SyriaTel Customer churn prediction

1. Business Understanding

Problem statement

syriaTel is a telecommunications company in Syria. They have been informed that some of their customers have started to churn, leading to them discontinuing their services and looking for other service providers. This analysis will help identify factors that are most likely lead to churning and predict what model can predict which customers are more likely to be lost therefore trying to work on customer retention.

Summary of the dataset

`state` : The state where the customer resides.

`phone number` : The phone number of the customer.

`international plan` : Whether the customer has an international plan (Yes or No).

`voice mail plan` : Whether the customer has a voice mail plan (Yes or No).

Numeric Features:

`area code` : The area code associated with the customer's phone number.

`account length` : The number of days the customer has been an account holder.

`number vmail messages` : The number of voice mail messages received by the customer.

`total day minutes` : The total number of minutes the customer used during the day.

`total day calls` : The total number of calls made by the customer during the day.

`total day charge` : The total charges incurred by the customer for daytime usage.

`total eve minutes` : The total number of minutes the customer used during the evening.

`total eve calls` : The total number of calls made by the customer during the evening.

`total eve charge` : The total charges incurred by the customer for evening usage.

`total night minutes` : The total number of minutes the customer used during the night.

`total night calls` : The total number of calls made by the customer during the night.

`total night charge` : The total charges incurred by the customer for nighttime usage.

`total intl minutes` : The total number of international minutes used by the customer.

`total intl calls` : The total number of international calls made by the customer.

`total intl charge` : The total charges incurred by the customer for international usage.

`customer service calls` : The number of customer service calls made by the customer.

2. Data understanding

In [573…

```
#import modeles to be used
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.graph_objs as go
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix,classification_repor
from sklearn.preprocessing import OneHotEncoder
from sklearn import tree
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
```

In [522…

```
# Load the dataset
df = pd.read_csv('syria tel churn dataset/bigml_59c28831336c6604c800002a.csv')

df.head()
```

Out[522…

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	tot da charg
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.

5 rows × 21 columns

In [523…

```
# check the last rows in the dataset
df.tail()
```

Out[523…

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	cl
3328	AZ	192	415	414-4276	no	yes	36	156.2	77	
3329	WV	68	415	370-3271	no	no	0	231.1	57	
3330	RI	28	510	328-8230	no	no	0	180.8	109	
3331	CT	184	510	364-6381	yes	no	0	213.8	105	
3332	TN	74	415	400-4344	no	yes	25	234.4	113	

5 rows × 21 columns

In [524…

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

Out[524…

```
(3333, 21)
```

In [525…

```
#check the numerical data
df.describe()
```

Out[525…

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	

In [526…

```
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
```

In [527…

```
# highlight numerical and categorical columns
numeric_cols = ['account length', 'area code', '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']
```

Data cleaning

In [528…

```
#checking for duplicated rows
df.duplicated().sum()
```

Out[528…

```
0
```

In [529…

```
#checking for missing values
df.isna().sum()
```

Out[529…

```
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
```

In [530…

```
 #drop unused columns in all dataframes
data = df.drop(['area code','phone number'], axis =1)
data.head()
```

Out[530…

	state	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	tot e' cal
0	KS	128	no	yes	25	265.1	110	45.07	197.4	!
1	OH	107	no	yes	26	161.6	123	27.47	195.5	1(
2	NJ	137	no	no	0	243.4	114	41.38	121.2	1'
3	OH	84	yes	no	0	299.4	71	50.90	61.9	{
4	OK	75	yes	no	0	166.7	113	28.34	148.3	1:

In [531…

```
# Remove any trailing white spaces in all columns
data.columns = data.columns.str.strip()
```

3. Exploratory Data Analysis

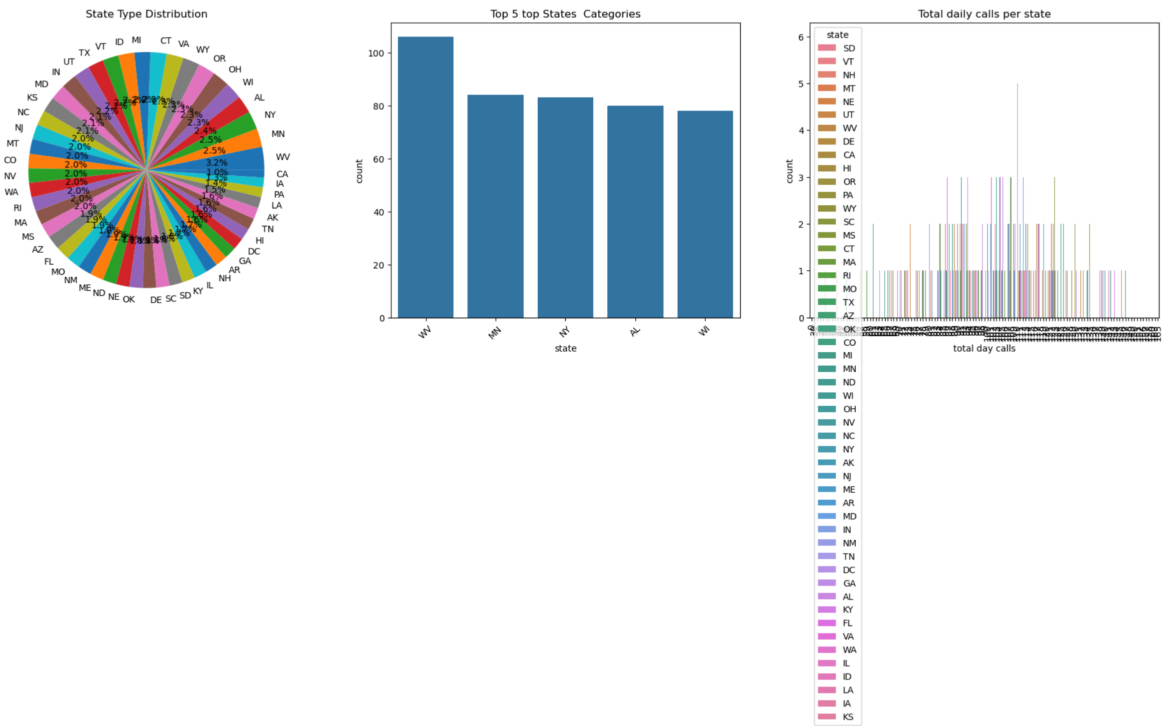
In [574…

```
#plotting the target variable distribution
class_counts = data.groupby("churn").size()

# Create a bar chart of the value counts using Plotly
fig = go.Figure(
    data=[go.Bar(x=class_counts.index, y=class_counts.values)],
    layout=go.Layout(title="Churn Distribution", xaxis=dict(tickvals=[0, 1], tic
          hovermode = 'closest',width=600)
)

# Show the chart
fig.show()
```

In [532…

```
# Compute counts of each state type
state_counts = df['state'].value_counts()

# Get the top 5 injury categories based on count
top_5_categories = df['state'].value_counts().nlargest(5).index

# Create subplots
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(24, 6))  # Set figsize

# Pie chart for Investigation Type Distribution
ax1.pie(state_counts, labels=state_counts.index, autopct='%1.1f%%') # Label and
ax1.set_title('State Type Distribution')

# Injury severity distribution
sns.countplot(x='state', data=df, order=top_5_categories, ax=ax2)
ax2.set_title('Top 5 top States  Categories')
ax2.tick_params(axis='x', rotation=45)

# Relationship between Aircraft Category and Injury Severity
sns.countplot(x='total day calls', hue='state', data=df, ax=ax3)
ax3.set_title('Total daily calls per state')
ax3.tick_params(axis='x', rotation=90)

# Display the plots
plt.tight_layout()
plt.show()
```

