BUSINESS UNDERSTANDING.

Customer churn refers to when a customer stops using a company's services. In the telcommunications industry, this is a critical issue as it directly impacts the company's revenue and growth. For SyriaTeL, it is important to understand the churn rate to be able to manage the customer base to ensure long-term profitability.

Business Problem Statement

SyriaTel is facing a level of customer turnover, resulting in substantial revenue decline. This study seeks to address this challenge by analysing the different factors that contribute to this challenge. Ultimately, the goal is to forecast which customers are likely to discontinue their service and deploy effective retention measures to mitigate this rate. We will be builiding a classification system and to evaluate the performance of the classifier we will use classification metrics including accuarcy, recall, f1score and precision.

Objectives

1. Create different models to discover the patterns which lead to a high rate of customer churn.
2. Develop targeted retention strategies to enhance customer loyalty.

DATA UNDERSTANDING.

We first import the Churn dataset that we will be using for this project.

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import zscore


data = pd.read_csv(r"C:\Users\Administrator\Downloads\
bigml_59c28831336c6604c800002a.csv")
data.head()
```

```
  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 calls  total eve charge  \
0             45.07  ...               99             16.78
1             27.47  ...              103             16.62
2             41.38  ...              110             10.30
3             50.90  ...               88              5.26
4             28.34  ...              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

[5 rows x 21 columns]
```

COLUMN NAMES AND DESCRIPTION OF THE DATASET.

The dataset contains data on the customers of a SyriaTel company. Each row represents a customer and the columns contain customer's attributes which are described in the following:

- state: the state the user lives in
- account length: the number of days the user has this account
- area code: the code of the area the user lives in
- phone number: the phone number of the user

- international plan: true if the user has the international plan.
- voice mail plan: true if the user has the voice mail plan.
- number vmail messages: the number of voice mail messages the user has sent.
- total day minutes: total number of minutes the user has been in calls during the day.
- total day calls: total number of calls the user has done during the day.
- total day charge: total amount of money the user was charged by SyriaTel company for calls during the day.
- total eve minutes: total number of minutes the user has been in calls during the evening.
- total eve calls: total number of calls the user has done during the evening.
- total eve charge: total amount of money the user was charged by SyriaTel company for calls during the evening.
- total night minutes: total number of minutes the user has been in calls during the night.
- total night calls: total number of calls the user has done during the night.
- total night charge: total amount of money the user was charged by SyriaTel company for calls during the night.
- total intl minutes: total number of minutes the user has been in international calls.
- total intl calls: total number of international calls the user has done.
- total intl charge: total amount of money the user was charged by the Telecom company for international calls.
- customer service calls: number of customer service calls the user has done.
- churn: true if the user terminated the contract, or false the user is still using the company's services.

```
data.tail()

     state  account length  area code phone number international plan  \
3328    AZ             192        415     414-4276                 no   

3329    WV              68        415     370-3271                 no   

3330    RI              28        510     328-8230                 no   

3331    CT             184        510     364-6381                yes   

3332    TN              74        415     400-4344                 no   


     voice mail plan  number vmail messages  total day minutes  \
3328             yes                     36              156.2   
3329              no                      0              231.1   
3330              no                      0              180.8   
3331              no                      0              213.8   
3332             yes                     25              234.4   

      total day calls  total day charge  ...  total eve calls  \
3328               77             26.55  ...              126   
3329               57             39.29  ...               55   
```

```
3330               109             30.74  ...               58
3331               105             36.35  ...               84
3332               113             39.85  ...               82

      total eve charge  total night minutes  total night calls  \
3328             18.32                279.1                 83
3329             13.04                191.3                123
3330             24.55                191.9                 91
3331             13.57                139.2                137
3332             22.60                241.4                 77

      total night charge  total intl minutes  total intl calls  \
3328               12.56                 9.9                 6
3329                8.61                 9.6                 4
3330                8.64                14.1                 6
3331                6.26                 5.0                10
3332               10.86                13.7                 4

      total intl charge  customer service calls  churn
3328               2.67                       2  False
3329               2.59                       3  False
3330               3.81                       2  False
3331               1.35                       2  False
3332               3.70                       0  False

[5 rows x 21 columns]
```

```
data.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

data.shape

(3333, 21)
```

The dataset has 3333 rows and 21 columns .It comprised of different data types i.e integer, floats, boolean and strings.

DATA CLEANING

Data cleaning involves the process of identifying and resolving issues related to the quality of the dataset. Its primary objective is to ensure that the data is accurate, consistent, and devoid of errors.

```
#creating a copy of the dataset first.
df = data.copy()
df.head()

  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 calls  total eve charge  \
0             45.07  ...               99             16.78
1             27.47  ...              103             16.62
```

```
2             41.38  ...              110             10.30
3             50.90  ...               88              5.26
4             28.34  ...              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

[5 rows x 21 columns]
```

```python
#Checking for missing values.
df.isnull().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
```

The dataset has no missing values.

We will then change the column names and make them into titles.

```
#making the columns into titles and changing
#some of the column names to full column names.

df.rename(columns={
    'total eve minutes': 'total evening minutes',
    'number vmail messages': 'number of voicemail messages',
    'total eve charge': 'total evening charge',
    'total eve calls' : 'total evening calls',
    'total intl calls' : ' total international calls',
    'total intl charge' : 'total international charge',
    'total intl minutes' : 'total international minutes'
}, inplace=True)

df.columns = df.columns.str.title()

df.columns

Index(['State', 'Account Length', 'Area Code', 'Phone Number',
       'International Plan', 'Voice Mail Plan', 'Number Of Voicemail
Messages',
       'Total Day Minutes', 'Total Day Calls', 'Total Day Charge',
       'Total Evening Minutes', 'Total Evening Calls', 'Total Evening
Charge',
       'Total Night Minutes', 'Total Night Calls', 'Total Night
Charge',
       'Total International Minutes', ' Total International Calls',
       'Total International Charge', 'Customer Service Calls',
'Churn'],
      dtype='object')
```

Checking for duplicate values.

```
df.duplicated().any

<bound method Series.any of 0       False
1       False
2       False
3       False
4       False
        ...
3328    False
3329    False
3330    False
```

```
3331    False
3332    False
Length: 3333, dtype: bool>
```

There are no duplicates in this dataset

We will then check for placeholders in the dataset.

These denote missing values in the dataset. Common placeholders used are "",'N/A', 'NULL','?', 'nan', 'unknown'. Identifying placeholders will helps us to improve model performance and get more accurate analysis.

```
# Define a list of potential placeholder values
common_placeholders = ["", "NA", "N/A", "nan", "none", "null", "?", 
"unknown", "missing"]

# Loop through each column and check for potential placeholders
found_placeholder = False
for column in df.columns:
    unique_values = df[column].unique()
    for value in unique_values:
        if pd.isna(value) or (isinstance(value, str) and 
value.strip().lower() in common_placeholders):
            count = (df[column] == value).sum()
            print(f"Column '{column}': Found {count} occurrences of 
potential placeholder '{value}'")
            found_placeholder = True

if not found_placeholder:
    print("No placeholders found in the DataFrame.")

No placeholders found in the DataFrame.

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 Of Voicemail 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 Evening Minutes          3333 non-null   float64
 11  Total Evening Calls            3333 non-null   int64
 12  Total Evening 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 International Minutes    3333 non-null   float64
 17   Total International Calls     3333 non-null   int64
 18  Total International 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

#Drop the phone number column.
df = df.drop(['Phone Number'],axis=1)
```

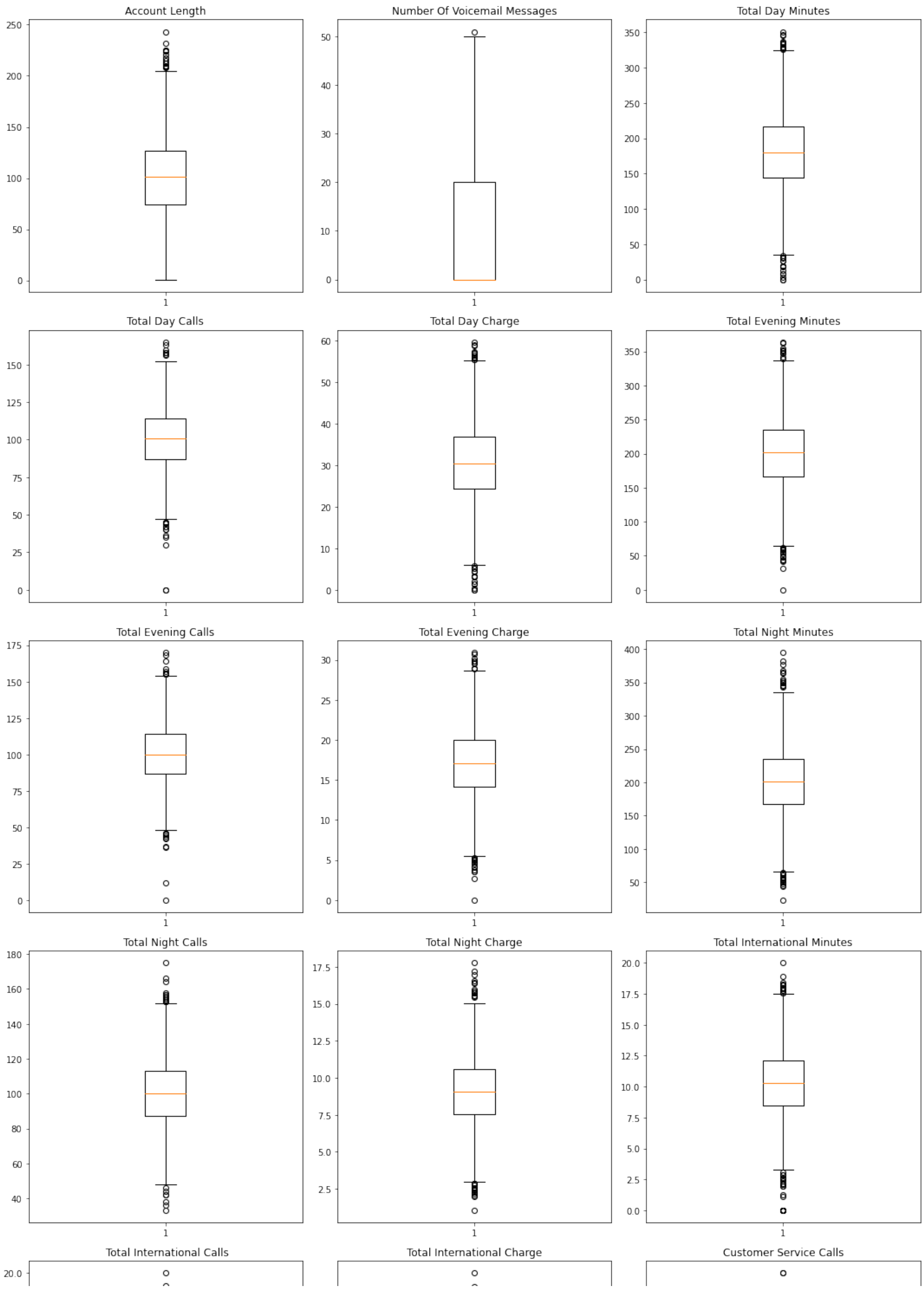
We drop the phone number column since it is a unique identifier for each customer , it does not provide any meaningeful information about a customer's characteristics.

We will change the Area Code column datatype from integer to object. It should be considered as a categorical column since it is a nominal variable. Also convert the churn column to an integer. And also change the datatype of churn from boolean to int.

```
df['Area Code'] = df['Area Code'].astype(str)

df['Churn'] = df['Churn'].astype(int)
```

Let us check for outliers on numeric columns. We will visualize the data to see its distribution. We will then handle the outliers as they will significantly affect the models' performance.

```
numeric_columns = df.select_dtypes(include=['float64', 'int64',
'int32'])

# Plot box plots for each numeric column
num_cols = len(numeric_columns.columns)
cols_per_row = 3
num_rows = (num_cols - 1) // cols_per_row + 1

plt.figure(figsize=(15, 5 * num_rows))
for i, col in enumerate(numeric_columns.columns):
    plt.subplot(num_rows, cols_per_row, i+1)
    plt.boxplot(numeric_columns[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```


Account Length
Number Of Voicemail Messages
Total Day Minutes
Total Day Calls
Total Day Charge
Total Evening Minutes
Total Evening Calls
Total Evening Charge
Total Night Minutes
Total Night Calls
Total Night Charge
Total International Minutes
Total International Calls
Total International Charge
Customer Service Calls

We will use the z-score method to identify rows which have outliers.

```
z_scores = np.abs(zscore(df.select_dtypes(include=[np.number])))

# Set threshold for Z-scores
threshold = 3

# Identify rows with any Z-score above the threshold
outliers = (z_scores > threshold).any(axis=1)

# Print the identified outliers
print("Outliers detected using Z-score:")
print(df[outliers])
```

```
Outliers detected using Z-score:
     State  Account Length Area Code International Plan Voice Mail
Plan  \
22      AZ             130       415                 no
no
32      LA             172       408                 no
no
41      MD             135       408                yes
yes
58      WI              68       415                 no
no
115     ME              36       510                yes
yes
...    ...             ...       ...                ...              ..
.
3247    OK             146       510                 no
no
3275    NY             120       510                 no
yes
3290    CA             127       510                 no
no
3291    MI             119       510                yes
yes
3310    NY              94       415                 no
no

      Number Of Voicemail Messages  Total Day Minutes  Total Day Calls
\
22                               0              183.0              112

32                               0              212.0              121

41                              41              173.1               85

58                               0              148.8               70

115                             42              196.8               89
```

```
...                                ...          ...         ...
3247                                 0        138.4         104
3275                                27        128.5         115
3290                                 0        107.9         128
3291                                22        172.1         119
3310                                 0        190.4          91

      Total Day Charge  Total Evening Minutes  Total Evening Calls  \
22               31.11                   72.9                   99
32               36.04                   31.2                  115
41               29.43                  203.9                  107
58               25.30                  246.5                  164
115              33.46                  254.9                  122
...                ...                    ...                  ...
3247             23.53                  158.9                  122
3275             21.85                  163.7                   91
3290             18.34                  187.0                   77
3291             29.26                  223.6                  133
3310             32.37                   92.0                  107

      Total Evening Charge  Total Night Minutes  Total Night Calls  \
22                    6.20                181.8                 78
32                    2.65                293.3                 78
41                   17.33                122.2                 78
58                   20.95                129.8                103
115                  21.67                138.3                126
...                    ...                  ...                ...
3247                 13.51                 47.4                 73
3275                 13.91                242.9                121
3290                 15.90                218.5                 95
3291                 19.01                150.0                 94
3310                  7.82                224.8                108

      Total Night Charge  Total International Minutes  \
22                  8.18                          9.5
32                 13.20                         12.6
41                  5.50                         14.6
58                  5.84                         12.1
115                 6.22                         20.0
...                  ...                          ...
3247                2.13                          3.9
3275               10.93                          0.0
3290                9.83                          0.0
```

```
3291                  6.75                          13.9
3310                 10.12                          13.6

       Total International Calls  Total International Charge  \
22                            19                        2.57
32                            10                        3.40
41                            15                        3.94
58                             3                        3.27
115                            6                        5.40
...                          ...                         ...
3247                           9                        1.05
3275                           0                        0.00
3290                           0                        0.00
3291                          20                        3.75
3310                          17                        3.67

      Customer Service Calls  Churn
22                         0      0
32                         3      0
41                         0      1
58                         3      0
115                        0      1
...                      ...    ...
3247                       4      1
3275                       1      0
3290                       0      0
3291                       1      1
3310                       2      0

[164 rows x 20 columns]
```

```
#Removing the outliers.
df1 = df[~outliers]

print("DataFrame after removing outliers:")
print(df1)
```

```
DataFrame after removing outliers:
     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
```

```
...    ...               ...       ...                 ...              ..
.
3328    AZ               192       415                  no
yes
3329    WV                68       415                  no
no
3330    RI                28       510                  no
no
3331    CT               184       510                 yes
no
3332    TN                74       415                  no
yes

      Number Of Voicemail 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

...                            ...                ...              ...

3328                            36              156.2               77

3329                             0              231.1               57

3330                             0              180.8              109

3331                             0              213.8              105

3332                            25              234.4              113


      Total Day Charge  Total Evening Minutes  Total Evening Calls  \
0                45.07                  197.4                   99
1                27.47                  195.5                  103
2                41.38                  121.2                  110
3                50.90                   61.9                   88
4                28.34                  148.3                  122
...                ...                    ...                  ...
3328             26.55                  215.5                  126
3329             39.29                  153.4                   55
3330             30.74                  288.8                   58
3331             36.35                  159.6                   84
3332             39.85                  265.9                   82
```

```
      Total Evening Charge  Total Night Minutes  Total Night Calls  \
0                    16.78                244.7                 91   
1                    16.62                254.4                103   
2                    10.30                162.6                104   
3                     5.26                196.9                 89   
4                    12.61                186.9                121   
...                    ...                  ...                ...   
3328                 18.32                279.1                 83   
3329                 13.04                191.3                123   
3330                 24.55                191.9                 91   
3331                 13.57                139.2                137   
3332                 22.60                241.4                 77   

      Total Night Charge  Total International Minutes  \
0                  11.01                         10.0   
1                  11.45                         13.7   
2                   7.32                         12.2   
3                   8.86                          6.6   
4                   8.41                         10.1   
...                  ...                          ...   
3328               12.56                          9.9   
3329                8.61                          9.6   
3330                8.64                         14.1   
3331                6.26                          5.0   
3332               10.86                         13.7   

       Total International Calls  Total International Charge  \
0                              3                        2.70   
1                              3                        3.70   
2                              5                        3.29   
3                              7                        1.78   
4                              3                        2.73   
...                          ...                         ...   
3328                           6                        2.67   
3329                           4                        2.59   
3330                           6                        3.81   
3331                          10                        1.35   
3332                           4                        3.70   

      Customer Service Calls  Churn  
0                          1      0  
1                          1      0  
2                          0      0  
3                          2      0  
4                          3      0  
...                      ...    ...  
3328                       2      0  
3329                       3      0  
3330                       2      0  
3331                       2      0  
```

```
3332                           0      0

[3169 rows x 20 columns]

df1.shape

(3169, 20)
```

After handling the outliers, we remain with 3169 rows, 164 rows removed.

