Introduction

The telecommunication industry is one of the fastest growing industries as consumer communication needs increase and diversify and as new technologies emerge. The telecommunications landscape is therefore quickly evolving to meet these needs to and to integrate the new emerging technologies such as cloud computing, decentralized telecom networks, virtualized network services and artificial technologies amongst others.

Consequently, service providers are increasingly assessing its capacities and its customer base in order optimize profits and reduce losses. In this regard, SyriaTel intends to predict customer churn to reduce losses that are associated with customer churn. Customer churn refers to the loss of customers or subscribers for various reasons. Telecommunication companies amongst other business therefore measure and track churn as a percentage of customers lost vis-a-vis the total number of customers subscribing to their services over a given period of time.

Problem Statement

Customer churning is one of the main killers of business growth. Therefore there is need to undertake an assessment of SyriaTel to predict customer churning and put in place interventions to mitigate against it to reduce losses incurred from churning, identify customers who are at risk of churning and take proactive steps to retain them, stabilize their market value and optimize profits.

Objective(s)

The main objective of this is to build a classification model that can predict whether or not a customer will churn.

To achieve the said main objective, the project will focus on the following specific objectives-

(i) Conduct exploratory data analysis of the dataset;

(ii)Fit various classification algorithm models to determine the one that can provide the best churn predictions;

(iii) Make predictions using the best prediction model; and

(iv) Check the accuracy of the predicted variables

1. Data Understanding

```
#Data manipulation
import pandas as pd
import numpy as np

#Data visualization
import seaborn as sns
```

```
import matplotlib.pyplot as plt
%matplotlib inline

#Modelling
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from scipy.stats import zscore
from sklearn.metrics import confusion_matrix, classification_report, ConfusionMat
from sklearn.metrics import accuracy_score, recall_score, f1_score, precision_sco
from sklearn import tree
from imblearn.over_sampling import SMOTE, SMOTENC

#Algorithms for supervised learning methods
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.model_selection import GridSearchCV


#Filtering future warnings
import warnings
warnings.filterwarnings('ignore')


#Data loading & viewing of afew rows

df = pd.read_csv("customer-churning.csv")
df.head
```

```
<bound method NDFrame.head of      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
...    ...             ...        ...          ...                ...
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  \
0                yes                     25              265.1
1                yes                     26              161.6
2                 no                      0              243.4
3                 no                      0              299.4
4                 no                      0              166.7
...              ...                    ...                ...
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  \
0                 110             45.07  ...               99
1                 123             27.47  ...              103
2                 114             41.38  ...              110
3                  71             50.90  ...               88
4                 113             28.34  ...              122
...               ...               ...  ...              ...
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  \
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 intl minutes  total intl calls  \
0                  11.01                10.0                 3
1                  11.45                13.7                 3
2                   7.32                12.2                 5
```

```
#Overview of the data frame

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
```

```
#numerical columns
numerical_columns = df.select_dtypes(include=['number']).columns.tolist()
print("Numerical Columns:", numerical_columns)
```

```
Numerical Columns: ['account length', 'area code', 'number vmail messages', '
```

```
#categorical columns

categorical_columns = df.select_dtypes(include=['object']).columns.tolist()
print("Categorical Columns:", categorical_columns)
```

```
Categorical Columns: ['state', 'phone number', 'international plan', 'voice ma
```

```
df.columns
```

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

```
#General statistics of the numeric columns

df.describe().transpose()
```

	count	mean	std	min	25%	50%	75%	max
account length	3333.0	101.064806	39.822106	1.00	74.00	101.00	127.00	243.00
area code	3333.0	437.182418	42.371290	408.00	408.00	415.00	510.00	510.00
number vmail messages	3333.0	8.099010	13.688365	0.00	0.00	0.00	20.00	51.00
total day minutes	3333.0	179.775098	54.467389	0.00	143.70	179.40	216.40	350.80
total day calls	3333.0	100.435644	20.069084	0.00	87.00	101.00	114.00	165.00
total day charge	3333.0	30.562307	9.259435	0.00	24.43	30.50	36.79	59.64
total eve minutes	3333.0	200.980348	50.713844	0.00	166.60	201.40	235.30	363.70
total eve calls	3333.0	100.114311	19.922625	0.00	87.00	100.00	114.00	170.00
total eve charge	3333.0	17.083540	4.310668	0.00	14.16	17.12	20.00	30.91
total night minutes	3333.0	200.872037	50.573847	23.20	167.00	201.20	235.30	395.00
total night calls	3333.0	100.107711	19.568609	33.00	87.00	100.00	113.00	175.00
total night charge	3333.0	9.039325	2.275873	1.04	7.52	9.05	10.59	17.77
total intl minutes	3333.0	10.237294	2.791840	0.00	8.50	10.30	12.10	20.00
total intl calls	3333.0	4.479448	2.461214	0.00	3.00	4.00	6.00	20.00
total intl charge	3333.0	2.764581	0.753773	0.00	2.30	2.78	3.27	5.40
customer service	3333.0	1.562856	1.315491	0.00	1.00	1.00	2.00	9.00

2. Data Cleaning & Exploration

```
#Check 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
```

```
#Check duplicated data

df.duplicated().sum()
```

```
0
```

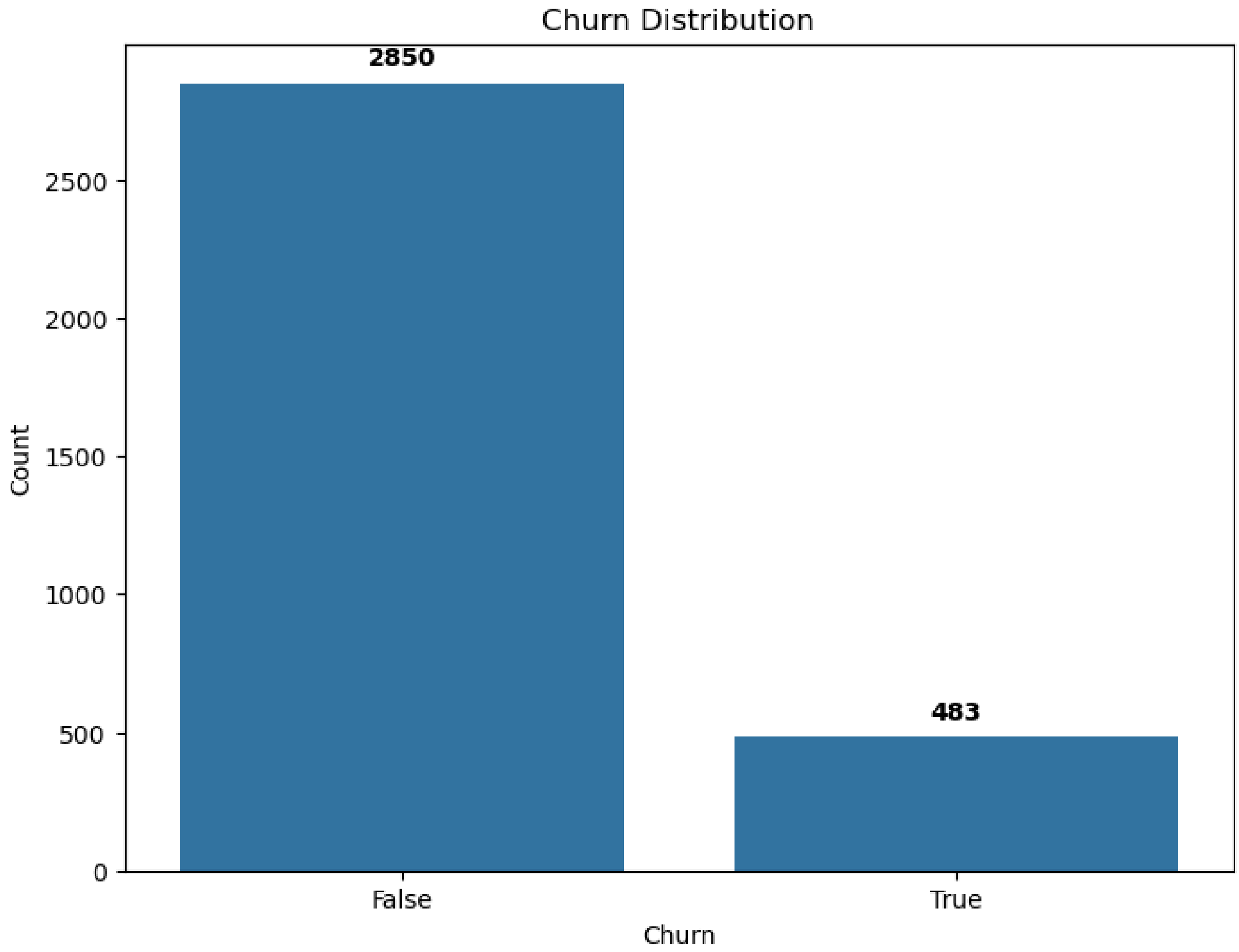
```
#Drop the phone number column

df = df.drop("phone number", axis=1)
```

```
#convert area code datatype

df["area code"] = df["area code"].astype(object)
```

