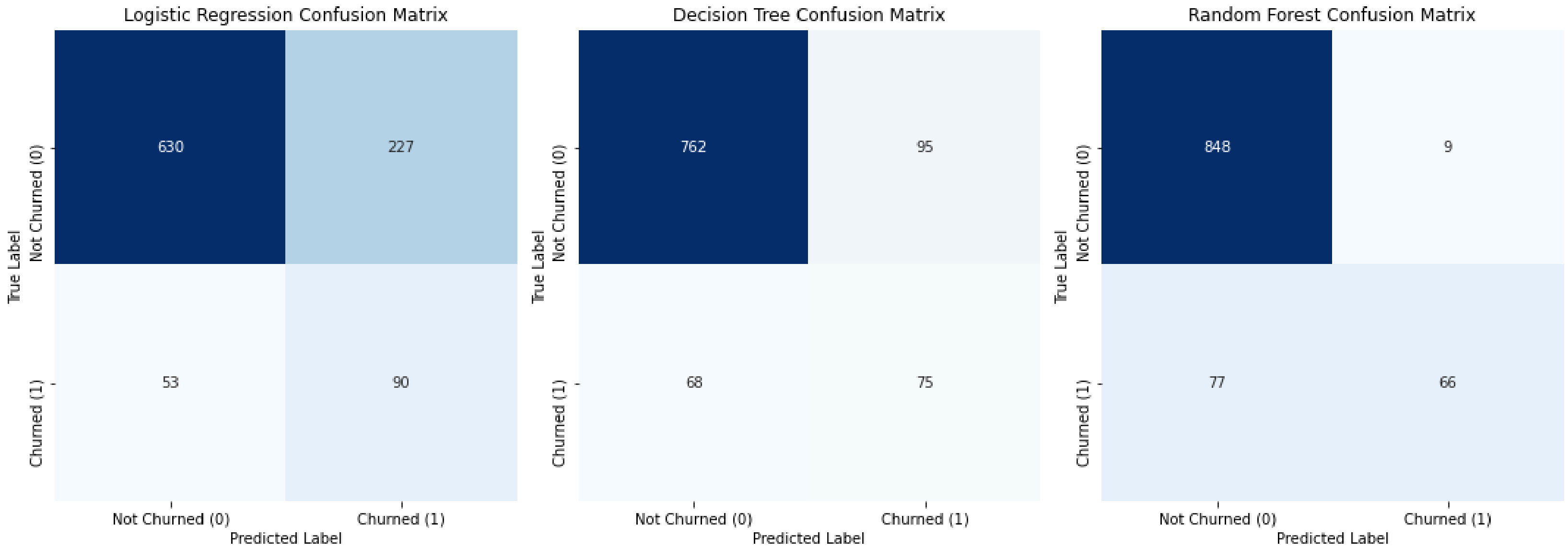
#### 10.3.2Visualize the Decision Tree

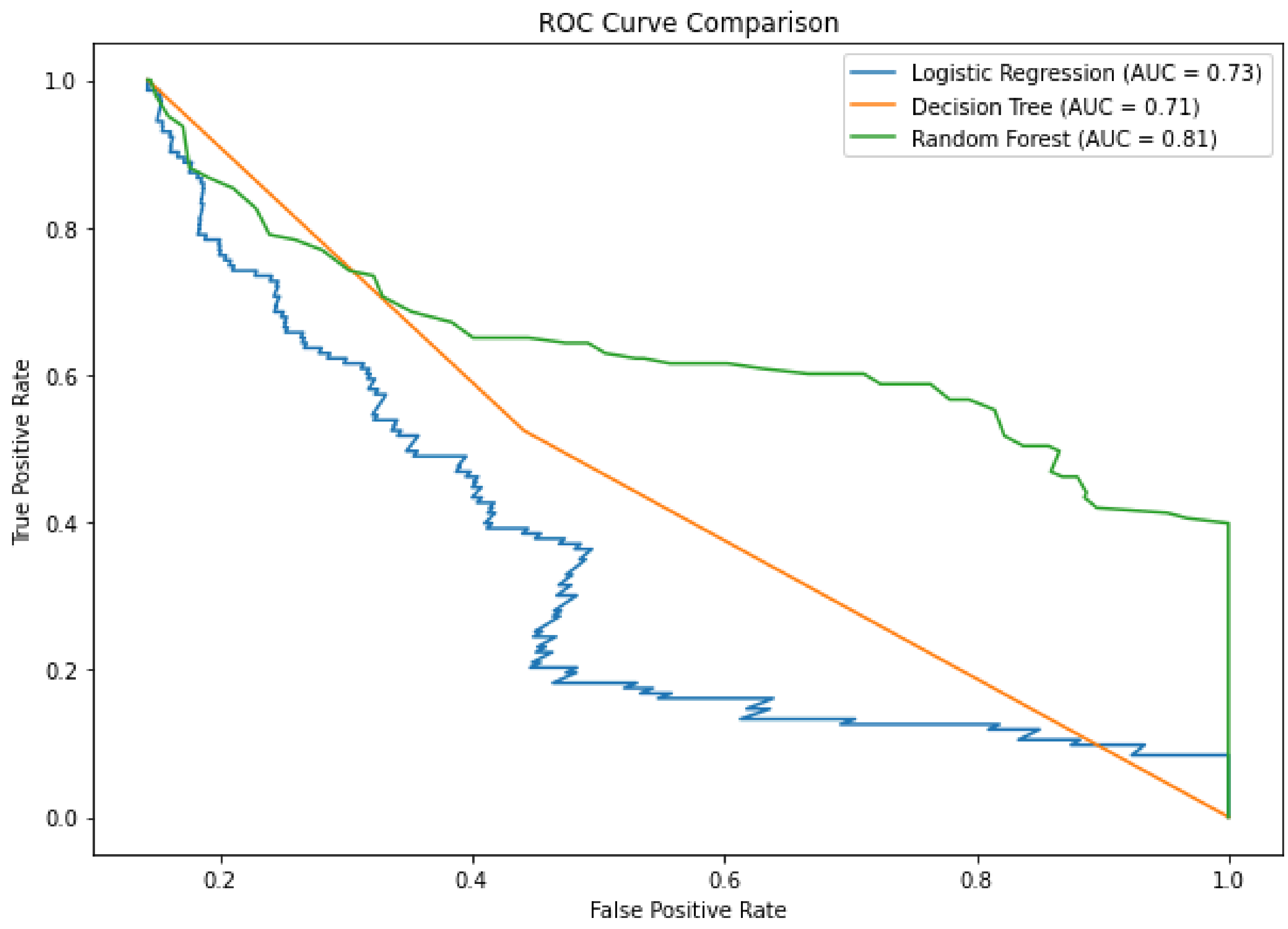
Visualizing the Decision Tree can help understand how the model makes decisions.

In [ ]:
```
# Plot the Decision Tree without feature names
plt.figure(figsize=(20, 10))
plot_tree(best_dt_classifier, filled=True, class_names=['Class 0', 'Class 1'], rounded=True)
plt.title('Best Decision Tree Visualization')
plt.show()
```



In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score, precision_rec
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

# Sample data
# Replace this with your actual data loading process
# X = features, y = target
# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize models
models = {
    "Logistic Regression": LogisticRegression(class_weight='balanced', random_state=42),
    "Decision Tree": DecisionTreeClassifier(class_weight='balanced', random_state=42),
    "Random Forest": RandomForestClassifier(class_weight='balanced', random_state=42)
}

# Fit models and make predictions
results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_prob = model.predict_proba(X_test)[:, 1]

    # Evaluate model
    conf_matrix = confusion_matrix(y_test, y_pred)
    report = classification_report(y_test, y_pred, output_dict=True)
    auc_score = roc_auc_score(y_test, y_prob)

    results[name] = {
        "Confusion Matrix": conf_matrix,
        "Classification Report": report,
        "AUC-ROC Score": auc_score
    }

# Plot confusion matrix
plt.figure(figsize=(15, 10))
for i, (name, result) in enumerate(results.items(), 1):
    plt.subplot(2, 3, i)
    sns.heatmap(result["Confusion Matrix"], annot=True, fmt='d', cmap='Blues', cbar=False,
                xticklabels=['Not Churned (0)', 'Churned (1)'], yticklabels=['Not Churned (0)', '
    plt.title(f'{name} Confusion Matrix')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')

plt.tight_layout()
plt.show()

# Plot ROC curve
plt.figure(figsize=(10, 7))
for name, result in results.items():
    fpr, tpr, _ = precision_recall_curve(y_test, models[name].predict_proba(X_test)[:, 1])
    plt.plot(fpr, tpr, label=f'{name} (AUC = {result["AUC-ROC Score"]:.2f})')

plt.title('ROC Curve Comparison')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='best')
plt.show()

