# Phase 3 Project - Customer Churn Analysis

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## INTRODUCTION

SyriaTel is a telecommunications company in Syria. They have been informed that some of their customers have started to churn, discontinue their service. This analysis will determine what features will indicate if a customer will ("soon") discontinue their service.

In this report, a dataset on churn data of a Telecom company is analysed. It can be found here: https://www.kaggle.com/becksddf/churn-in-telecoms-dataset.

## BUSINESS UNDERSTANDING

In the highly competitive telecom industry, customer churn represents a critical challenge that directly impacts profitability and market share. The dataset under analysis offers essential insights into customer behavior, helping to identify the key factors influencing churn. By utilizing predictive analytics, telecom companies can proactively mitigate customer attrition, thereby optimizing retention strategies and improving overall business performance.

## PROBLEM STATEMENT

The objective of this analysis is to develop a predictive model to anticipate customer churn in the telecom sector. By leveraging supervised classification techniques, we aim to identify key attributes and patterns that indicate potential churn among telecom customers. Accurate churn prediction will enable telecom companies to implement targeted retention initiatives, such as personalized offers and proactive customer service interventions, ultimately reducing customer attrition and fostering long-term customer loyalty.

## DATA UNDERSTANDING

Customer Churn indicates if a customer has terminated their contract with SyriaTel. Predicting churn can help a telecom company focus its customer retention marketing efforts (such as providing special offers) on the subset of clients most likely to switch service providers. Therefore, the “churn” column has been chosen as the target variable for this predictive analysis, which is a supervised classification problem.

**Target Variable** - churn

**Unique identifier** - phone number

## OBJECTIVES

**Main Objective:**

Our primary objective is to accurately identify customers who are likely to churn. By leveraging advanced predictive analytics and machine learning techniques, we aim to enable the implementation of targeted, special-purpose marketing strategies designed to preemptively address and mitigate churn events, thereby fostering customer retention and long-term loyalty.

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# 1. DATA EXPLORATION

```
# Import Relevant Libraries, Modules, Functions and Packages

# Data Manipulation
import pandas as pd
import numpy as np

# Data Visualization
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px

# Data Modeling
from sklearn.model_selection import train_test_split, cross_val_score,
GridSearchCV # splitting the dataset into test-train
from imblearn.over_sampling import SMOTE # SMOTE technique to deal
with unbalanced data problem
from sklearn.metrics import accuracy_score, f1_score, recall_score,
precision_score, confusion_matrix, roc_curve, roc_auc_score,
classification_report # performance metrics
from sklearn.preprocessing import MinMaxScaler # to scale the numeric
features
from scipy import stats

# Feature Selection, XAI, Feature Importance
from sklearn.inspection import permutation_importance

# Algorithms for supervised learning methods
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier

# Filtering future warnings
```

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

!pip install --upgrade scikit-learn
!pip install --upgrade imbalanced-learn
```

```
Defaulting to user installation because normal site-packages is not
writeable
Requirement already satisfied: scikit-learn in c:\users\
charles.egambi\appdata\roaming\python\python311\site-packages (1.4.2)
Requirement already satisfied: numpy>=1.19.5 in c:\programdata\
anaconda3\lib\site-packages (from scikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in c:\programdata\
anaconda3\lib\site-packages (from scikit-learn) (1.11.4)
Requirement already satisfied: joblib>=1.2.0 in c:\programdata\
anaconda3\lib\site-packages (from scikit-learn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\programdata\
anaconda3\lib\site-packages (from scikit-learn) (2.2.0)
Defaulting to user installation because normal site-packages is not
writeable
Requirement already satisfied: imbalanced-learn in c:\users\
charles.egambi\appdata\roaming\python\python311\site-packages (0.12.2)
Requirement already satisfied: numpy>=1.17.3 in c:\programdata\
anaconda3\lib\site-packages (from imbalanced-learn) (1.26.4)
Requirement already satisfied: scipy>=1.5.0 in c:\programdata\
anaconda3\lib\site-packages (from imbalanced-learn) (1.11.4)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\
charles.egambi\appdata\roaming\python\python311\site-packages (from
imbalanced-learn) (1.4.2)
Requirement already satisfied: joblib>=1.1.1 in c:\programdata\
anaconda3\lib\site-packages (from imbalanced-learn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\programdata\
anaconda3\lib\site-packages (from imbalanced-learn) (2.2.0)
```

```
# Import Data and create dataframe. Print the first 5 rows.

df = pd.read_csv('churn_in_telecoms.csv')
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]

#check the the datatypes and meta data for data
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   state                   3333 non-null   object
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   int64
```

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

We notice that 4 of the columns are of data type 'Object'. 16 are of data types 'integer' and 'float', and 1 is 'boolean'

```
# Checking the shape of the dataframe
df.shape

(3333, 21)
```

The dataset has 3333 Rows and 21 columns.

## 2. STATISTICAL ANALYSIS

```
# Concise statistical description of numeric features
df.describe()

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

```
75%        127.000000   510.000000              20.000000
216.400000
max        243.000000   510.000000              51.000000
350.800000

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

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

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

       total intl charge  customer service calls
count        3333.000000             3333.000000
mean            2.764581                1.562856
std             0.753773                1.315491
min             0.000000                0.000000
25%             2.300000                1.000000
```

```
50%                 2.780000                    1.000000
75%                 3.270000                    2.000000
max                 5.400000                    9.000000
```

## 3. DATA CLEANING

Checking the Dataset for:

- Duplicated rows
- Missing values
- Irrelevant columns as they may not add to the analysis

```
# Checking for duplicates using the unique identifier - 'phone number'
df.duplicated(subset=['phone number']).sum()

0
```

We can clearly see that there are no Duplicates

```
# Checking the Dataset for missing/null 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 does not contain any missing or null values

```
# Remove 'phone number' feature, since it does not help in predicting
'churn'
```

```python
# Recheck dataframe
df.drop(['phone number'],axis=1,inplace=True)
df.head()
```

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

1    OH             107        415                 no             yes   

2    NJ             137        415                 no              no   

3    OH              84        408                yes              no   

4    OK              75        415                yes              no   


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

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

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01   
1                254.4                103               11.45   
2                162.6                104                7.32   
3                196.9                 89                8.86   
4                186.9                121                8.41   

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

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

## 4. EXPLORATORY DATA ANALYSIS

```
# Checking for unique values:
df.nunique()
```

```
state                       51
account length             212
area code                    3
international plan           2
voice mail plan              2
number vmail messages       46
total day minutes         1667
total day calls            119
total day charge          1667
total eve minutes         1611
total eve calls            123
total eve charge          1440
total night minutes       1591
total night calls          120
total night charge         933
total intl minutes         162
total intl calls            21
total intl charge          162
customer service calls      10
churn                        2
dtype: int64
```

### Feature Types

Continuous (Numeric):

- account length
- number vmail messages
- total day minutes
- total day calls
- total day charge
- total eve minutes
- total eve calls
- total eve charge
- total night minutes
- total night calls

- total night charge
- total intl minutes
- total intl charge
- customer service calls

Categorical Features:

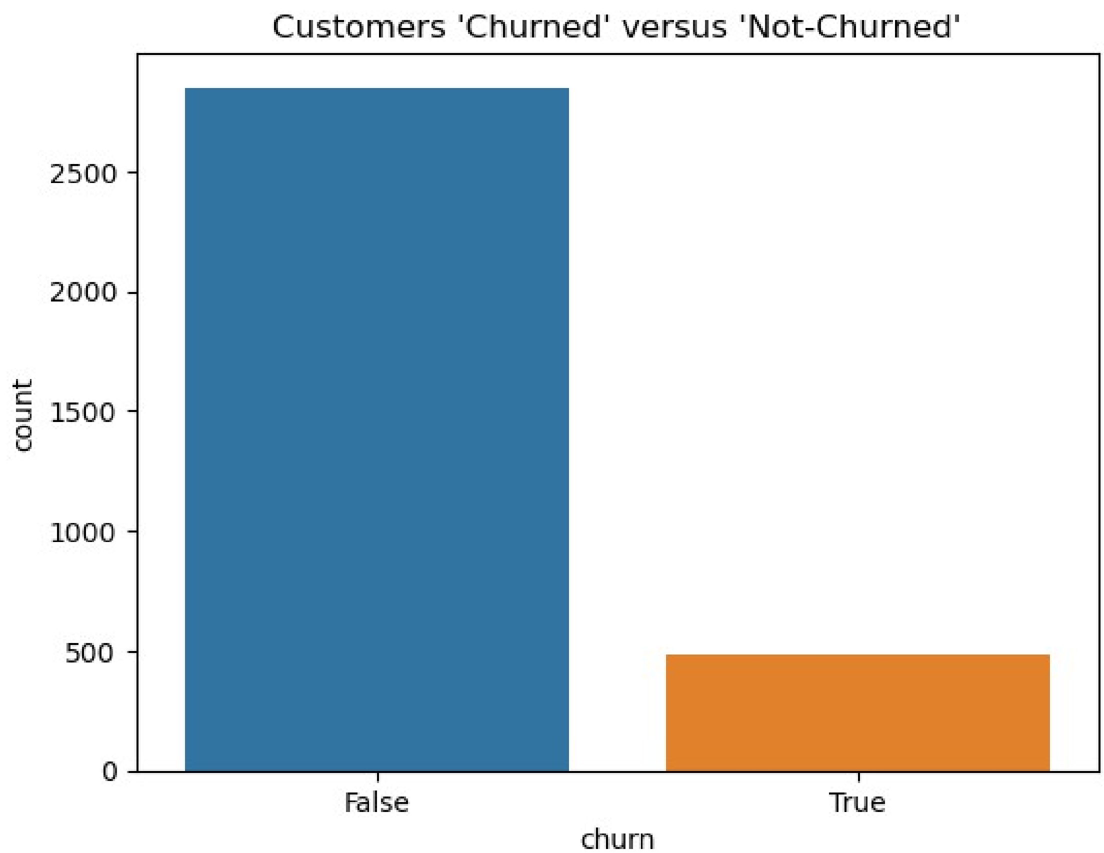
- state
- area code
- international plan
- voicemail plan

```
# Creating Numerical and Categorical lists

numerical_cols = ['account length','number vmail messages','total day
minutes','total day calls','total day charge',
                'total eve minutes','total eve calls','total eve
charge','total night minutes','total night calls',
                'total night charge','total intl minutes','total intl
calls','total intl charge','customer service calls']

categorical_cols = ['state','area code','international plan','voice
mail plan']
```

## 5. FEATURE ANALYSIS (Churn)

- Churn indicates if a customer has terminated his or her contract with SyriaTel.
- True indicates contract terminated and False indicates contract not terminated.
- The target variable Churn is a binary variable, hence we'll be solving a CLASSIFICATION problem.
- Let's take a look at distribution of churn.