EXPLORATORY DATA ANALYSIS

Let us see the statistical overview of the data.

```
df1.describe()

       Account Length  Number Of Voicemail Messages  Total Day Minutes
\
count     3169.000000                   3169.000000        3169.000000

mean       100.856737                      7.974440         180.280120

std         39.474815                     13.586481          53.835965

min          1.000000                      0.000000          17.600000

25%         74.000000                      0.000000         144.000000

50%        100.000000                      0.000000         179.900000

75%        127.000000                     19.000000         217.000000

max        217.000000                     49.000000         337.400000


       Total Day Calls  Total Day Charge  Total Evening Minutes  \
count       3169.00000       3169.000000            3169.000000
mean         100.60650         30.648157             201.086904
std           19.72475          9.152086              50.080338
min           42.00000          2.990000              49.200000
25%           87.00000         24.480000             166.800000
50%          101.00000         30.580000             201.400000
75%          114.00000         36.890000             235.100000
max          160.00000         57.360000             351.600000

       Total Evening Calls  Total Evening Charge  Total Night Minutes
\
count          3169.000000           3169.000000          3169.000000
```

```
mean          100.195014            17.092603            200.924361

std            19.614413             4.256827             49.990627

min            42.000000             4.180000             50.100000

25%            87.000000            14.180000            167.000000

50%           100.000000            17.120000            201.100000

75%           114.000000            19.980000            235.600000

max           159.000000            29.890000            352.500000


       Total Night Calls  Total Night Charge  Total International
Minutes  \
count        3169.000000         3169.000000
3169.000000
mean          100.023982            9.041682
10.309340
std            19.405317            2.249643
2.665854
min            42.000000            2.250000
2.000000
25%            87.000000            7.520000
8.500000
50%           100.000000            9.050000
10.300000
75%           113.000000           10.600000
12.100000
max           158.000000           15.860000
18.400000

        Total International Calls  Total International Charge  \
count                 3169.000000                  3169.000000
mean                     4.367939                     2.784033
std                      2.156224                     0.719748
min                      1.000000                     0.540000
25%                      3.000000                     2.300000
50%                      4.000000                     2.780000
75%                      6.000000                     3.270000
max                     11.000000                     4.970000

       Customer Service Calls        Churn
count             3169.000000  3169.000000
mean                 1.513411     0.139476
std                  1.215649     0.346497
min                  0.000000     0.000000
25%                  1.000000     0.000000
```

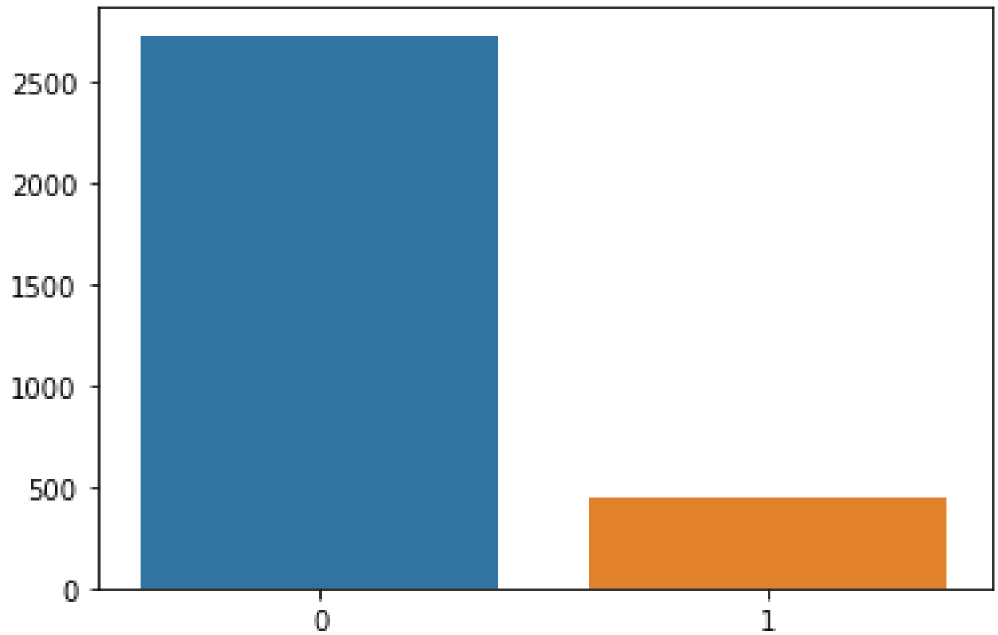
```
50%                    1.000000     0.000000
75%                    2.000000     0.000000
max                    5.000000     1.000000
```

The rows provide descriptive statistics including count, mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum values for each column in the dataset. We will then perform various analysis i.e univariate, bivariate and multivariate.

Univariate Analysis.

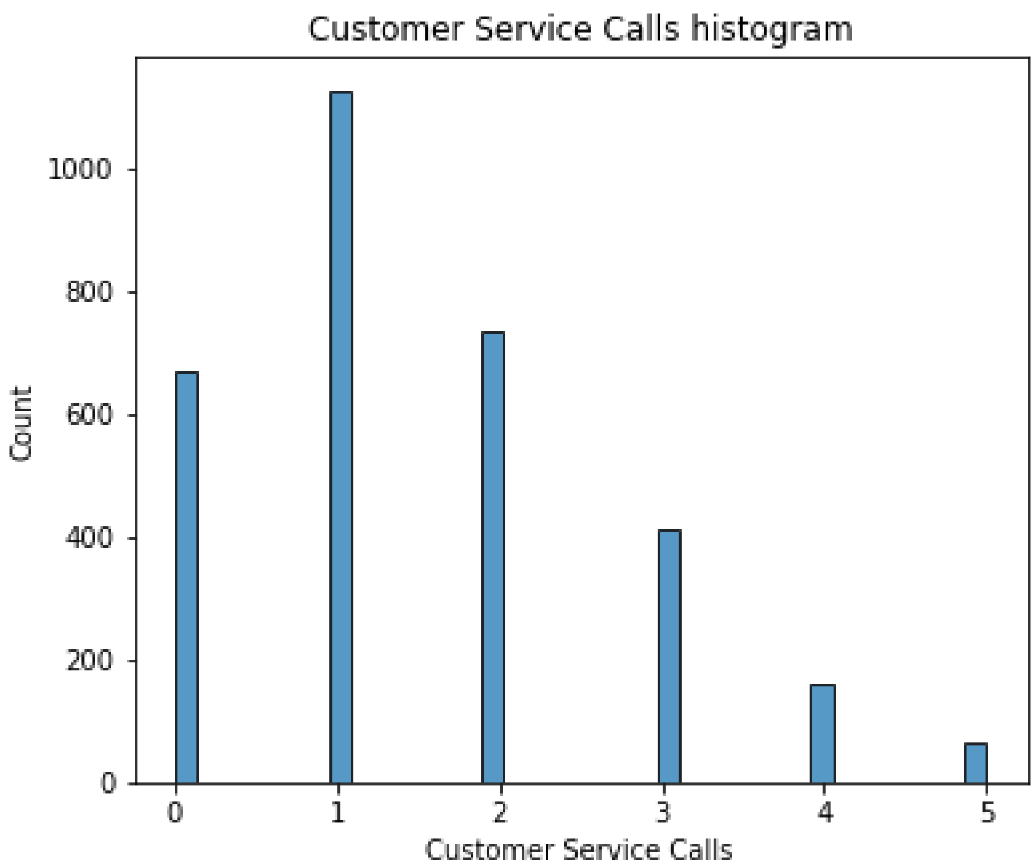
We will first look at the distribution of our target variable which Churn.

```
y = df1["Churn"].value_counts()
churn_percentage = y / len(df1) * 100
print(y)
print("")
print(churn_percentage)
sns.barplot(y.index, y.values)

0    2727
1     442
Name: Churn, dtype: int64

0    86.052382
1    13.947618
Name: Churn, dtype: float64

c:\Users\Administrator\anaconda3\envs\learn-env\lib\site-packages\
seaborn\_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(

<AxesSubplot:>
```



This shows approximately 86% of the customers have not terminated the contract. We have a calss imbalance for the target variable which could lead to biased predictions towards the no churn category. We will investigate into the use to oversampling when building the models.

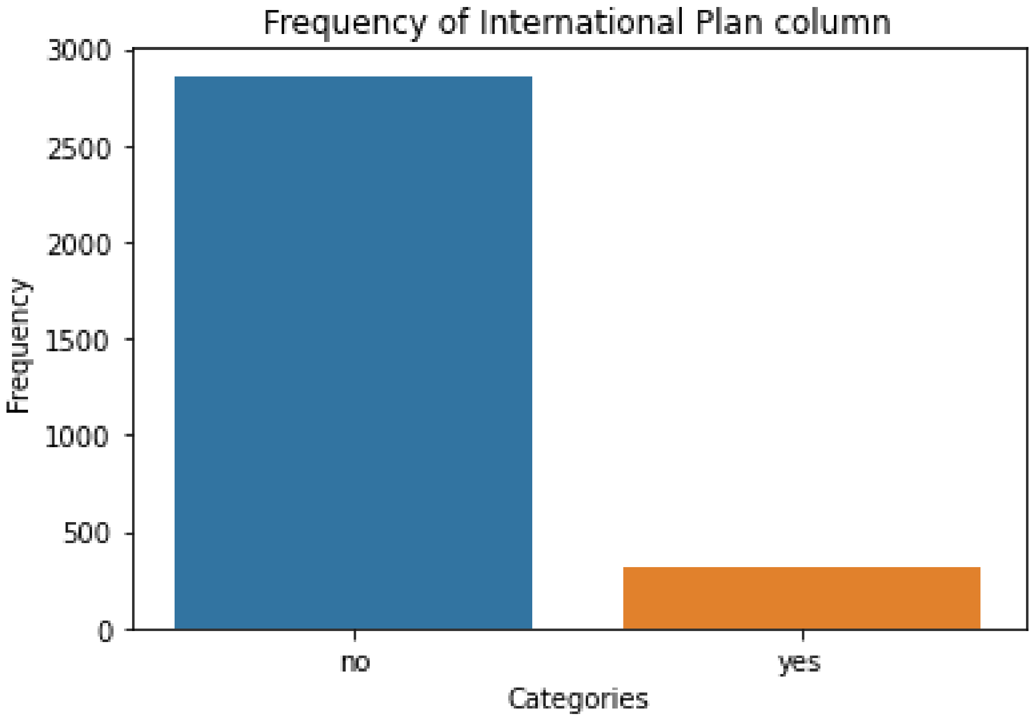
```
#Distribution of the customer service calls.
plt.figure(figsize=(6, 5))

# Price boxplot

sns.histplot(x=df1['Customer Service Calls'])
plt.title('Customer Service Calls histogram')


plt.show()
```




```
df1["Customer Service Calls"].value_counts()

1    1127
2     734
0     670
3     414
4     161
5      63
Name: Customer Service Calls, dtype: int64
```

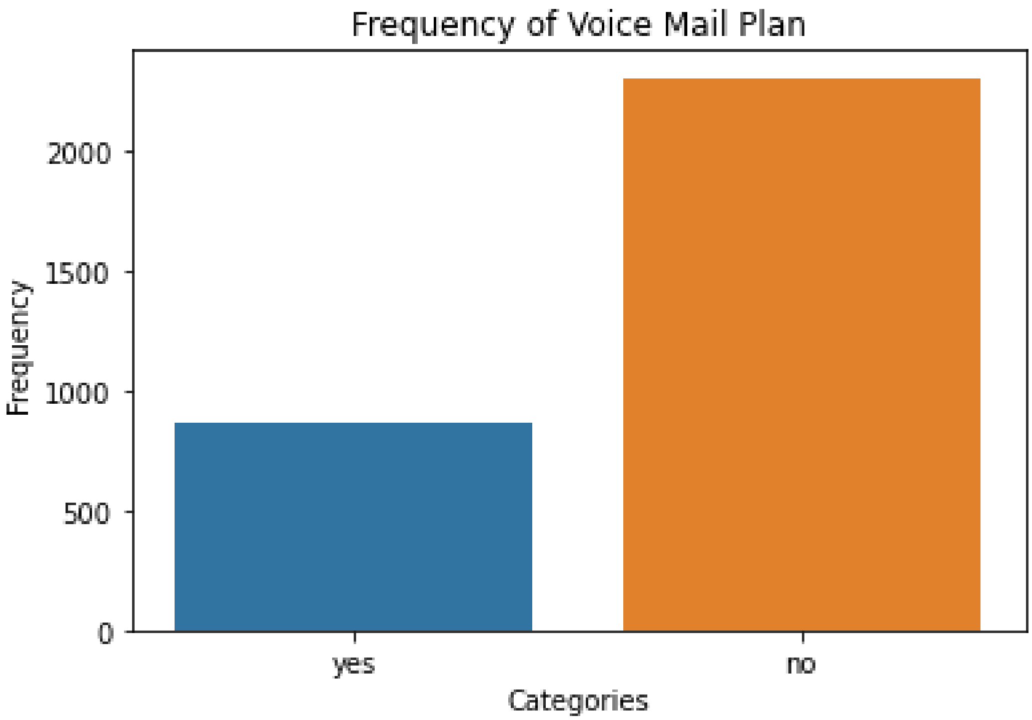
Over 1000 customers have made 1 customer service call to the company. This is quite a huge number and might signify that there is one common problem. 0 customer service calls indicate that 670 customers are satisfied with the company's services. Although it is still a lower value compared to the customers who called once or twice.

```
#showing the distribution of the international column.
sns.countplot(x='International Plan', data=df1)
plt.title('Frequency of International Plan column')
plt.xlabel('Categories')
plt.ylabel('Frequency')
plt.show()
```



