1 1 BUSINESS UNDERSTANDING

1.1 1.1 Project overview

This project aim to build a model that will predict whether a customer is likely to leave SyriaTel soon

1.2 1.2 Business problem

SyriaTel, a telecommunication firm, is facing a significant issue of customer churn that may adversely affect its revenue and future. The firm should identify the customers who are likely to discontinue using their services and the reasons why they decide to do so. Through this learning, SyriaTel can implement measures to resolve customer problems and prevent them from leaving.

1.3 1.3 Project objectives

1.3.1 1.3.1 Main objective

This project forecasts SyriaTel customer churn by identifying those most likely to stop usage and determines the most significant drivers of churn. This will enable SyriaTel to take proactive measures to retain customers and prevent revenue loss.

1.3.2 1.3.2 Specific objectives

1. To identify customer behavour by analyzing day,night calls and their correlation to churn.
2. Analyze customer behavior, usage patterns, and service interactions to determine the main factors influencing churn.
3. To identify how the number of customer service interactions relates to the possibility of customer churn for your business.
4. Provide actionable insights that help SyriaTel implement targeted retention efforts, such as personalized offers or improved customer service.

2 2 DATA UNDERSTANDING

In [1469]:

```
#importing libraries

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

from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,confusion_matrix,classifi
from sklearn.model_selection import train_test_split

from imblearn.over_sampling import SMOTE

from sklearn import tree
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix, classi

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

In [1470]:

```
#load the csv datast
df = pd.read_csv("bigml.csv")
df
```

Out[1470]:

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

3333 rows × 21 columns

In [1471]:

```
#check the top 5 rows
df.head()
```

Out[1471]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	tota da charg
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.0
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.4
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.3
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.9
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.3

5 rows × 21 columns

In [1472]:

```
# check the bottom 5 rows
df.tail()
```

Out[1472]:

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

5 rows × 21 columns

In [1473]:

```
#check the shape
print(f"The dataset has records {df.shape[0]} and {df.shape[1]} vari
```

```
The dataset has records 3333 and 21 variables
```

In [1474]:
```
#check the dat type
df.dtypes
```

Out[1474]:
```
state                      object
account length              int64
area code                   int64
phone number               object
international plan         object
voice mail plan            object
number vmail messages       int64
total day minutes         float64
total day calls             int64
total day charge          float64
total eve minutes         float64
total eve calls             int64
total eve charge          float64
total night minutes       float64
total night calls           int64
total night charge        float64
total intl minutes        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
churn                        bool
dtype: object
```

In [1475]:
```
#check data type
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 [1476]:

```
#check column name
df.columns
```

Out[1476]:

```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', 'number vmail message
s',
       '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 charg
e',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn'],
      dtype='object')
```

In [1477]:

```
#checking for the statistical information
df.describe()
```

Out[1477]:

	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
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 [1478]:
```
#checking for the statistical information with transpose
df.describe().T
```

Out[1478]:

	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 calls	3333.0	1.562856	1.315491	0.00	1.00	1.00	2.00	9.00

3 3 DATA PREPARATION

3.1 3.0 Data cleaning

In [1479]:
```
#missing value
df.isna().sum()
```

Out[1479]:
```
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 [1480]:
```
#duplicate
df.duplicated().sum()
```

Out[1480]:
```
0
```

Observation: No duplicates.

In [1481]:
```
##Checking for unique values in the categorical values
df.groupby("churn")["churn"].count()
```

Out[1481]:
```
churn
False    2850
True      483
Name: churn, dtype: int64
```

In [1482]:
```
##Checking for unique values in the categorical values
df.groupby("international plan")["international plan"].count()
```

Out[1482]:
```
international plan
no     3010
yes     323
Name: international plan, dtype: int64
```

In [1483]:
```
##Checking for unique values in the categorical values
df.groupby("voice mail plan")["voice mail plan"].count()
```

Out[1483]:
```
voice mail plan
no     2411
yes     922
Name: voice mail plan, dtype: int64
```

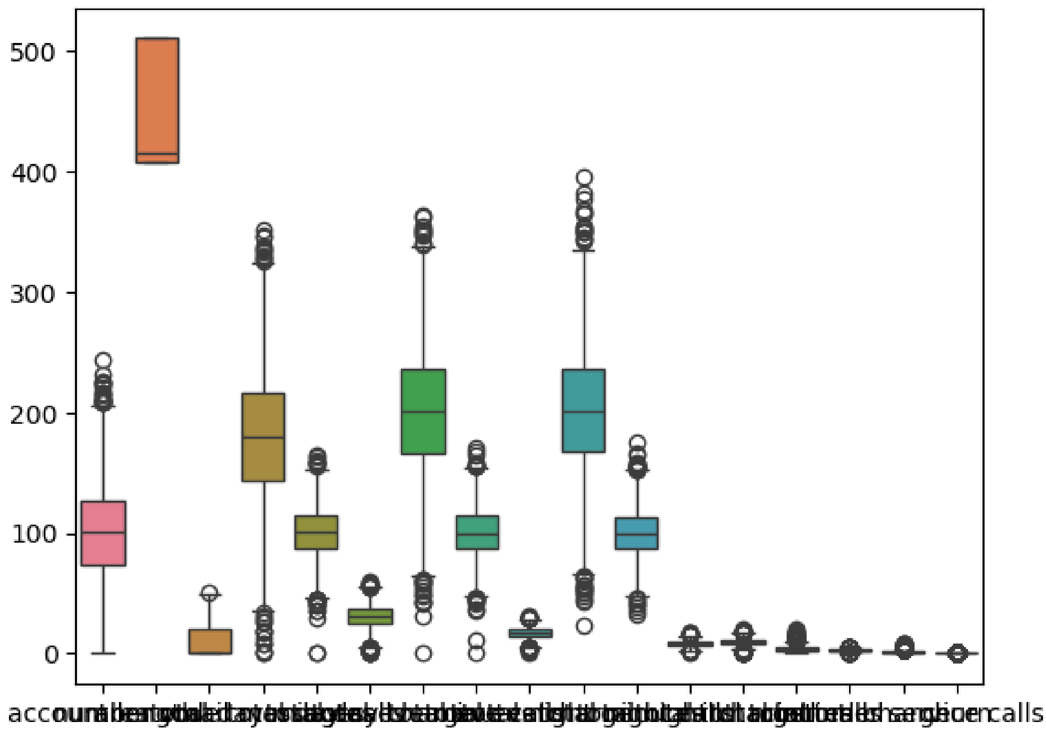
In [1484]:
```
##Drop unnecessary column
del df["phone number"]
```

In [1485]:
```
##confirm if the phone number has been removed
df.head()
```

Out[1485]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	tot ev minute
0	KS	128	415	no	yes	25	265.1	110	45.07	197
1	OH	107	415	no	yes	26	161.6	123	27.47	195
2	NJ	137	415	no	no	0	243.4	114	41.38	121
3	OH	84	408	yes	no	0	299.4	71	50.90	61
4	OK	75	415	yes	no	0	166.7	113	28.34	148

In [1486]:
```
#checking the outlier
sns.boxplot(df)
plt.show()
```



In [1487]:

```
##identify numerical columns except area code
numericals_cols = df.select_dtypes(include=['number']).columns.drop(
numericals_cols
```

Out[1487]:

```
Index(['account length', 'number vmail messages', 'total day minute
s',
       '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 minute
s',
       'total intl calls', 'total intl charge', 'customer service cal
ls'],
      dtype='object')
```

In [1488]:

```
# Caclculating upper Q3 (75th percentile) and Lower Q1 (25th percent
Q1 = df[numericals_cols].quantile(0.25)
Q3 = df[numericals_cols].quantile(0.75)
# Calculating interquatile range
IQR = Q3 - Q1
# Define the lower and upper bounds for outlier removal
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
# Remove outliers (keeping "area code" unchanged)
df_cleaned = df[~((df[numericals_cols] < lower_bound) | (df[numerica
```

In [1489]:

```
# Save the cleaned dataset
df_cleaned.to_csv("Ashley_cleaned_bigml.csv", index=False)
df_cleaned.head()
```

Out[1489]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	tot ev minute
0	KS	128	415	no	yes	25	265.1	110	45.07	197
1	OH	107	415	no	yes	26	161.6	123	27.47	195
2	NJ	137	415	no	no	0	243.4	114	41.38	121
4	OK	75	415	yes	no	0	166.7	113	28.34	148
5	AL	118	510	yes	no	0	223.4	98	37.98	220

4 4 EDA

1. Univariate analysis
2. Bivarite analysis
3. Multivariate analysis

In [1490]:

```
##Loading the clean dataset
df2=pd.read_csv("Ashley_cleaned_bigml.csv")
df2
```

Out[1490]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	mi
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	OK	75	415	yes	no	0	166.7	113	28.34	
4	AL	118	510	yes	no	0	223.4	98	37.98	
...	...	...	...	...	...	...	...	...	...	
2799	AZ	192	415	no	yes	36	156.2	77	26.55	
2800	WV	68	415	no	no	0	231.1	57	39.29	
2801	RI	28	510	no	no	0	180.8	109	30.74	
2802	CT	184	510	yes	no	0	213.8	105	36.35	
2803	TN	74	415	no	yes	25	234.4	113	39.85	

2804 rows × 20 columns

4.1 4.1 Univariate analysis

It is the analysis of one variable

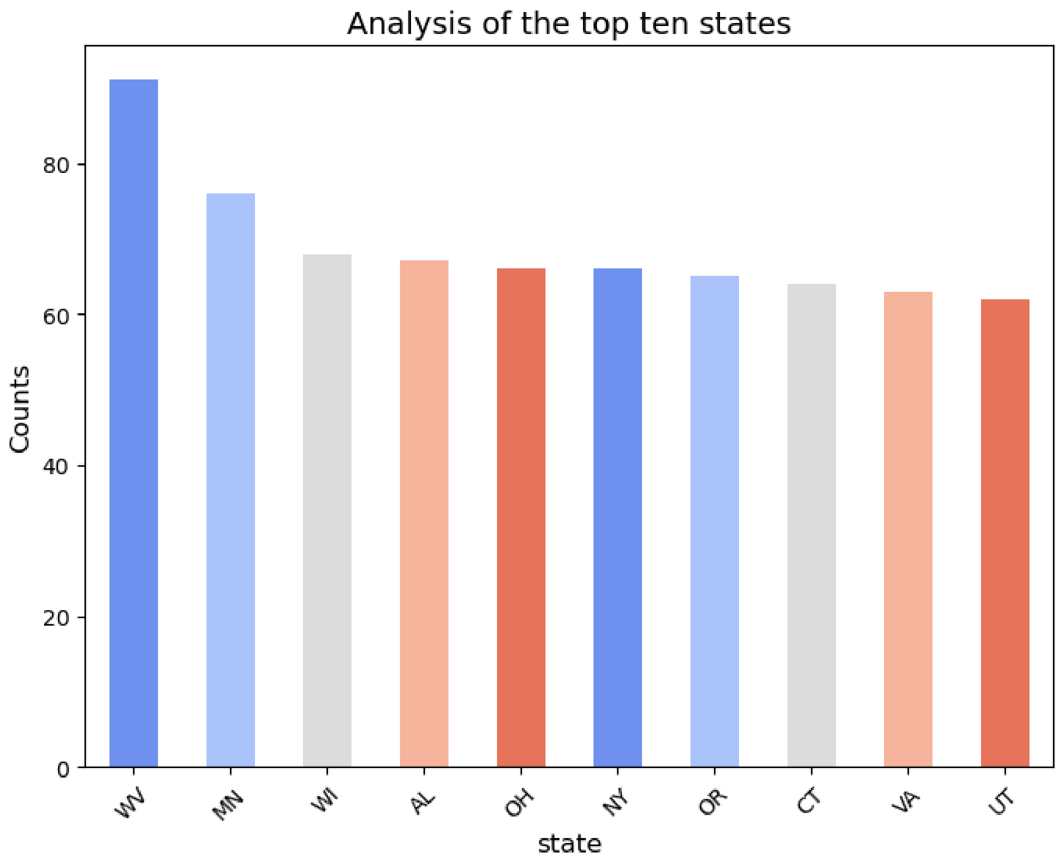
4.1.1 4.1.1 Analysis of the top ten states

In [1491]:

```
  # Increased figure size
plt.figure(figsize=(8,6))
  # Changed color palette
sns.set_palette('coolwarm')

df2["state"].value_counts().head(10).plot(kind='bar', figsize=(8,6),
  # Increased font size
plt.title("Analysis of the top ten states", fontsize=14)
plt.ylabel("Counts", fontsize=12)
plt.xlabel("state", fontsize=12)
plt.xticks(rotation=45, fontsize=10)
plt.yticks(fontsize=10)

plt.show()
```



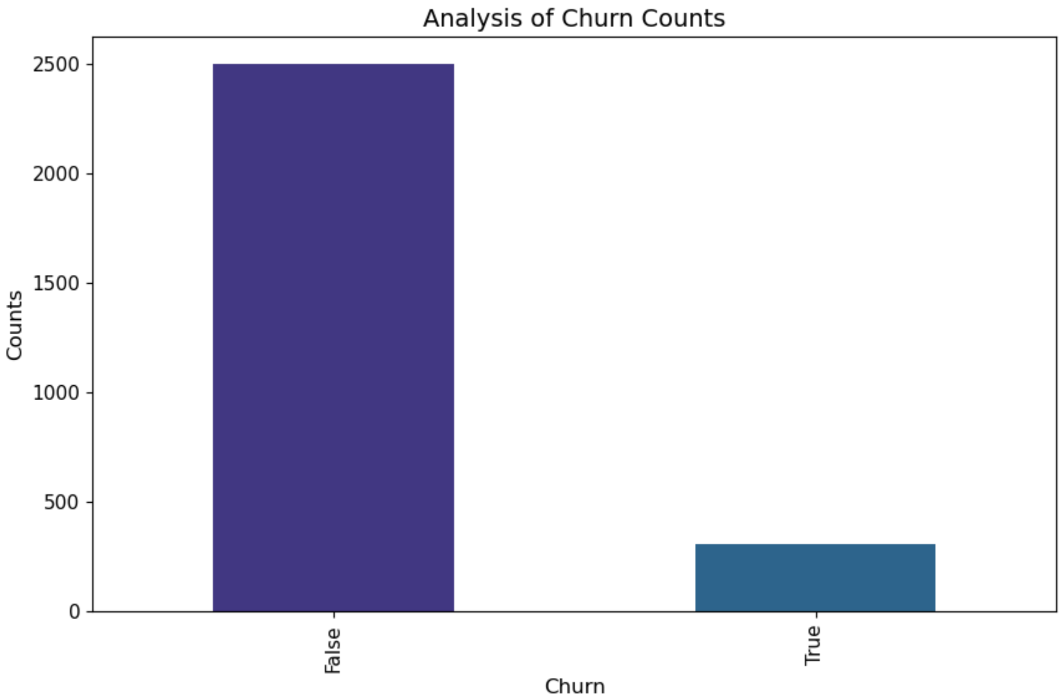
In [1492]:

```
 # Slightly larger figure size
plt.figure(figsize=(10,6))
  # Changed color palette
sns.set_palette('pastel')

df2["churn"].value_counts().plot(kind='bar', figsize=(10,6), color=s

 # Adjusted title style
plt.title("Analysis of Churn Counts", fontsize=14)  # Adjusted title
plt.ylabel("Counts", fontsize=12)
plt.xlabel("Churn", fontsize=12)
plt.xticks(fontsize=11)
plt.yticks(fontsize=11)

plt.show()
```

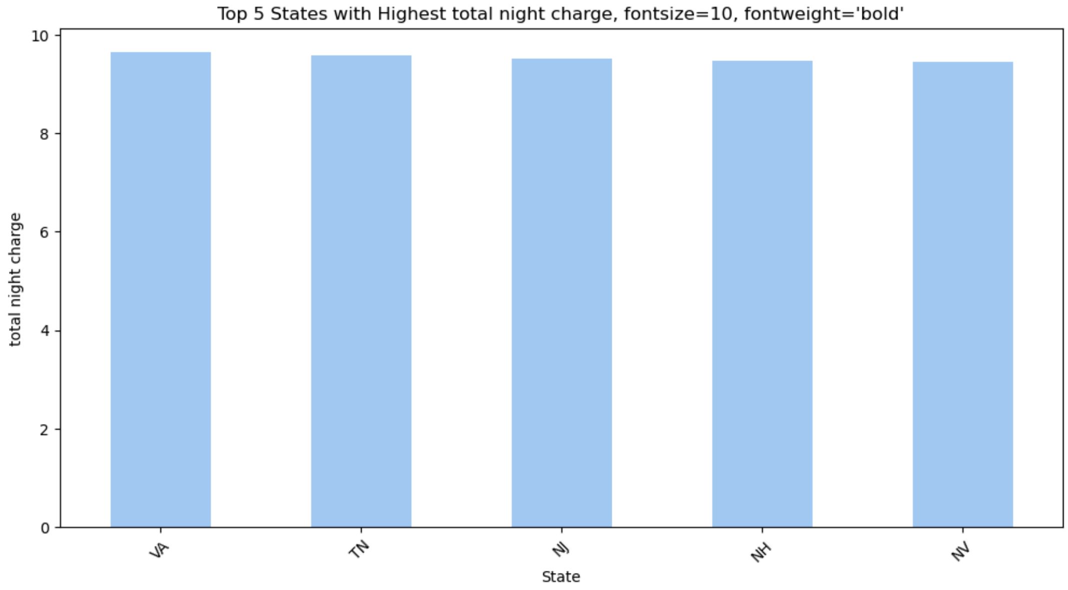


4.2 4.2 Bivariate analysis

Its the analysis of two variables.

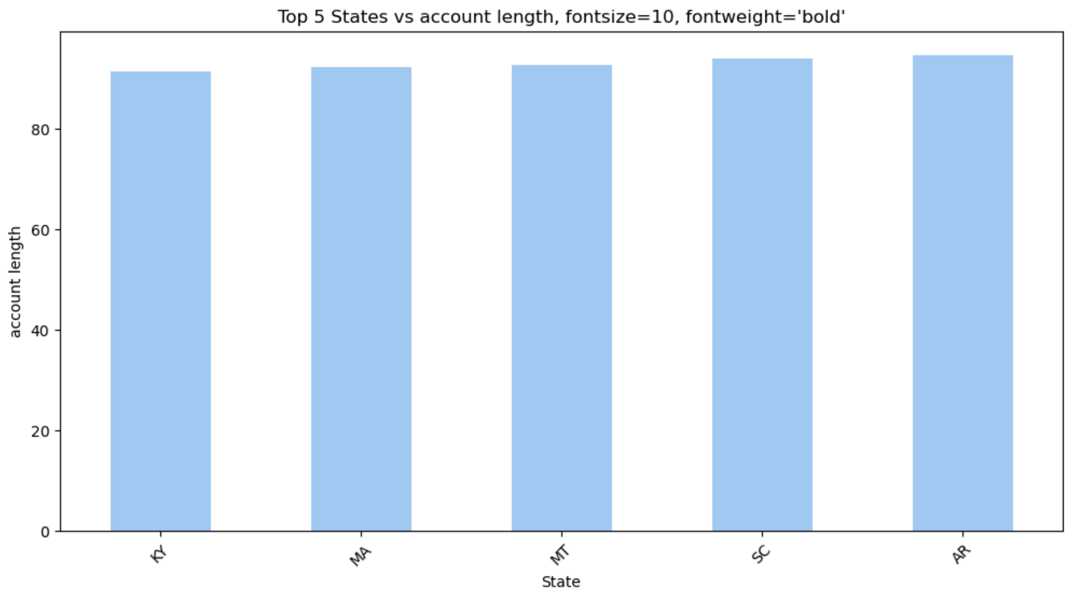
4.2.1 4.2.1 Analysis between state vs total night charge

In [1493]:
```
plt.figure(figsize=(12, 6))
df2.groupby("state")["total night charge"].mean().sort_values(ascend
plt.title("Top 5 States with Highest total night charge, fontsize=10
plt.ylabel("total night charge")