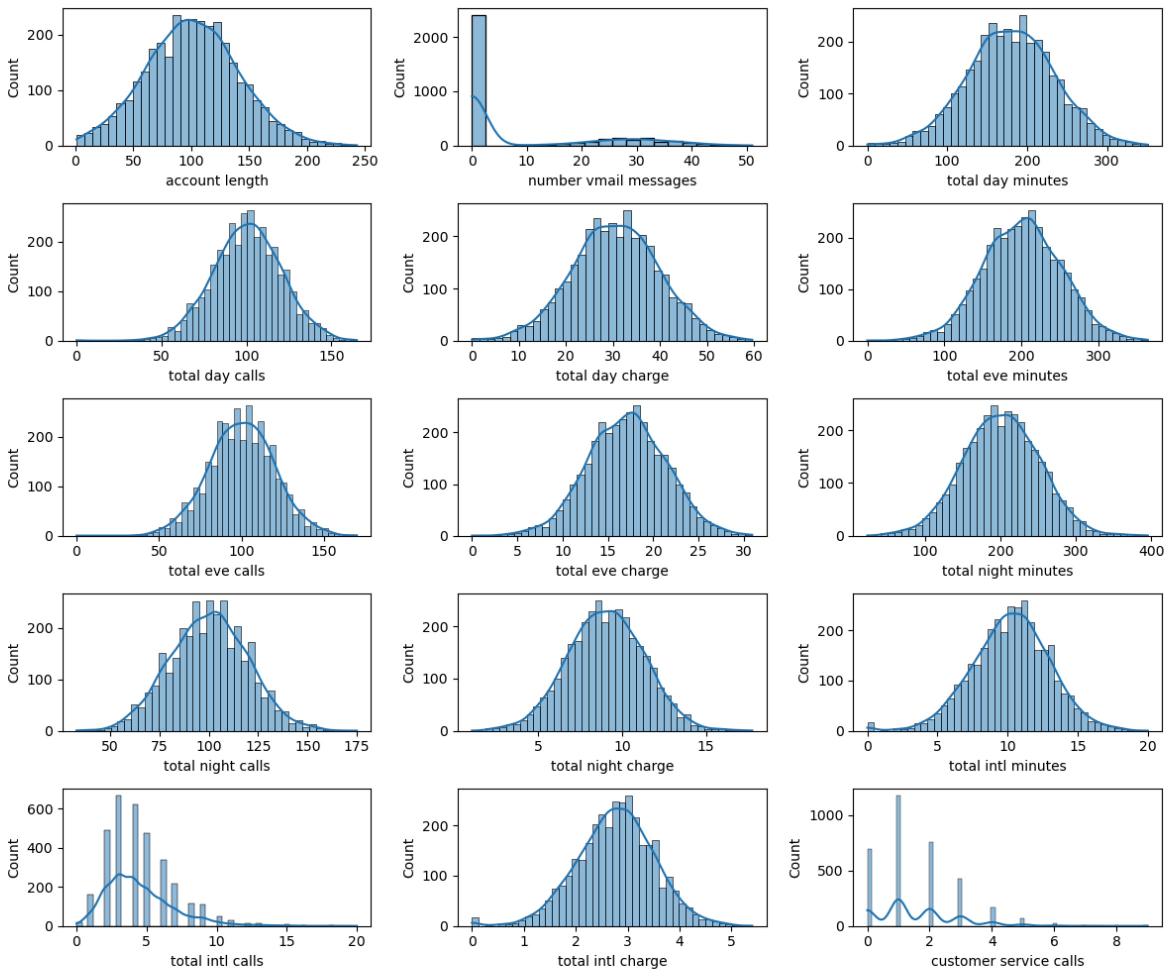
```
C:\Users\karay\AppData\Local\Temp\ipykernel_3004\875484896.py:25: UserWarning: Ti
ght layout not applied. The bottom and top margins cannot be made large enough to
accommodate all axes decorations.
  plt.tight_layout()
```



Observation: West virginia, minnesota, newyork, alabama and wisconsin had many customers respectively.

In [533…

```
#checking for distribution of the numeric features
numeric_features = ['account length', 'number vmail messages', 'total day minute
'total eve minutes', 'total eve calls', 'total eve charge', 'total night minutes
'total night charge', 'total intl minutes', 'total intl calls', 'total intl char

# Calculate the number of rows and columns for subplots
nrows = (len(numeric_features) -1) // 4 + 2
ncols = min(3, len(numeric_features))

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

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

# Plot numeric features
for i, feature in enumerate(numeric_features):
    ax = axes[i]
    sns.histplot(data[feature], kde=True, ax=ax)
    ax.set_xlabel(feature)
    ax.set_ylabel("Count")

# Remove empty subplots
if len(numeric_features) < nrows * ncols:
    for i in range(len(numeric_features), nrows * ncols):
        fig.delaxes(axes[i])

# Adjust subplot spacing
fig.tight_layout()

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



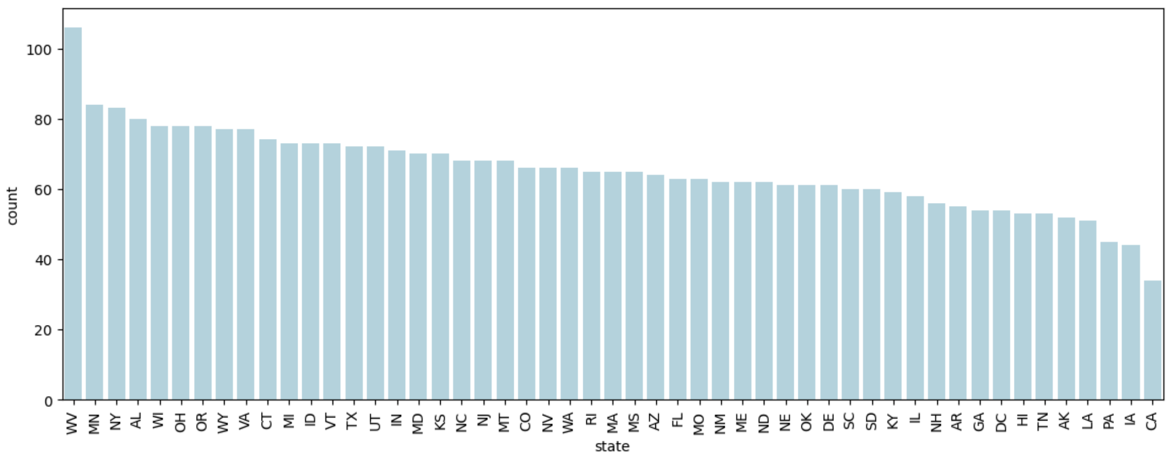
From the distribution, most categories had a normal distribution except voice mail customers who showed unskewness on the right side showing very few customers made calls. International calls and customer servvice calls also had few cutomers.

In [534…

```
#checking the distribution of categorical features
def plot_categorical_distribution(data, feature):

    plt.figure(figsize=(14, 5))
    sns.countplot(x=feature, data=data,color='lightblue', order=data[feature].va
    plt.xticks(rotation=90)
    plt.show()
```

In [535…