# Print classification reports and AUC-ROC Scores
for name, result in results.items():
    print(f'\n{name} Classification Report:')
    print(classification_report(y_test, models[name].predict(X_test)))
    print(f'AUC-ROC Score: {result["AUC-ROC Score"]:.2f}')
```




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

           0       0.92      0.74      0.82       857
           1       0.28      0.63      0.39       143

    accuracy                           0.72      1000
   macro avg       0.60      0.68      0.60      1000
weighted avg       0.83      0.72      0.76      1000

AUC-ROC Score: 0.73

Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.89      0.90       857
           1       0.44      0.52      0.48       143

    accuracy                           0.84      1000
   macro avg       0.68      0.71      0.69      1000
weighted avg       0.85      0.84      0.84      1000

AUC-ROC Score: 0.71

Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.99      0.95       857
           1       0.88      0.46      0.61       143

    accuracy                           0.91      1000
   macro avg       0.90      0.73      0.78      1000
weighted avg       0.91      0.91      0.90      1000

AUC-ROC Score: 0.81
```

# Let's compare the performance of the three models—Logistic Regression, Decision Tree, and Random Forest :

**1. Logistic Regression**

Classification Report:

Precision for 0 (Not Churned): 0.92

Recall for 0: 0.74

F1-Score for 0: 0.82

Precision for 1 (Churned): 0.28

Recall for 1: 0.63

F1-Score for 1: 0.39

Accuracy: 0.72

Macro Average Precision: 0.60

Macro Average Recall: 0.68

Macro Average F1-Score: 0.60

Weighted Average Precision: 0.83

Weighted Average Recall: 0.72

Weighted Average F1-Score: 0.76

AUC-ROC Score: 0.73

# Explanation:

**Strengths:** High precision for non-churned customers (0) and a reasonable AUC-ROC score.

**Weaknesses:** Low precision for churned customers (1) indicates that the model often predicts churn incorrectly, and overall recall for churned customers is not very high. The model has a moderate accuracy.

**2. Decision Tree**

Classification Report:

Precision for 0: 0.92

Recall for 0: 0.89

F1-Score for 0: 0.90

Precision for 1: 0.44

Recall for 1: 0.52

F1-Score for 1: 0.48

Accuracy: 0.84

Macro Average Precision: 0.68

Macro Average Recall: 0.71

Macro Average F1-Score: 0.69

Weighted Average Precision: 0.85

Weighted Average Recall: 0.84

Weighted Average F1-Score: 0.84

AUC-ROC Score: 0.71

## Explanation:

**Strengths:** Good precision and recall for non-churned customers (0), and decent overall accuracy. The F1-score for non-churned customers is high, indicating the model performs well in this category.

**Weaknesses:** Lower precision and recall for churned customers (1) compared to the non-churned class. The overall AUC-ROC score is lower than the Random Forest model, indicating it may not distinguish between classes as well.

**3. Random Forest**

Classification Report:

Precision for 0: 0.92

Recall for 0: 0.99

F1-Score for 0: 0.95

Precision for 1: 0.88

Recall for 1: 0.46

F1-Score for 1: 0.61

Accuracy: 0.91

Macro Average Precision: 0.90

Macro Average Recall: 0.73

Macro Average F1-Score: 0.78

Weighted Average Precision: 0.91

Weighted Average Recall: 0.91

Weighted Average F1-Score: 0.90

AUC-ROC Score: 0.81

### Explanation:

**Strengths:** Excellent precision and recall for non-churned customers (0) and a high AUC-ROC score. Overall accuracy and weighted F1-score are very high.

**Weaknesses:** Lower recall for churned customers (1), meaning the model misses some churned customers. However, its precision for the churned class is good.

## Summary of Comparison:

Random Forest performs the best overall, with the highest accuracy and AUC-ROC score. It shows strong performance in identifying non-churned customers and has good precision for churned customers, though its recall for churned customers is still moderate.

Decision Tree provides a decent balance, with good performance for non-churned customers and reasonable accuracy, but its AUC-ROC score is lower compared to Random Forest. Precision and recall for churned customers are better than Logistic Regression but not as high as Random Forest.

Logistic Regression has lower overall performance compared to the other two models, especially in terms of precision and recall for churned customers. Its AUC-ROC score is also lower, indicating less ability to distinguish between churned and non-churned customers compared to Random Forest.

## Recommendations:

Random Forest would be the preferred model based on overall performance, particularly if identifying churned customers is critical.

Decision Tree could be a good alternative if interpretability is a key requirement.

Logistic Regression may still be useful for its simplicity and speed but might require further tuning or feature engineering to improve performance.

## Feature Impact on Customer Churn based on our best performing model

**High Impact Features**

**State (Importance: 0.140654)**

The state where a customer is located is the most influential feature in predicting churn. Differences in churn rates between states could reflect regional factors affecting customer satisfaction or service quality.

**Account Length (Importance: 0.135059)**

The length of the customer's account plays a significant role. Customers with longer account durations may exhibit different churn patterns compared to newer customers, possibly due to varying levels of loyalty or satisfaction over time.

**Area Code (Importance: 0.087748)**

The area code is also a notable predictor of churn. This might be related to regional service quality, pricing, or competition.