plt.xlabel("State")
plt.xticks(rotation=45)
plt.show()
```



4.2.2 4.2.2 States vs Account Length

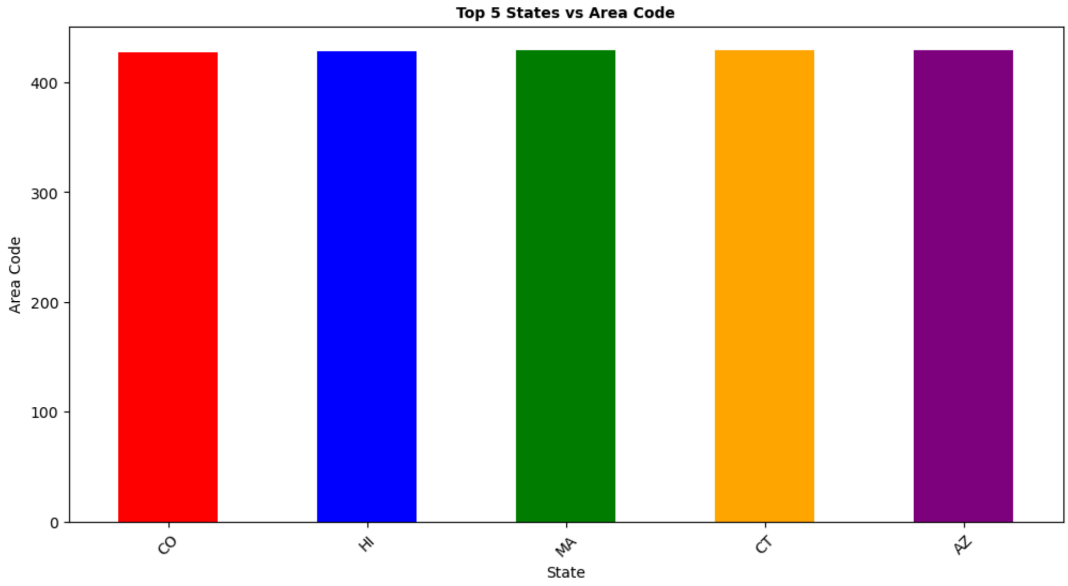
In [1494]:
```
plt.figure(figsize=(12, 6))
df2.groupby("state")["account length"].mean().sort_values(ascending=
plt.title("Top 5 States vs account length, fontsize=10, fontweight='
plt.ylabel("account length")
plt.xlabel("State")
plt.xticks(rotation=45)
plt.show()
```



4.2.3 4.2.3 State vs Area Code

In [1495]:

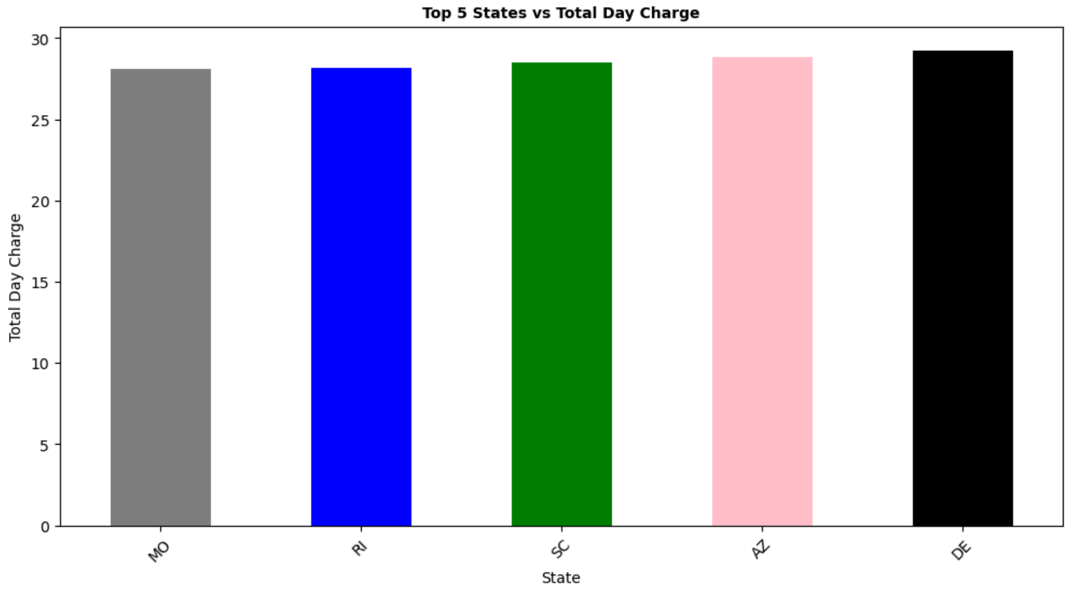
```
plt.figure(figsize=(12, 6))
colors = ['red', 'blue', 'green', 'orange', 'purple']
df2.groupby("state")["area code"].mean().sort_values(ascending=True)
plt.title("Top 5 States vs Area Code", fontsize=10, fontweight='bold
plt.ylabel("Area Code")
plt.xlabel("State")
plt.xticks(rotation=45)
plt.show()
```



4.2.4 4.2.4 State vs Total day charge