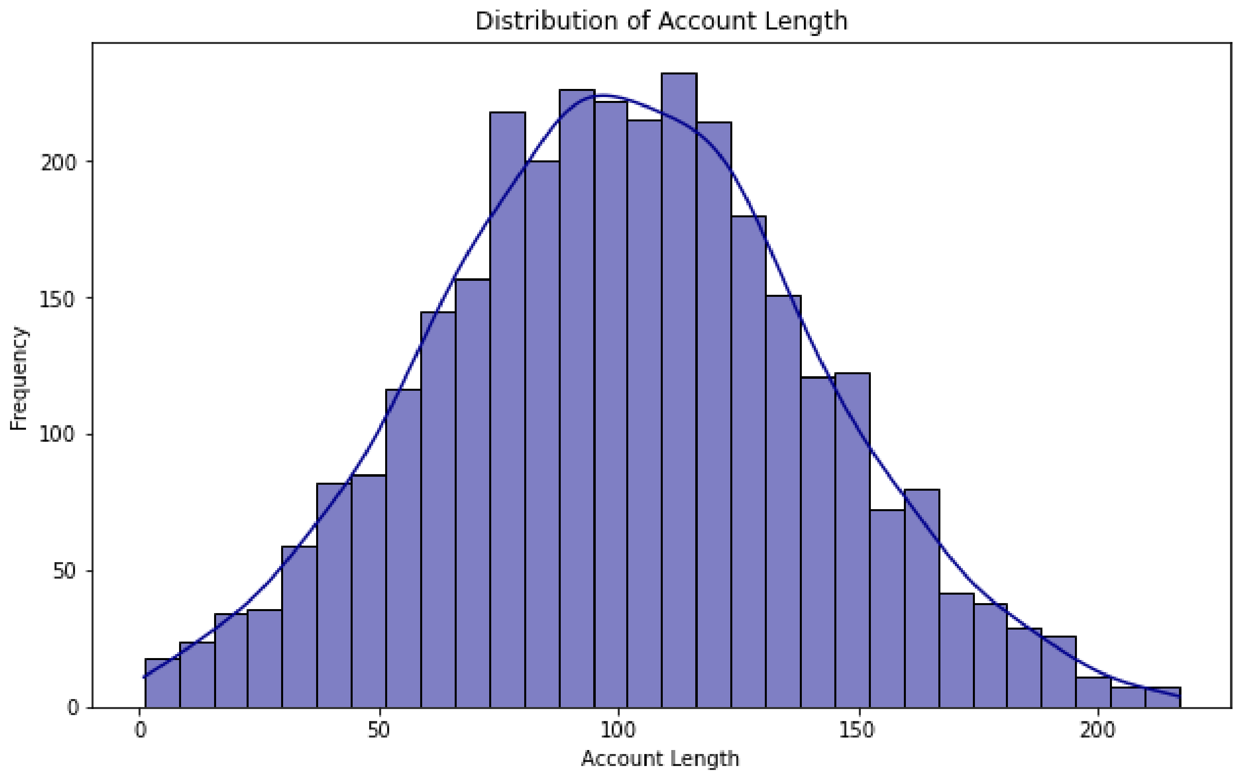
Less than 500 people have the international plan while almost 3000 people do not have the international plan.

```
#Visualizing the distribution of the Voice Mail plan.
sns.countplot(x='Voice Mail Plan', data=df1)
plt.title('Frequency of Voice Mail Plan')
plt.xlabel('Categories')
plt.ylabel('Frequency')
plt.show()
```



More than 2000 customers do not have the Voice Mail Plan while less than 1000 people have the voice mail plan.

```
plt.figure(figsize=(10, 6))
sns.histplot(df1['Account Length'], bins=30, kde=True,
color='darkblue')
plt.title('Distribution of Account Length')
plt.xlabel('Account Length')
plt.ylabel('Frequency')
plt.show()
```

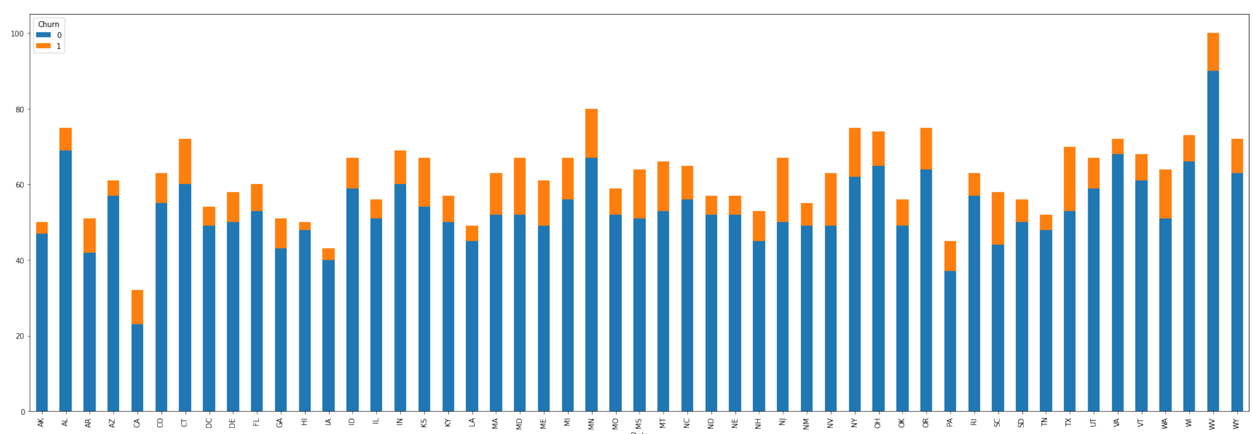


It shows that its distribution is a Gaussian distribution meaning it is symmetrical around the mean showing that data near the mean are more frequent in occurrence than data far from the mean.

Bivariate analysis.

We will visualize the relationship between Churn and State to see which states have the most and least churn rates.

```
df1.groupby(["State", "Churn"]).size().unstack().plot(kind='bar',
stacked=True, figsize=(30,10))

<AxesSubplot:xlabel='State'>
```



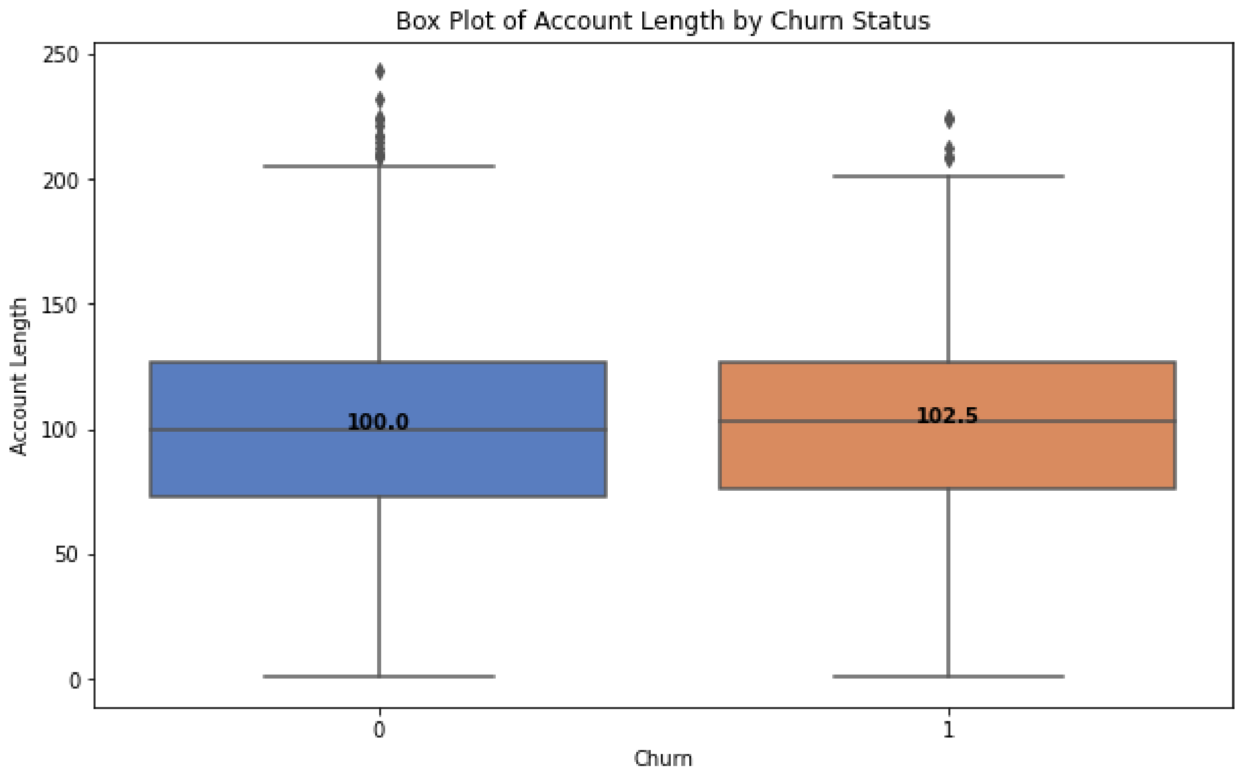
The above graph shows there are states with less rates of churn like AK, IA, LA and HI while there are states with higher rates of churn like TX, SC and NY.

Relationship between Churn and Account Length.

```
#calculating he median position for each churn category.
medians = df1.groupby('Churn')['Account Length'].median()
print("Medians:\n", medians)
```

```
Medians:
 Churn
0    100.0
1    102.5
Name: Account Length, dtype: float64
```

```
plt.figure(figsize=(10, 6))
ax = sns.boxplot(x='Churn', y='Account Length', data=df,
palette='muted')

# Annotate the medians on the box plot
for tick, label in enumerate(ax.get_xticklabels()):
    x_position = tick
    y_position = medians[tick]
    ax.text(x_position, y_position, f'{y_position:.1f}',
            horizontalalignment='center', size='medium',
color='black', weight='semibold')

plt.title('Box Plot of Account Length by Churn Status')
plt.xlabel('Churn')
plt.ylabel('Account Length')
plt.show()
```

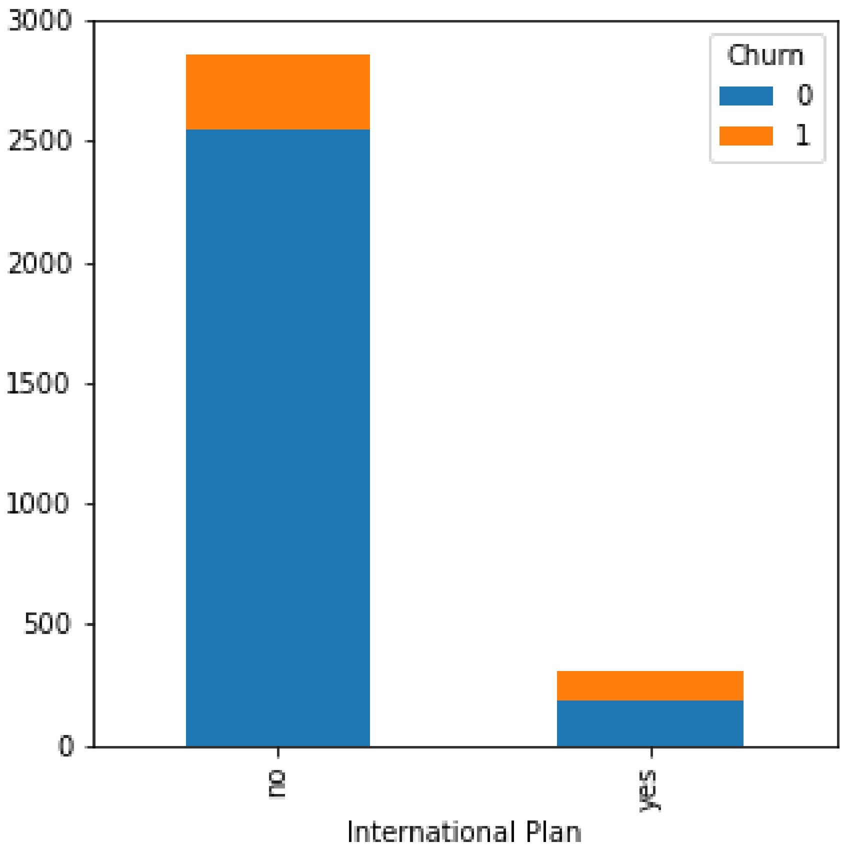


There is a slight difference in the medians of the churn categories. The customers who churn have a median of 102.5, which shows that the customers with longer account lengths stop usingthe company's services. But when we look at the outliers, the category false has more outliers which shows a higher variability in the account length, showing that the values are less consistent.

Relationship between Churn and International plan.

```
df1.groupby(["International Plan",
"Churn"]).size().unstack().plot(kind='bar', stacked=True,
figsize=(5,5))
```

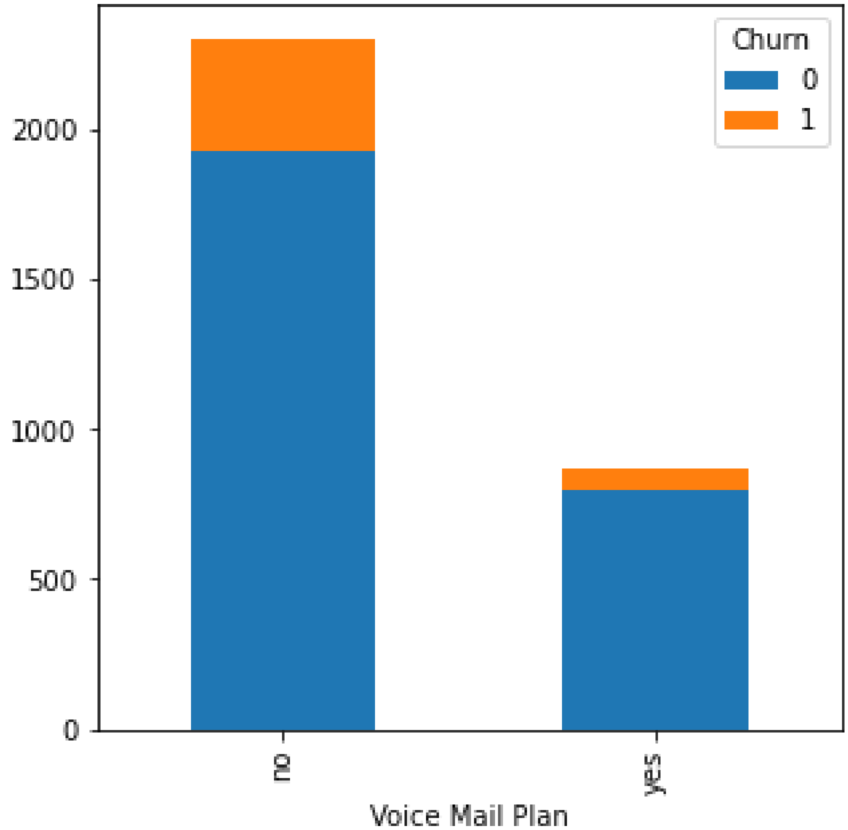
```
<AxesSubplot:xlabel='International Plan'>
```



Both with or without the international plan have churn rates. Interestingly, those without the international plan have a much higher rate of churn compared to those with an international plan.

Relationship between churn and voice mail plan

```
df1.groupby(["Voice Mail Plan",
"Churn"]).size().unstack().plot(kind='bar', stacked=True,
figsize=(5,5))

<AxesSubplot:xlabel='Voice Mail Plan'>
```

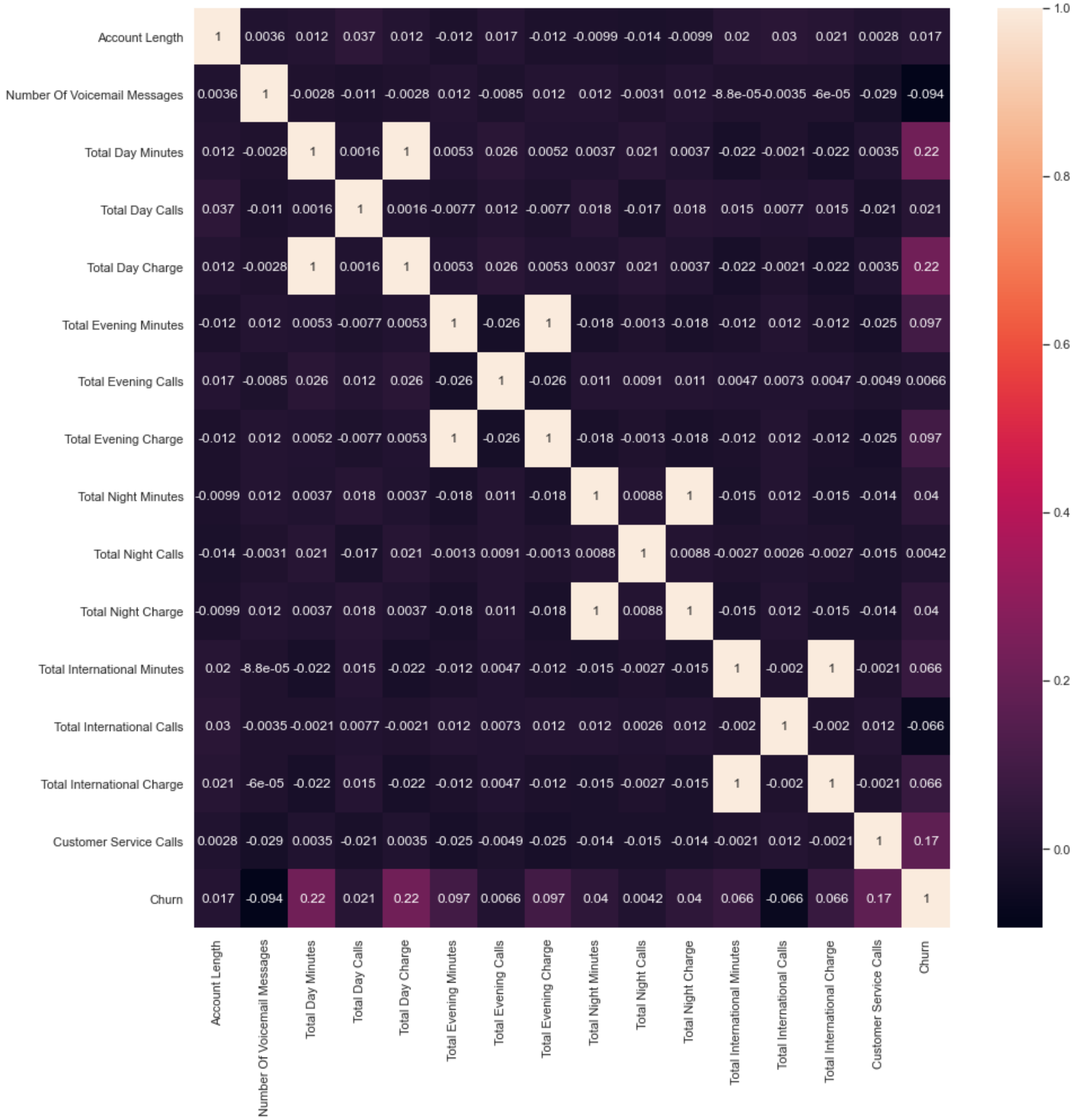


Almost similar to the previous graph, the customers without a voice mail plan have a higher rate of churn compared to those with a voicemail plan.