3. Data Analysis

3.1 Univariate data analysis

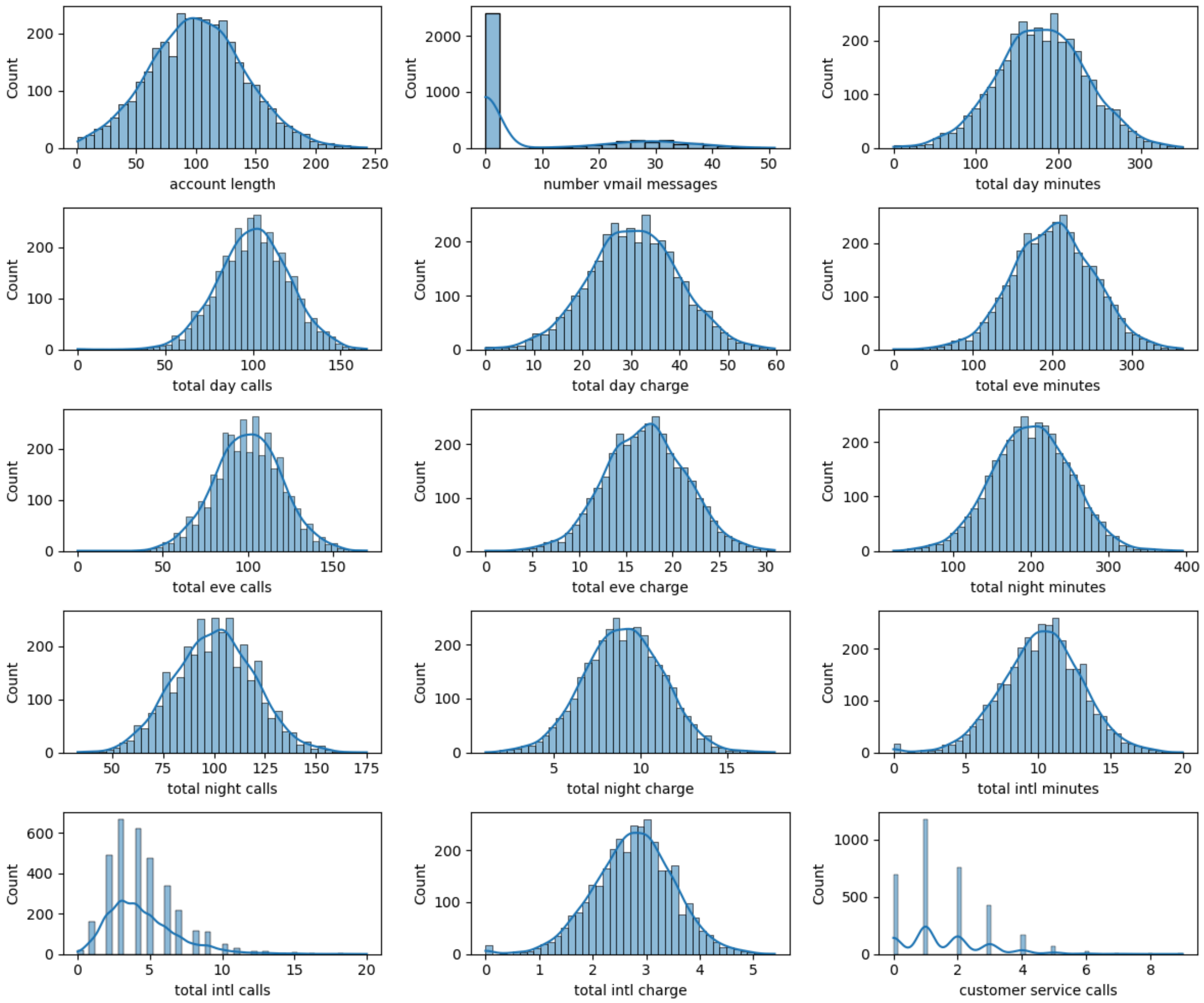
```
#Distribution of churn

class_counts = df.groupby("churn").size()
plt.figure(figsize=(8,6))
ax = sns.countplot(data=df, x="churn")

for p in ax.patches:
    ax.annotate(f'{p.get_height():.0f}',
        (p.get_x() + p.get_width() / 2., p.get_height()),
        ha='center', va='center',
        fontsize=10, color='black', fontweight='bold',
        xytext=(0, 10),
        textcoords='offset points')

plt.title("Churn Distribution")
plt.xlabel("Churn")
plt.ylabel("Count")
plt.show()
```



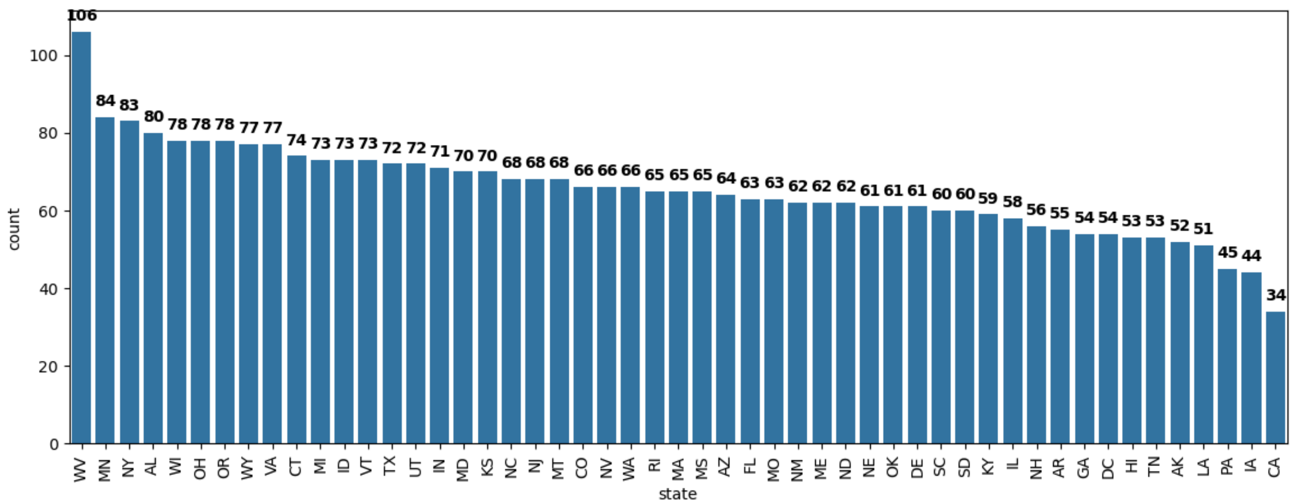
Out of the 3,333 customers, 483 terminated their contracts, which is equivalent to 14.5% of customers lost.

```
#Distrbution of the numerical features

numerical_columns =['account length', 'area code', 'number vmail messages', 'tota

numerical_columns = df[numerical_columns].select_dtypes(include=['number']).colum

nrows = (len(numerical_columns) - 1) // 3 + 1
ncols = min(3, len(numerical_columns))

fig, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=(12,10))

axes = axes.flatten() if nrows > 1 else [axes]

for i, feature in enumerate(numerical_columns):
    ax = axes[i]
    sns.histplot(df[feature], kde=True, ax=ax)
    ax.set_xlabel(feature)
    ax.set_ylabel("Count")

if len(numerical_columns) < nrows * ncols:
```

```
        for i in range(len(numerical_columns), nrows * ncols):
            fig.delaxes(axes[i])

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


Count
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

```
def plot_categorical_distribution(df, feature):
    """
    Plots the categorical feature distribution and adds data labels on top of eac
    """
    plt.figure(figsize=(14,5))
    ax = sns.countplot(x=feature, data=df, order=df[feature].value_counts().index

    for p in ax.patches:

        ax.annotate(f'{p.get_height():.0f}',
            (p.get_x() + p.get_width() / 2., p.get_height()),
            ha='center', va='center',
            fontsize=10, color='black', fontweight='bold',
            xytext=(0,10),
            textcoords='offset points')

    plt.xticks(rotation=90)
    plt.show()


# Distribution of customers across states

plot_categorical_distribution(df, 'state')
```

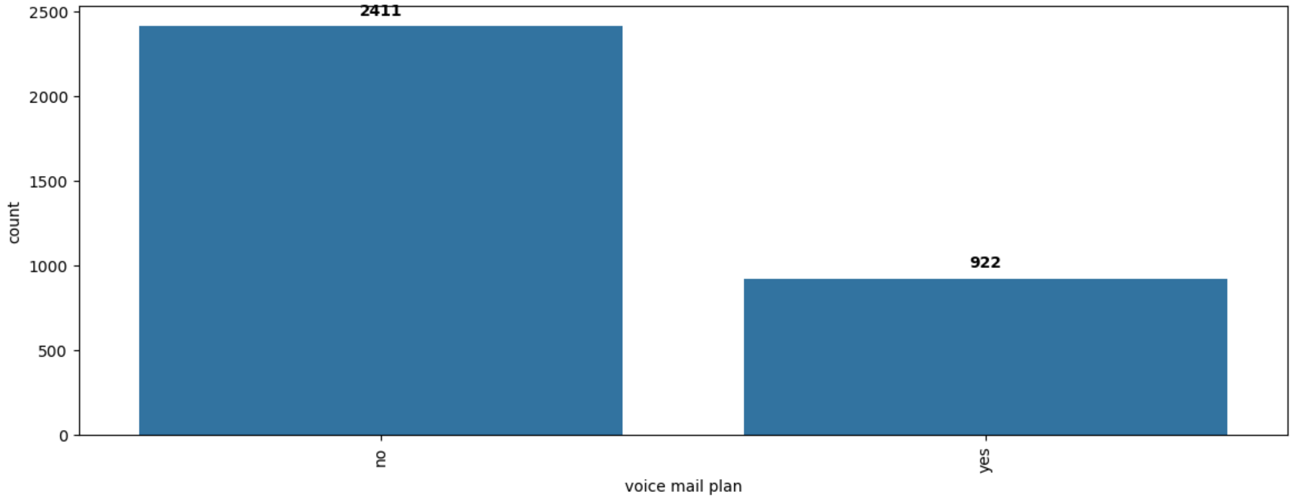