```
plot_categorical_distribution(data,'state')
```



Most of the customers are from `West Virginia`, `Minnesota`, `NewYork`, `Alabama` and `Wisconsin`.

In [536…

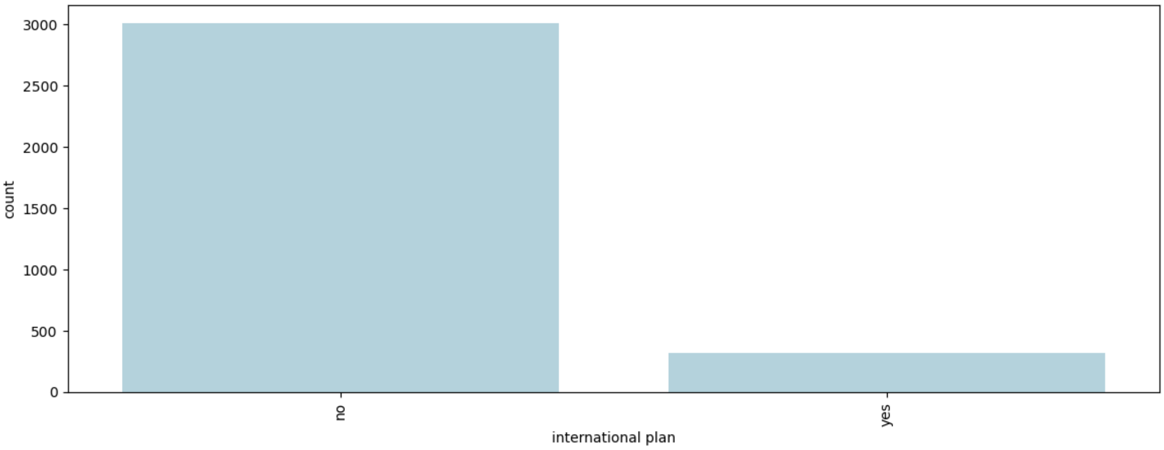
```
data['international plan'].value_counts()
```

Out[536…

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

In [537…

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



From the 3333 customers,323 of them have an international plan.

In [538…

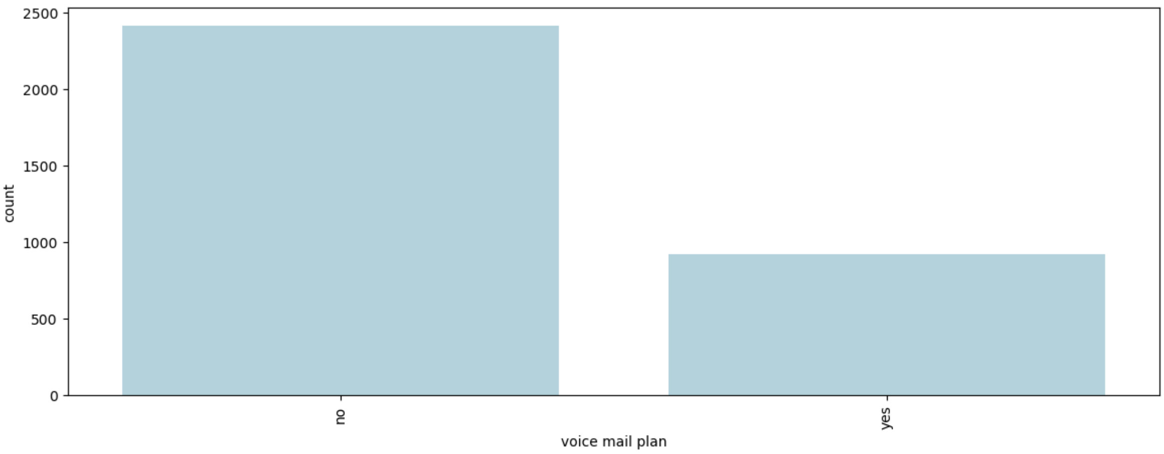
```
data['voice mail plan'].value_counts()
```

Out[538…

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

In [539…

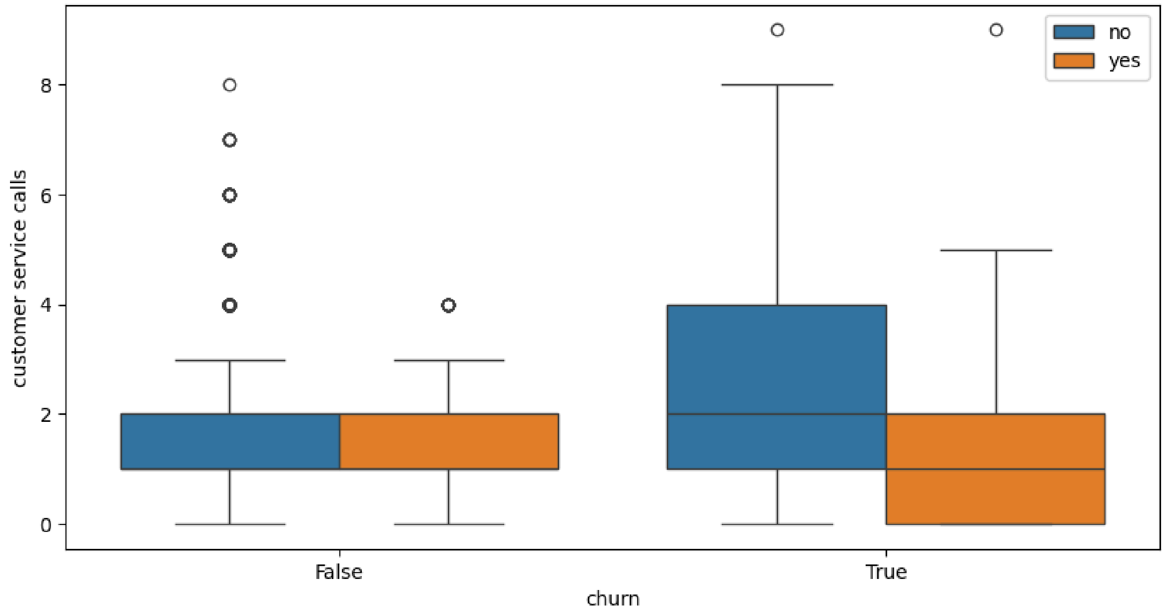
```
plot_categorical_distribution(data, 'voice mail plan')
```



From 3333 customers,922 customers have a voicemail plan.

In [540…

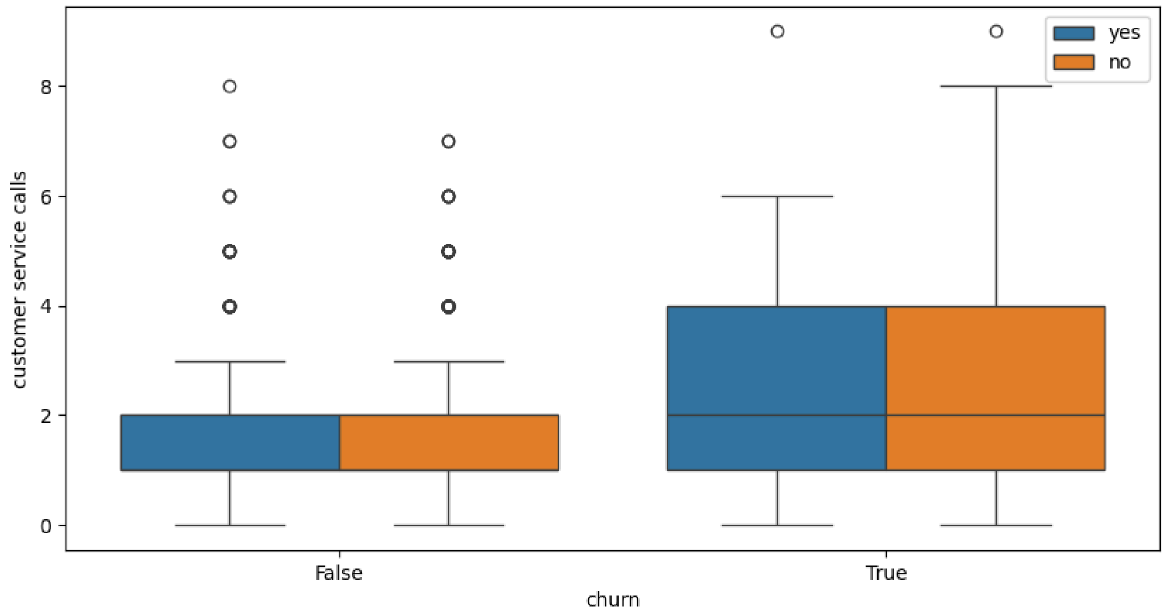
```
 #Boxplot to see whether customers on international plan  has the highest churn
plt.figure(figsize=(10,5))
sns.boxplot(data=data,x='churn',y='customer service calls',hue='international pl
plt.legend(loc='upper right');
```



From the customers who have terminated their account, most of them were not on international plan.

In [541…