Multivariate analysis.

Creating a heat map to show correlation of the entire dataset,in which high correlations are coloured more to the red and lower ones more to purple.

```
sns.set(rc={'figure.figsize':(15, 15)})
#Use the .heatmap method to depict the relationship visually

sns.heatmap(df1.corr(), annot=True, annot_kws={"size": 12})
plt.show()
```

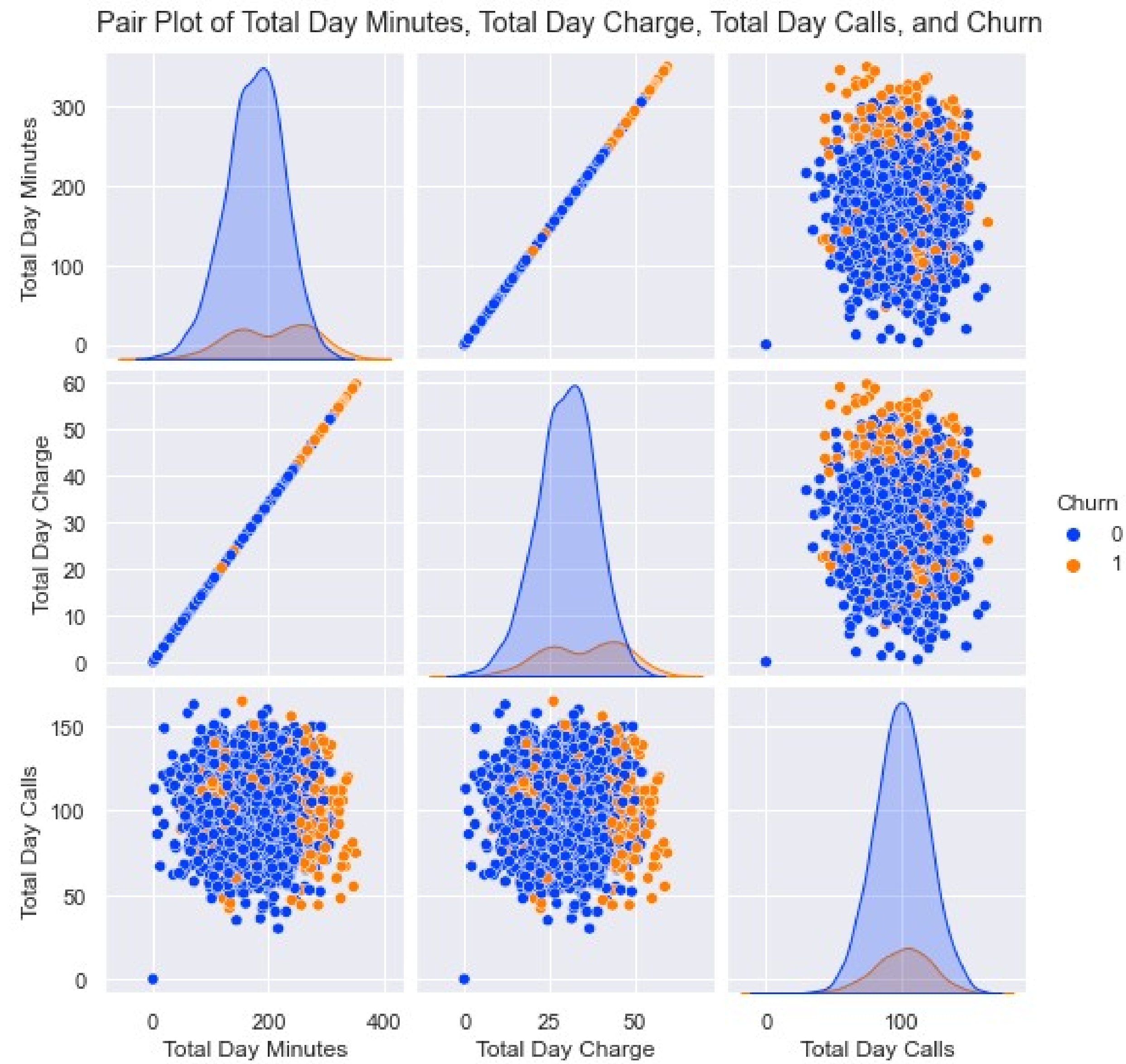


From the above , we can see the columns that highly correlated to churn are Customer Service Calls, total day minutes and total day charge.

Let us now visualize the correlation between different columns.

```
#visualizing the relationship between total day minutes, total day charge , total day calls and churn
plt.figure(figsize=(12, 10))
sns.pairplot(df, vars=['Total Day Minutes', 'Total Day Charge', 'Total Day Calls'], hue='Churn', palette='bright')
plt.suptitle('Pair Plot of Total Day Minutes, Total Day Charge, Total
```

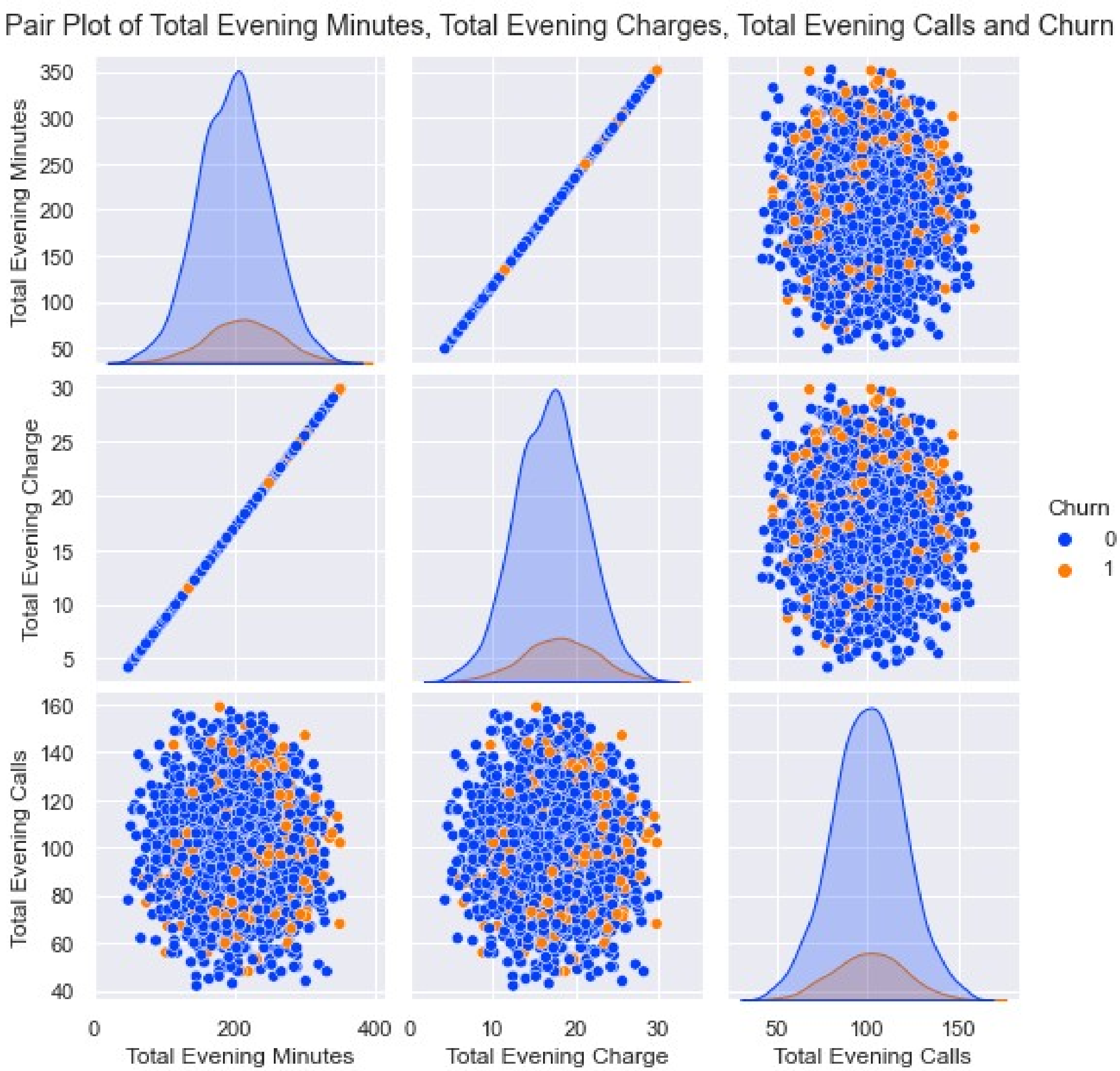
```
Day Calls, and Churn', y=1.02)
plt.show()

<Figure size 864x720 with 0 Axes>
```



We see that there is a linear relationship between total day charge and total day minutes charge, in relation with the churn rate the higher day charge show more customers tend to leave the company. The cluster points show higher churn rate when the total day minutes and total day charge increase.

```
#visualizing the relationship between total evening minutes, total
evening charge,total evening calls and churn
sns.pairplot(df1, vars=['Total Evening Minutes', 'Total Evening
Charge','Total Evening Calls'], hue='Churn', palette='bright',
```

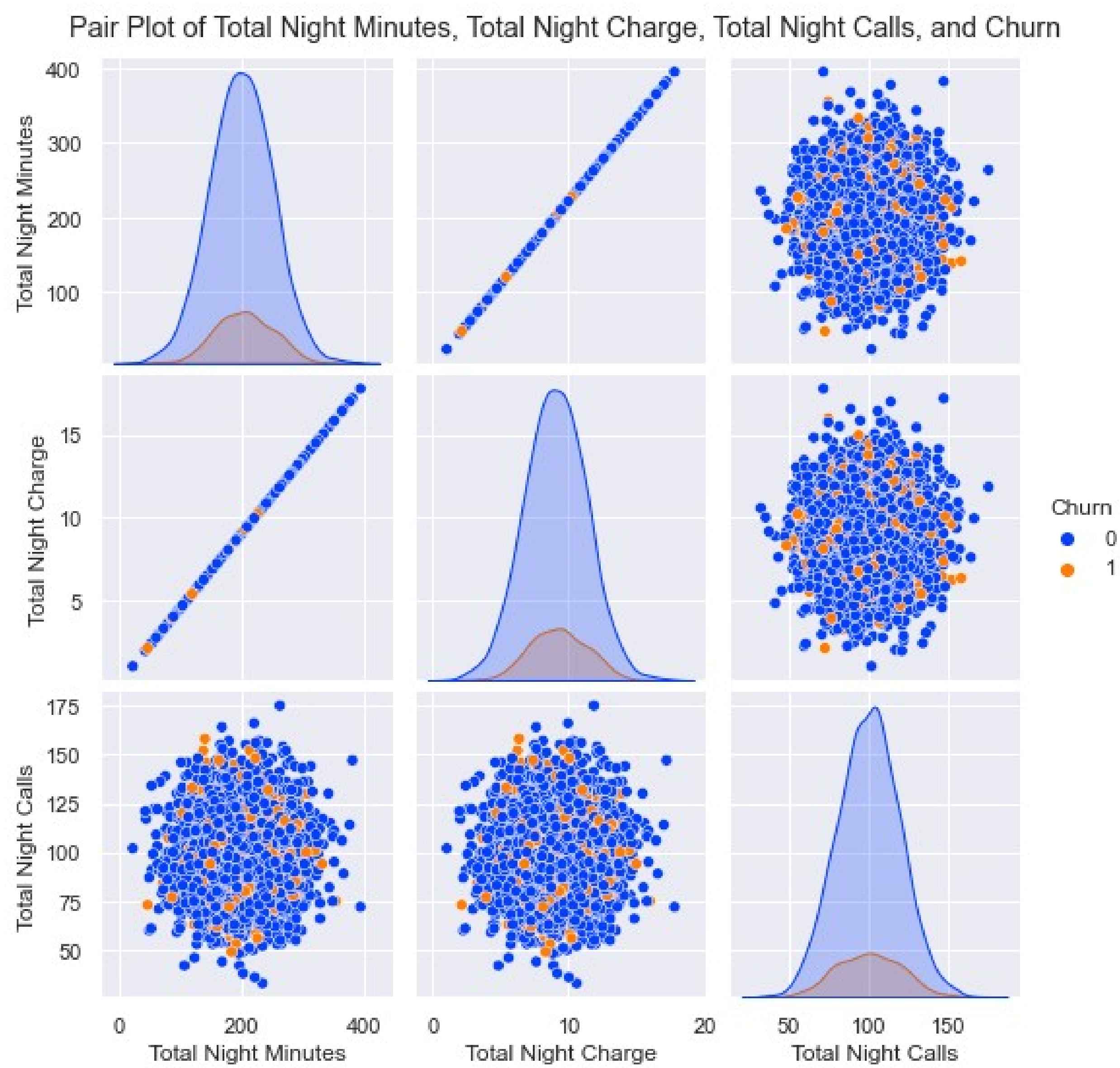
```
diag_kind='kde')
plt.suptitle('Pair Plot of Total Evening Minutes, Total Evening
Charges, Total Evening Calls and Churn', y=1.02)
plt.show()
```



There is a clear linear relationship between the total evening charges and total evening minutes. The cluster points show a low churn rate and seem to be unevely distributed. It spread across the different columns.

```
#visualizing the relationship betweeen total night calls, total night
charge, total night minutes and churn
plt.figure(figsize=(12, 10))
sns.pairplot(df, vars=['Total Night Minutes', 'Total Night Charge',
'Total Night Calls'], hue='Churn', palette='bright')
```

```
plt.suptitle('Pair Plot of Total Night Minutes, Total Night Charge,
Total Night Calls, and Churn', y=1.02)
plt.show()

<Figure size 864x720 with 0 Axes>
```



There is a clear linear relationship between the total night charges and total night minutes. The cluster points show a low churn rate and seem to be unevely distributed. It spread across the different columns.

Feature Engineering.

We will create new columns from different columns.

```python
#We will create new columns namely, total calls, average call duration, customer tenure and total charges. Customer
#tenure refers to the average time a customer stays in business with a company. It will be calculated in months.
df1.loc[:, 'Total Charges'] = df1['Total Day Charge'] + df1['Total Evening Charge'] + df1['Total Night Charge'] + df1['Total International Charge']
df1.loc[:, 'Total Calls'] = df1['Total Day Calls'] + df1['Total Evening Calls'] + df1['Total Night Calls'] + df1[' Total International Calls']
df1.loc[:, 'Average Call Duration'] = (df1['Total Day Minutes'] + df1['Total Evening Minutes'] + df1['Total Night Minutes'] + df1['Total International Minutes'])/4
df1.loc[:, 'Customer Tenure'] = df1['Account Length'] / 30
```

```
c:\Users\Administrator\anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexing.py:1596: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self.obj[key] = _infer_fill_value(value)
c:\Users\Administrator\anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexing.py:1745: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  isetter(ilocs[0], value)
```

```python
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3169 entries, 0 to 3332
Data columns (total 24 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   State                         3169 non-null   object
 1   Account Length                3169 non-null   int64
 2   Area Code                     3169 non-null   object
 3   International Plan            3169 non-null   object
 4   Voice Mail Plan               3169 non-null   object
 5   Number Of Voicemail Messages  3169 non-null   int64
 6   Total Day Minutes             3169 non-null   float64
 7   Total Day Calls               3169 non-null   int64
 8   Total Day Charge              3169 non-null   float64
```

```
 9   Total Evening Minutes         3169 non-null   float64
 10  Total Evening Calls           3169 non-null   int64
 11  Total Evening Charge          3169 non-null   float64
 12  Total Night Minutes           3169 non-null   float64
 13  Total Night Calls             3169 non-null   int64
 14  Total Night Charge            3169 non-null   float64
 15  Total International Minutes   3169 non-null   float64
 16   Total International Calls    3169 non-null   int64
 17  Total International Charge    3169 non-null   float64
 18  Customer Service Calls        3169 non-null   int64
 19  Churn                         3169 non-null   int32
 20  Total Charges                 3169 non-null   float64
 21  Total Calls                   3169 non-null   int64
 22  Average Call Duration         3169 non-null   float64
 23  Customer Tenure               3169 non-null   float64
dtypes: float64(11), int32(1), int64(8), object(4)
memory usage: 766.6+ KB
```

Pre-processing data.