```
df['state'].value_counts()
```

```
state
WV    106
MN     84
NY     83
```

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

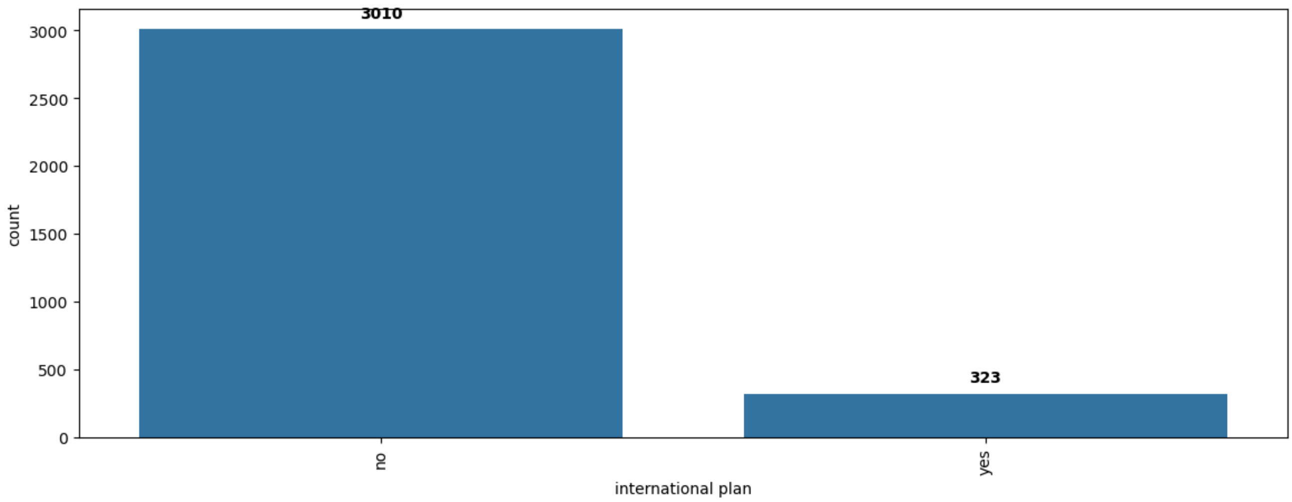
```
plot_categorical_distribution(df, 'voice mail plan')
```




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

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

```
plot_categorical_distribution(df, 'international plan')
```

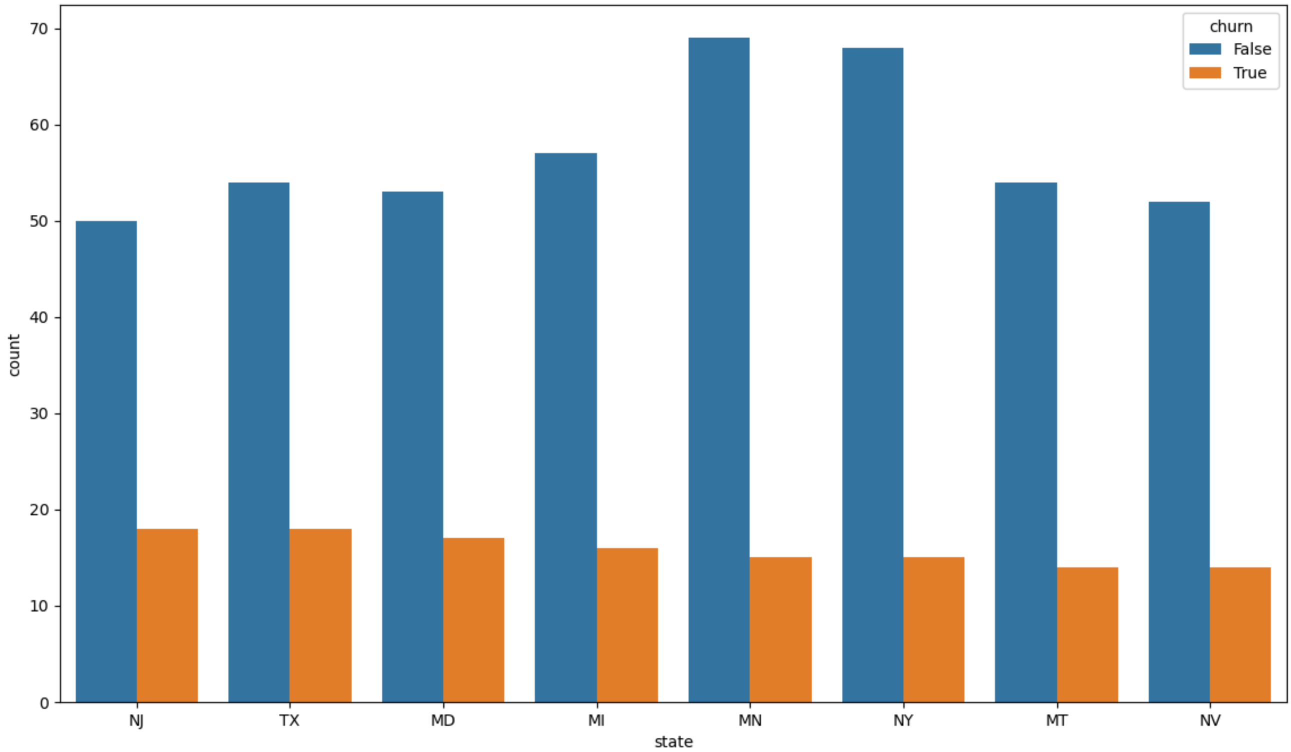



```
df['international plan'].value_counts()
```

```
international plan
no     3010
yes     323
Name: count, dtype: int64
```

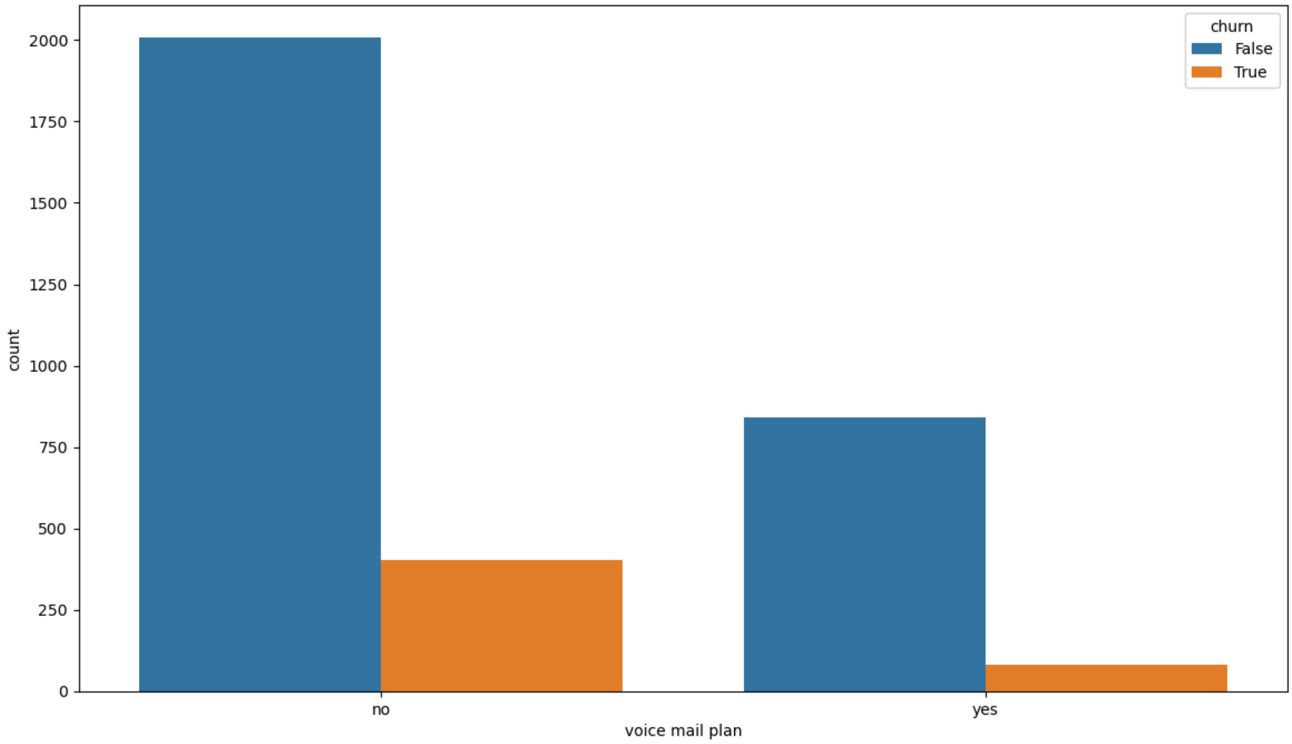
3.2 Bivariate data analysis