```
#Boxplot to see whether customers on voivemail plan had the highest churn
plt.figure(figsize=(10,5))
sns.boxplot(data=data,x='churn',y='customer service calls',hue='voice mail plan'
plt.legend(loc='upper right');
```

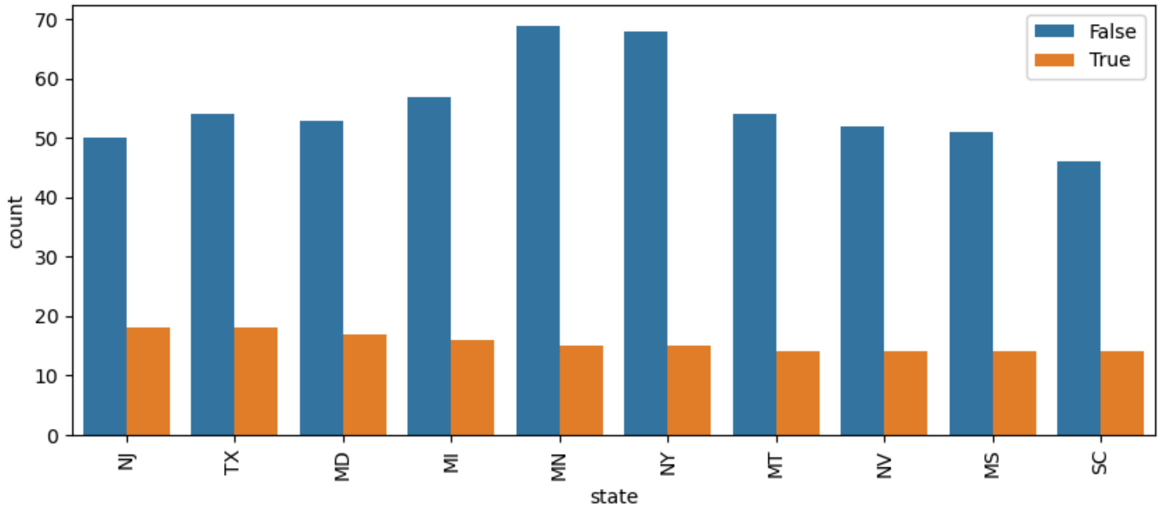


In [542…

```
#Checking the distribution of categorical features based on churn rate
def plot_categorical_distribution(data, feature):
    """
    Plots the distribution of a categorical feature in the given data.
    """
    plt.figure(figsize=(10, 4))
    churn_counts = data.groupby(feature)["churn"].sum().sort_values(ascending=Fa
    top_10_categories = churn_counts.head(10).index.tolist()
    sns.countplot(x=feature, hue="churn", data=data, order=top_10_categories)
    plt.xticks(rotation=90)
    plt.legend(loc="upper right")
    plt.show()
```

In [543…

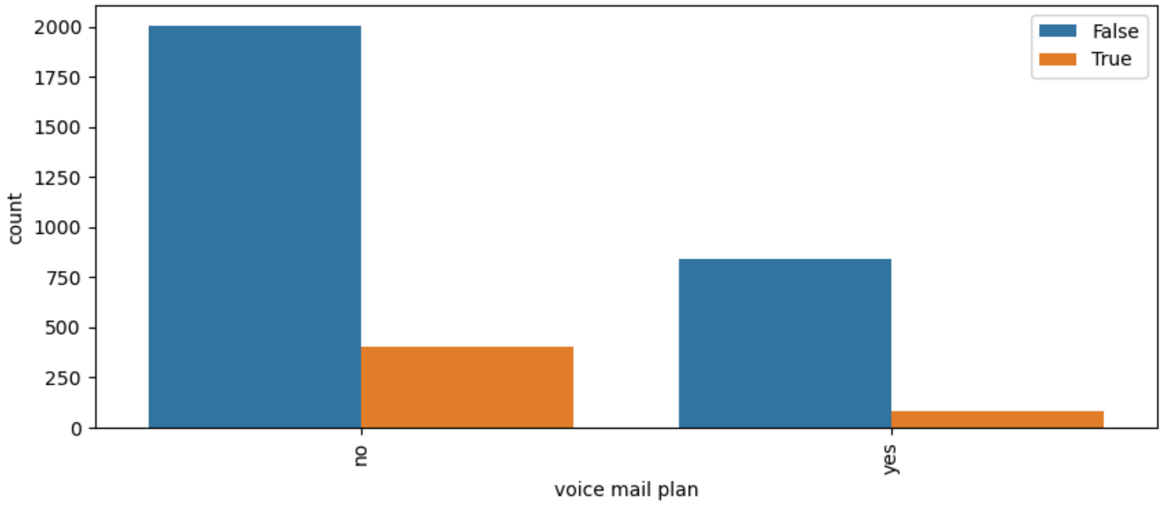
```
plot_categorical_distribution(data, 'state')
```



Of all the customers that churned, majority are from `Texas`, `New Jersey`, `Maryland`, `Miami` and `NewYork`.

In [544…

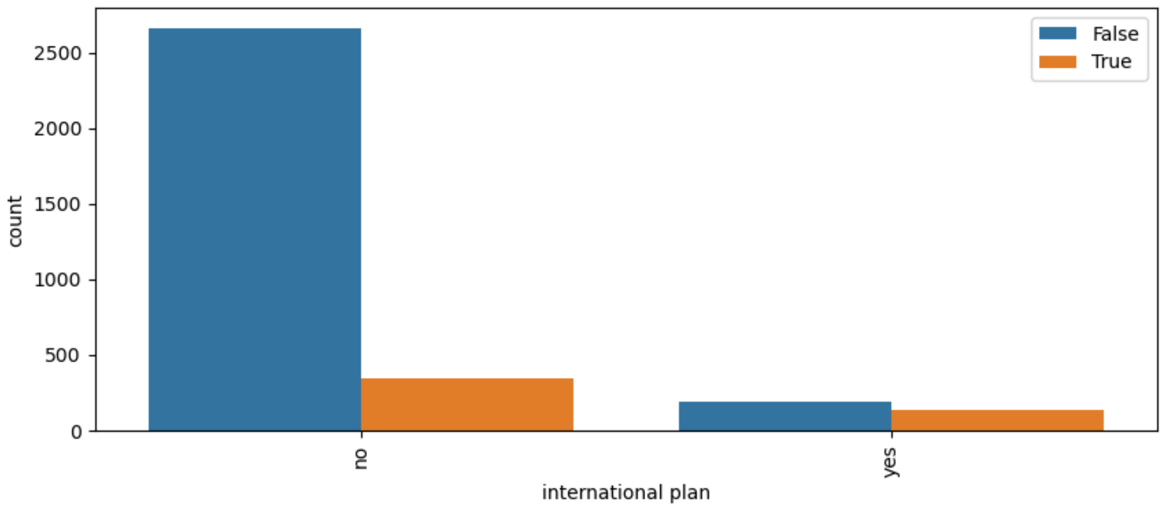
```
plot_categorical_distribution(data, 'voice mail plan')
```



The majority of customers who churned did not have voicemail plan.

In [545…

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



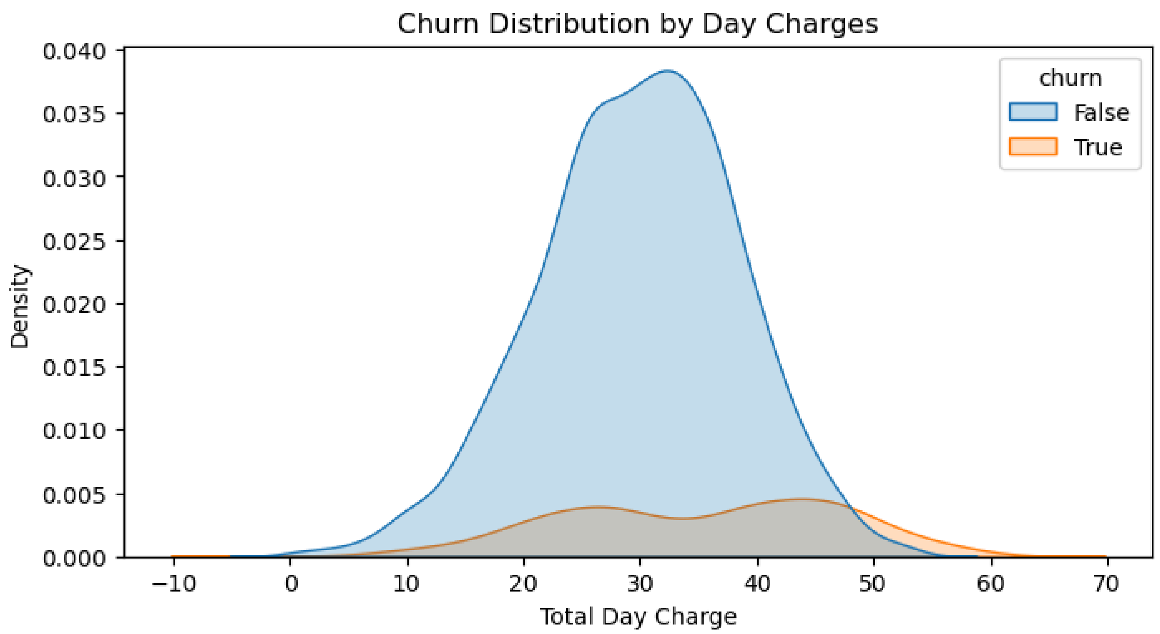
The majority of customers who churned did not have an international plan.

In [546…