```
# Countplot of churn feature
print(df.churn.value_counts())
sns.countplot(data=df, x='churn');
plt.title("Customers 'Churned' versus 'Not-Churned'");

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

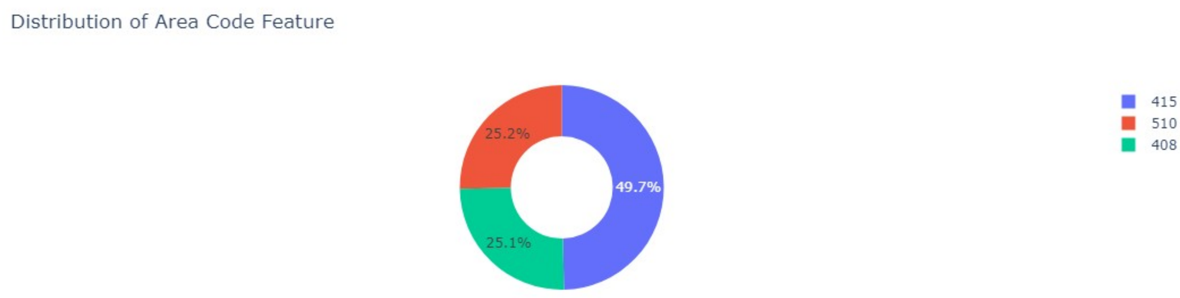



- Out of the 3,333 customers in the dataset, 483 have terminated their contract, translating to about 14.5% of customers lost.
- The distribution of the binary classes shows a data imbalance. This needs to be addressed before modeling as an unbalanced feature can cause the model to make false predictions.

## 6. UNIVARIATE, BIVARIATE AND MULTIVARIATE ANALYSIS

### Analysis on "area code"

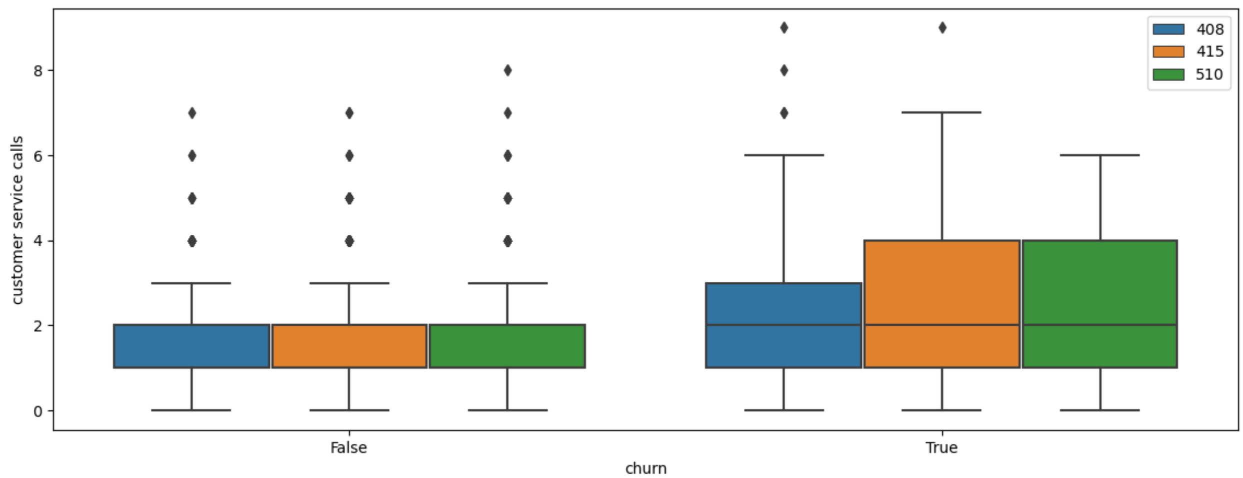
```
# Pie chart of area code feature
area = df['area code'].value_counts()
transuction = area.index
quantity = area.values

# draw pie circule with plotly
figure = px.pie(df,
               values = quantity,
               names = transuction,
               hole = .5,
               title = 'Distribution of Area Code Feature')
figure.show()
```




We can clearly see that:

- About Half of the customers have the area code 415.
- A quarter of customers have the area code 510
- A quarter of the customers have the area code 408.

```
# Boxplot to see which area code has the highest churn
plt.figure(figsize=(14,5))
sns.boxplot(data=df,x='churn',y='customer service calls',hue='area code');
plt.legend(loc='upper right');
```

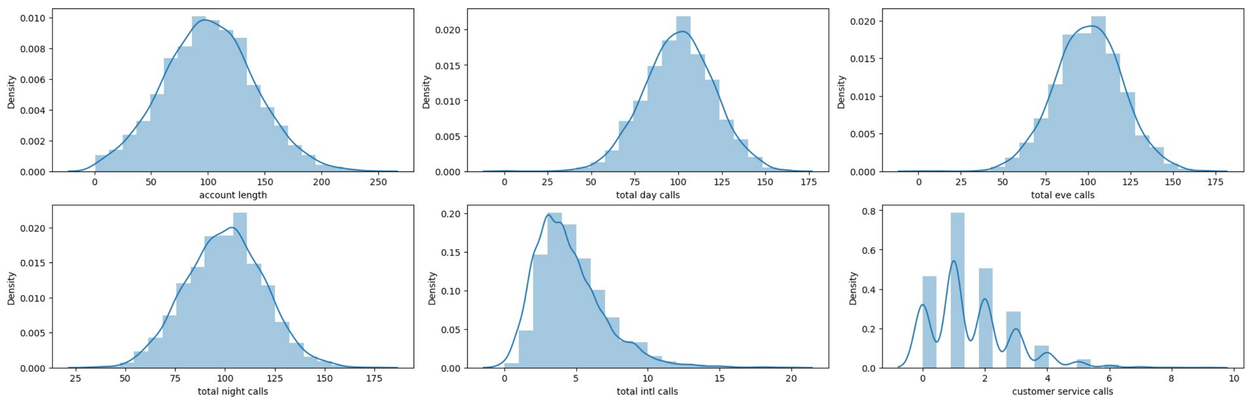



- There are some existing outliers, in all area codes, amongst the customers who have not terminated their contracts.
- Of the customers who have terminated their contracts, they more likely have a 415 or a 510 area code.

## Distrubution Plots for Numeric Features

```
f,ax=plt.subplots(2,3,figsize=(19,6),constrained_layout = True)
sns.distplot(df["account length"],bins=20,ax=ax[0,0]);
```

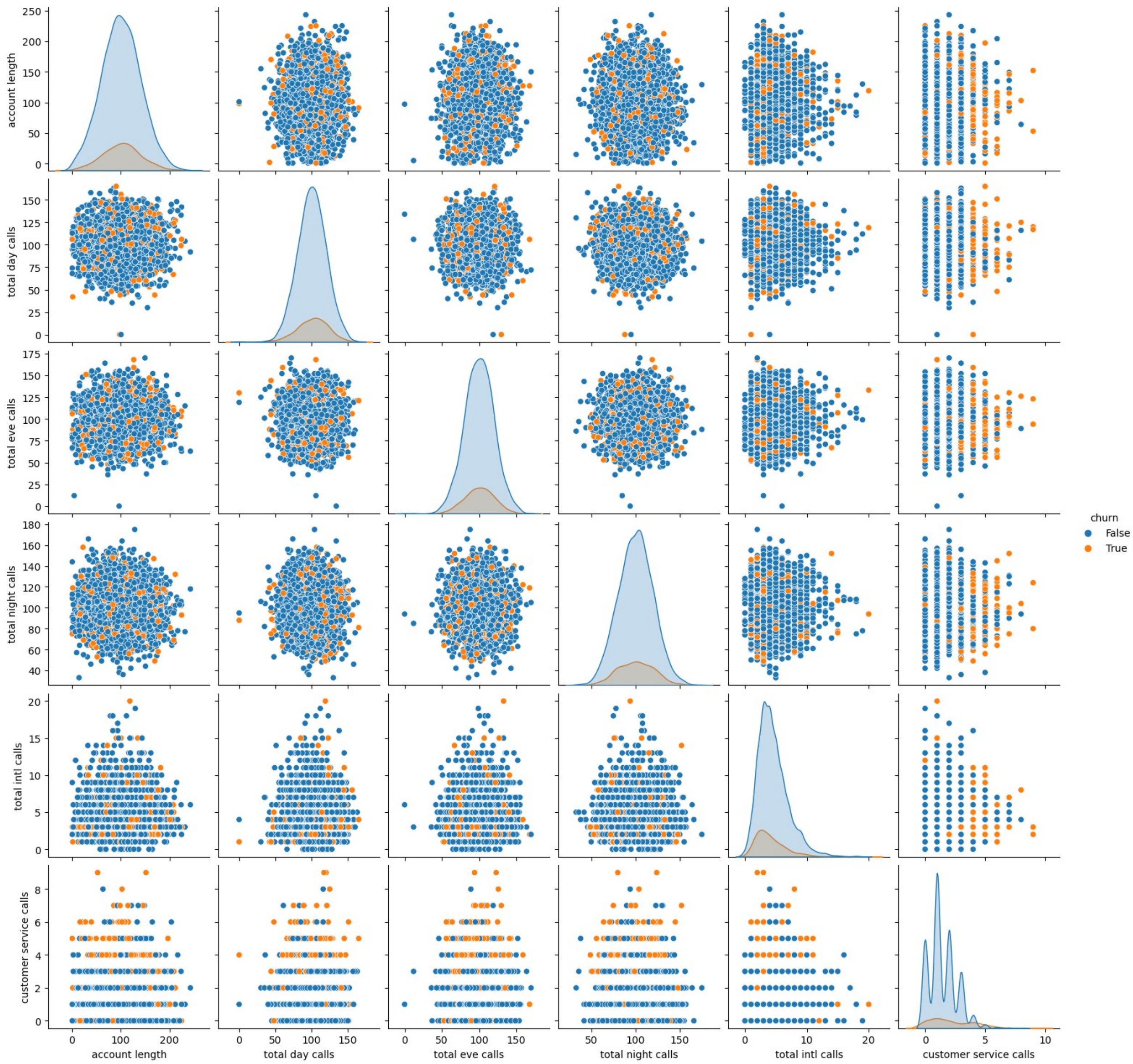
```
sns.distplot(df["total day calls"],bins=20,ax=ax[0,1]);

sns.distplot(df["total eve calls"],bins=20,ax=ax[0,2]);

sns.distplot(df["total night calls"],bins=20,ax=ax[1,0]);

sns.distplot(df["total intl calls"],bins=20,ax=ax[1,1]);

sns.distplot(df["customer service calls"],bins=20,ax=ax[1,2]);
```