In [1496]:

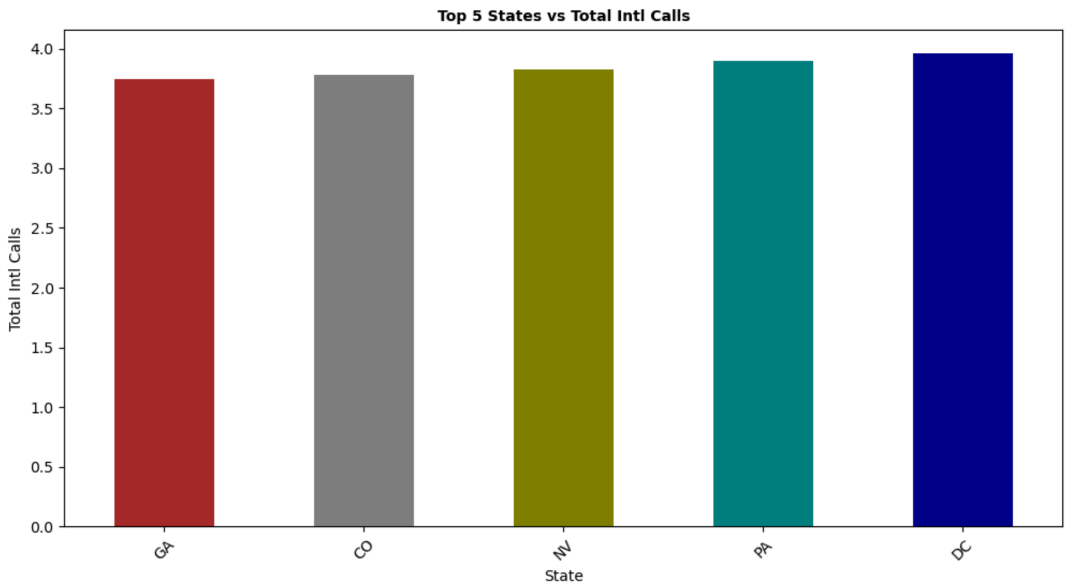
```
plt.figure(figsize=(12, 6))
colors = ['grey', 'blue', 'green', 'pink', 'black']
df2.groupby("state")["total day charge"].mean().sort_values(ascendin
plt.title("Top 5 States vs Total Day Charge", fontsize=10, fontweigh
plt.ylabel("Total Day Charge")
plt.xlabel("State")
plt.xticks(rotation=45)
plt.show()
```



4.2.5 4.2.5 State vs Total Intl Calls

In [1497]:

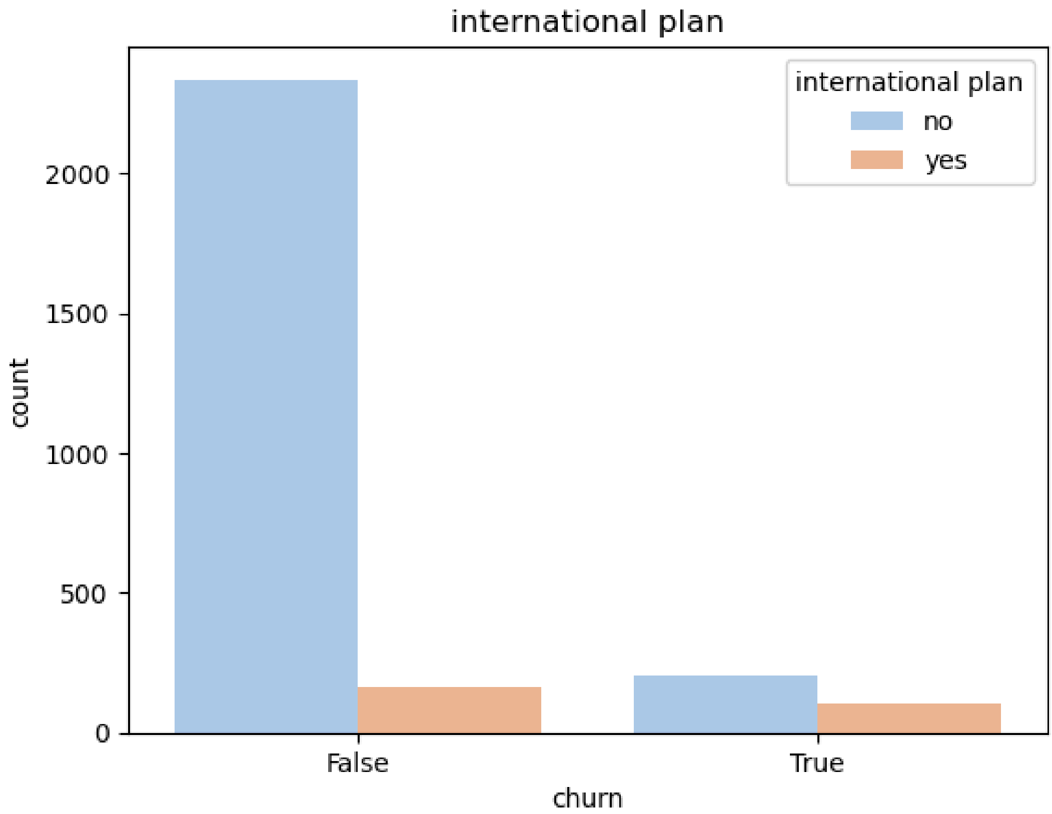
```
plt.figure(figsize=(12, 6))
colors = ['brown', 'gray', 'olive', 'teal', 'darkblue']
df2.groupby("state")["total intl calls"].mean().sort_values(ascendin
plt.title("Top 5 States vs Total Intl Calls", fontsize=10, fontweigh
plt.ylabel("Total Intl Calls")
plt.xlabel("State")
plt.xticks(rotation=45)
plt.show()
```



4.2.6 4.2.6 Churn vs International Plan

In [1498]:

```
sns.countplot(x=df2["churn"],hue=df2["international plan"], palette=
plt.title("international plan")
plt.show()
cort=pd.crosstab(df2["churn"],df2["international plan"])
cort
```

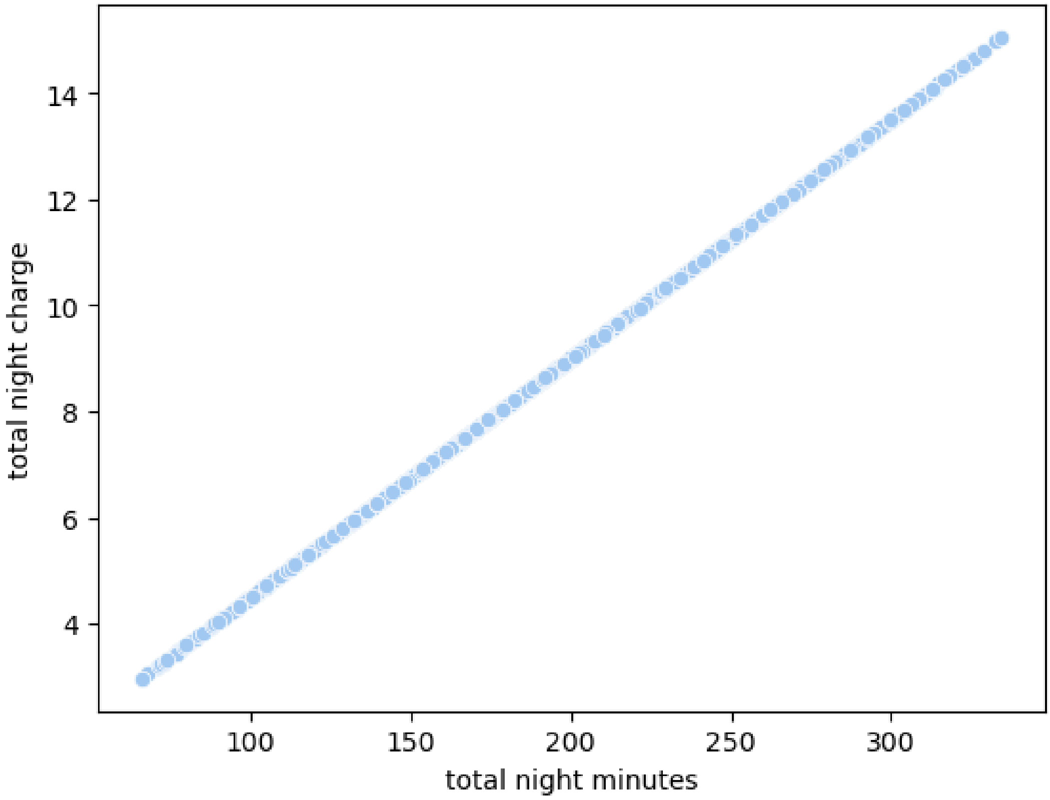


Out[1498]:

international plan	no	yes
churn		
False	2335	164
True	201	104

4.2.7 4.2.7 Analysis of the total night minutes vs total night charge

In [1499]:
```
sns.scatterplot(data=df2, x='total night minutes', y='total night ch
```

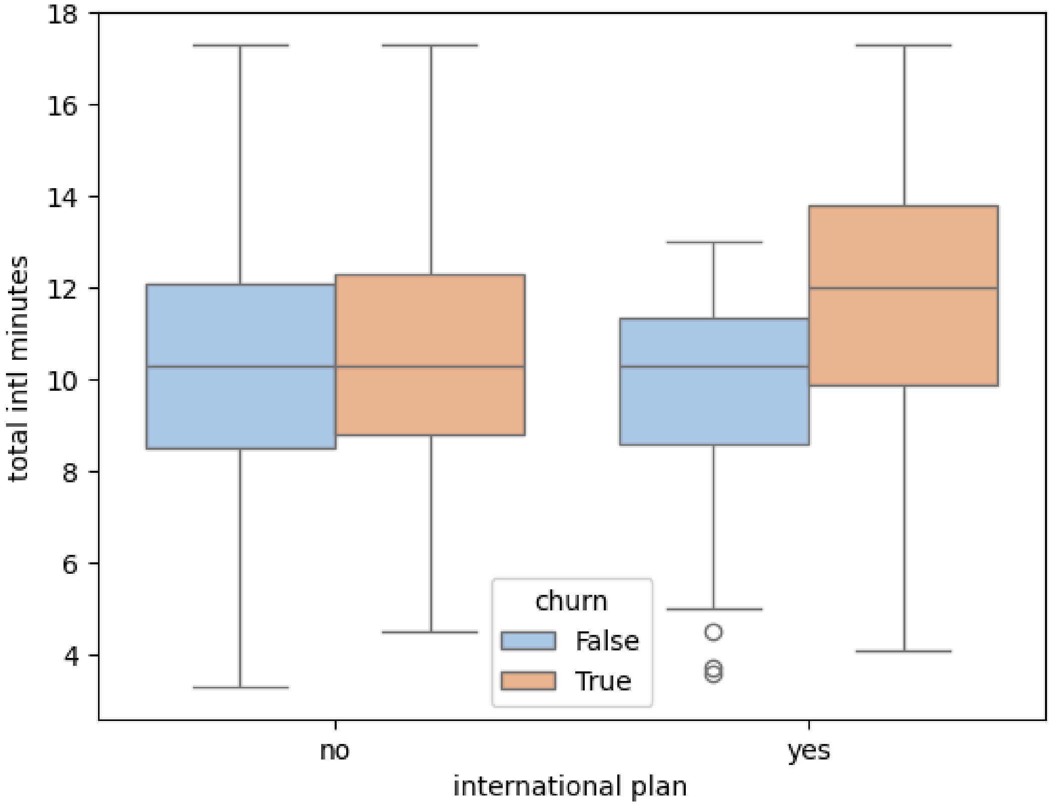


4.3 4.3 Multivariate analysis

It is the analysis of more than two variables

4.3.1 4.3.1 Analysis of the international plan,'total intl minutes and churn

In [1500]:
```
sns.boxplot(data=df2, x='international plan', y='total intl minutes'
plt.legend
plt.show()
```



4.4 5. MODELING

Models that will be used are

1. Logistic regression
2. Decision tree

4.4.1 5.1 LOGISTIC REGRESSION

4.4.1.1 with imbalanced class

In [1501]:

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

from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,confusion_matrix,classifi
from sklearn.model_selection import train_test_split
```