This includes splitting the dataset, normalize/standardize the data, performing one hot encoding and label encoding and addressing multicollinearity.

```
from sklearn.model_selection import train_test_split

X = df1.drop('Churn', axis=1)
y = df1['Churn']
X_train, X_test, y_train, y_test = train_test_split(X, y, 
test_size=0.2, random_state=42)

from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.compose import ColumnTransformer



# Label encode the State and Are Code  columns
le = LabelEncoder()
X_train['Encoded State'] = le.fit_transform(X_train['State'])
X_test['Encoded State'] = le.transform(X_test['State'])
X_train['Encoded Area Code'] = le.fit_transform(X_train['Area Code'])
X_test['Encoded Area Code'] = le.transform(X_test['Area Code'])

# One-hot encode the voicemail plan and international plan columns
ohe = OneHotEncoder(drop='first', sparse=False)

# Fit and transform the voice mail plan and international_plan columns 
on the training set
onehot_encoded_train = ohe.fit_transform(X_train[['Voice Mail Plan', 
'International Plan']])
onehot_encoded_test = ohe.transform(X_test[['Voice Mail Plan', 
```

```
'International Plan']])

# Convert the one-hot encoded columns back to DataFrame
onehot_encoded_train_df = pd.DataFrame(onehot_encoded_train,
columns=ohe.get_feature_names_out(['Voice Mail Plan', 'International
Plan']))
onehot_encoded_test_df = pd.DataFrame(onehot_encoded_test,
columns=ohe.get_feature_names_out(['Voice Mail Plan', 'International
Plan']))

# Reset index to match original DataFrame after split
onehot_encoded_train_df.reset_index(drop=True, inplace=True)
onehot_encoded_test_df.reset_index(drop=True, inplace=True)
X_train.reset_index(drop=True, inplace=True)
X_test.reset_index(drop=True, inplace=True)

# Drop the original state, Area code voice mail plan, and
international plan columns
X_train.drop(['State', 'Area Code', 'Voice Mail Plan', 'International
Plan'], axis=1, inplace=True)
X_test.drop(['State', 'Area Code', 'Voice Mail Plan', 'International
Plan'], axis=1, inplace=True)

# Concatenate the new one-hot encoded columns with the original
DataFrame
X_train_final = pd.concat([X_train, onehot_encoded_train_df], axis=1)
X_test_final = pd.concat([X_test, onehot_encoded_test_df], axis=1)
```

```
c:\Users\Administrator\anaconda3\envs\learn-env\lib\site-packages\
sklearn\preprocessing\_encoders.py:975: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default
value.
  warnings.warn(
```

```
X_train_final.head()
```

```
   Account Length  Number Of Voicemail Messages  Total Day Minutes  \
0              45                             0              159.8
1             119                            19              178.1
2             104                             0              183.6
3             125                             0              298.4
4              84                             0              216.1

   Total Day Calls  Total Day Charge  Total Evening Minutes  \
0               91             27.17                  120.4
1              110             30.28                  212.8
2              133             31.21                  120.7
```

```
3                78            50.73                  270.5
4               114            36.74                  197.5

   Total Evening Calls  Total Evening Charge  Total Night Minutes  \
0                   86                 10.23                163.0
1                  100                 18.09                226.3
2                   98                 10.26                215.1
3                  142                 22.99                107.3
4                  107                 16.79                217.8

   Total Night Calls  ...  Total International Charge  Customer
Service Calls  \
0                 93  ...                        2.86
2
1                123  ...                        2.70
1
2                112  ...                        3.43
1
3                 84  ...                        3.29
0
4                104  ...                        2.65
1

   Total Charges  Total Calls  Average Call Duration  Customer Tenure
\
0          47.60          273                113.450         1.500000

1          61.25          339                156.800         3.966667

2          54.58          345                133.025         3.466667

3          81.84          306                172.100         4.166667

4          65.98          328                160.300         2.800000


   Encoded State  Encoded Area Code  Voice Mail Plan_yes  \
0             12                  2                  0.0
1             30                  1                  1.0
2             50                  0                  0.0
3             30                  1                  0.0
4             23                  1                  0.0

   International Plan_yes
0                     0.0
1                     0.0
2                     0.0
3                     1.0
4                     0.0
```

```
[5 rows x 23 columns]

X_test_final.head()

   Account Length  Number Of Voicemail Messages  Total Day Minutes  \
0             155                             0              262.4
1              96                             0              106.6
2              87                             0              146.3
3             133                             0              277.3
4             162                             0              220.6

   Total Day Calls  Total Day Charge  Total Evening Minutes  \
0               55             44.61                  194.6
1              128             18.12                  284.8
2              108             24.87                  171.8
3              138             47.14                  228.4
4              117             37.50                  155.2

   Total Evening Calls  Total Evening Charge  Total Night Minutes  \
0                  113                 16.54                146.5
1                   87                 24.21                178.9
2                  102                 14.60                167.5
3                  117                 19.41                117.3
4                  121                 13.19                186.7

   Total Night Calls  ...  Total International Charge  Customer
Service Calls  \
0                 85  ...                        2.24
2
1                 92  ...                        4.02
1
2                 66  ...                        1.43
1
3                103  ...                        3.46
2
4                 89  ...                        2.84
1

   Total Charges  Total Calls  Average Call Duration  Customer Tenure
\
0          69.98          259                152.950         5.166667

1          54.40          314                146.300         3.200000

2          48.44          285                122.725         2.900000

3          75.29          362                158.950         4.433333

4          61.93          338                143.250         5.400000
```

```
   Encoded State  Encoded Area Code  Voice Mail Plan_yes  \
0             27                  0                  0.0
1             35                  1                  0.0
2             44                  1                  0.0
3             22                  0                  0.0
4             46                  2                  0.0

   International Plan_yes
0                     0.0
1                     0.0
2                     0.0
3                     0.0
4                     0.0

[5 rows x 23 columns]
```

Standardizing the data.

From the describe function, we can see that our data is not on a consistent scale of 0 to 1. We will use the StandardScaler to normalize the data. Ensures amean of 0 and standard deviation of 1.

```
from sklearn.preprocessing import StandardScaler

#intialize the scaler
scaler = StandardScaler()

# Fit and transform the training set
X_train_scaled = scaler.fit_transform(X_train_final)

# Transform the test set
X_test_scaled = scaler.transform(X_test_final)

# Convert the scaled data back to DataFrame
X_train_df = pd.DataFrame(X_train_scaled,
columns=X_train_final.columns)
X_test_df = pd.DataFrame(X_test_scaled, columns=X_test_final.columns)

X_train_df.describe()

       Account Length  Number Of Voicemail Messages  Total Day Minutes
\
count    2.535000e+03                  2.535000e+03       2.535000e+03

mean    -1.709787e-16                  4.204395e-17       1.541611e-17

std      1.000197e+00                  1.000197e+00       1.000197e+00

min     -2.531471e+00                 -5.874908e-01      -3.022368e+00
```

```
25%    -6.786879e-01                          -5.874908e-01     -6.686012e-01

50%     6.587939e-03                          -5.874908e-01     -8.432386e-03

75%     6.664832e-01                           8.083504e-01      6.758776e-01

max     2.950736e+00                           2.938845e+00      2.916366e+00


       Total Day Calls  Total Day Charge  Total Evening Minutes  \
count     2.535000e+03      2.535000e+03           2.535000e+03
mean     -2.985120e-16     -2.074168e-16           8.128497e-17
std       1.000197e+00      1.000197e+00           1.000197e+00
min      -2.962570e+00     -3.022653e+00          -3.023636e+00
25%      -6.842309e-01     -6.686067e-01          -6.841885e-01
50%       2.458590e-02     -8.818209e-03           1.824114e-02
75%       6.827729e-01      6.760947e-01           6.690799e-01
max       3.011742e+00      2.916535e+00           2.976780e+00

       Total Evening Calls  Total Evening Charge  Total Night Minutes
\
count         2.535000e+03          2.535000e+03         2.535000e+03

mean         -2.858989e-16         -1.653729e-16        -2.102197e-16

std           1.000197e+00          1.000197e+00         1.000197e+00

min          -2.936851e+00         -3.024156e+00        -3.023809e+00

25%          -6.572674e-01         -6.850550e-01        -6.786380e-01

50%           1.278925e-03          1.760908e-02         4.743154e-03

75%           6.598252e-01          6.689156e-01         6.921383e-01

max           2.990066e+00          2.977669e+00         3.045338e+00


       Total Night Calls  ...  Total International Charge  \
count       2.535000e+03  ...                2.535000e+03
mean       -1.023069e-16  ...               -1.289348e-16
std         1.000197e+00  ...                1.000197e+00
min        -3.008707e+00  ...               -3.126444e+00
25%        -6.700071e-01  ...               -6.541066e-01
50%         5.617391e-03  ...                2.648052e-02
75%         6.812419e-01  ...                6.653990e-01
max         3.019942e+00  ...                3.026620e+00

       Customer Service Calls  Total Charges   Total Calls  \
count            2.535000e+03   2.535000e+03  2.535000e+03
mean            -7.567911e-17  -5.269508e-16  2.662783e-17
```

```
std             1.000197e+00   1.000197e+00  1.000197e+00
min            -1.244978e+00  -3.286807e+00 -3.330667e+00
25%            -4.200907e-01  -6.795813e-01 -6.809919e-01
50%            -4.200907e-01  -8.738943e-03  7.045241e-03
75%             4.047970e-01   6.664408e-01  6.804432e-01
max             2.879460e+00   3.148847e+00  3.022697e+00

       Average Call Duration  Customer Tenure  Encoded State  \
count           2.535000e+03     2.535000e+03   2.535000e+03
mean            4.092278e-16     3.573736e-16  -5.746006e-17
std             1.000197e+00     1.000197e+00   1.000197e+00
min            -3.477911e+00    -2.531471e+00  -1.773496e+00
25%            -6.622008e-01    -6.786879e-01  -8.218433e-01
50%             1.652125e-02     6.587939e-03  -6.140563e-03
75%             6.687703e-01     6.664832e-01   8.775374e-01
max             3.257489e+00     2.950736e+00   1.625265e+00

       Encoded Area Code  Voice Mail Plan_yes  International Plan_yes

count       2.535000e+03         2.535000e+03            2.535000e+03

mean        5.710970e-17         6.446739e-17            7.007325e-18

std         1.000197e+00         1.000197e+00            1.000197e+00

min        -1.432145e+00        -6.139780e-01           -3.263491e-01

25%        -2.443365e-02        -6.139780e-01           -3.263491e-01

50%        -2.443365e-02        -6.139780e-01           -3.263491e-01

75%         1.383278e+00         1.628723e+00           -3.263491e-01

max         1.383278e+00         1.628723e+00            3.064204e+00


[8 rows x 23 columns]
```

```
X_test_df.describe()
```

```
       Account Length  Number Of Voicemail Messages  Total Day Minutes
\
count      634.000000                    634.000000         634.000000

mean         0.014755                     -0.008227          -0.006865

std          1.009357                      0.990605           0.998689

min         -2.480710                     -0.587491          -2.615681

25%         -0.678688                     -0.587491          -0.702956
```

```
50%        -0.018793                       -0.587491          -0.007504

75%         0.685519                        0.789984           0.695841

max         2.899975                        3.012310           2.743664


       Total Day Calls  Total Day Charge  Total Evening Minutes  \
count       634.000000        634.000000             634.000000
mean          0.023308         -0.006863              -0.048977
std           0.993054          0.998689               0.967202
min          -2.861311         -2.615201              -2.724013
25%          -0.633601         -0.702470              -0.731315
50%           0.075216         -0.007726              -0.071051
75%           0.682773          0.695757               0.638324
max           2.606704          2.743942               2.522383

       Total Evening Calls  Total Evening Charge  Total Night Minutes
\
count           634.000000            634.000000           634.000000

mean              0.055772             -0.048966             0.016120

std               0.966336              0.967207             1.016347

min              -2.734221             -2.723014            -2.875292

25%              -0.657267             -0.731744            -0.673620

50%               0.102594             -0.071099             0.023810

75%               0.761140              0.637984             0.734787

max               2.736779              2.522455             3.039317


       Total Night Calls  ...  Total International Charge  \
count         634.000000  ...                  634.000000
mean            0.034308  ...                   -0.047918
std             1.041470  ...                    0.997560
min            -3.008707  ...                   -3.084775
25%            -0.670007  ...                   -0.723554
50%             0.057589  ...                   -0.084636
75%             0.733213  ...                    0.623730
max             2.864029  ...                    2.943282

       Customer Service Calls  Total Charges  Total Calls  \
count              634.000000     634.000000   634.000000
mean                 0.017074      -0.026108     0.063523
std                  1.013692       0.991107     0.983035
```

```
min                    -1.244978      -3.142228    -2.803659
25%                    -0.420091      -0.727051    -0.600477
50%                    -0.420091      -0.019823     0.065602
75%                     0.404797       0.688850     0.680443
max                     2.879460       2.939691     2.876306

       Average Call Duration  Customer Tenure  Encoded State  \
count             634.000000       634.000000     634.000000
mean               -0.024364         0.014755      -0.028334
std                 0.992871         1.009357       1.034717
min                -3.151224        -2.480710      -1.773496
25%                -0.725004        -0.678688      -0.957794
50%                -0.012205        -0.018793      -0.006141
75%                 0.670742         0.685519       0.928519
max                 2.764078         2.899975       1.625265

       Encoded Area Code  Voice Mail Plan_yes  International Plan_yes

count         634.000000           634.000000              634.000000

mean           -0.091045            -0.005548                0.021263

std             0.998668             0.997953                1.029288

min            -1.432145            -0.613978               -0.326349

25%            -1.432145            -0.613978               -0.326349

50%            -0.024434            -0.613978               -0.326349

75%            -0.024434             1.628723               -0.326349

max             1.383278             1.628723                3.064204


[8 rows x 23 columns]
```

Multicollinearity

In machine learning, multicollinearity is not such a big deal since it should not mess with the predictive power in classification models hence we will not handle multicollinearity.

Feature Selection

This process is important and is used to make the machine learning process accurate. It increases the prediction power by selecting the most critical values and eliminating the redundant ones. We will use a filter method called Variance threshhold.

```
from sklearn.feature_selection import VarianceThreshold

# Specify the threshold value
```

```
threshold_value = 0.5

# Initialize the variance threshold selector with the specified
threshold
selector = VarianceThreshold(threshold=threshold_value)

# Fit the selector on the training data
selector.fit(X_train_df)

# Get the indices of the features with non-zero variance
selected_indices = selector.get_support(indices=True)

# Get the selected features
selected_features = X_train_df.columns[selected_indices]

# Create a new DataFrame with the selected features
X_train_new= X_train_df[selected_features]
X_test_new = X_test_df[selected_features]

# Display the selected features
print("Selected features after variance thresholding:")
X_test_new.head()
```

```
Selected features after variance thresholding:

   Account Length  Number Of Voicemail Messages  Total Day Minutes  \
0        1.377140                     -0.587491           1.523605
1       -0.120315                     -0.587491          -1.369624
2       -0.348740                     -0.587491          -0.632389
3        0.818767                     -0.587491           1.800300
4        1.554804                     -0.587491           0.747373

   Total Day Calls  Total Day Charge  Total Evening Minutes  \
0        -2.304383          1.523770              -0.138516
1         1.391590         -1.369905               1.651291
2         0.378994         -0.632559              -0.590928
3         1.897887          1.800138               0.532166
4         0.834662          0.747098              -0.920316

   Total Evening Calls  Total Evening Charge  Total Night Minutes  \
0             0.659825             -0.138798            -1.089068
1            -0.657267              1.651711            -0.438802
2             0.102594             -0.591678            -0.667599
3             0.862455              0.531184            -1.675110
4             1.065084             -0.920833            -0.282257

   Total Night Calls  ...  Total International Charge  Customer
Service Calls  \
0          -0.773949  ...                   -0.765223
0.404797
1          -0.410152  ...                    1.707114                -
```

```
0.420091
2          -1.761401  ...                        -1.890275               -
0.420091
3           0.161531  ...                         0.929300
0.404797
4          -0.566065  ...                         0.068149               -
0.420091

   Total Charges  Total Calls  Average Call Duration  Customer Tenure
\
0       0.998489    -1.339751               0.211407         1.377140

1      -0.503196     0.270549              -0.088244        -0.120315

2      -1.077653    -0.578518              -1.150543        -0.348740

3       1.510295     1.675901               0.481770         0.818767

4       0.222586     0.973225              -0.225678         1.554804


   Encoded State  Encoded Area Code  Voice Mail Plan_yes  \
0       0.061835          -1.432145            -0.613978
1       0.605636          -0.024434            -0.613978
2       1.217414          -0.024434            -0.613978
3      -0.278041          -1.432145            -0.613978
4       1.353364           1.383278            -0.613978

   International Plan_yes
0               -0.326349
1               -0.326349
2               -0.326349
3               -0.326349
4               -0.326349

[5 rows x 23 columns]
```

With the variance threshold of 0.5, it seems all features are relevant for modeling.