- From the distribution plots, all of the features apart from customer service calls, have a normal distribution. Although total international calls appears skewed to the right, it still maintains a normal distribution pattern.
- Customer service calls has multiple peaks, indicating several modes in the population.

## Pairplots for Numeric Features (Hue as "Churn")

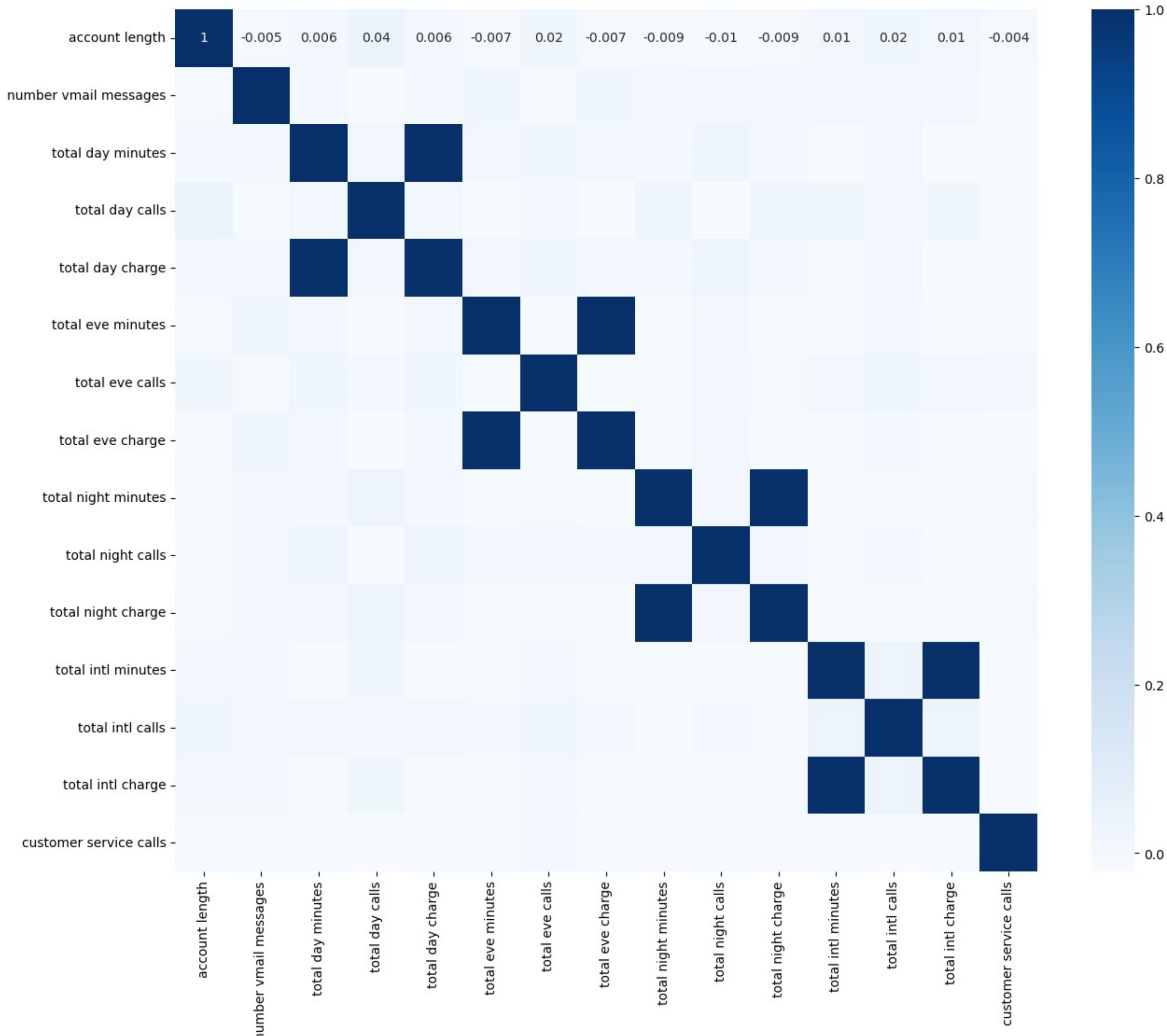
```
data_temp = df[["account length","total day calls","total eve calls","total night calls",
                "total intl calls","customer service calls","churn"]]
sns.pairplot(data_temp, hue="churn",height=2.5);
plt.show();
```




- There appears to be a clear relationship between customer service calls and true churn values. After 4 calls, customers are a lot more likely to discontinue their service.

## Correlation Heatmap for Numeric Features

```
corr_mat = df[numerical_cols].corr()
mask = np.triu(np.ones_like(corr_mat, dtype=bool))
plt.subplots(figsize=(15,12))
sns.heatmap(corr_mat, annot=True, cmap='Blues',
square=True,fmt='.0g');
plt.xticks(rotation=90);
plt.yticks(rotation=0);
```



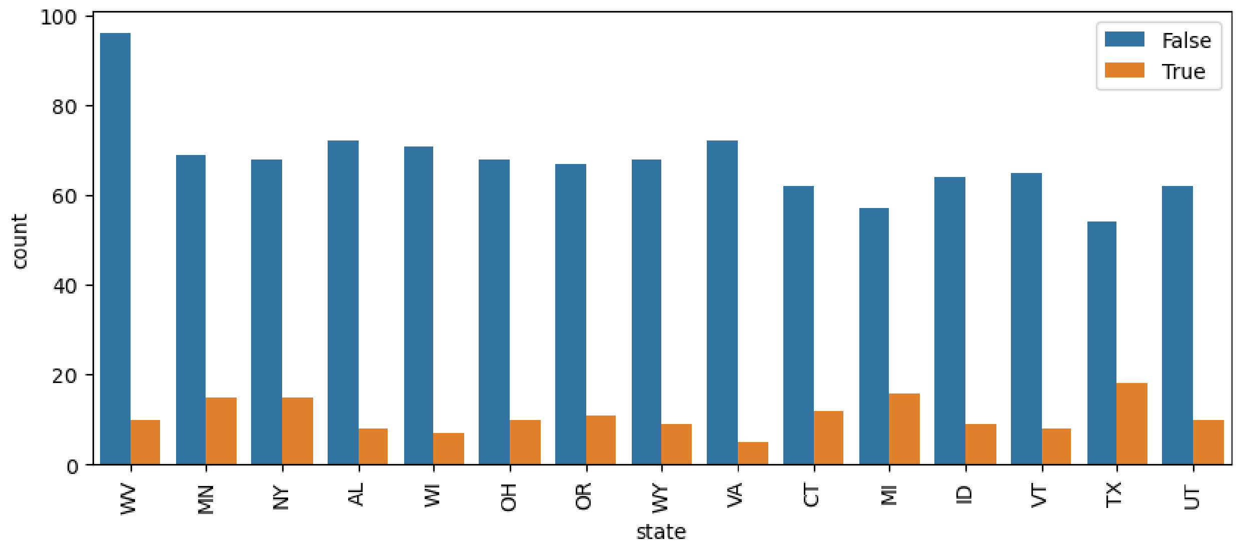

- Most of the features are not correlated however some have a perfect correlation:
    - Total day charge and total day minutes are perfectly positively correlated.
    - Total eve charge and total eve minutes are perfectly positively correlated.
    - Total night charge and total night minutes are perfectly positively correlated.
    - Total int charge and total int minutes are perfectly positively correlated.
- This makes sense because the charge is directly proportional to the minutes used.