```
#Distribution of categorical features against customer churn

def plot_categorical_distribution(df, feature):
    """
    Plots distribution of a categorical feature in the given data.
    """
    plt.figure(figsize=(14,8))
    churn_counts = df.groupby(feature)["churn"].sum().sort_values(ascending=False
    top_8_categories = churn_counts.head(8).index.tolist()
    sns.countplot(x=feature, hue="churn", data=df, order=top_8_categories)
    plt.show()


plot_categorical_distribution(df, 'state')
```



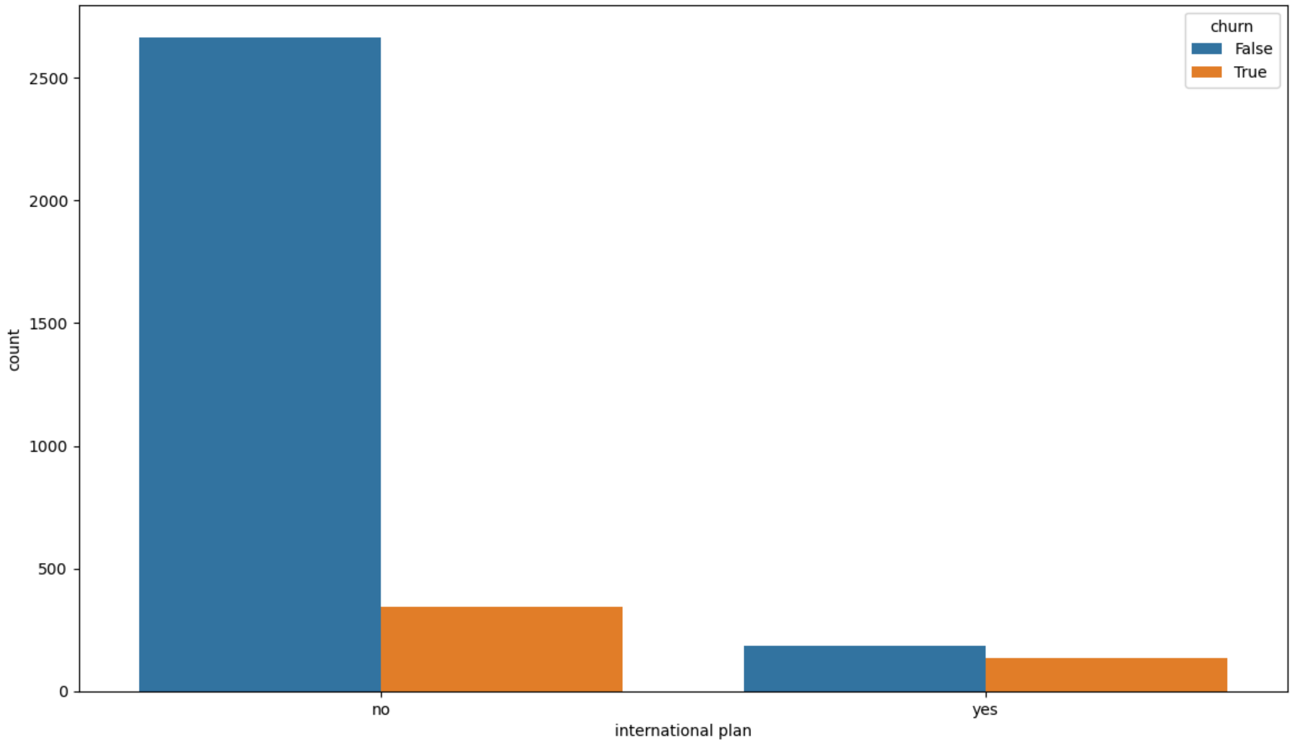
Texas and New Jersey had the most customers who churned.

```
plot_categorical_distribution(df, 'voice mail plan')
```



Majority of the customers who churned did not have a voice mail plan

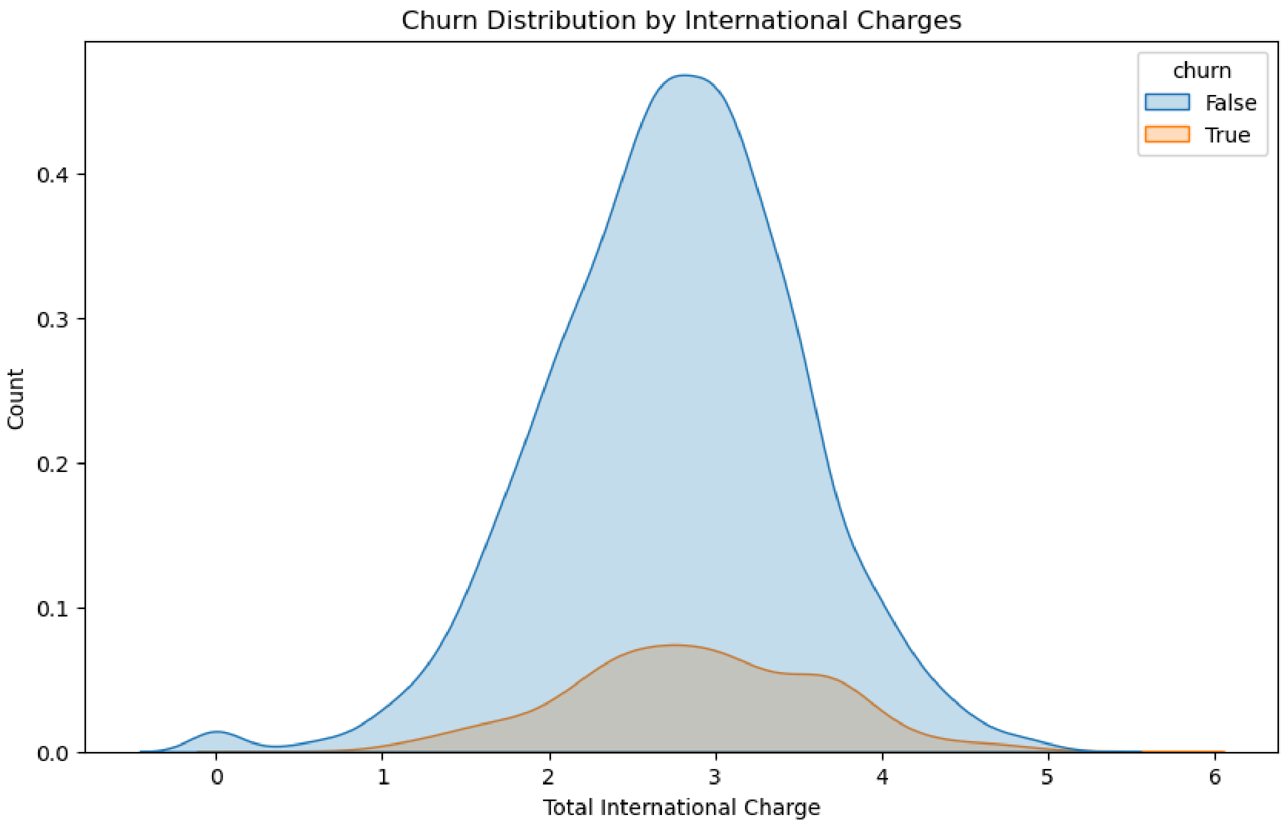
```
plot_categorical_distribution(df, 'international plan')
```



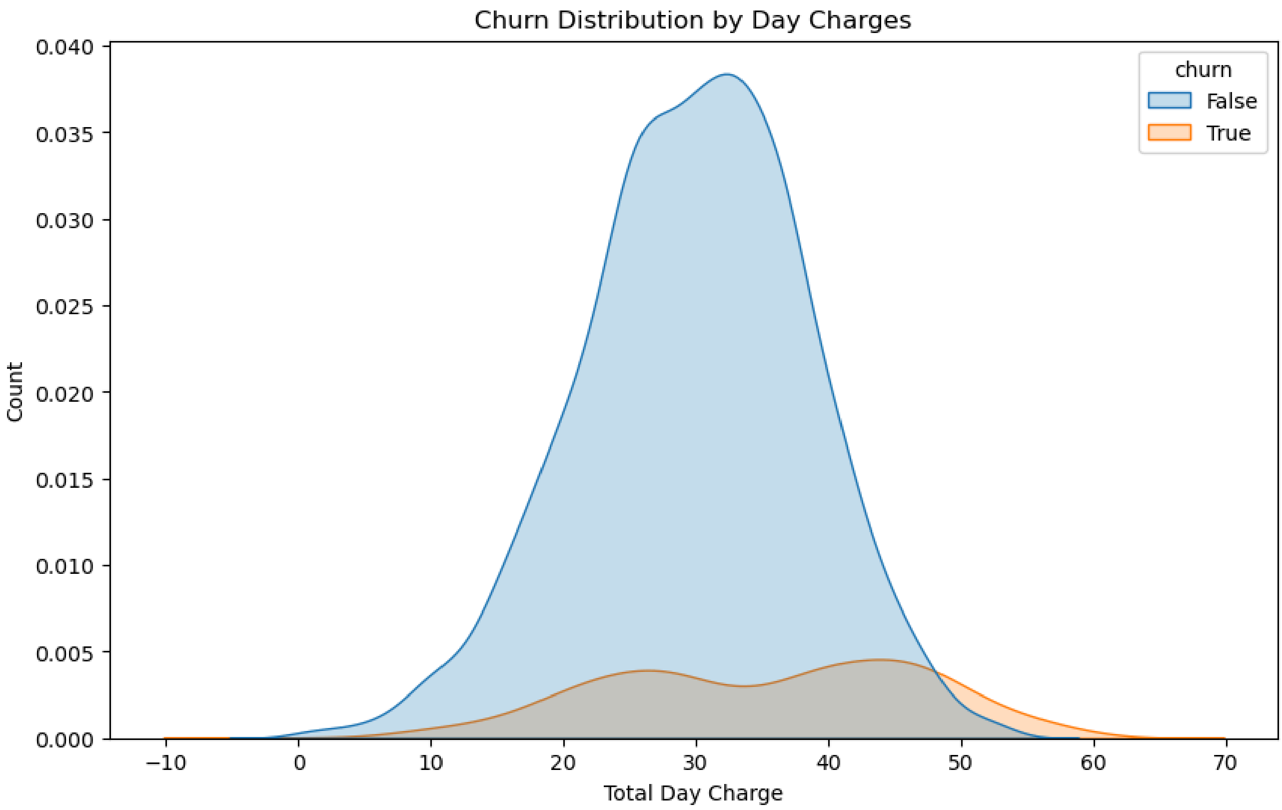
Majority of the customers who churned did not have an international plan