```
def plot_churn_kde(data, x_column, charge_type):
    """
    A function to plot features based on churn rate
    """
    plt.figure(figsize=(8, 4))
    sns.kdeplot(data=data, x=x_column, hue='churn', fill=True)
    plt.xlabel(f'Total {charge_type} Charge')
    plt.ylabel('Density')
    plt.title(f'Churn Distribution by {charge_type} Charges')
    plt.show()
```

In [547…

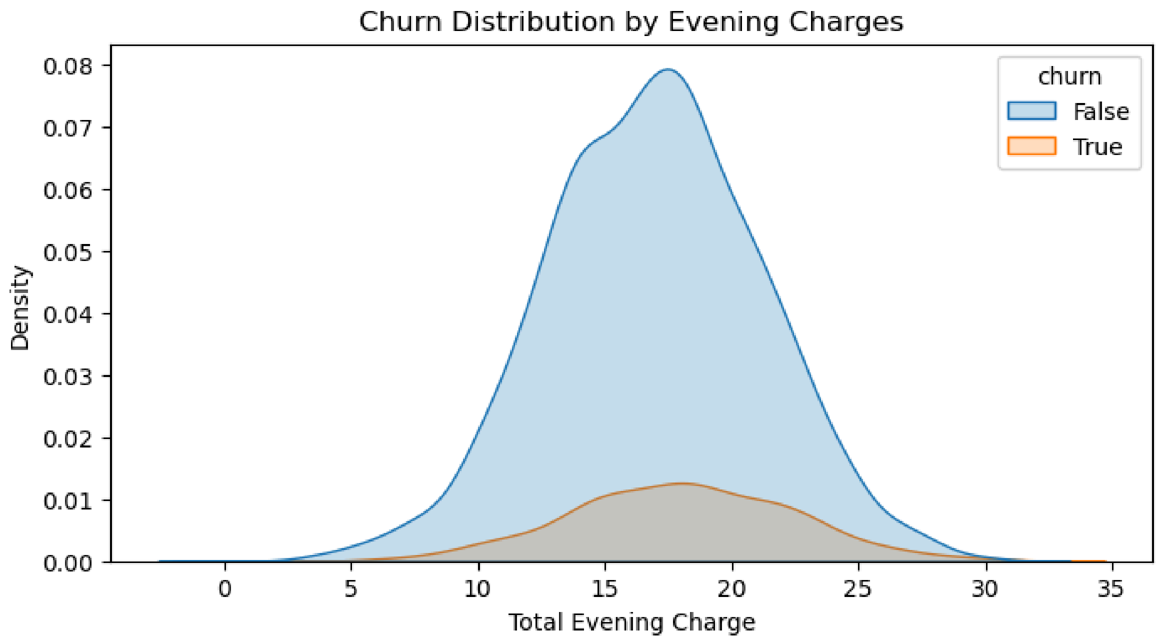
```
# Churn by day charges
plot_churn_kde(data, 'total day charge', 'Day')
```



From the analysis, customers who have terminated their accounts have higher total day changes than those who have not terminated their accounts.

In [548…

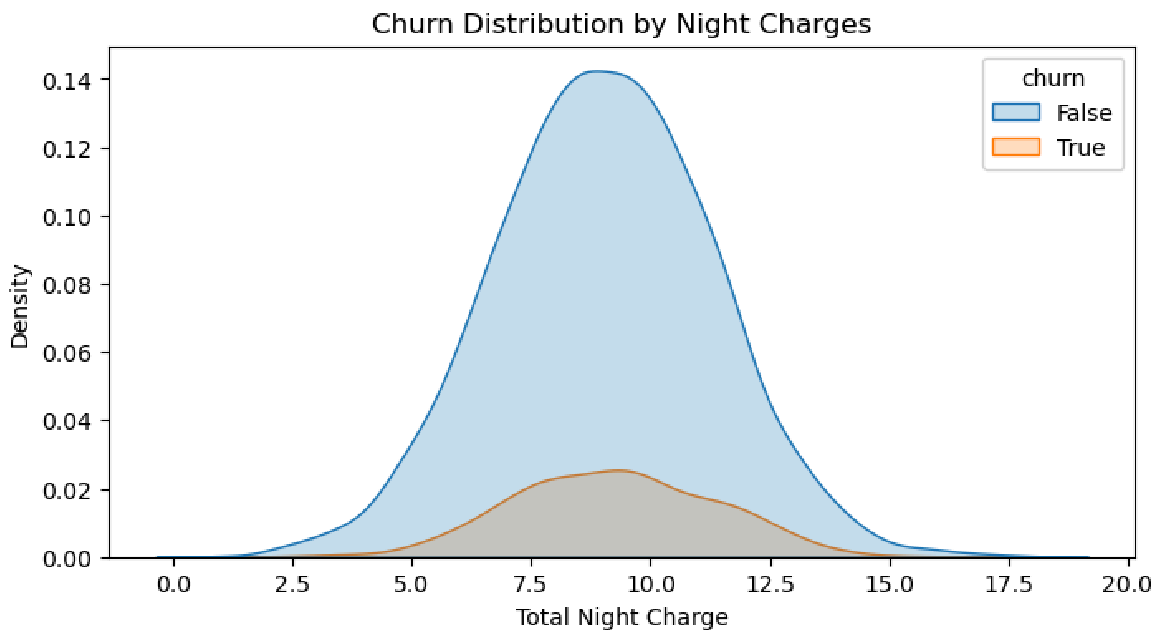
```
# Churn by evening charges
plot_churn_kde(data, 'total eve charge', 'Evening')
```



From the analysis, customers who have terminated their accounts have higher total day changes than those who have not terminated their accounts.

In [549…

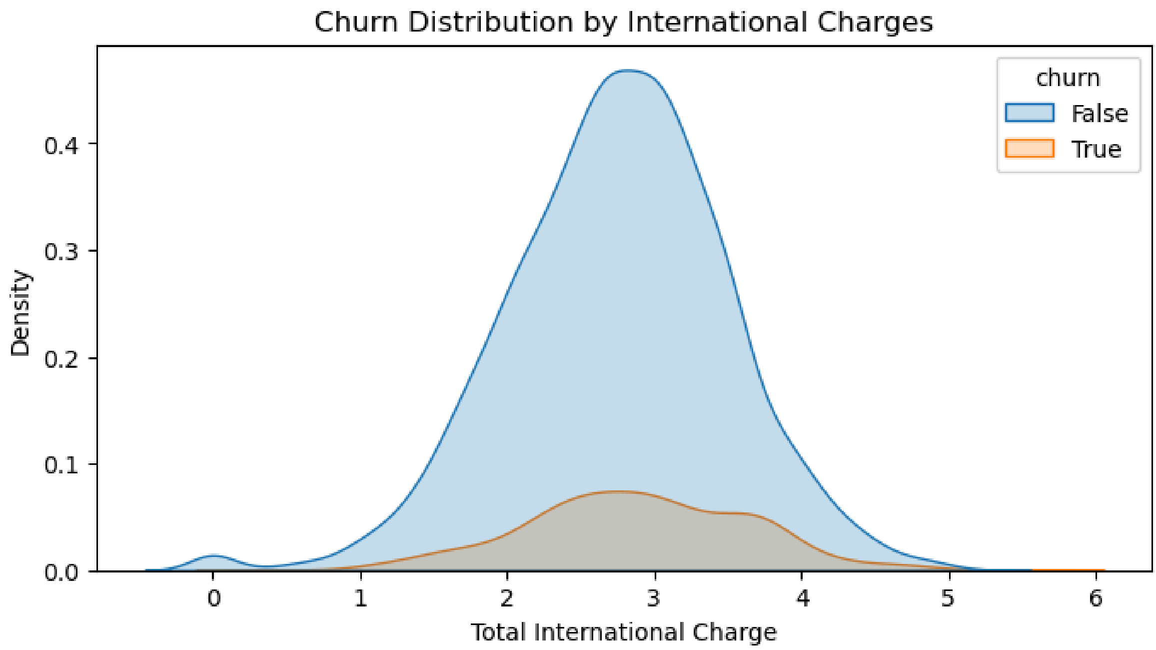
```
#Churn by night charges
plot_churn_kde(data, 'total night charge', 'Night')
```



From the analysis, customers who have terminated their accounts have higher total day changes than those who have not terminated their accounts.

In [550…

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



From the analysis, customers who have terminated their accounts have higher total day changes than those who have not terminated their accounts.

Modelling

Perform One-hot encoding on specific categorical columns in the dataframe creating a new binary colums

In [551…