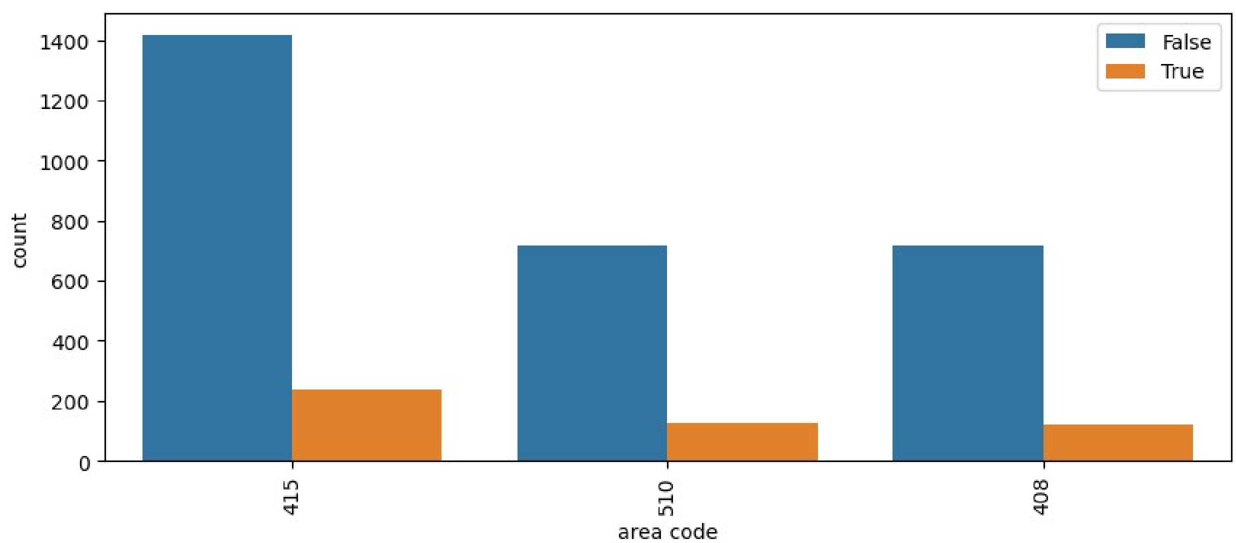
- The perfect correlation of 1 indicates perfect multicollinearity.

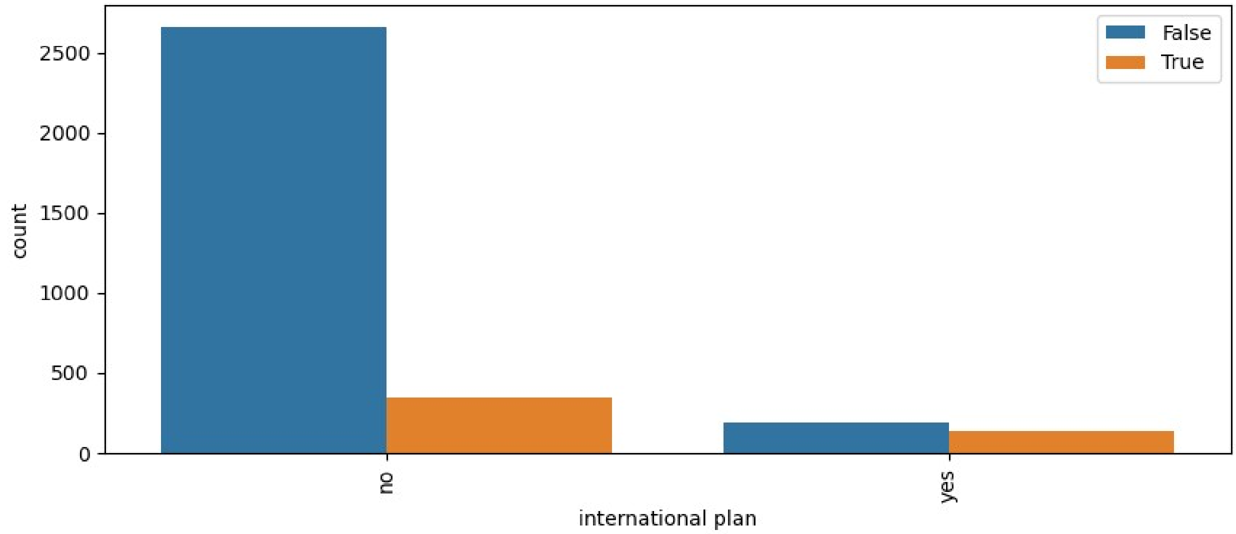
## Categorical Features Analysis

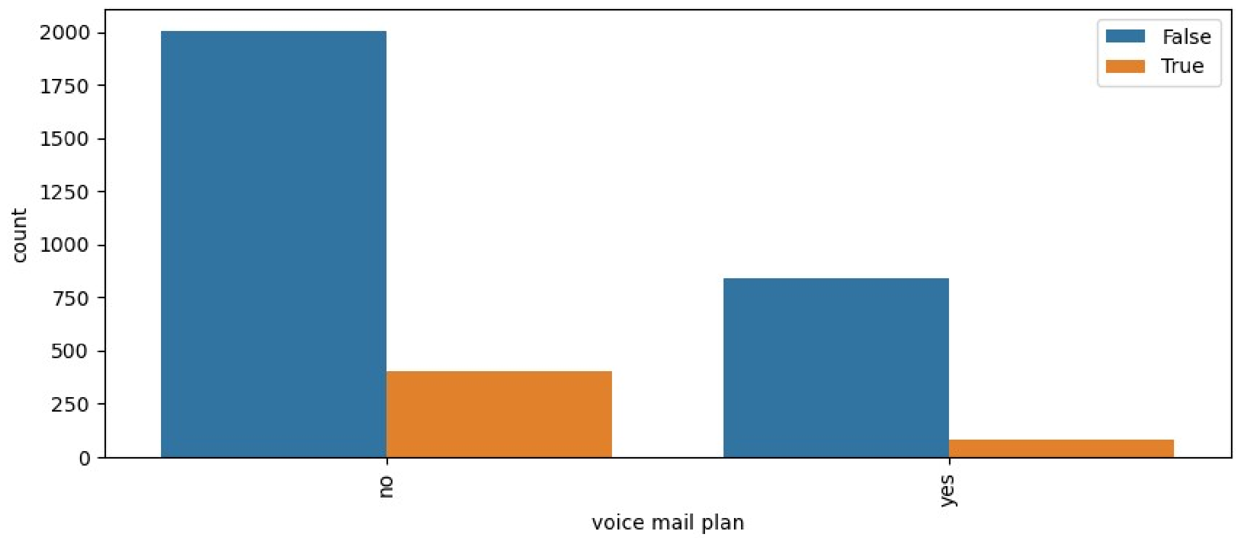
```
for i in categorical_cols:
    plt.figure(figsize=(10, 4))
    sns.countplot(x=i, hue=df["churn"].astype(str), data=df,
order=df[i].value_counts().iloc[0:15].index)
    plt.xticks(rotation=90)
```

```
    plt.legend(loc="upper right")
    plt.show()  # Ensure that each plot is displayed properly
```






## Handling Outliers

- Dropping outliers past 3 standard deviations.

```
print("Before dropping numerical outliers, length of the dataframe is:
",len(df))
def drop_numerical_outliers(df, z_thresh=3):
    constrains = df.select_dtypes(include=[np.number]).apply(lambda x:
np.abs(stats.zscore(x)) < z_thresh) \
        .all(axis=1)
    df.drop(df.index[~constrains], inplace=True)

drop_numerical_outliers(df)
print("After dropping numerical outliers, length of the dataframe is:
",len(df))
```

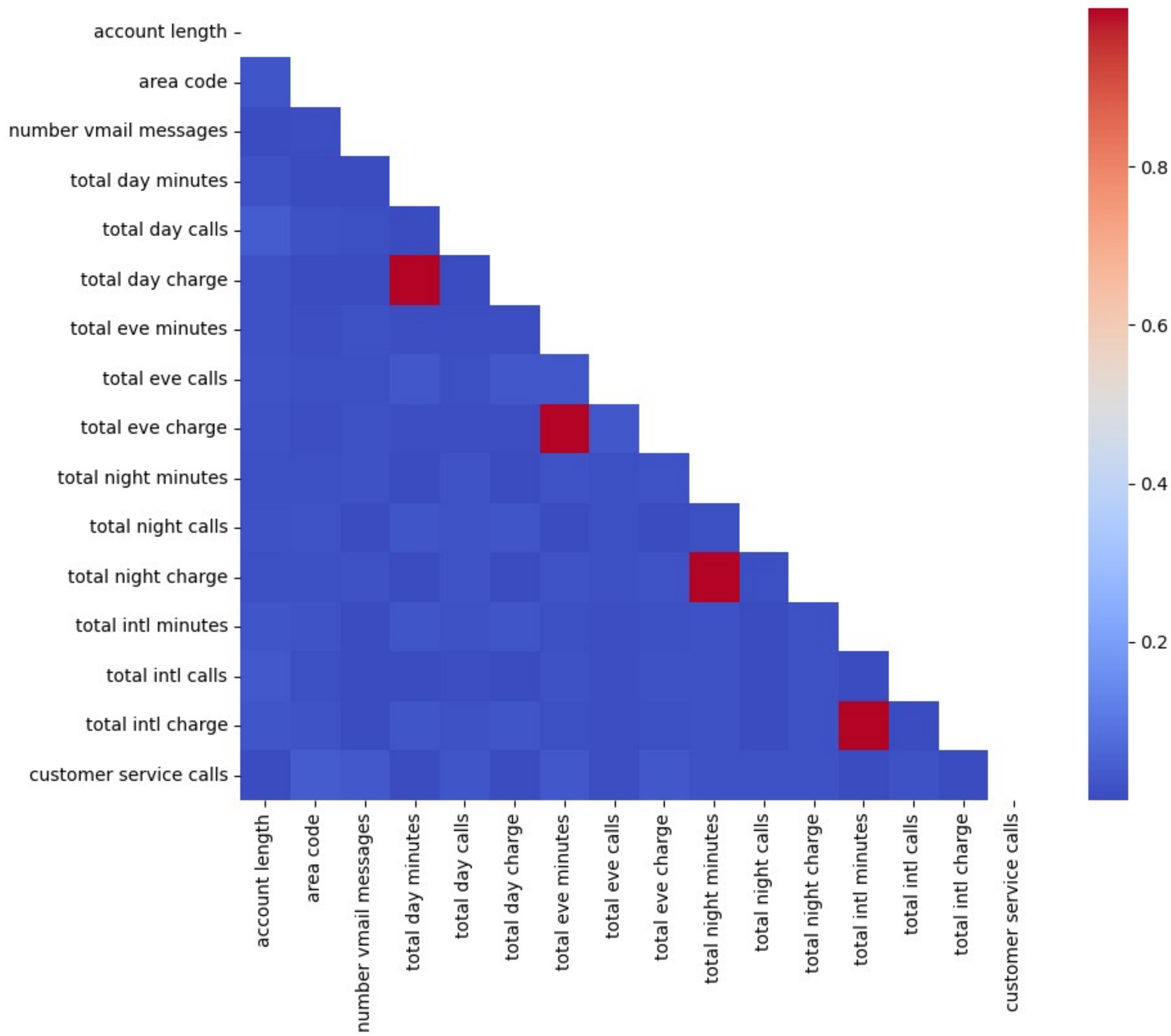
```
Before dropping numerical outliers, length of the dataframe is:  3333
After dropping numerical outliers, length of the dataframe is:  3169
```