Modeling

We will start with a baseline model and go ahead and build more models and compare their performances.

Baseline metrics.

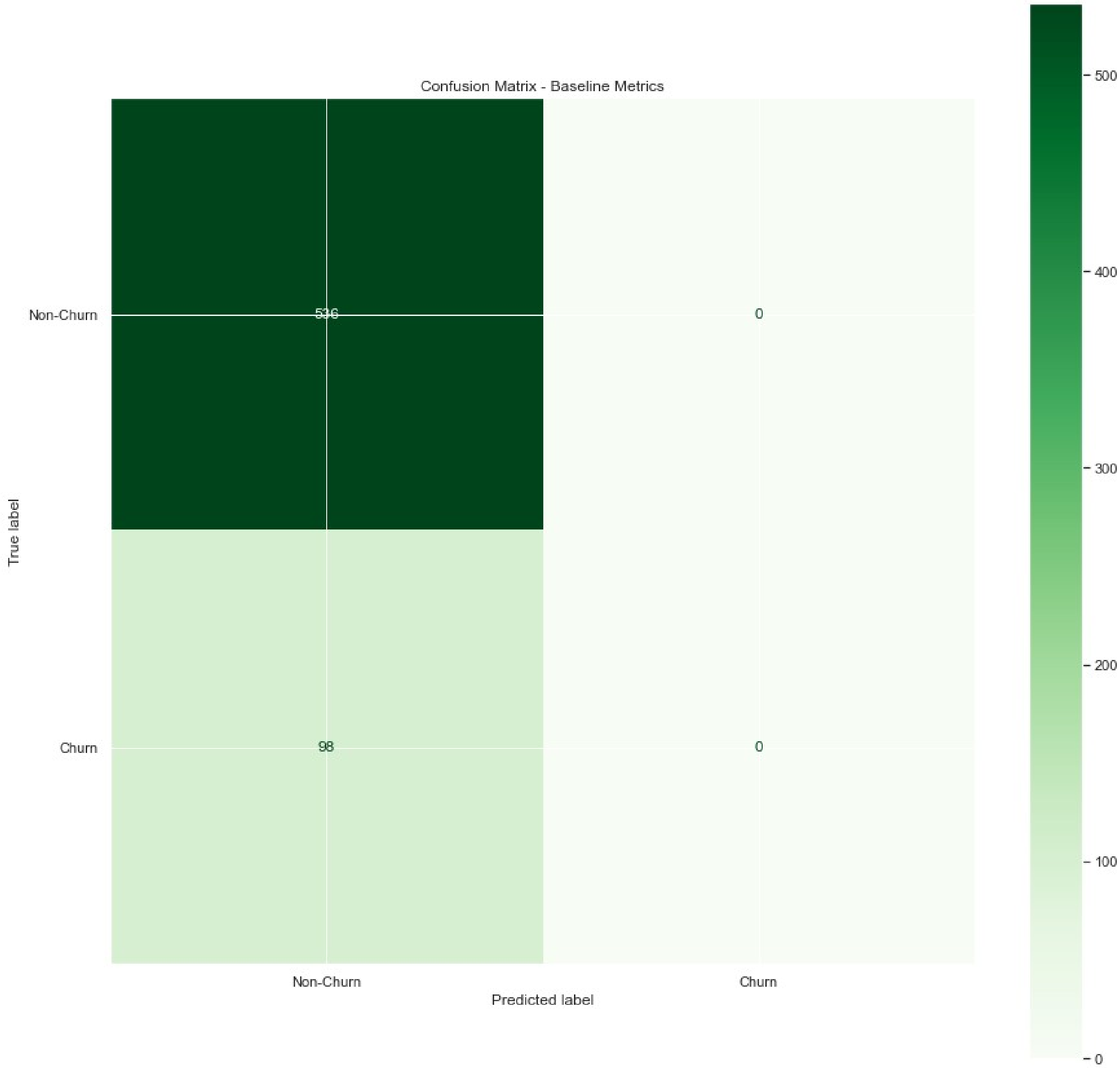
Before we perform any modeling, let's start with a dummy classifier that always predicts the positive class. This will be useful for detecting imbalanced classes by providing a comparison point. We will focus on the test data.

```
np.bincount(y_test)
```

```
array([536,  98], dtype=int64)
```

We will then calculate using different classification metrics to evaluate the model's performance from both positive and negative values.

```
#The confusion matrix

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

majority_class = y_train.mode()[0]
y_pred_baseline = [majority_class] * len(y_test)
conf_matrix = confusion_matrix(y_test, y_pred_baseline)
ConfusionMatrixDisplay(conf_matrix, display_labels=['Non-Churn',
'Churn']).plot(cmap='Greens')
plt.title('Confusion Matrix - Baseline Metrics')
plt.show()
```




```
#Calculate the baseline accuracy, precision, f1score and recall.
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, classification_report
#evaluate the baseline model
baseline_accuracy = accuracy_score(y_test, y_pred_baseline)
baseline_precision = precision_score(y_test, y_pred_baseline,
pos_label=majority_class)
baseline_recall = recall_score(y_test, y_pred_baseline,
pos_label=majority_class)
baseline_f1 = f1_score(y_test, y_pred_baseline,
pos_label=majority_class)


report = classification_report(y_test, y_pred_baseline)
```

```
print(f'Baseline Model Metrics:')
print(f'Accuracy: {baseline_accuracy}')
print(f'Precision: {baseline_precision}')
print(f'Recall: {baseline_recall}')
print(f'F1-Score: {baseline_f1}')

print('Classification Report:')
print(report)
```

```
Baseline Model Metrics:
Accuracy: 0.8454258675078864
Precision: 0.8454258675078864
Recall: 1.0
F1-Score: 0.9162393162393162
Classification Report:
              precision    recall  f1-score   support

           0       0.85      1.00      0.92       536
           1       0.00      0.00      0.00        98

    accuracy                           0.85       634
   macro avg       0.42      0.50      0.46       634
weighted avg       0.71      0.85      0.77       634


c:\Users\Administrator\anaconda3\envs\learn-env\lib\site-packages\
sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\Users\Administrator\anaconda3\envs\learn-env\lib\site-packages\
sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\Users\Administrator\anaconda3\envs\learn-env\lib\site-packages\
sklearn\metrics\_classification.py:1471: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control
this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Logistic Regreesion

Instantiate and Fit the Logistic Regression model.

```
#importing the class
from sklearn.linear_model import LogisticRegression
#Instantiate the model
model = LogisticRegression(fit_intercept=False, C=1e12,
solver='liblinear', random_state = 42)
#fitting the model on scaled data
model.fit(X_train_new, y_train)
# evaluate performance on the train set
y_pred_train = model.predict(X_train_new)

train_residuals = np.abs(y_train - y_pred_train)
print(pd.Series(train_residuals, name="Residuals
(counts)").value_counts())
print()
print(pd.Series(train_residuals, name="Residuals
(proportions)").value_counts(normalize=True))
```

```
0    1649
1     886
Name: Residuals (counts), dtype: int64

0    0.650493
1    0.349507
Name: Residuals (proportions), dtype: float64
```

Our model was about 65% correct on the training data.

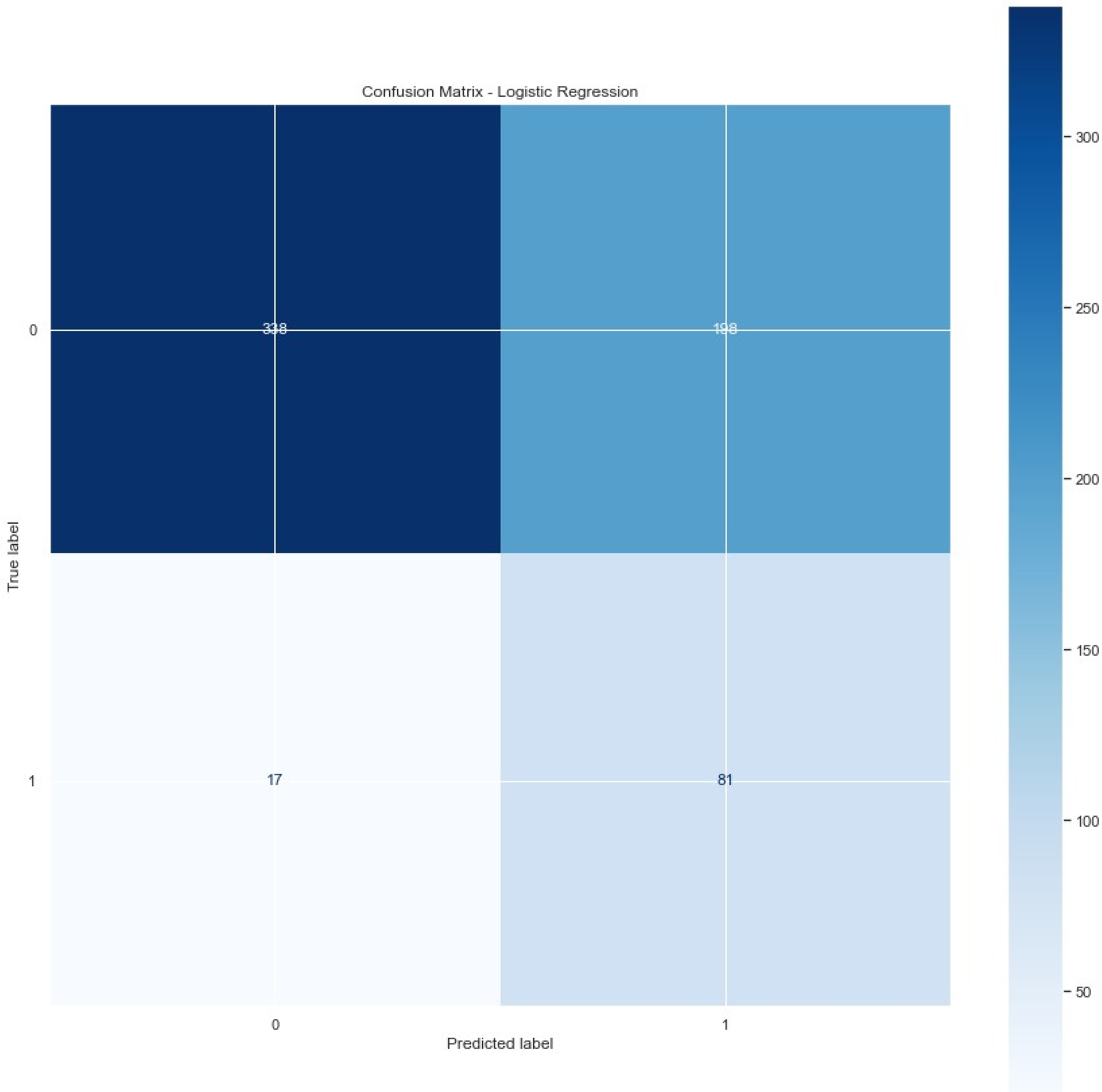
```
#evaluate performance on the test set.
y_pred_test = model.predict(X_test_new)

test_residuals = np.abs(y_test - y_pred_test)
print(pd.Series(test_residuals, name="Residuals
(counts)").value_counts())
print()
print(pd.Series(test_residuals, name="Residuals
(proportions)").value_counts(normalize=True))
```

```
0    419
1    215
Name: Residuals (counts), dtype: int64

0    0.660883
1    0.339117
Name: Residuals (proportions), dtype: float64
```

The model was about 66% correct on the test data.

NOTE: 0 means the prediction and the actual value matched, whereas 1 means the prediction and the actual value did not match. The accuracies are very close (Ie 65% and 66%); this ia a good sign to show that there's neither underfitting nor overfitting. But, remember the churn data is imbalanced and we will later review that.

```
#Compute the confusion matrix
cm = confusion_matrix(y_test, y_pred_test)

# Display the confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=model.classes_)
disp.plot(cmap='Blues')
plt.title('Confusion Matrix - Logistic Regression')
plt.show()
```



We will go ahead and use cross validation to further evaluate our fitted model.

```
# Import the function
from sklearn.model_selection import cross_val_score

# Perform cross-validation
cv_scores = cross_val_score(model, X_train_new, y_train, cv=3)
print(cv_scores)
print("Mean_accuracy:", np.mean(cv_scores))

[0.66982249 0.63076923 0.63550296]
Mean_accuracy: 0.6453648915187377
```

The values are generally close which shows the model is consistent across the subsets. The mean accuray score 64%, which is generally acceptable but we need a higher accuracy.

We can now compare the metrics values for the fitted model and the baseline metrics.

```
model_accuracy = accuracy_score(y_test, [1] * len(y_test))
model_recall = recall_score(y_test, [1] * len(y_test))
model_precision = precision_score(y_test, [1] * len(y_test))
model_f1 = f1_score(y_test, [1] * len(y_test))

print(f"""
Accuracy
Baseline: {baseline_accuracy:1.3f} Fitted Model: {model_accuracy:1.3f}
Recall
Baseline: {baseline_recall:1.3f} Fitted Model: {model_recall:1.3f}
Precision
Baseline: {baseline_precision:1.3f} Fitted Model:
{model_precision:1.3f}
F1 Score
Baseline: {baseline_f1:1.3f} Fitted Model: {model_f1:1.3f}
""")


Accuracy
Baseline: 0.845 Fitted Model: 0.155
Recall
Baseline: 1.000 Fitted Model: 1.000
Precision
Baseline: 0.845 Fitted Model: 0.155
F1 Score
Baseline: 0.916 Fitted Model: 0.268
```

The baseline metrics show high accuracy, precision and f1 scores showing generally that the model performs well. The fitted model has very low scores compared to the baseline metrics. It has a poor perfromance showing that it interprets most of positive values incorrectly hence the low scores in accuracy and precision.

Handling imbalance in the data.

We will use SMOTE i.e is Synthetic Minority Oversampling. We increase the number of the minority class instances.

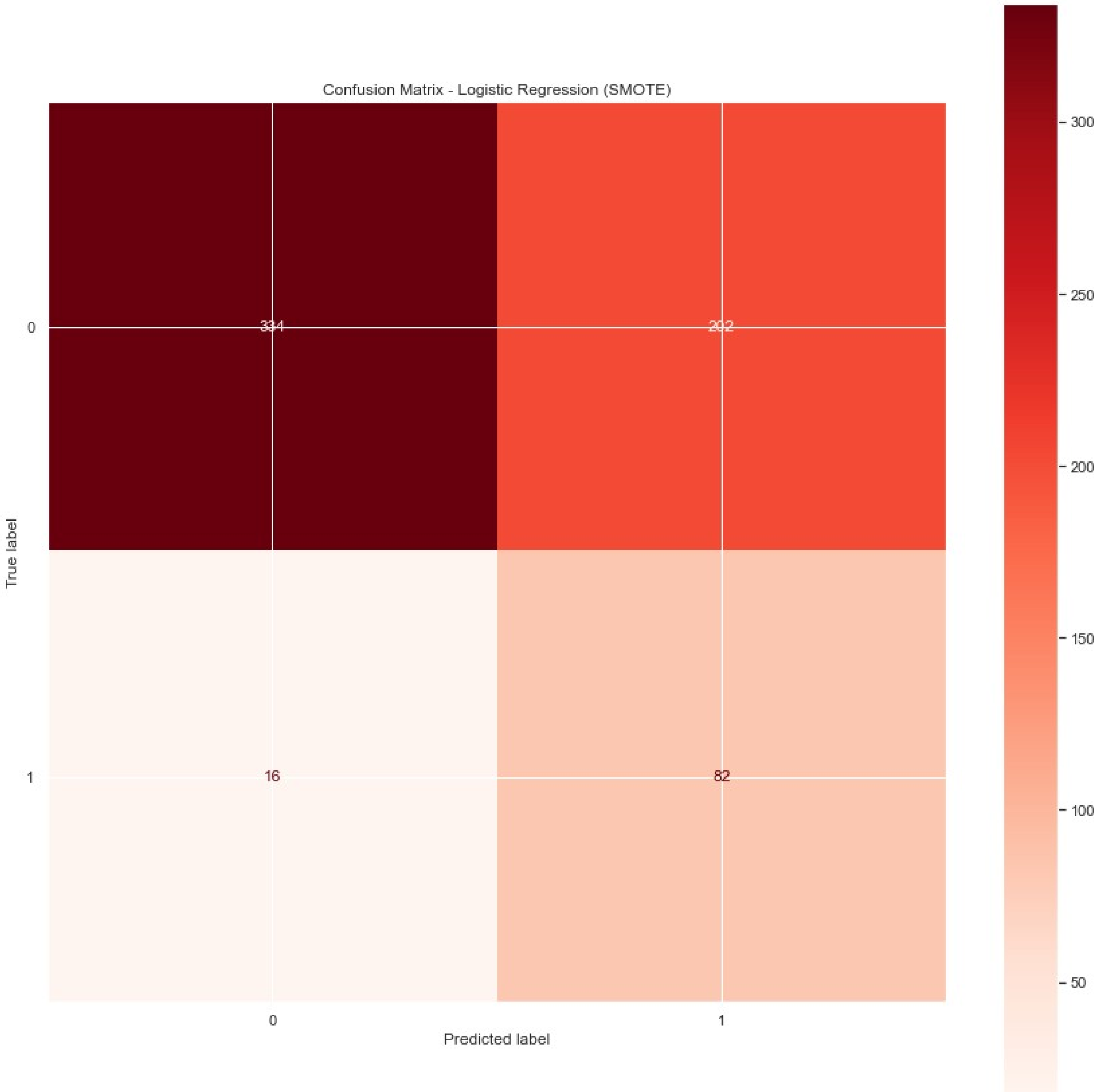
```
from imblearn.over_sampling import SMOTE
# Original class distribution
print('Original class distribution: \n')
print(y.value_counts())
smote = SMOTE()
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_new,
y_train)
# Preview synthetic sample class distribution
print('-----------------------------------------')
print('Synthetic sample class distribution: \n')
print(pd.Series(y_train_resampled).value_counts())
```