**International Plan (Importance: 0.083961)**

Whether a customer has an international plan influences their likelihood of churning. This feature might reflect the customer’s usage pattern and preferences for international communication.

**Total Day Calls (Importance: 0.071853)**

The number of daytime calls a customer makes has a moderate impact on churn prediction. It could be indicative of the customer’s engagement with the service.

# Medium Impact Features

**Voice Mail Plan (Importance: 0.071775)**

Having a voice mail plan affects churn probability. It could be linked to customer satisfaction with available features.

**Total Day Minutes (Importance: 0.067029)**

The total duration of daytime calls contributes moderately to churn predictions, reflecting usage patterns and possibly customer satisfaction with daytime service.

**Number of Voicemail Messages (Importance: 0.065312)**

The count of voicemail messages received affects churn likelihood, potentially indicating customer engagement with voice mail services.

# Based on the feature importance analysis, here are some recommendations for SyriaTel to reduce customer churn and improve retention:

**1.Enhance Regional Service Quality**

**Action:** Invest in improving service quality in regions with higher churn rates. Conduct surveys or gather feedback to understand regional issues and address them.

**Rationale:** Since the state has a significant impact on churn, regional service improvements can directly influence customer satisfaction and reduce churn.

**2.Optimize Account Management and Loyalty Programs**

**Action:** Develop targeted loyalty programs and personalized offers for customers based on their account length. Offer incentives for long-term customers to stay engaged.

**Rationale:** Customers with longer account durations are valuable. Retaining them through loyalty programs can enhance their satisfaction and reduce the likelihood of churn.

**3.Review and Enhance International Plans**

**Action:** Assess and potentially improve the features and pricing of international plans. Offer competitive rates and additional benefits for customers who frequently use international services.

**Rationale:** Customers with international plans are more likely to churn. Improving these plans can help retain customers who value international communication.

**4.Improve Daytime Call Services**

**Action:** Monitor and optimize daytime call services to ensure high quality and customer satisfaction. Consider offering promotions or features that enhance the daytime calling experience.

**Rationale:** Total daytime calls have a moderate impact on churn. Enhancing this service can improve customer experience and reduce churn rates.

**5. Optimize Voice Mail and Messaging Services**

**Action:** Monitor and optimize voice mail and messaging services to ensure high quality and customer satisfaction. Consider offering promotions or features that enhance the voice mail experience.

**Rationale:** The count of voicemail messages received has a moderate impact on churn. Enhancing this service can improve customer experience and reduce churn rates.

**6. Implement a Customer Satisfaction Score System**

**Action:** Implement a customer satisfaction score system to assess customer satisfaction levels and provide targeted customer service interventions.

**Rationale:** A customer satisfaction score system can help in identifying high-value customers and proactively engaging with them through targeted customer service interventions.

**7.Monitor and Address Customer Service Interactions**

**Action:** Analyze customer service interactions to identify and address common issues. Train customer service representatives to handle inquiries more effectively and improve the overall customer service experience.

**Rationale:** Although customer service calls have a lower impact, addressing any issues related to customer service can still contribute to overall retention and satisfaction.

**8.Evaluate and Adjust Billing Strategies**

**Action:** Review billing strategies related to nighttime and international calls. Consider offering flexible plans or discounts to customers who are high users of these services.

**Rationale:** Adjusting billing strategies can help in reducing costs and improving customer satisfaction, which in turn can lead to lower churn rates.

**Rationale:** While the impact of charges for nighttime and international calls is relatively low, adjusting billing strategies can still positively affect customer retention.

**9.Conduct Regular Customer Feedback Surveys**

**Action:** Implement regular feedback surveys to gather insights from customers about their experiences and satisfaction levels. Use this feedback to make data-driven improvements.

**Rationale:** Regular feedback helps in identifying areas for improvement and ensuring that customer needs and concerns are addressed promptly.

**10.Personalize Communication and Offers**

**Action:** Use data insights to create personalized communication and offers based on customer usage patterns and preferences.

**Rationale:** Personalization can enhance customer satisfaction and loyalty, making customers feel valued and reducing the likelihood of churn.

**11.Invest in Predictive Analytics**

**Action:** Utilize predictive analytics to identify customers at high risk of churn and proactively engage with them through targeted retention strategies.

**Rationale:** Advanced analytics can help in early identification of at-risk customers, allowing for timely interventions and improved retention efforts.

# Conclusion:

By focusing on targeted retention efforts, improving customer service, optimizing pricing, and personalizing engagement, SyriaTel can better address the factors leading to customer churn. Continuous monitoring and model refinement will ensure these strategies remain effective as customer needs and behaviors evolve.

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