## Dropping Highly-Correlated Features

- Dropping features that have a correlation of 0.9 or above.

```
print("The original dataframe has {} columns.".format(df.shape[1]))

# Select only the numeric columns
numeric_df = df.select_dtypes(include=[np.number])

# Calculate the correlation matrix and take the absolute value
corr_matrix = numeric_df.corr().abs()

# Create a True/False mask and apply it
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))

# Plotting the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, mask=mask, annot=True, fmt='.2f',
cmap='coolwarm')
plt.show()

tri_df = corr_matrix.mask(mask)

# List column names of highly correlated features (r > 0.90)
to_drop = [c for c in tri_df.columns if any(tri_df[c] >  0.90)]

reduced_df = df.drop(to_drop, axis=1) # Drop the features
print("The reduced dataframe has {}
columns.".format(reduced_df.shape[1]))
```

```
The original dataframe has 20 columns.
```




```
The reduced dataframe has 16 columns.
```

## 7. DATA PREPROCESSING

**international plan**, **voice mail plan** are binary features. We will do the Mapping: yes → 1 and no → 0.

```
df['churn'].value_counts()
```

```
churn
False    2727
True      442
Name: count, dtype: int64
```

```
df['churn'] = df['churn'].map({True: 1, False: 0}).astype('int')
df.head()
```

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

1    OH             107        415                 no             yes

2    NJ             137        415                 no              no

3    OH              84        408                yes              no

4    OK              75        415                yes              no


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

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

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
4                186.9                121                8.41

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

   customer service calls  churn
0                       1      0
1                       1      0
2                       0      0
```

```
3                         2      0
4                         3      0
```

## One-Hot Encoding

- Transforming categorical features into dummy variables as 0 and 1 to be able to use them in classification models.

```
dummy_df_state =
pd.get_dummies(reduced_df["state"],dtype=np.int64,prefix="state_is")
dummy_df_area_code = pd.get_dummies(reduced_df["area
code"],dtype=np.int64,prefix="area_code_is")
dummy_df_international_plan = pd.get_dummies(reduced_df["international
plan"],dtype=np.int64,prefix="international_plan_is",drop_first =
True)
dummy_df_voice_mail_plan = pd.get_dummies(reduced_df["voice mail
plan"],dtype=np.int64,prefix="voice_mail_plan_is",drop_first = True)


reduced_df =
pd.concat([reduced_df,dummy_df_state,dummy_df_area_code,dummy_df_inter
national_plan,dummy_df_voice_mail_plan],axis=1)
reduced_df = reduced_df.loc[:,~reduced_df.columns.duplicated()]
reduced_df = reduced_df.drop(['state','area code','international
plan','voice mail plan'],axis=1)

reduced_df.head()

   account length  number vmail messages  total day calls  total day
charge  \
0             128                     25              110
45.07
1             107                     26              123
27.47
2             137                      0              114
41.38
3              84                      0               71
50.90
4              75                      0              113
28.34

   total eve calls  total eve charge  total night calls  total night
charge  \
0               99             16.78                 91
11.01
1              103             16.62                103
11.45
2              110             10.30                104
7.32
3               88              5.26                 89
8.86
```

```
4               122              12.61                 121
8.41

   total intl calls  total intl charge  ...  state_is_VT  state_is_WA
\
0                 3               2.70  ...            0            0

1                 3               3.70  ...            0            0

2                 5               3.29  ...            0            0

3                 7               1.78  ...            0            0

4                 3               2.73  ...            0            0


   state_is_WI  state_is_WV  state_is_WY  area_code_is_408
area_code_is_415  \
0            0            0            0                 0
1
1            0            0            0                 0
1
2            0            0            0                 0
1
3            0            0            0                 1
0
4            0            0            0                 0
1

   area_code_is_510  international_plan_is_yes  voice_mail_plan_is_yes

0                 0                          0                       1

1                 0                          0                       1

2                 0                          0                       0

3                 0                          1                       0

4                 0                          1                       0


[5 rows x 68 columns]
```

## 8. SCALING

### Scaling Numerical Features

- We will apply MinMaxScaler in order to reduce the effects of outliers in the dataset.

```
transformer = MinMaxScaler()

def scaling(columns):
    return
transformer.fit_transform(reduced_df[columns].values.reshape(-1,1))

for i in reduced_df.select_dtypes(include=[np.number]).columns:
    reduced_df[i] = scaling(i)
reduced_df.head()
```

```
   account length  number vmail messages  total day calls  total day
charge  \
0        0.587963               0.510204         0.576271
0.773956
1        0.490741               0.530612         0.686441
0.450248
2        0.629630               0.000000         0.610169
0.706088
3        0.384259               0.000000         0.245763
0.881184
4        0.342593               0.000000         0.601695
0.466250

   total eve calls  total eve charge  total night calls  total night
charge  \
0         0.487179          0.490082           0.422414
0.643644
1         0.521368          0.483858           0.525862
0.675974
2         0.581197          0.238040           0.534483
0.372520
3         0.393162          0.042007           0.405172
0.485672
4         0.683761          0.327888           0.681034
0.452608

   total intl calls  total intl charge  ...  state_is_VT  state_is_WA
\
0               0.2           0.487585  ...          0.0          0.0

1               0.2           0.713318  ...          0.0          0.0

2               0.4           0.620767  ...          0.0          0.0

3               0.6           0.279910  ...          0.0          0.0

4               0.2           0.494357  ...          0.0          0.0


   state_is_WI  state_is_WV  state_is_WY  area_code_is_408
```

```
area_code_is_415  \
0           0.0          0.0          0.0                0.0
1.0
1           0.0          0.0          0.0                0.0
1.0
2           0.0          0.0          0.0                0.0
1.0
3           0.0          0.0          0.0                1.0
0.0
4           0.0          0.0          0.0                0.0
1.0

   area_code_is_510  international_plan_is_yes  voice_mail_plan_is_yes

0               0.0                        0.0                     1.0

1               0.0                        0.0                     1.0

2               0.0                        0.0                     0.0

3               0.0                        1.0                     0.0

4               0.0                        1.0                     0.0


[5 rows x 68 columns]
```

## Train-Test Split

- We will split the dataset into training at 75% and testing at 25%

```
X=reduced_df.drop(['churn'],axis=1)
y=reduced_df['churn']

X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.25,random_state=123)
```

## Applying SMOTE Technique to address Overfitting

```
reduced_df.churn.value_counts()

churn
False    2727
True      442
Name: count, dtype: int64

from imblearn.over_sampling import SMOTE

sm = SMOTE(k_neighbors=5, random_state=123)
X_train_over, y_train_over = sm.fit_resample(X_train, y_train)
print('Before OverSampling, the shape of X_train:
```

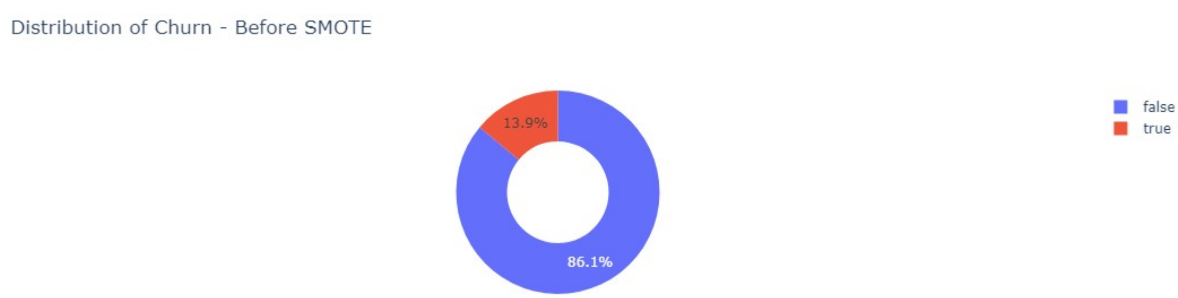
```
{}'.format(X_train.shape))
print('Before OverSampling, the shape of y_train:
{}'.format(y_train.shape))
print('After OverSampling, the shape of X_train_over:
{}'.format(X_train_over.shape))
print('After OverSampling, the shape of y_train_over:
{}'.format(y_train_over.shape))
```