```
data = pd.get_dummies(data,columns = ['state','international plan','voice mail p
data.head()
```

Out[551…

	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
0	128	25	265.1	110	45.07	197.4	99	16.78	244.7	91
1	107	26	161.6	123	27.47	195.5	103	16.62	254.4	103
2	137	0	243.4	114	41.38	121.2	110	10.30	162.6	104
3	84	0	299.4	71	50.90	61.9	88	5.26	196.9	89
4	75	0	166.7	113	28.34	148.3	122	12.61	186.9	121

5 rows × 71 columns

> In this phase, we will build a model that can predict the customer churn based on the features in our dataset. The model will be evaluated on the recall score. Specifically, if it achieves an recall score of 80% or higher, it will be considered a success.

In [552…
```
#Defining X and y
X = data.drop("churn", axis=1)
y = data["churn"]
```

Train test split

Splitting data into train and test sets using a test size of 0.5

In [553…
```
#splitting the data in to train and test sets
X_train,X_test,y_train,y_test = train_test_split(X,y, test_size=0.5, random_stat
```

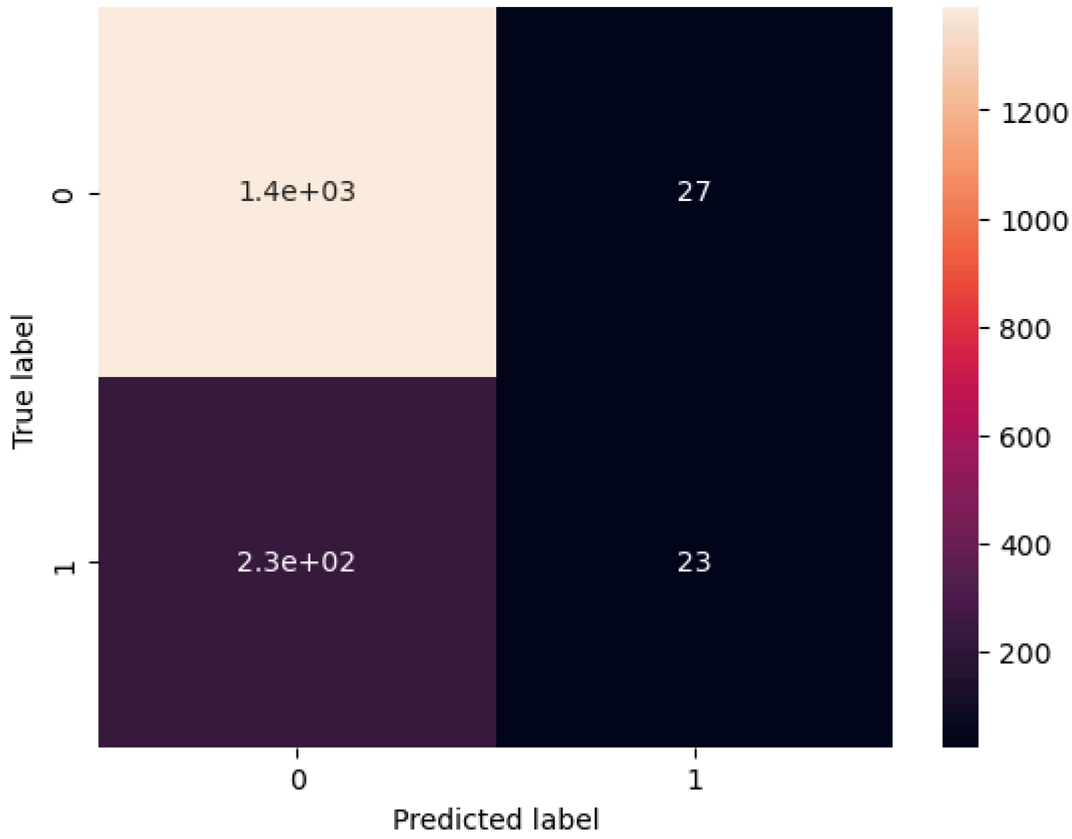
In [554…
```
#instantiate the Logistic regression
model = LogisticRegression(random_state=42)
```

In [555…
```
# Fit the model on the training data
model.fit(X_train,y_train)
#predict on the labels of test set
y_pred = model.predict(X_test)
```

```
c:\Users\karay\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:469:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

In [556…
```
def plot_confusion_matrix(y_true, y_pred):
    cfn = confusion_matrix(y_true=y_test,y_pred=y_pred)
    plt.figure()
    sns.heatmap(cfn,annot=True)
    plt.xlabel('Predicted label')
    plt.ylabel('True label')
    plt.show()
```

In [557…
```
plot_confusion_matrix(y_test, y_pred)
```



In [558…

```
cfn = confusion_matrix(y_true=y_test,y_pred=y_pred)
cfn
```

Out[558…

```
array([[1390,   27],
       [ 227,   23]], dtype=int64)
```

In [559…

```
TP = cfn[1][1]
TN = cfn[0][0]
FP = cfn[0][1]
FN = cfn[1][0]
```

In [560…

```
# manualy calculate accuracy
acc = (TP+TN)/(TP+TN+FP+FN)
acc
```

Out[560…

```
0.847630473905219
```

This model has a 85% accuracy which shows that the model impressive

In [561…

```
report = classification_report(y_true=y_test,y_pred=y_pred)

print(report)
```

```
              precision    recall  f1-score   support

       False       0.86      0.98      0.92      1417
        True       0.46      0.09      0.15       250

    accuracy                           0.85      1667
   macro avg       0.66      0.54      0.53      1667
weighted avg       0.80      0.85      0.80      1667
```

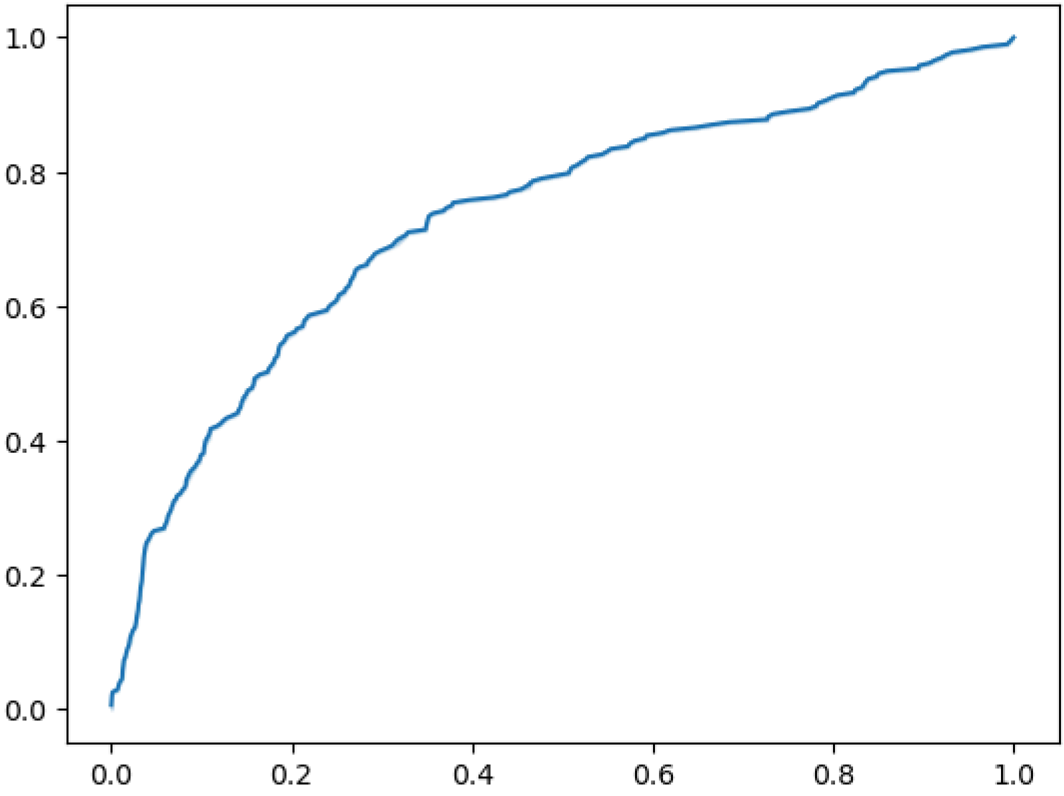
This model has a good score on precision,recall and f1 which is very good for a model. The confusion matrix evaluation showed that the model had a higher number of true positives and true negatives than false positives and false negatives. This indicates that the model is making correct predictions more often than incorrect ones and is not overfitting.