```
Original class distribution: 

0    2727
1     442
Name: Churn, dtype: int64
-----------------------------------------
Synthetic sample class distribution: 

1    2191
0    2191
Name: Churn, dtype: int64
```

```
logreg = LogisticRegression(fit_intercept=False, C=1e12,
solver='liblinear')
logreg.fit(X_train_resampled, y_train_resampled)
print(logreg)

# Predict
y_hat_test = logreg.predict(X_test_new)
```

```
LogisticRegression(C=1000000000000.0, fit_intercept=False,
solver='liblinear')
```

```
#Compute the confusion matrix for the resampled data
cm = confusion_matrix(y_test, y_hat_test)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=logreg.classes_)
disp.plot(cmap='Reds')
plt.title('Confusion Matrix - Logistic Regression (SMOTE)')
plt.show()
```




```
class_report = classification_report(y_test, y_hat_test)
print(class_report)
```

```
              precision    recall  f1-score   support

           0       0.95      0.62      0.75       536
           1       0.29      0.84      0.43        98

    accuracy                           0.66       634
   macro avg       0.62      0.73      0.59       634
weighted avg       0.85      0.66      0.70       634
```

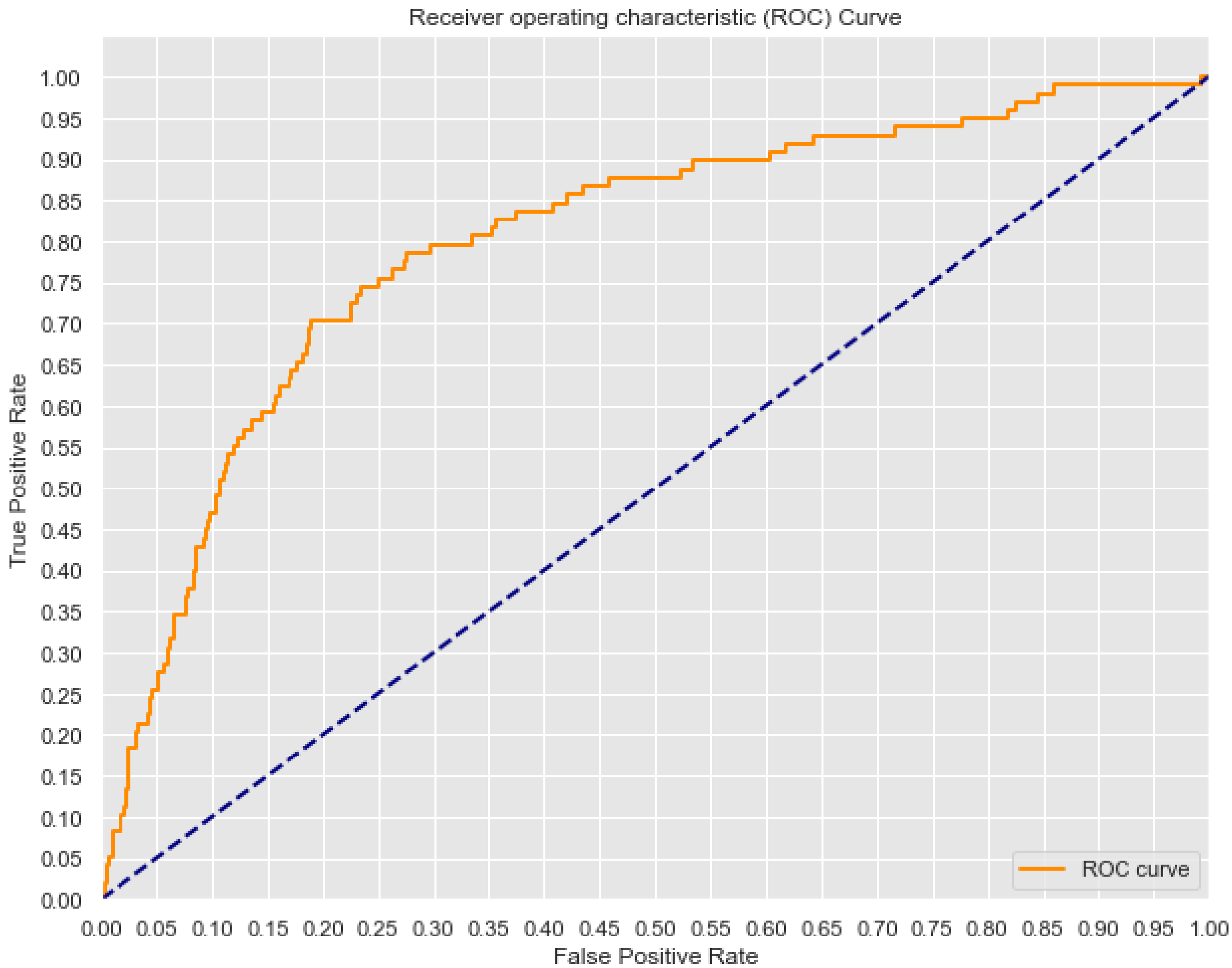
We will use the ROC and AUC, to evaluate the logistic model after balancing the the dataset.

```
from sklearn.metrics import roc_curve, auc

fpr, tpr, thresholds = roc_curve(y_test, y_score)
print('AUC: {}'.format(auc(fpr, tpr)))
```

```
AUC: 0.7994593359731954
```

```
# Visualizing the ROC and AUC for Logistic Regression Smote
sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

print('AUC: {}'.format(auc(fpr, tpr)))
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
AUC: 0.7994593359731954
```



AUC of 0.79946 demonstrates an outstanding discriminatory power; it is capable of accurately identifying customers who will churn.

Hypertuning

Hypertuning parameters is the process of tweaking model parameters to improve its performance. It will help achieve a maximum perfomance. We will tweak the parameters for the SMOTE logistic regression like changing the C intercept values and specifiying the L1 penalty and perform GridSearch with cross validation.

```
from sklearn.model_selection import GridSearchCV

log1 = LogisticRegression(penalty = 'l1',
solver='liblinear',random_state=42)
log1.fit(X_train_resampled,y_train_resampled)
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100]  # Different values for the inverse
of regularization strength
}
#Perform GridSearch with cross validation.
```

```python
# Set up the grid search
grid_search = GridSearchCV(logreg, param_grid, cv=5,
scoring='roc_auc', n_jobs=-1, verbose=1)

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

# Get the best model
best_model = grid_search.best_estimator_

print(f'Best C parameter: {grid_search.best_params_}')
print(f'Best AUC: {grid_search.best_score_:.4f}')
```

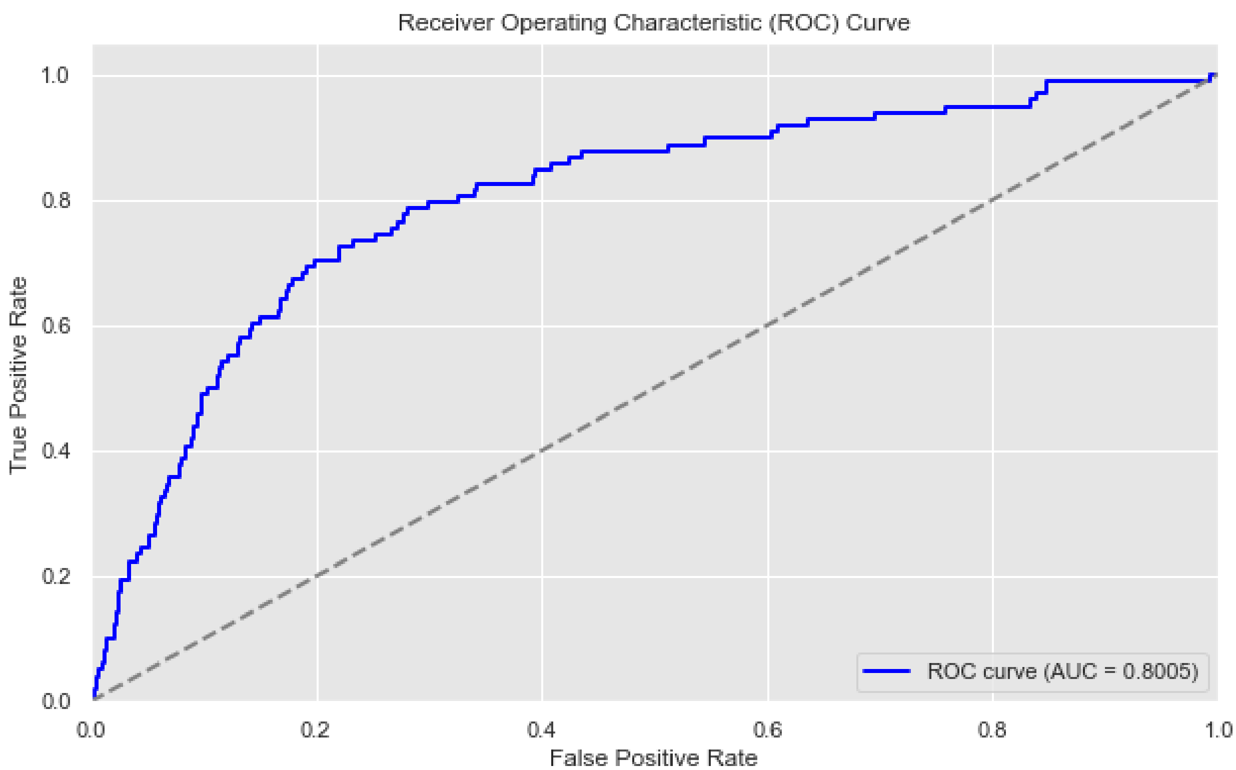
```
Fitting 5 folds for each of 5 candidates, totalling 25 fits
Best C parameter: {'C': 100}
Best AUC: 0.8449
```

```python
from sklearn.metrics import roc_auc_score
#Evaluate the model
# Make predictions on the test set
y_pred = grid_search.predict(X_test_new)
y_pred_prob = grid_search.predict_proba(X_test_new)[:, 1]

# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# ROC AUC score
roc_auc = roc_auc_score(y_test, y_pred_prob)
print(f"ROC AUC: {roc_auc:.4f}")
```

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

           0       0.95      0.61      0.74       536
           1       0.28      0.83      0.42        98

    accuracy                           0.65       634
   macro avg       0.62      0.72      0.58       634
weighted avg       0.85      0.65      0.69       634

ROC AUC: 0.8005
```

```python
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (AUC =
{roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='grey', 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) Curve')
plt.legend(loc="lower right")
plt.show()
```



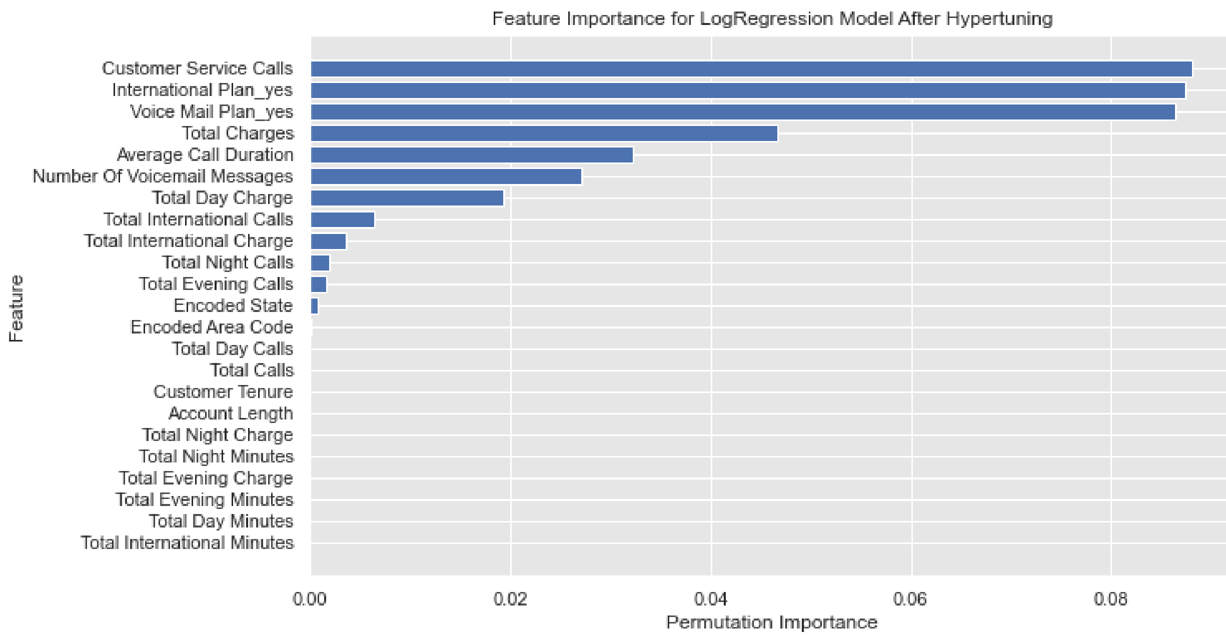
After tuning the parameters, we see the training set , after using different C interceptvalues we get the best parameter combination AUC of 0.8455. On the test set we get an AUC of 0.8004. The slight difference on the AUC shows there's no overfitting. 0.8455 shows that the model has an impressive ability to distinguish between the the churn and no churn within the training dataset. An AUC of 0.8004 on the test set shows that the model generalizes well to the unseen data hence validating the model's use for practical use. It definitely performs better than the original logistic regression mode with the AUC of 0.799945

```
from sklearn.inspection import permutation_importance
perm_importance = permutation_importance(log1, X_train_resampled,
y_train_resampled, n_repeats=10, random_state=42)

# Extract importance scores
importance_scores = perm_importance.importances_mean

# Create a DataFrame for better visualization
feature_importance_df = pd.DataFrame({
    'Feature': X_train_resampled.columns,
    'Importance': importance_scores
}).sort_values(by='Importance', ascending=False)
```

```python
print(feature_importance_df)
```

```
                          Feature  Importance
14         Customer Service Calls    0.087951
22         International Plan_yes    0.087449
21            Voice Mail Plan_yes    0.086353
15                  Total Charges    0.046737
17          Average Call Duration    0.032337
1    Number Of Voicemail Messages    0.027134
4                Total Day Charge    0.019283
12      Total International Calls    0.006458
13     Total International Charge    0.003651
9               Total Night Calls    0.001963
6             Total Evening Calls    0.001575
19                  Encoded State    0.000799
20              Encoded Area Code    0.000183
3                 Total Day Calls    0.000068
16                    Total Calls    0.000000
18                Customer Tenure    0.000000
0                  Account Length    0.000000
10             Total Night Charge    0.000000
8             Total Night Minutes    0.000000
7            Total Evening Charge    0.000000
5           Total Evening Minutes    0.000000
2               Total Day Minutes    0.000000
11    Total International Minutes    0.000000
```

```python
# Plot the feature importance
plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df['Feature'],
feature_importance_df['Importance'])
plt.xlabel('Permutation Importance')
plt.ylabel('Feature')
plt.title('Feature Importance for LogRegression Model After
Hypertuning')
plt.gca().invert_yaxis()
plt.show()
```



K-Nearest Neighbours.