```
Before OverSampling, the shape of X_train: (2376, 67)
Before OverSampling, the shape of y_train: (2376,)
After OverSampling, the shape of X_train_over: (4126, 67)
After OverSampling, the shape of y_train_over: (4126,)
```

```
y_train_over.value_counts()
```

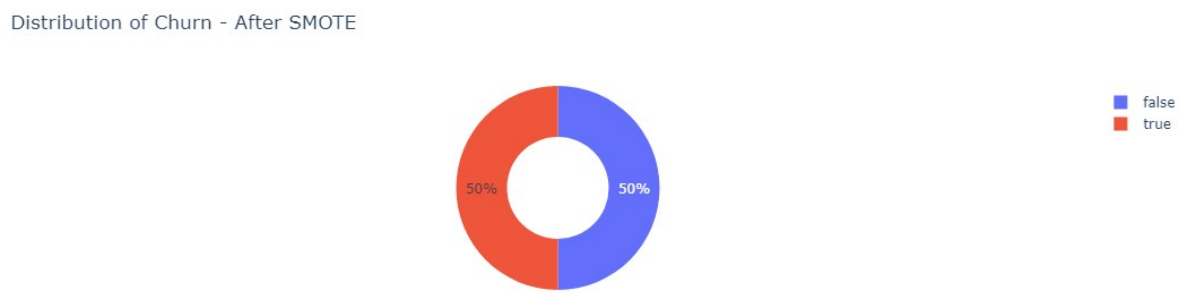
```
churn
False    2063
True     2063
Name: count, dtype: int64
```

```
churn = reduced_df['churn'].value_counts()
transuction = churn.index
quantity = churn.values

# draw pie circule with plotly
figure = px.pie(y_train_over,
               values = quantity,
               names = transuction,
               hole = .5,
               title = 'Distribution of Churn - Before SMOTE')
figure.show()
```




```
y_train_over_df = y_train_over.to_frame()
churn = y_train_over_df['churn'].value_counts()
transuction = churn.index
quantity = churn.values
```

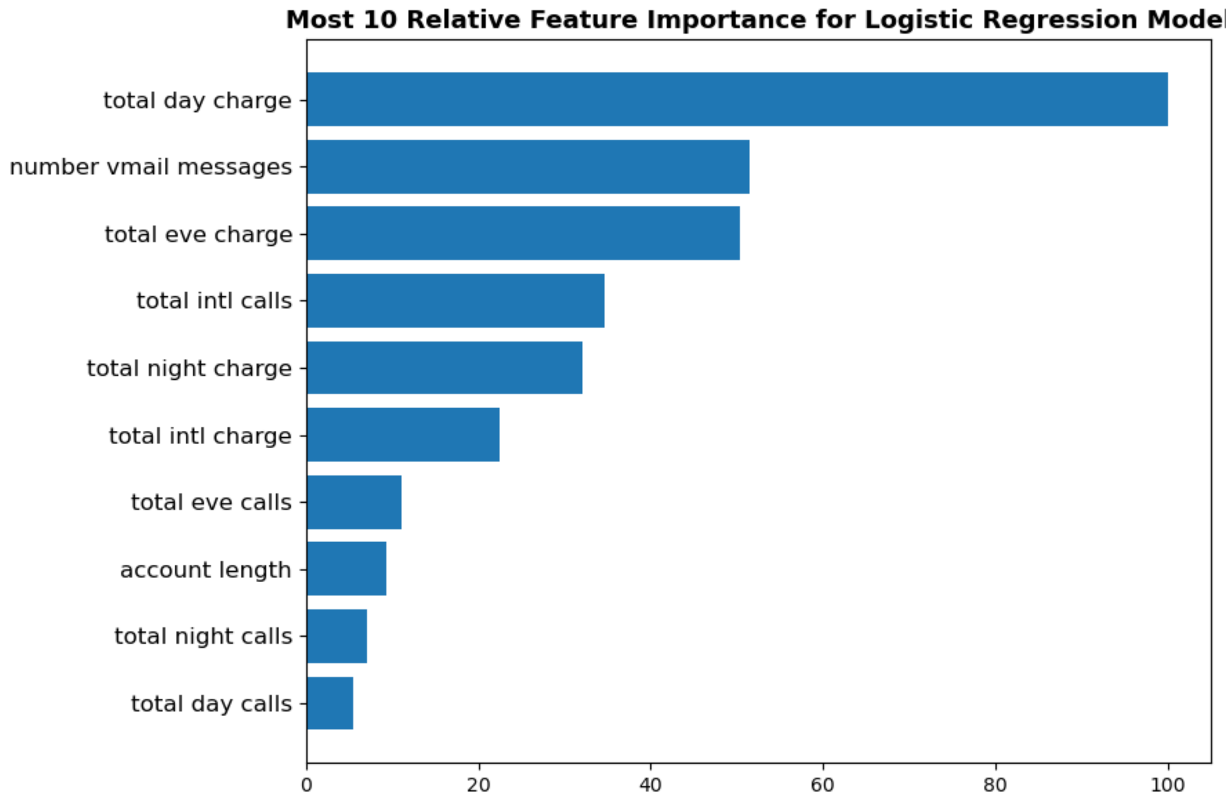
```
# draw pie circule with plotly
figure = px.pie(y_train_over_df,
               values = quantity,
               names = transuction,
               hole = .5,
               title = 'Distribution of Churn - After SMOTE')
figure.show()
```




## 9. DATA MODELLING

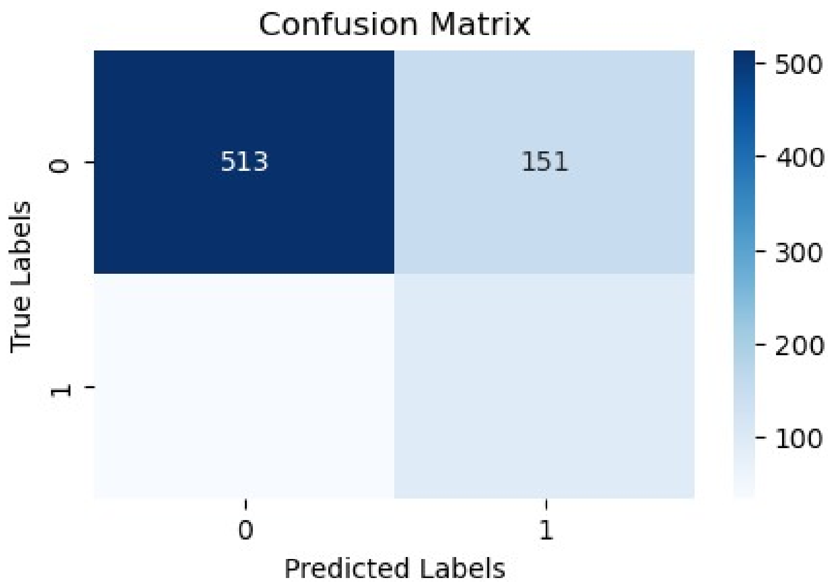
### Model 1 - Logistic Regression Model

```
# Object creation, fitting the data and getting predictions
lr= LogisticRegression()
lr.fit(X_train_over,y_train_over)
y_pred_lr = lr.predict(X_test)

# Feature Importances
feature_importance = abs(lr.coef_[0])
feature_importance = 100.0 * (feature_importance /
feature_importance.max())[0:10]
sorted_idx = np.argsort(feature_importance)[0:10]
pos = np.arange(sorted_idx.shape[0]) + .5

featfig = plt.figure(figsize=(9, 6))
featax = featfig.add_subplot(1, 1, 1)
featax.barh(pos, feature_importance[sorted_idx], align='center')
plt.title('Most 10 Relative Feature Importance for Logistic Regression
Model', fontsize=13, fontweight='bold')
featax.set_yticks(pos)
featax.set_yticklabels(np.array(X.columns)[sorted_idx], fontsize=12)

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




```
print(classification_report(y_test, y_pred_lr, target_names=['0',
'1']))

              precision    recall  f1-score   support

           0       0.94      0.77      0.85       664
           1       0.38      0.73      0.50       129

    accuracy                           0.77       793
   macro avg       0.66      0.75      0.67       793
weighted avg       0.85      0.77      0.79       793


print("**************** LOGISTIC REGRESSION CLASSIFIER MODEL RESULTS
**************** ")
print('Accuracy score for testing set:
',round(accuracy_score(y_test,y_pred_lr),5))
print('F1 score for testing set:
',round(f1_score(y_test,y_pred_lr),5))
print('Recall score for testing set:
',round(recall_score(y_test,y_pred_lr),5))
print('Precision score for testing set:
',round(precision_score(y_test,y_pred_lr),5))
cm_lr = confusion_matrix(y_test, y_pred_lr)
f, ax= plt.subplots(1,1,figsize=(5,3))
```

```
sns.heatmap(cm_lr, annot=True, cmap='Blues', fmt='g', ax=ax)
ax.set_xlabel('Predicted Labels'); ax.set_ylabel('True Labels') ;
ax.set_title('Confusion Matrix')
ax.xaxis.set_ticklabels(['0', '1']) ; ax.yaxis.set_ticklabels(['0',
'1'])
plt.show();

**************** LOGISTIC REGRESSION CLASSIFIER MODEL RESULTS
****************
Accuracy score for testing set:  0.76545
F1 score for testing set:  0.50267
Recall score for testing set:  0.72868
Precision score for testing set:  0.38367
```