```
#Rate of customer churn against charges

def plot_churn_kde(df, x_column, charge_type):
    """
    Plot features based on churn rate
    """
    plt.figure(figsize=(10,6))
    sns.kdeplot(data=df, x=x_column, hue="churn", fill=True)
    plt.xlabel(f'Total {charge_type} Charge')
    plt.ylabel('Count')
    plt.title(f'Churn Distribution by {charge_type} Charges')
    plt.show()
```

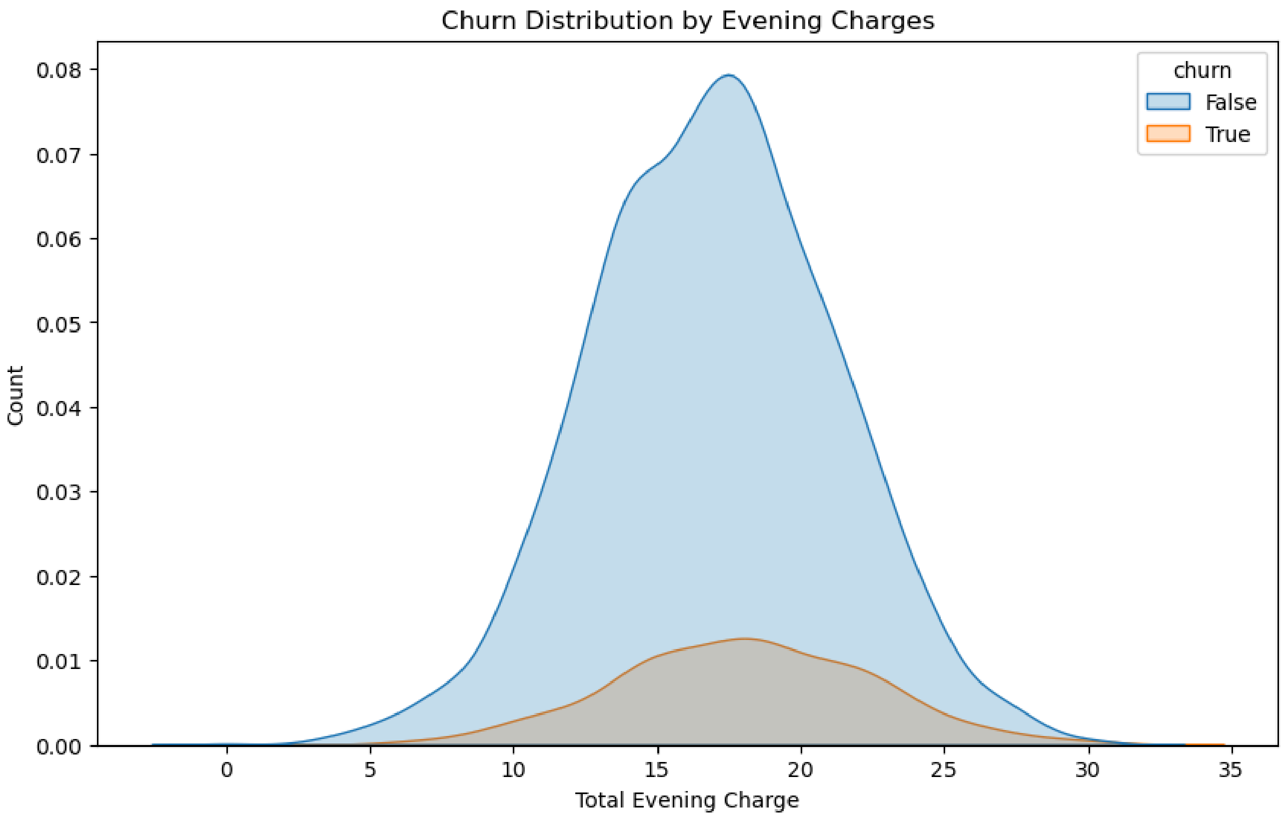
```
# Churn vis-a-vis international charges

plot_churn_kde(df, 'total intl charge', 'International')
```




```
plot_churn_kde(df, 'total day charge', 'Day')
```




```
plot_churn_kde(df, 'total eve charge', 'Evening')
```



3.3 Outliers

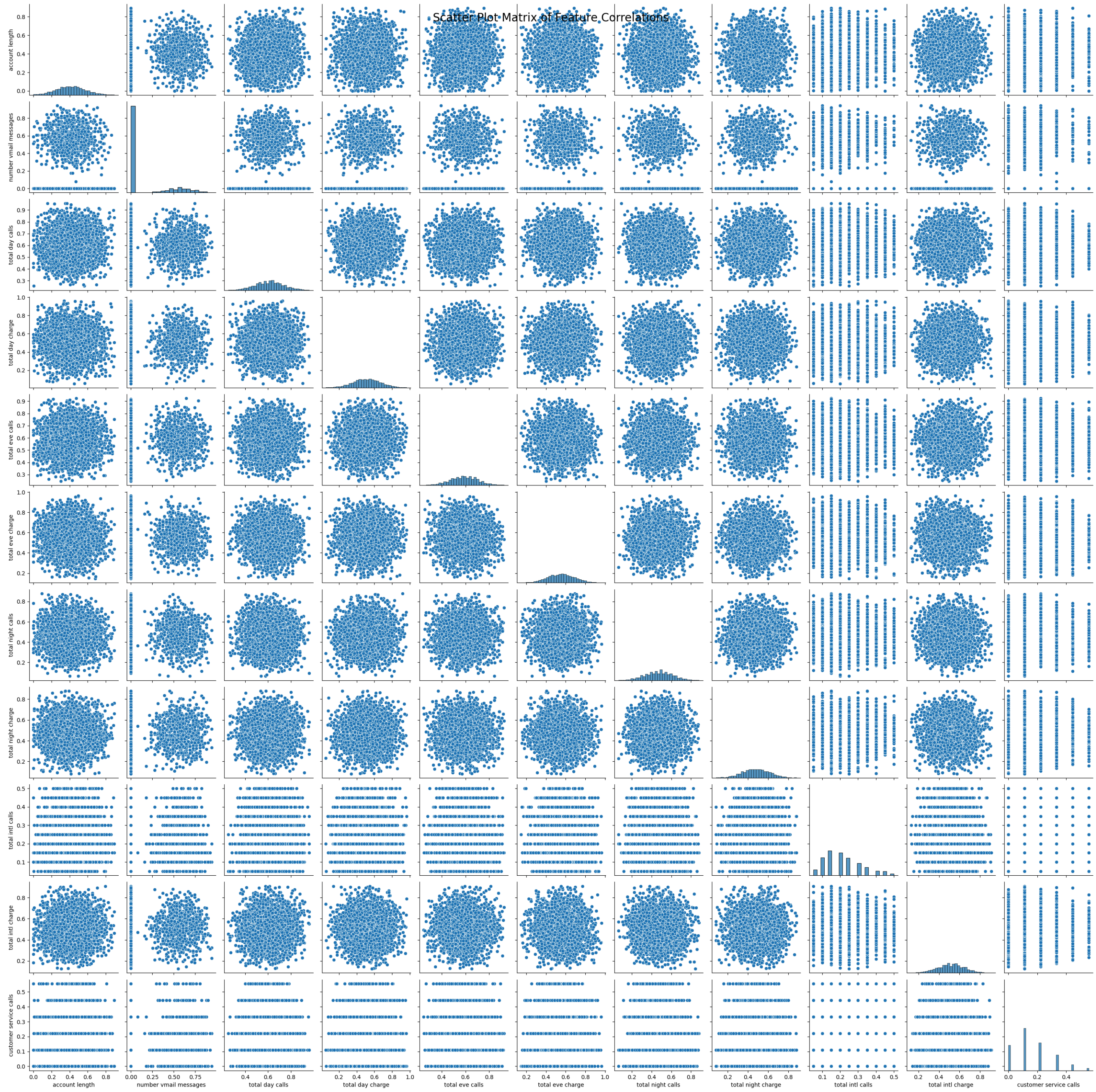
```
def drop_numerical_outliers(df, z_thresh=3):
    numerical_columns = df.select_dtypes(include=[np.number])
    z_scores = numerical_columns.apply(zscore)

    mask = (np.abs(z_scores) < z_thresh).all(axis=1)

    df = df[mask]