In [562…

```
fpr1,tpr1,_ = roc_curve(y_true=y_test,y_score=model.decision_function(X_test))
sns.lineplot(x=fpr1,y=tpr1)
```

Out[562…

```
<Axes: >
```



In [563…

```
area = auc(fpr1,tpr1)
area
```

Out[563…

```
0.7323528581510232
```

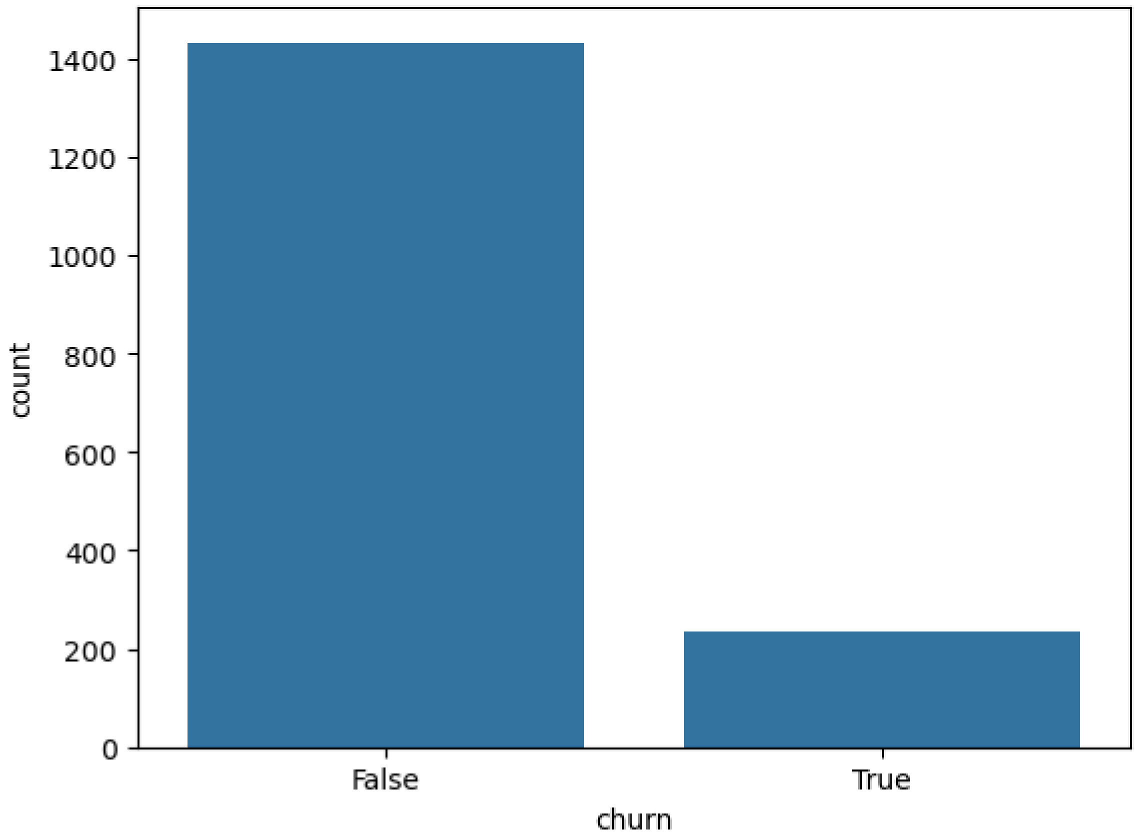
his model was able to identify about 73% of the churned customers.

In [564…

```
y_train.value_counts()
sns.countplot(x=y_train)
```

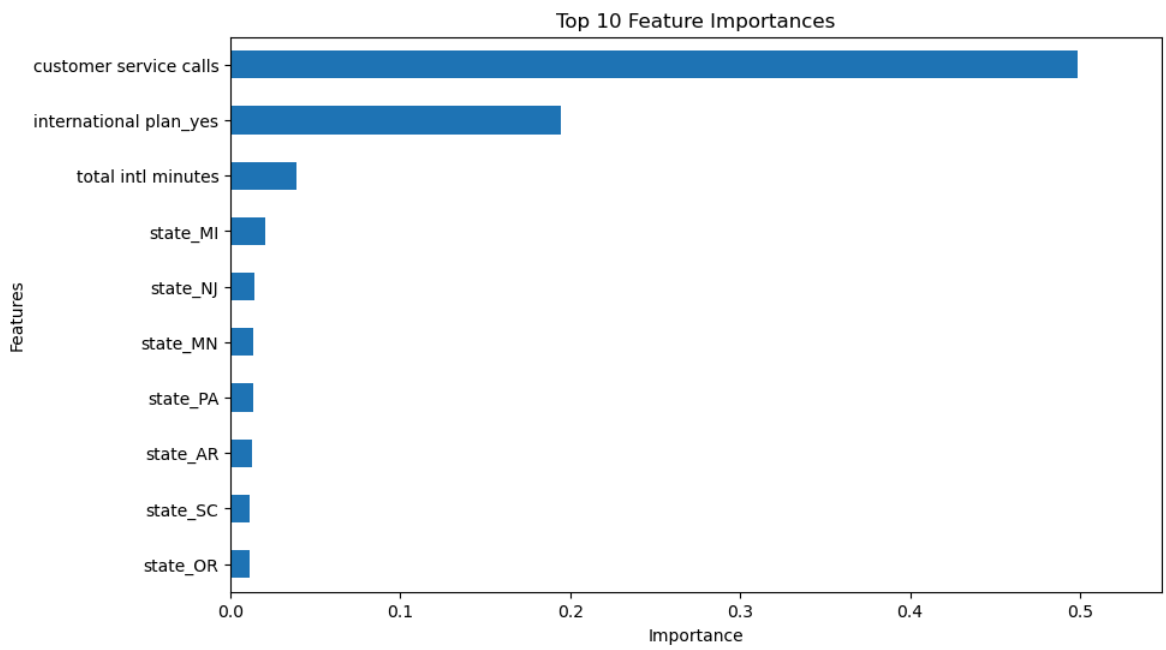
Out[564…

```
<Axes: xlabel='churn', ylabel='count'>
```



In [569…

```
# Feature Importances
importance = logreg.coef_[0]
feature_names = X_train.columns
feature_importances = pd.Series(importance,index=feature_names)
feature_importances = feature_importances.sort_values(ascending=False)
plt.figure(figsize=(10, 6))
top_features = feature_importances[:10]  # Select the top 10 features
top_features.sort_values().plot(kind='barh')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.title('Top 10 Feature Importances')
plt.xlim(0, max(top_features)* 1.1)  # Set the xlim to the maximum importance va
plt.show()
```



Decision tree

In [565…
```
ohe = OneHotEncoder()

ohe.fit(X_train)
X_train_ohe = ohe.transform(X_train).toarray()

# Creating this DataFrame is not necessary its only to show the result of the oh
ohe_df = pd.DataFrame(X_train_ohe, columns=ohe.get_feature_names_out(X_train.col

ohe_df.head()
```