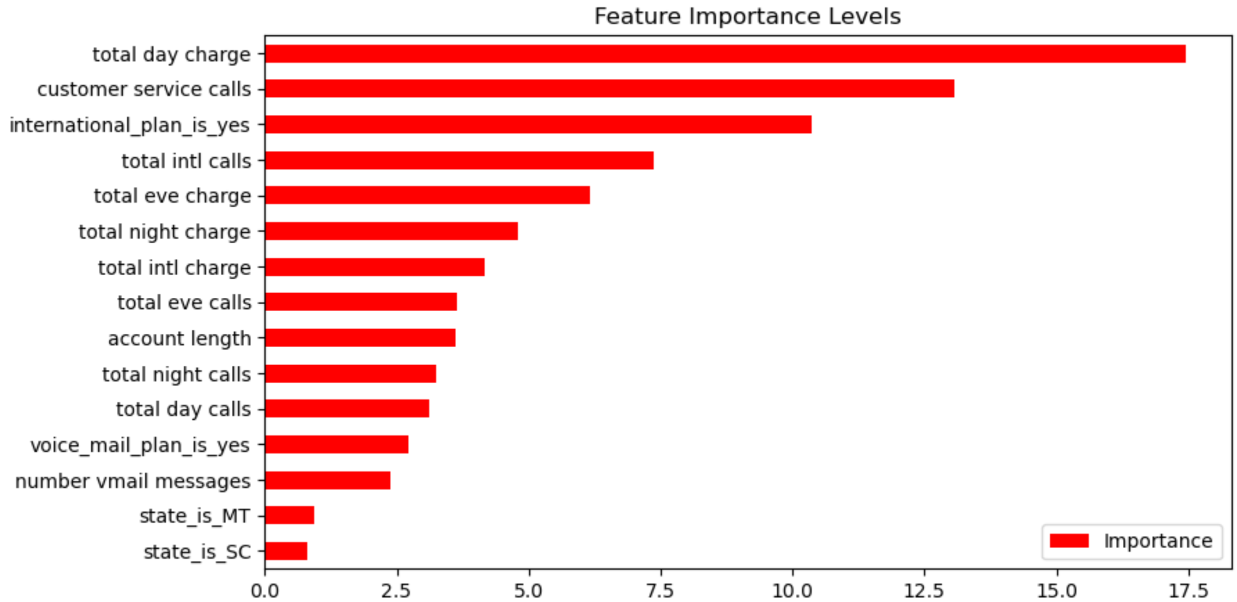



- According to the logistic regression classifier model, total day charge, number of voicemail messages and total evening charge are the top three important features.
- Model accuracy is 76.5%, which is not bad. F1 score is only 50.2% which means the test will only be accurate half the times it is run.

## Model 2 - Random Forest Model

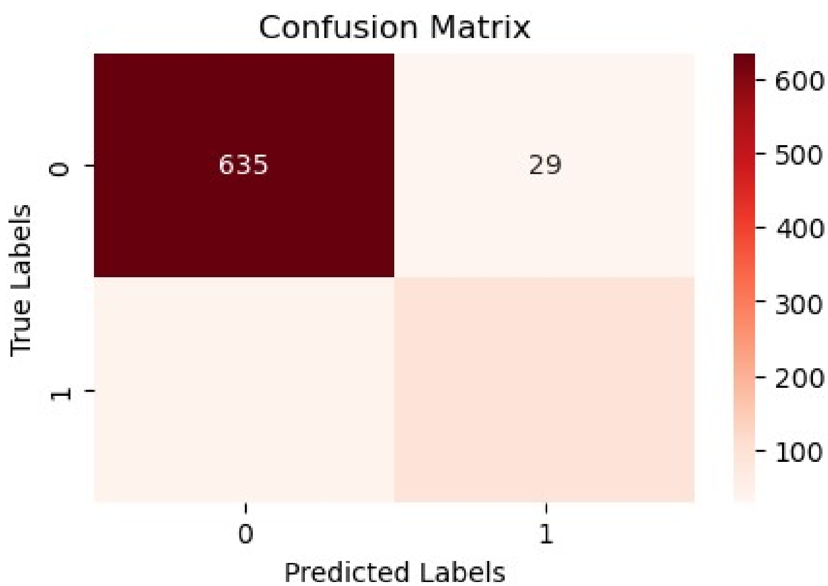
```
# Object creation, fitting the data & getting predictions
rf_model_final = RandomForestClassifier()
rf_model_final.fit(X_train_over,y_train_over)
y_pred_rf = rf_model_final.predict(X_test)

Importance =pd.DataFrame({"Importance":
rf_model_final.feature_importances_*100},index = X_train_over.columns)
Importance.sort_values(by = "Importance", axis = 0, ascending =
True).tail(15).plot(kind ="barh", color = "r",figsize=(9, 5))
```

```python
plt.title("Feature Importance Levels");
plt.show()
```




```python
print(classification_report(y_test, y_pred_rf, target_names=['0',
'1']))

              precision    recall  f1-score   support

           0       0.94      0.96      0.95       664
           1       0.76      0.71      0.73       129

    accuracy                           0.92       793
   macro avg       0.85      0.83      0.84       793
weighted avg       0.91      0.92      0.91       793


print("*************** RANDOM FOREST MODEL RESULTS ***************
")
print('Accuracy score for testing set:
',round(accuracy_score(y_test,y_pred_rf),5))
print('F1 score for testing set:
',round(f1_score(y_test,y_pred_rf),5))
print('Recall score for testing set:
',round(recall_score(y_test,y_pred_rf),5))
print('Precision score for testing set:
',round(precision_score(y_test,y_pred_rf),5))
cm_rf = confusion_matrix(y_test, y_pred_rf)
f, ax= plt.subplots(1,1,figsize=(5,3))
sns.heatmap(cm_rf, annot=True, cmap='Reds', fmt='g', ax=ax)
ax.set_xlabel('Predicted Labels'); ax.set_ylabel('True Labels') ;
```

```
ax.set_title('Confusion Matrix')
ax.xaxis.set_ticklabels(['0', '1']) ; ax.yaxis.set_ticklabels(['0',
'1'])
plt.show();

**************** RANDOM FOREST MODEL RESULTS ****************
Accuracy score for testing set:  0.91551
F1 score for testing set:  0.73092
Recall score for testing set:  0.70543
Precision score for testing set:  0.75833
```

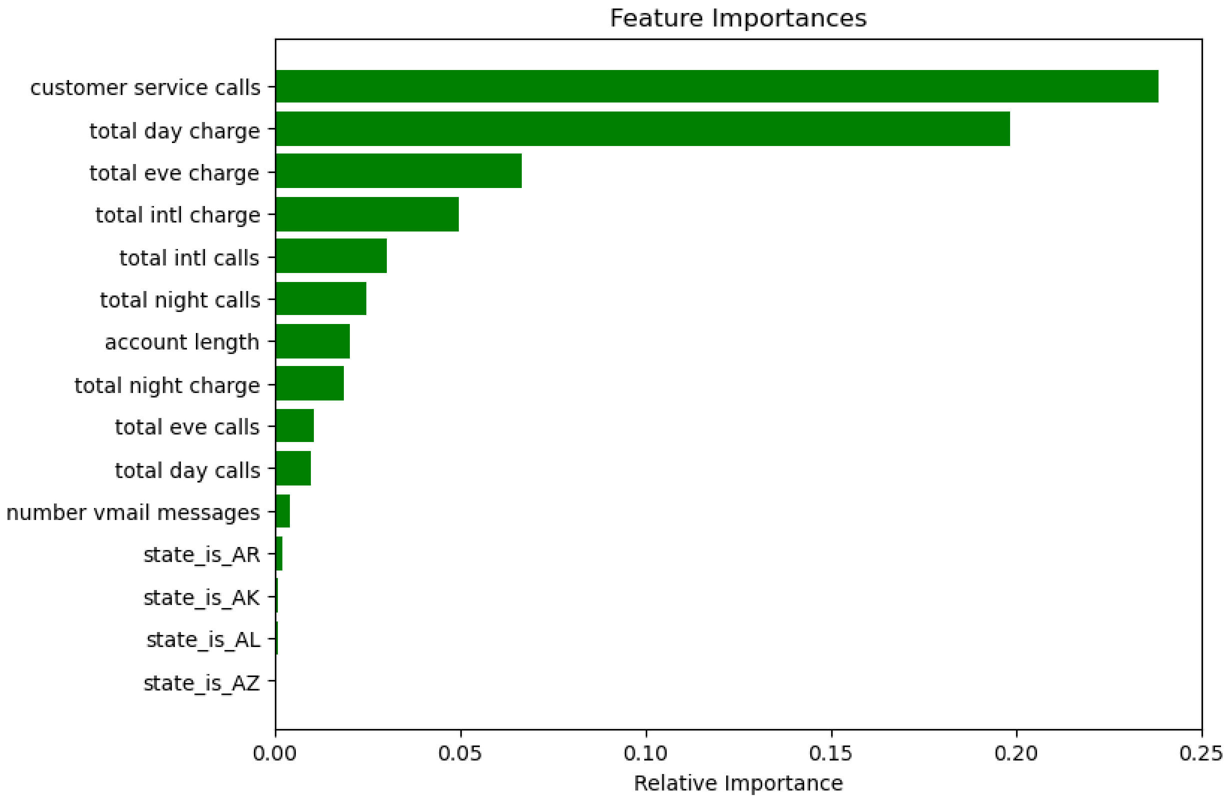



- According to the random forest classifier; 'total day charge', 'customer service calls' and 'international plan' features have the highest impact on the model.
- Accuracy and F1 score are much higher than the Logistics Regression Model

## Model 3 - Decision Tree Classifier

```
# Object creation, fitting the data and getting predictions
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train_over,y_train_over)
y_pred_dt = decision_tree.predict(X_test)

feature_names = list(X_train_over.columns)
importances = decision_tree.feature_importances_[0:15]
indices = np.argsort(importances)

plt.figure(figsize=(8,6))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='green',
align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
```