    return df

df = drop_numerical_outliers(data)
print(df.shape)
```

```
(3124, 71)
```

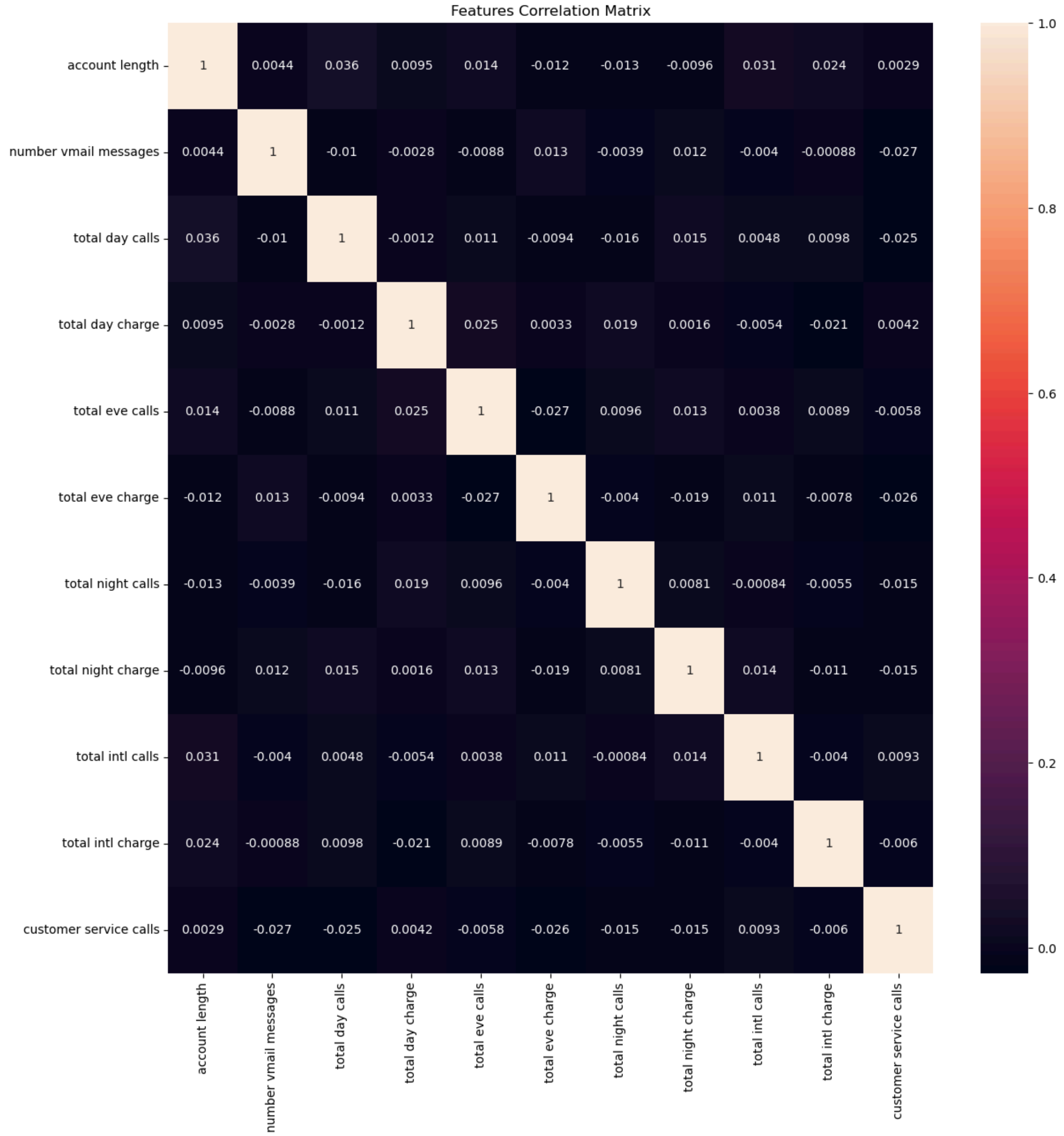
3.3 Correlations

```
numeric_df = df.select_dtypes(include=['number'])
sns.pairplot(numeric_df)
```

```
plt.suptitle('Scatter Plot Matrix of Feature Correlations', size=20)
plt.show()
```


Scatter Plot Matrix of Feature Correlations
account length
number vmail messages
total day calls
total day charge
total eve calls
total eve charge
total night calls
total night charge
total intl calls
total intl charge
customer service calls

```
#Correlation between features using a heatmap

numeric_df = df.select_dtypes(include=['number'])
corr_matrix = numeric_df.corr()

fig, ax = plt.subplots(figsize=(14,14))
sns.heatmap(corr_matrix, annot=True, ax=ax)
plt.title('Features Correlation Matrix')
plt.show()
```


Features Correlation Matrix
account length
number vmail messages
total day calls
total day charge
total eve calls
total eve charge
total night calls
total night charge
total intl calls
total intl charge
customer service calls
1.0
0.8
0.6
0.4
0.2
0.0

```
#calculate correlation matrix

corr_matrix = df.corr().abs()

mask = np.triu(np.ones_like(corr_matrix, dtype=bool))
tri_df = corr_matrix.mask(mask)

to_drop = [c for c in tri_df.columns if any(tri_df[c] > 0.90)]

df = df.drop(to_drop, axis=1)


#reloading the original dataset that was transformed due to running a one hot cod

df = pd.read_csv("customer-churning copy.csv")


#label coding

label_encoder = LabelEncoder()
df['churn'] = label_encoder.fit_transform(df['churn'])


#scaling data

scaler = MinMaxScaler()

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

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

df.head()
```

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge
0	KS	128	415	no	yes	25	265.1	110	45.07
1	OH	107	415	no	yes	26	161.6	123	27.47
2	NJ	137	415	no	no	0	243.4	114	41.38
3	OH	84	408	yes	no	0	299.4	71	50.90

```
df = df.drop(["state", "area code"], axis=1)
```

4. MODELLING

In this section i will use logistic regression, decision tree and random forest algorithms to predict customer churn based on the dataset availed. I will evaluate the performance of the model on a recall score of 80% or higher whereupon it will be considered a success.

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

```
X_train,X_test,y_train,y_test = train_test_split(X,y, test_size=0.25, random_stat
```

```
smote=SMOTENC(categorical_features = [1,2], random_state= 123)
resampled_X_train, resampled_y_train = smote.fit_resample(X_train, y_train)
```

```
#define x and y then split the data into train and test sets using a test size of

X = df.drop("churn", axis=1)
y = df["churn"]
```

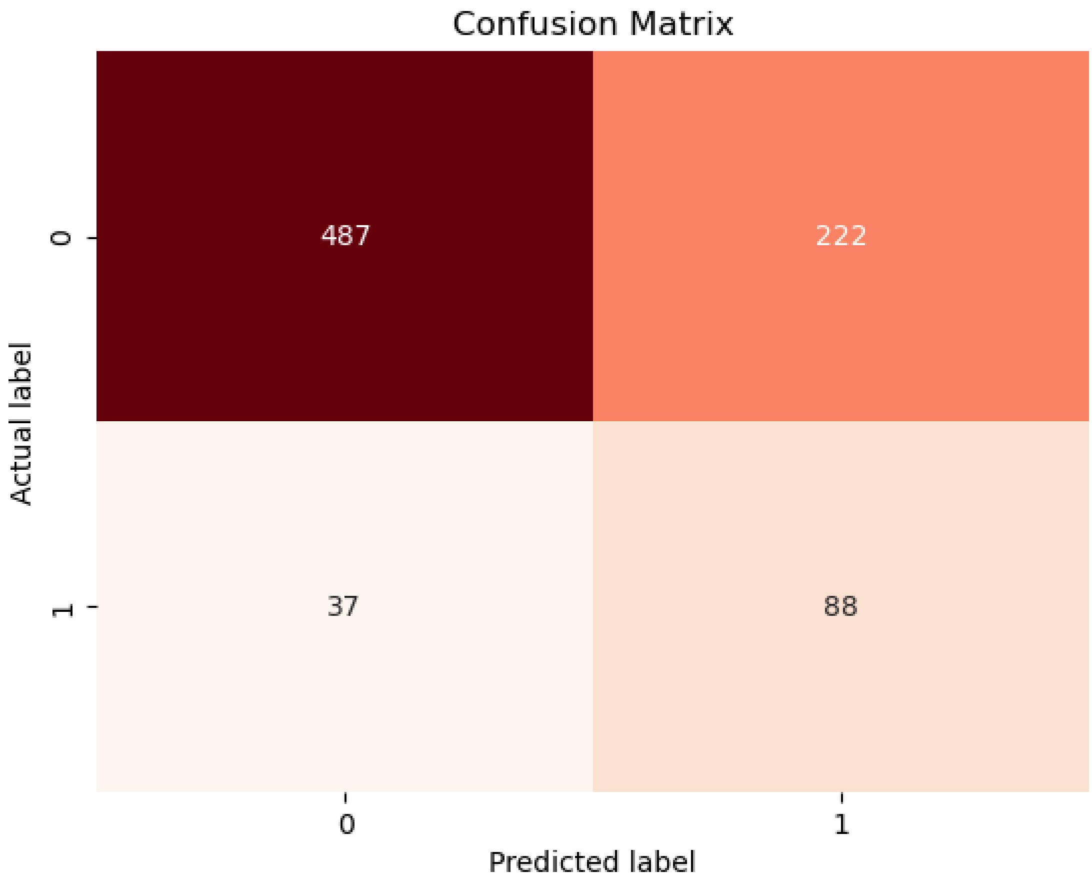
```
X_train,X_test,y_train,y_test = train_test_split(X, y, test_size=0.25, random_sta
```

4.1 Logistic regression

```
logreg = LogisticRegression(random_state=123)
```

```
label_encoder = LabelEncoder()

resampled_X_train['international plan'] = label_encoder.fit_transform(resampled_X
resampled_X_train['voice mail plan'] = label_encoder.fit_transform(resampled_X_tr

X_test['international plan'] = label_encoder.fit_transform(X_test['international
```