This is a more complex model. It relies on the idea that similar data points tend to have similar labels or values. We will use it to make more predictions and compare the results to the logistic regression.

```
from sklearn.pipeline import Pipeline
from sklearn.neighbors import KNeighborsClassifier
#Initialize the KNN model
knn = KNeighborsClassifier(n_neighbors=5)

# Train the model on the resampled training set
knn.fit(X_train_resampled, y_train_resampled)

# Define the pipeline
pipeline = Pipeline([
    ('knn', KNeighborsClassifier())
])

# Define the hyperparameter grid
param_grid = {
    'knn__n_neighbors': [3, 5, 7, 9],
    'knn__weights': ['uniform', 'distance'],
    'knn__metric': ['euclidean', 'manhattan']
}

# Initialize GridSearchCV
grid_search = GridSearchCV(pipeline, param_grid, cv=5,
scoring='roc_auc', n_jobs=-1, verbose=2)

# Perform the grid search
```

```python
grid_search.fit(X_train_resampled, y_train_resampled)

# Get the best parameters and best score
best_params = grid_search.best_params_
best_score = grid_search.best_score_
print(f"Best parameters: {best_params}")
print(f"Best ROC AUC: {best_score}")
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
Best parameters: {'knn__metric': 'manhattan', 'knn__n_neighbors': 9,
'knn__weights': 'distance'}
Best ROC AUC: 0.9882564713385434
```

```python
# Train the final model with the best parameters on the entire
training set
final_model = grid_search.best_estimator_

# Evaluate the final model
# Make predictions on the training set
y_train_pred = final_model.predict(X_train_resampled)
y_train_pred_proba = final_model.predict_proba(X_train_resampled)[:,
1]

# Make predictions on the test set
y_test_pred = final_model.predict(X_test_new)
y_test_pred_proba = final_model.predict_proba(X_test_new)[:, 1]


# Generate classification report for training set
print("Classification Report for Training Set:")
print(classification_report(y_train_resampled, y_train_pred))

# Generate classification report for test set
print("Classification Report for Test Set:")
print(classification_report(y_test, y_test_pred))
```

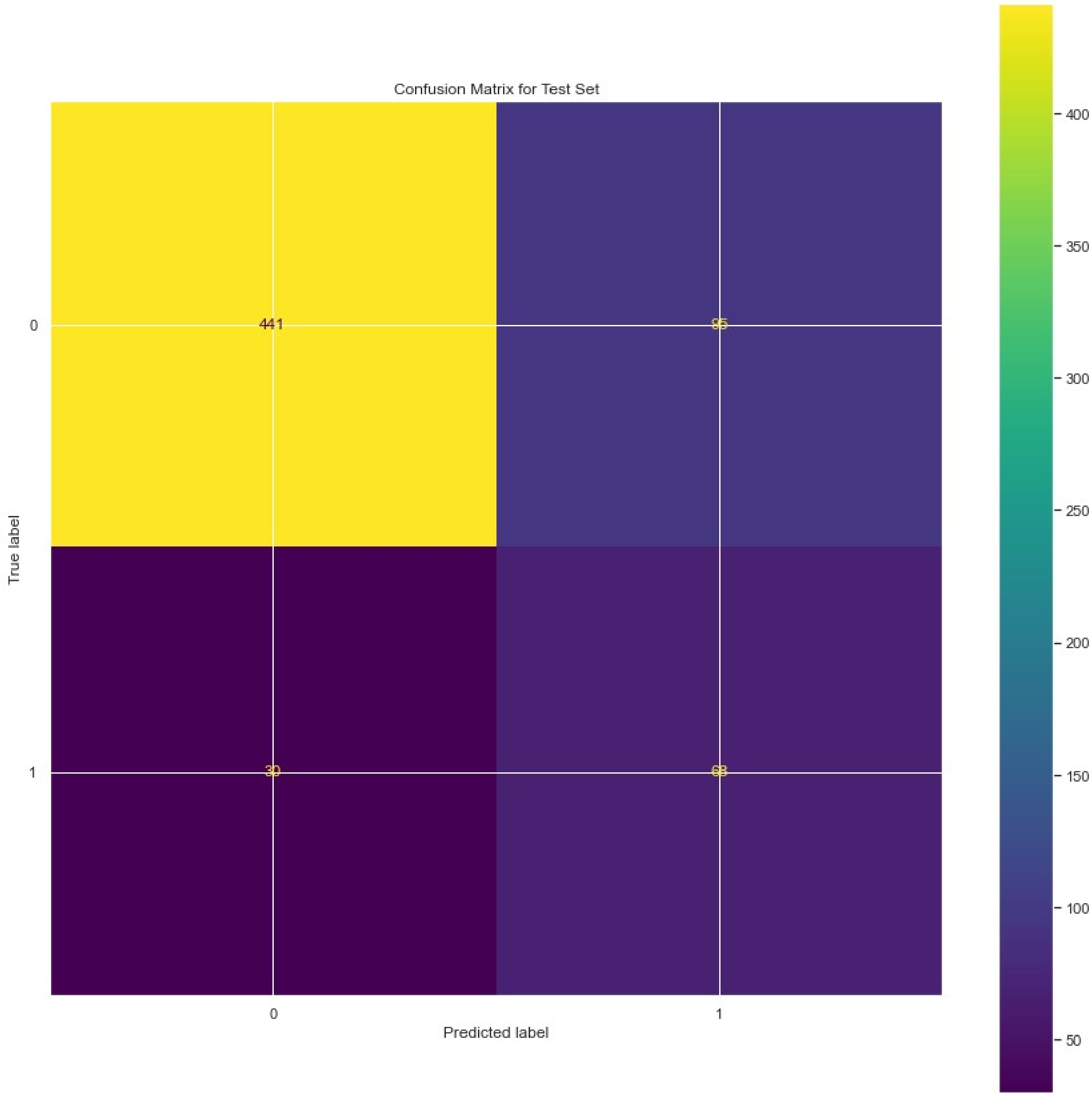
```
Classification Report for Training Set:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2191
           1       1.00      1.00      1.00      2191

    accuracy                           1.00      4382
   macro avg       1.00      1.00      1.00      4382
weighted avg       1.00      1.00      1.00      4382

Classification Report for Test Set:
              precision    recall  f1-score   support
```

```
           0       0.94      0.82      0.88       536
           1       0.42      0.69      0.52        98

    accuracy                           0.80       634
   macro avg       0.68      0.76      0.70       634
weighted avg       0.86      0.80      0.82       634
```

```python
#ROC AUC for training set
roc_auc_train = roc_auc_score(y_train_resampled, y_train_pred_proba)
print(f"AUC for Training Set: {roc_auc_train:.4f}")

# ROC AUC score for test set
roc_auc_test = roc_auc_score(y_test, y_test_pred_proba)
print(f"AUC for Test Set: {roc_auc_test:.4f}")
```

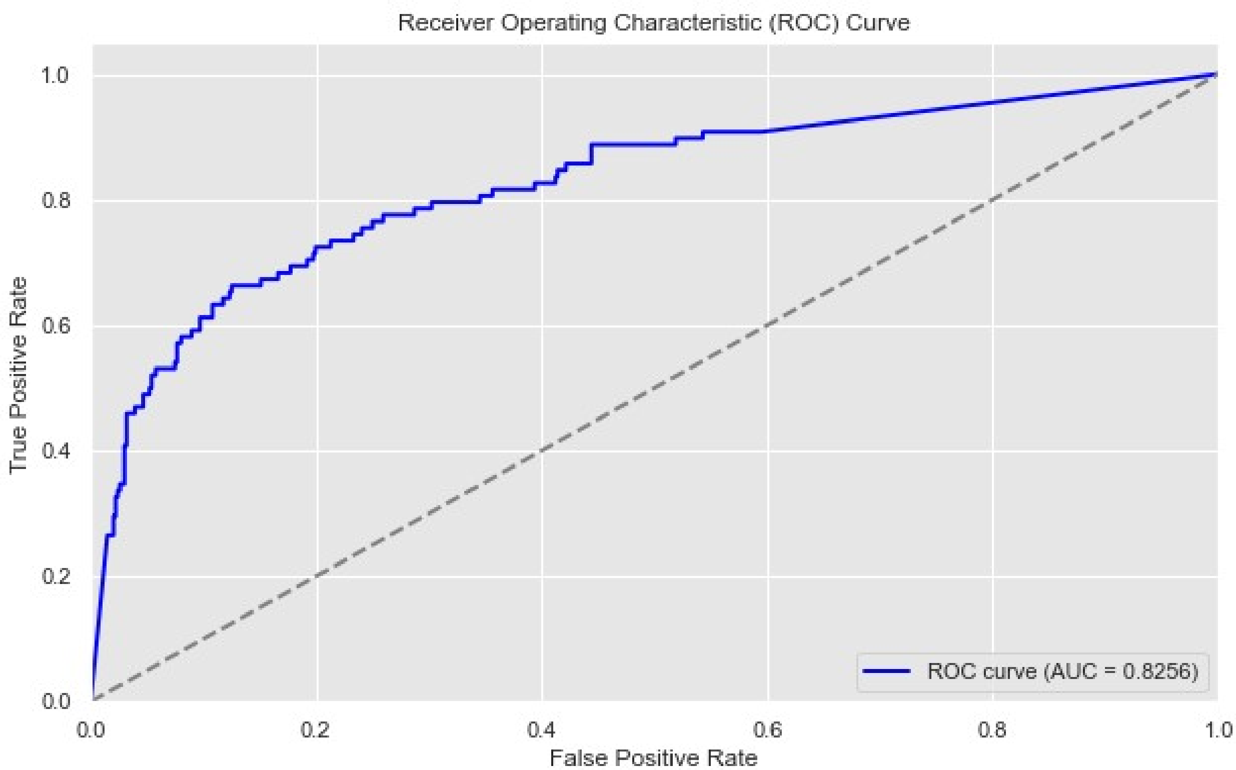
```
AUC for Training Set: 1.0000
AUC for Test Set: 0.8256
```

```python
# Plot the confusion matrix for the test set
ConfusionMatrixDisplay.from_predictions(y_test, y_test_pred)
plt.title('Confusion Matrix for Test Set')
plt.show()
```




```python
# Plot the ROC curve
from sklearn.metrics import roc_curve

fpr, tpr, _ = roc_curve(y_test, y_test_pred_proba)
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (AUC =
{roc_auc_test:.4f})')
plt.plot([0, 1], [0, 1], color='grey', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
```

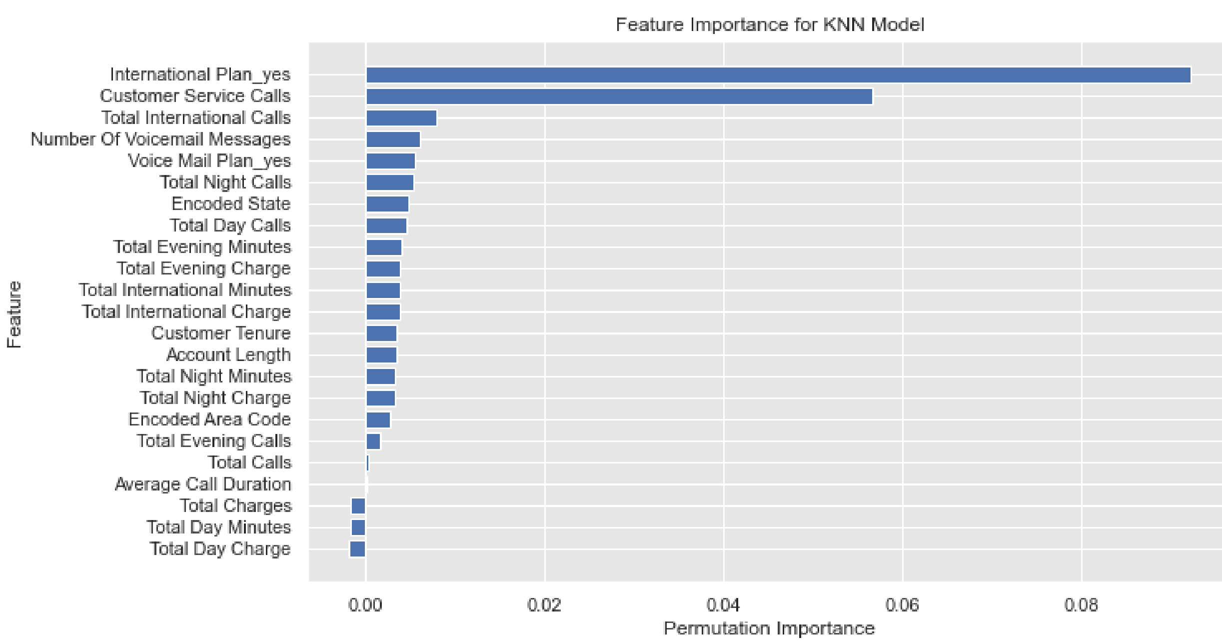
```
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```




```
from sklearn.inspection import permutation_importance
perm_importance = permutation_importance(knn, X_train_resampled,
y_train_resampled, n_repeats=10, random_state=42)

# Extract importance scores
importance_scores = perm_importance.importances_mean

# Create a DataFrame for better visualization
feature_importance_df = pd.DataFrame({
    'Feature': X_train_resampled.columns,
    'Importance': importance_scores
}).sort_values(by='Importance', ascending=False)

print(feature_importance_df)
```

	Feature	Importance
22	International Plan_yes	0.092173
14	Customer Service Calls	0.056709
12	Total International Calls	0.007964
1	Number Of Voicemail Messages	0.006162
21	Voice Mail Plan_yes	0.005568

```
9                 Total Night Calls    0.005431
19                    Encoded State    0.004792
3                   Total Day Calls    0.004564
5             Total Evening Minutes    0.004016
7              Total Evening Charge    0.003994
11   Total International Minutes      0.003971
13    Total International Charge      0.003857
18                  Customer Tenure    0.003583
0                    Account Length    0.003583
8               Total Night Minutes    0.003400
10               Total Night Charge    0.003355
20                Encoded Area Code    0.002875
6               Total Evening Calls    0.001712
16                      Total Calls    0.000411
17            Average Call Duration    0.000137
15                    Total Charges   -0.001597
2                 Total Day Minutes   -0.001712
4                  Total Day Charge   -0.001757

# Plot the feature importance
plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df['Feature'],
feature_importance_df['Importance'])
plt.xlabel('Permutation Importance')
plt.ylabel('Feature')
plt.title('Feature Importance for KNN Model')
plt.gca().invert_yaxis()
plt.show()
```



Summary

For all the models we have used, the results show low scores on the precisions with the highest being 0.42 ofr the KNN. This means that it can only 42% of the predicted values were correctly classified. It has the highest f1 value of 0.52, while the model with the second highest F1 score is the logistic regression(SMOTE) with a score of 0.43. Tis shows a low imbalance between precision and recall scores.

The model with the highest recall value is logistic(SMOTE)with a score of 0.84. This means that it correctly identified, captured te actual churners in the dataset but at the expense of precision as it has a low precision of 0.29. The classification metrics between the logistic(SMOTE) and logistic(SMOTE) after hypertuning has a slight diference of 0.1.

Recall is more useful for this analysis as we want to actually get the actual positive values. The models best for predicting unseen data are the LogisticRegression(SMOTE) and LogisticRegression(SMOTE) after hypertuning.

If we consider the ROC AUC values, the Logistic Regression after hypertuning showed 0.8449 on the best parameter combination for the training set and 0.80044 on the test set. There is a slight difference and overfitting should not be a big deal. Compared to the KNN, the score was 0.9882 on the best parameter combination on the train set. This showed that it performed really well on the training set. However, as much as it has a 0.8256 AUC score on the test set, which is still good, there is a significant difference between the two scores signifying overfitting.

With these results, the best models to be used to predict the uneen data for churners is the Logistic Regression(SMOTE) and LogisticRegression(SMOTE) after hypertuning.

Conclusions

In Conclusion, our goal was to identify clients which are likely to churn, so we can do special-purpose marketing strategies to avoid the churn event. From the feature importance graphs shown for both of the models, we can see which feataures contribute most to the prediction of the models. The top 4 are Customer Service Calls, International Plan, Voice Mail Plan and Total International Calls. SyriaTel can improve their products by focusing on these features.

Limitations

1. Overfitting - The KNN performed well on the train data, but reduced its generalization on the test data.
2. GridSearch with cross validation is time consuming hence could not build more models.
3. Imbalanced Data- SMOTE might not perfectly represent the true distribtuion.
4. Feature Selection method did not really have an effect to the data. It did not reduce the relevant features from the dataset.

Recommednations.

1. Use a more updated dataset to reduce the imbalance of data.
2. Use better and more convinient method for feature selection to reducing overfitting.