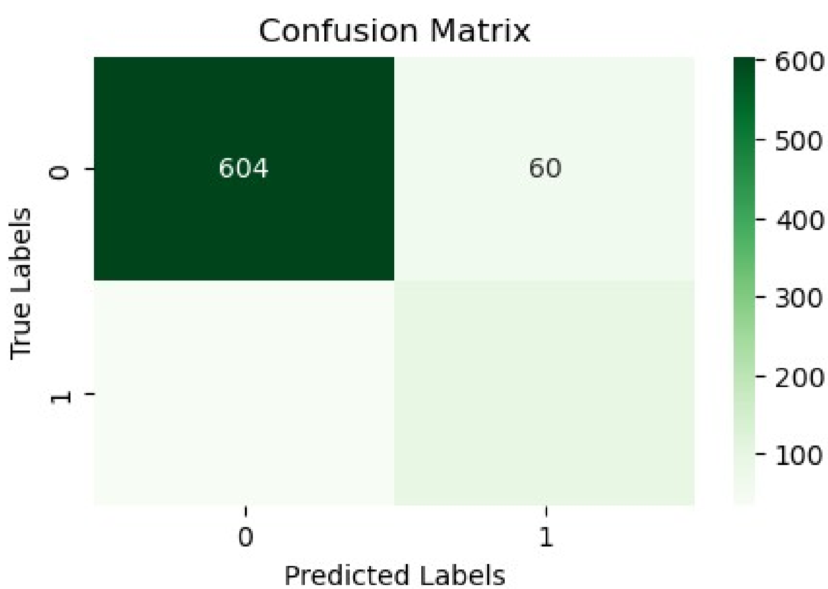
```
plt.xlabel('Relative Importance')
plt.show()
```




```
print(classification_report(y_test, y_pred_dt, target_names=['0',
'1']))

              precision    recall  f1-score   support

           0       0.95      0.91      0.93       664
           1       0.61      0.73      0.66       129

    accuracy                           0.88       793
   macro avg       0.78      0.82      0.80       793
weighted avg       0.89      0.88      0.88       793


print("**************** DECISION TREE CLASSIFIER MODEL RESULTS
**************** ")
print('Accuracy score for testing set:
',round(accuracy_score(y_test,y_pred_dt),5))
print('F1 score for testing set:
',round(f1_score(y_test,y_pred_dt),5))
print('Recall score for testing set:
',round(recall_score(y_test,y_pred_dt),5))
print('Precision score for testing set:
```

```
',round(precision_score(y_test,y_pred_dt),5))
cm_dt = confusion_matrix(y_test, y_pred_dt)
f, ax= plt.subplots(1,1,figsize=(5,3))
sns.heatmap(cm_dt, annot=True, cmap='Greens', fmt='g', ax=ax)
ax.set_xlabel('Predicted Labels'); ax.set_ylabel('True Labels') ;
ax.set_title('Confusion Matrix')
ax.xaxis.set_ticklabels(['0', '1']) ; ax.yaxis.set_ticklabels(['0',
'1'])
plt.show();
```

```
**************** DECISION TREE CLASSIFIER MODEL RESULTS
****************
Accuracy score for testing set:  0.8802
F1 score for testing set:  0.66431
Recall score for testing set:  0.72868
Precision score for testing set:  0.61039
```




- According to the decision tree Model, 'customer service calls', 'total day charge' and 'total evening charge' are the three most important for the model.
- The accuracy and F1 score for this model is lower than the Random Forest Model

# Models Comparison

## ROC Curve

```
classifiers = [LogisticRegression(), DecisionTreeClassifier(),
RandomForestClassifier()]

# Initialize result_table
result_table = pd.DataFrame(columns=['classifiers', 'fpr', 'tpr',
'auc'])
```

```
for cls in classifiers:
    model = cls.fit(X_train, y_train)
    yproba = model.predict_proba(X_test)[:, 1]

    fpr, tpr, _ = roc_curve(y_test, yproba)
    auc = roc_auc_score(y_test, yproba)

    # Use pd.concat to append the new row
    result_table = pd.concat([result_table,
pd.DataFrame({'classifiers': [cls.__class__.__name__],
                                                           'fpr':
[fpr],
                                                           'tpr':
[tpr],
                                                           'auc':
[auc]})], ignore_index=True)

# Print the result_table to verify
print(result_table)
```

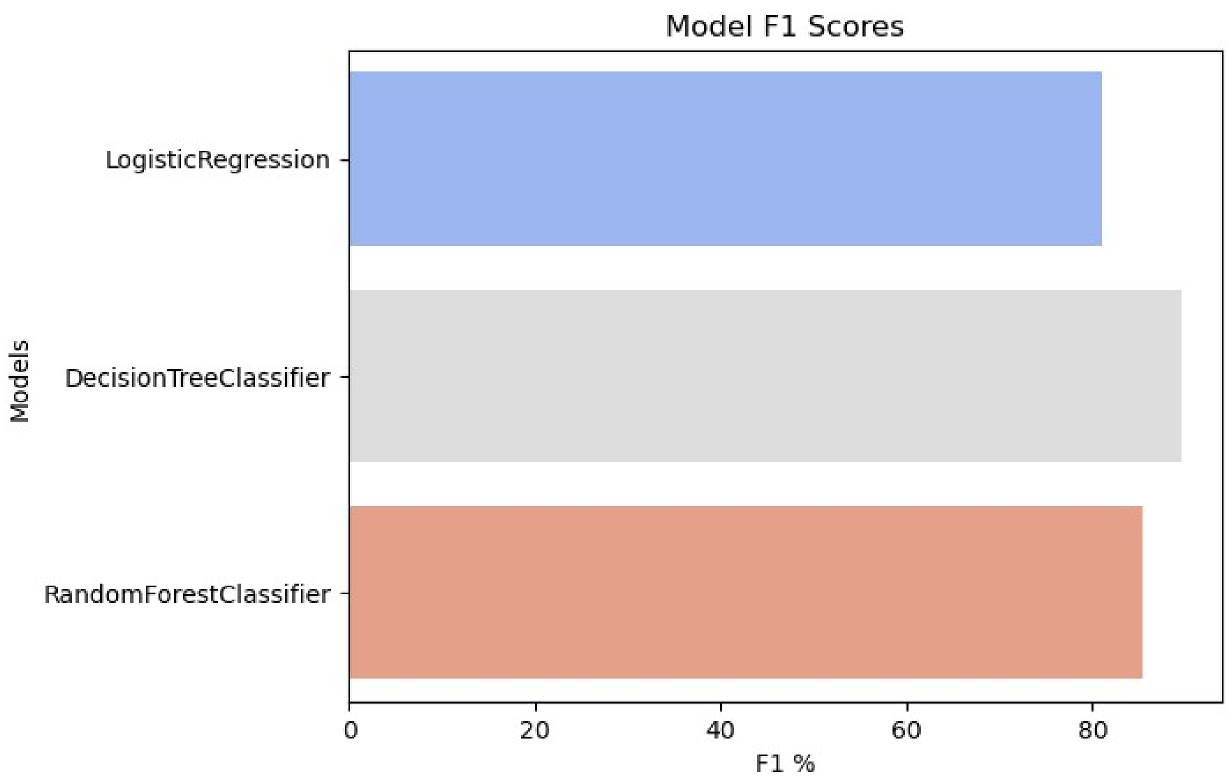
```
              classifiers
fpr  \
0      LogisticRegression  [0.0, 0.0, 0.0015060240963855422,
0.0015060240...
1  DecisionTreeClassifier                    [0.0,
0.04216867469879518, 1.0]
2  RandomForestClassifier  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, ...

                                                tpr       auc
0  [0.0, 0.007751937984496124, 0.0077519379844961...  0.799862
1                     [0.0, 0.7131782945736435, 1.0]  0.835505
2  [0.0, 0.015503875968992248, 0.0465116279069767...  0.889535
```

- The ROC curve illustrates the true positive rate against the false positive rate of our Models.

## Model Comparisons - F1 Score (10-fold cross-validated)

```
classifiers = [LogisticRegression(), DecisionTreeClassifier(),
RandomForestClassifier()]

# Initialize results DataFrame
results = pd.DataFrame(columns=["Models", "F1"])

for model in classifiers:
    names = model.__class__.__name__
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
```

```
    f1 = cross_val_score(model, X_test, y_test, cv=10,
scoring="f1_weighted").mean()
    result = pd.DataFrame([[names, f1 * 100]], columns=["Models",
"F1"])

    # Use pd.concat to add new rows to results DataFrame
    results = pd.concat([results, result], ignore_index=True)

# Plot the results
sns.barplot(x='F1', y='Models', data=results, palette="coolwarm")
plt.xlabel('F1 %')
plt.ylabel('Models')
plt.title('Model F1 Scores')
plt.show()
```




## 10. REGRESSION RESULTS

```
results.sort_values(by="F1",ascending=False)
```

| | Models | F1 |
|---|---|---|
| 1 | DecisionTreeClassifier | 89.501449 |
| 2 | RandomForestClassifier | 85.515864 |
| 0 | LogisticRegression | 81.077623 |

## 11. CONCLUSION

Looking at the results, we can see that Decision Tree Model performed well on our dataset compared to the Random Forest Model and Logistic Regression Model.

## 12. RECOMMENDATION

Based on the findings, it is recommended to focus on the Decision Tree Model for predicting customer churn in the telecom sector. This model has shown superior performance on the dataset. While the Random Forest and the Logistic regression did not perform as well, further exploration into advanced feature engineering and threshold adjustments could potentially enhance their effectiveness.