```
X_test['voice mail plan'] = label_encoder.fit_transform(X_test['voice mail plan']

logreg.fit(resampled_X_train, resampled_y_train)

y_pred_log = logreg.predict(X_test)


def plt_confusion_matrix(y_true, y_pred, classes):
    """
    Confusion matrix plot
    """
    cm = confusion_matrix(y_true, y_pred)
    plt.figure()
    sns.heatmap(cm, annot=True, fmt='d', cmap='Reds', xticklabels=classes, ytickl

    plt.xlabel('Predicted label')
    plt.ylabel('Actual label')
    plt.title('Confusion Matrix')
    plt.show()


plt_confusion_matrix(y_test, y_pred_log, [0,1])
```

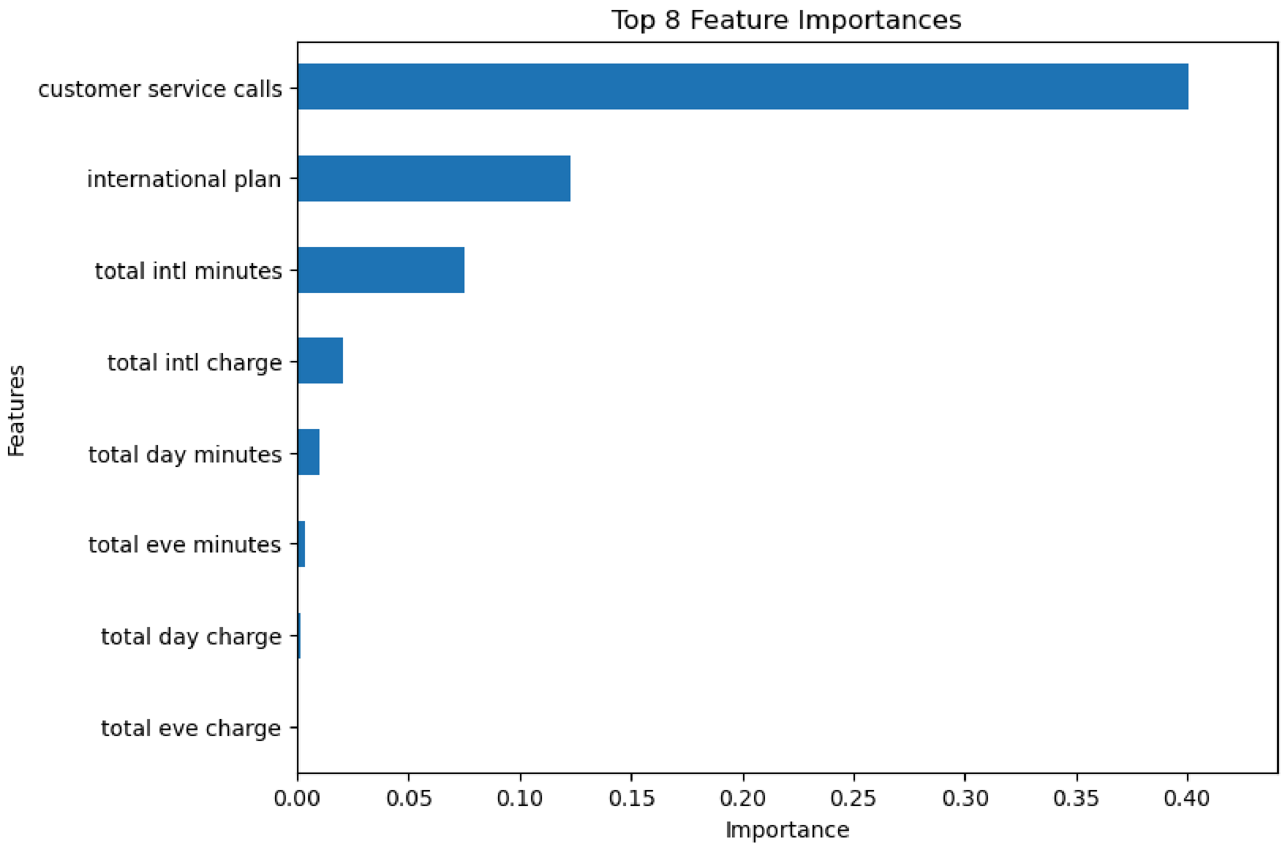



```
print(classification_report(y_test,y_pred_log))
```

```
              precision    recall  f1-score   support

           0       0.93      0.69      0.79       709
           1       0.28      0.70      0.40       125
```

```
    accuracy                          0.69       834
   macro avg       0.61      0.70      0.60       834
weighted avg       0.83      0.69      0.73       834
```

```
#Features importance

importance = logreg.coef_[0]
feature_names = resampled_X_train.columns
feature_importances = pd.Series(importance,index=feature_names)
feature_importances = feature_importances.sort_values(ascending=False)
plt.figure(figsize=(8,6))
top_features = feature_importances[:8]
top_features.sort_values().plot(kind='barh')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.title('Top 8 Feature Importances')
plt.xlim(0, max(top_features)* 1.1)
plt.show()
```

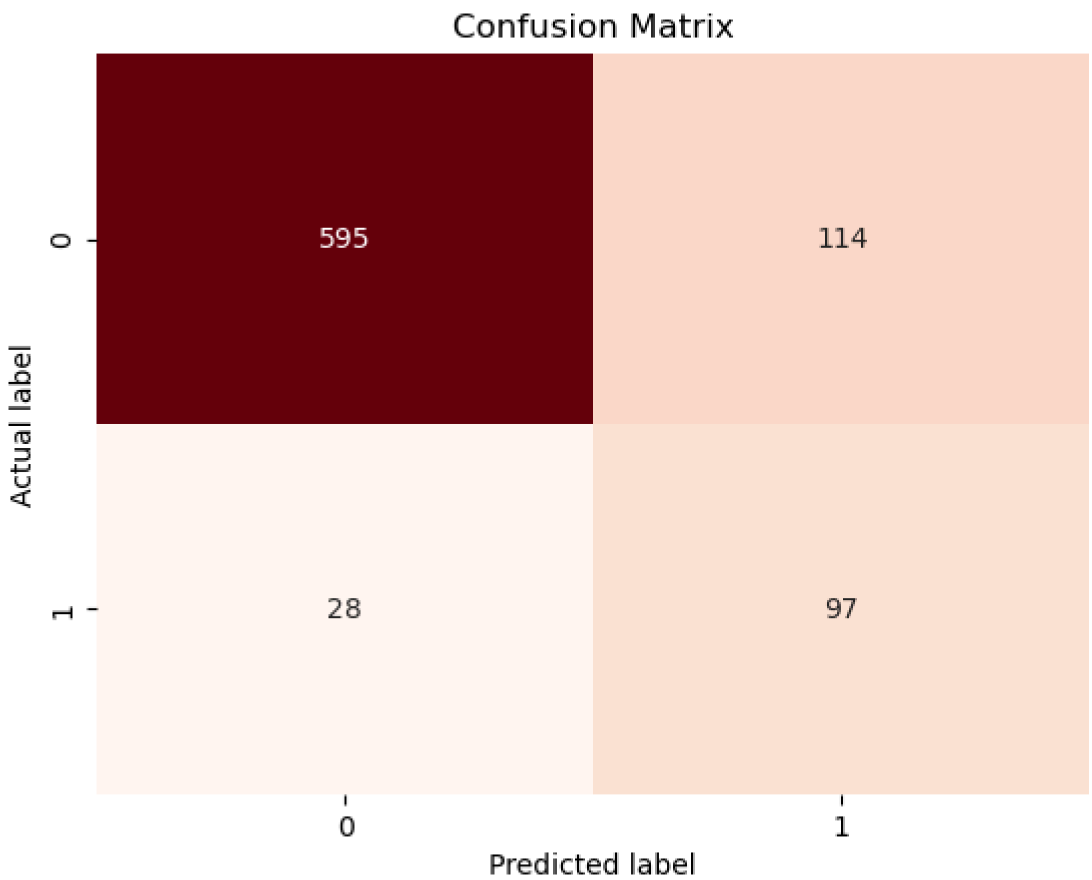


The logistic regression has a recall value of 0.70, which is a good baseline model. Meaning that the model can identify atleast 70% of the actual positive instances accurately.

As illustrated, customer service calls is the most important feature.

4.2 Decision Tree Classifier

```
dt_clf = DecisionTreeClassifier(random_state=123)

dt_clf.fit(resampled_X_train,resampled_y_train)

y_pred_dt = dt_clf.predict(X_test)

plt_confusion_matrix(y_test, y_pred_dt, [0,1])
```

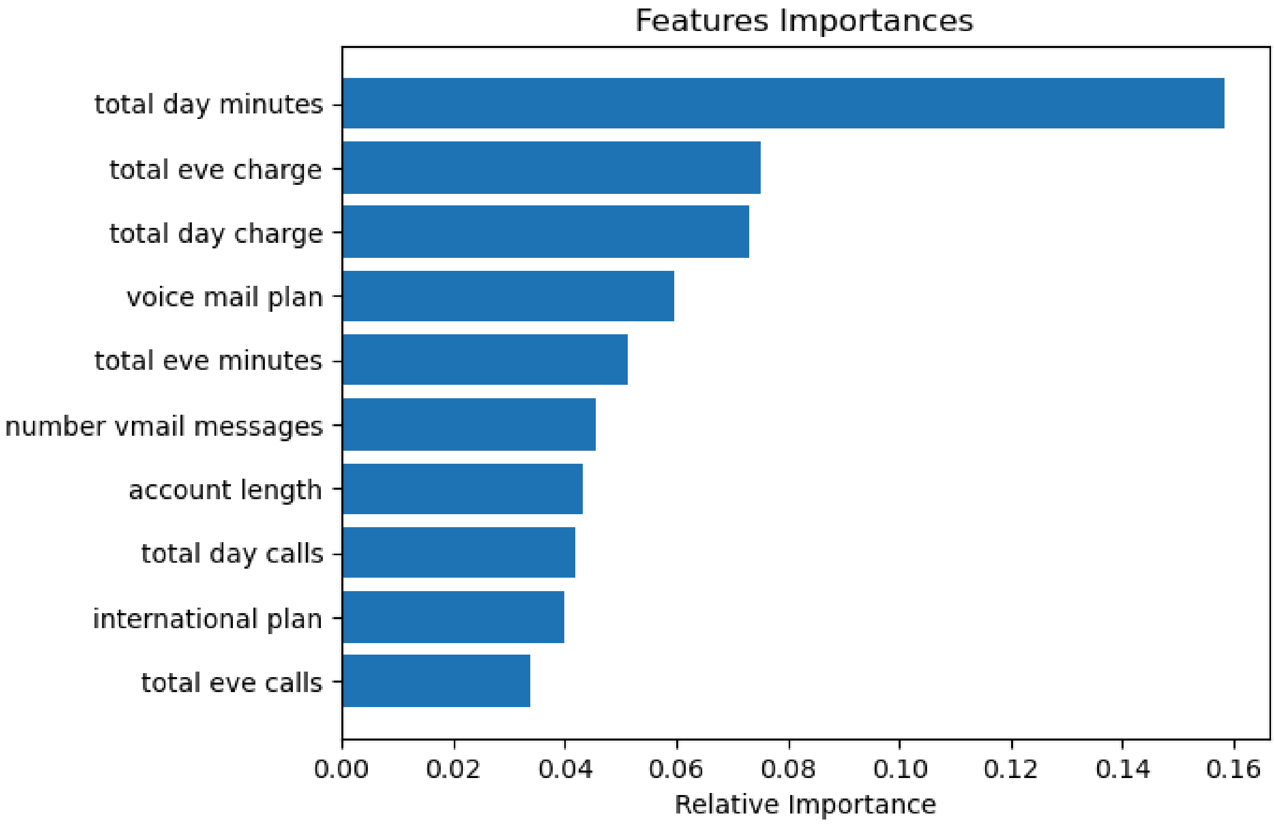