Out[565…

	account length_1	account length_3	account length_5	account length_6	account length_7	account length_9	account length_10	account length_11	le
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 7248 columns

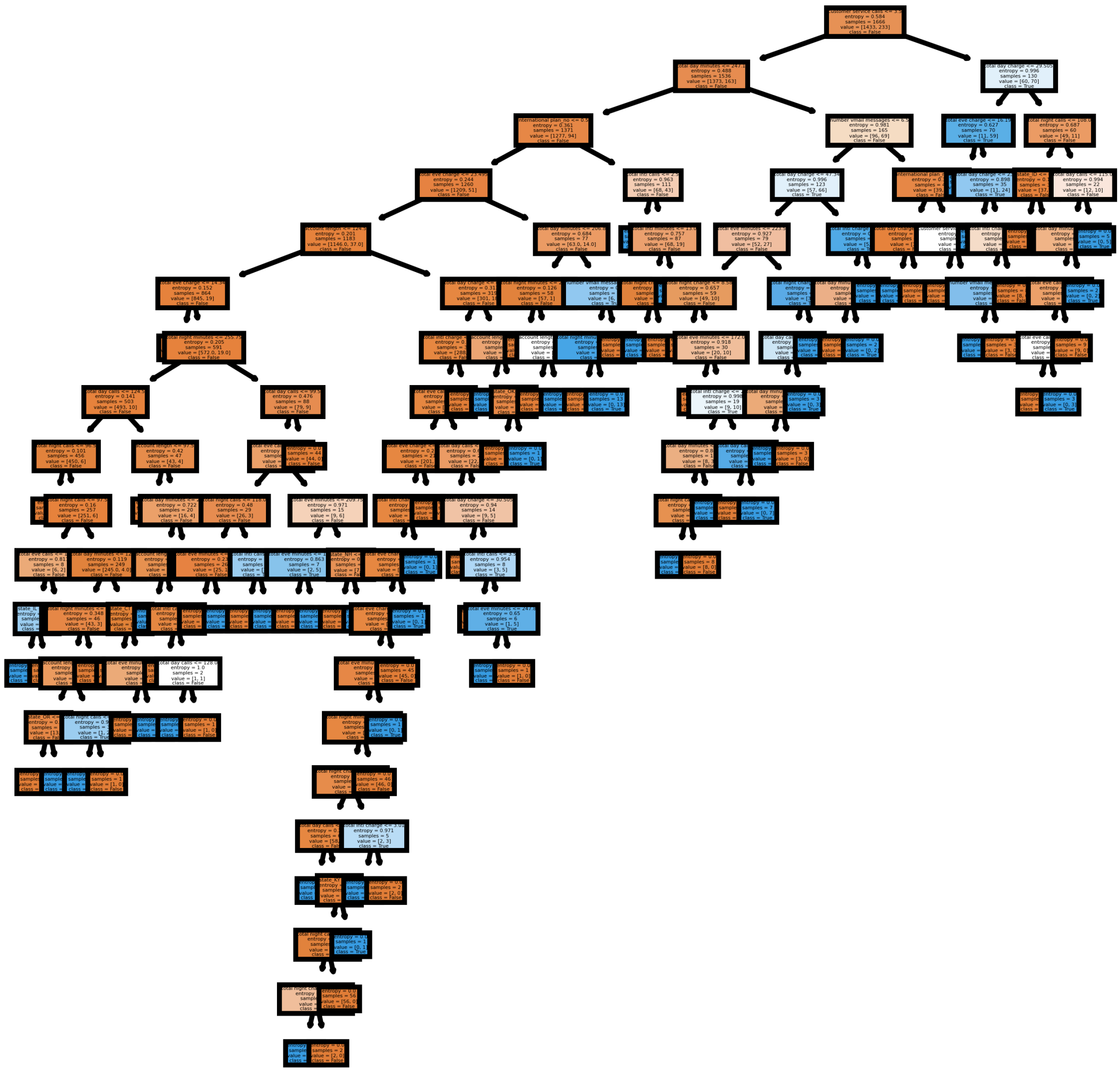
In [566…
```
#Create the classifier, fit it on the training data and make predictions on the
clf = DecisionTreeClassifier(criterion='entropy')
clf.fit(X_train,y_train)
```

Out[566…

```
DecisionTreeClassifier

DecisionTreeClassifier(criterion='entropy')
```

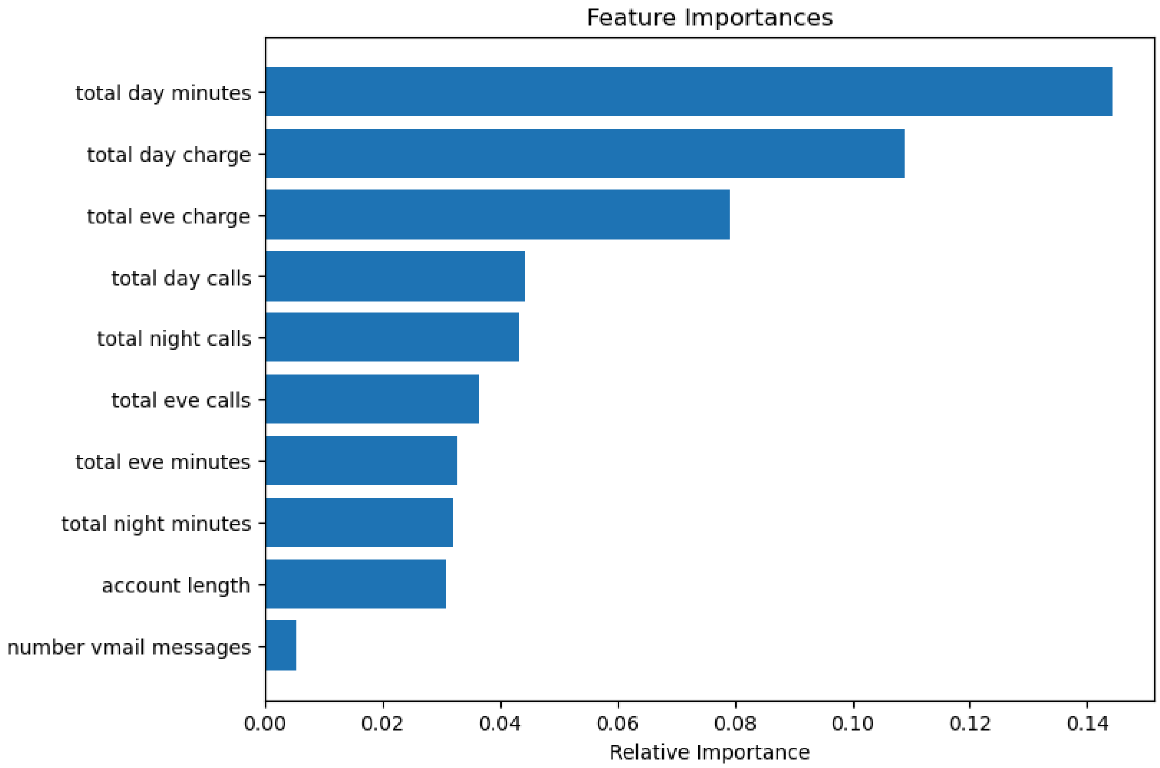
Plot the decision tree

In [567…
```
fig, axes = plt.subplots(nrows = 1,ncols = 1, figsize = (4,4), dpi=800)
tree.plot_tree(clf,
               feature_names =data.columns,
               class_names=np.unique(y).astype('str'),
               filled = True)
plt.show()
```



In [519…

```
#Feature Importances
feature_names = list(X_train.columns)
importances = clf.feature_importances_[0:10]
indices = np.argsort(importances)

plt.figure(figsize=(8,6))
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()
```



According to the model, `total day minutes` , `total day charge` , `total evening charge` are the top three most important features.

In [ ]:
```
X_test_ohe = ohe.transform(X_test)
y_preds = clf.predict(X_test_ohe)

print('Accuracy: ', accuracy_score(y_test, y_preds))
```

```
Accuracy:  0.6
```