```
print(classification_report(y_test, y_pred_dt))
```

```
              precision    recall  f1-score   support

           0       0.96      0.84      0.89       709
           1       0.46      0.78      0.58       125

    accuracy                           0.83       834
   macro avg       0.71      0.81      0.74       834
weighted avg       0.88      0.83      0.85       834
```

```
#Features Importances

feature_names = list(resampled_X_train.columns)
importances = dt_clf.feature_importances_[0:10]
```

```
indices = np.argsort(importances)

plt.figure()
plt.title('Features Importances')
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



The decision tree model has a recall score of 0.78, meaning that it can identify 78% of the actual positives instances accurately. Further meaning that its making predictions accurately more than inaccurately. Total day minutes is the most important feature.

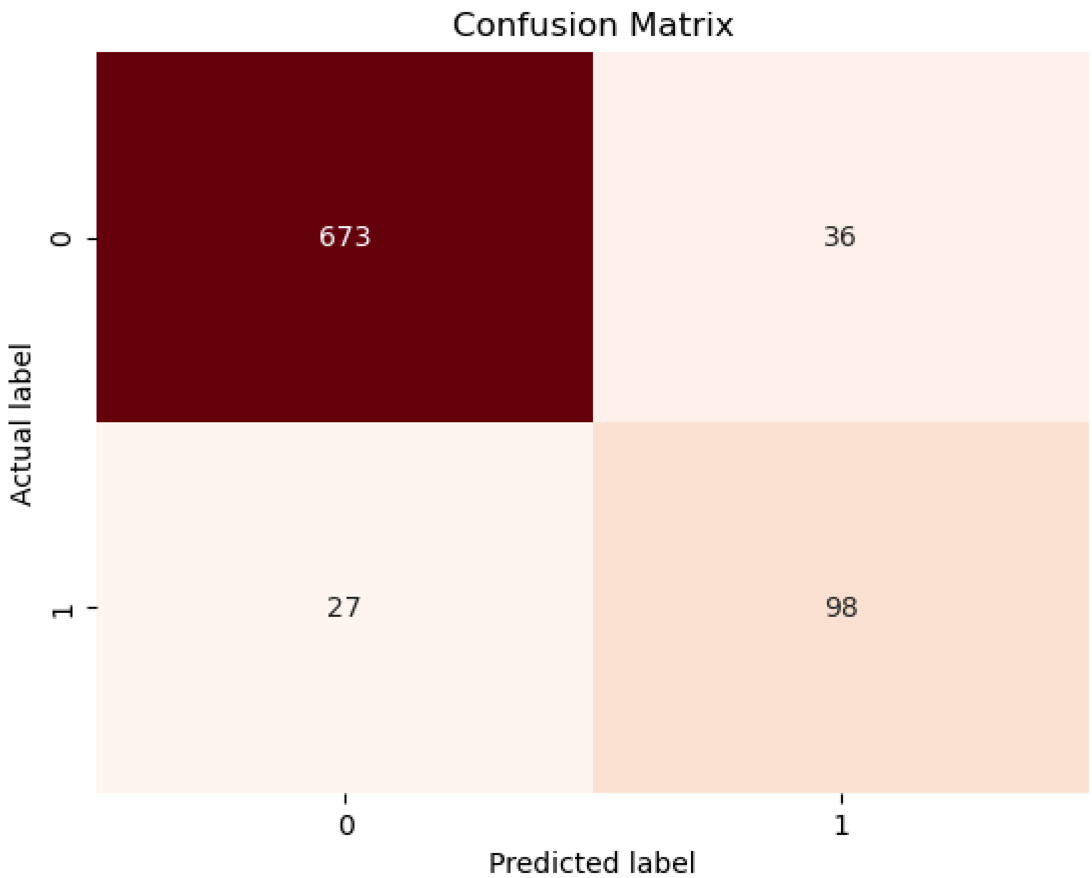
4.3 Random Forest Classifier

```
rf_clf = RandomForestClassifier(random_state=123)

rf_clf.fit(resampled_X_train, resampled_y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=123)
```

```
y_pred_rf = rf_clf.predict(X_test)
```

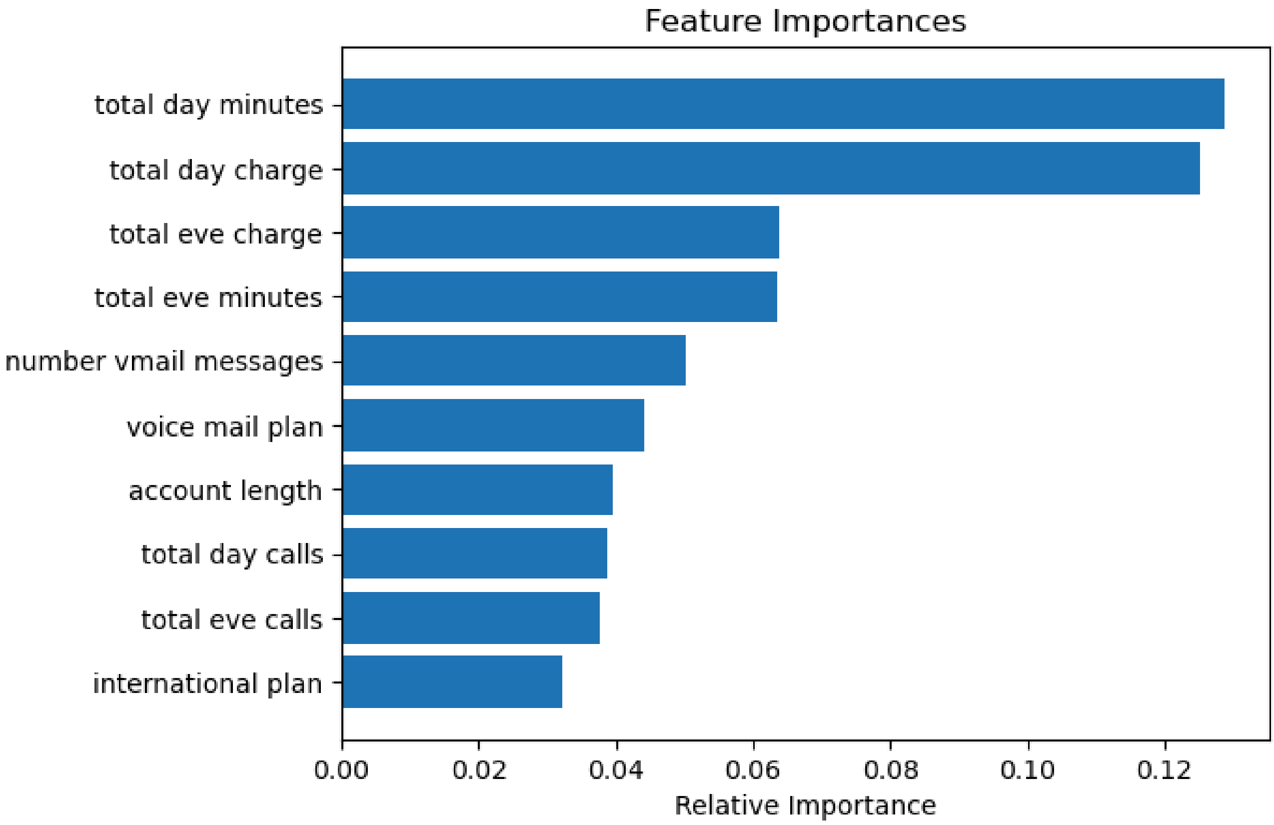
```
plt_confusion_matrix(y_test, y_pred_rf, [0,1])
```




```
print(classification_report(y_test,y_pred_rf))
```

```
              precision    recall  f1-score   support

           0       0.96      0.95      0.96       709
           1       0.73      0.78      0.76       125

    accuracy                           0.92       834
   macro avg       0.85      0.87      0.86       834
weighted avg       0.93      0.92      0.93       834
```

```
feature_names = list(resampled_X_train.columns)
importances = rf_clf.feature_importances_[0:10]
indices = np.argsort(importances)

plt.figure()
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



The random forest classifier model has a recall score of 0.78 which is similar to the decision tree classifier model, meaning that both models can accurately identify the positive accurances by 78%. According to the model, total day minutes if the most important feature.

5. Model Evaluation

In this section, i will evaluate the models based on the recall score and the ROC_AUC, whereupon i will use the best model to tune it for better performance.

5.1 Model comparison vis-a-vis the recall score

```
np.random.seed(123)

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

result_table = pd.DataFrame(columns=['classifiers', 'recall'])

for cls in classifiers:
    model = cls.fit(resampled_X_train, resampled_y_train)
    y_pred = model.predict(X_test)

    recall = recall_score(y_test, y_pred)
```

```
        result_df = pd.DataFrame({'classifiers' : [cls.__class__.__name__], 'recall'
        result_table = pd.concat([result_table, result_df], ignore_index=True)

    result_table.set_index('classifiers', inplace=True)
```