In [1502]:

```
#load the dataset
df3=pd.read_csv("Ashley_cleaned_bigml.csv")
df3
```

Out[1502]:

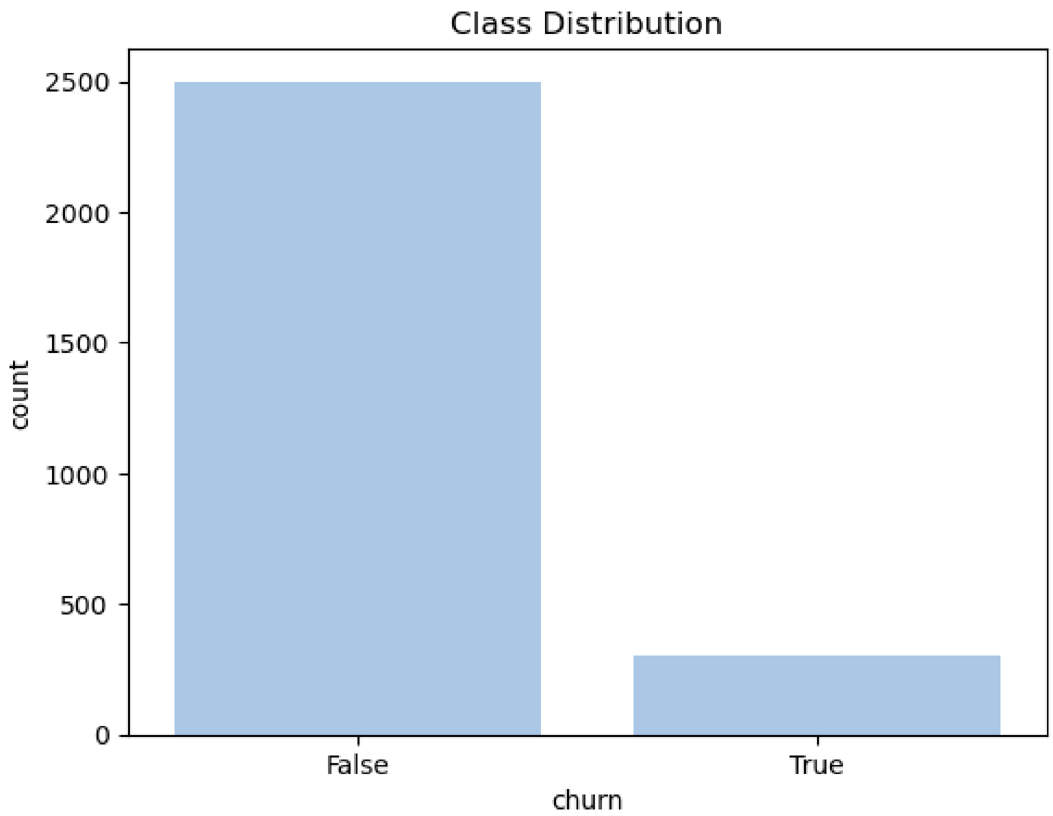
	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	mi
0	KS	128	415	no	yes	25	265.1	110	45.07	
1	OH	107	415	no	yes	26	161.6	123	27.47	
2	NJ	137	415	no	no	0	243.4	114	41.38	
3	OK	75	415	yes	no	0	166.7	113	28.34	
4	AL	118	510	yes	no	0	223.4	98	37.98	
...	...	...	...	...	...	...	...	...	...	
2799	AZ	192	415	no	yes	36	156.2	77	26.55	
2800	WV	68	415	no	no	0	231.1	57	39.29	
2801	RI	28	510	no	no	0	180.8	109	30.74	
2802	CT	184	510	yes	no	0	213.8	105	36.35	
2803	TN	74	415	no	yes	25	234.4	113	39.85	

2804 rows × 20 columns

In [1503]:
```
#Display class distribution
print(df3['churn'].value_counts())

# Plot class distribution
sns.countplot(x='churn', data=df3)
plt.title('Class Distribution')
plt.show()
```

```
churn
False    2499
True      305
Name: count, dtype: int64
```



4.4.1.2 5.1.1 Preprocessing

It is the changing of categorical variable to numerical variable

In [1504]:
```
df3 = pd.read_csv("Ashley_cleaned_bigml.csv", dtype={"international
df3
```

Out[1504]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	mi
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	OK	75	415	yes	no	0	166.7	113	28.34	
4	AL	118	510	yes	no	0	223.4	98	37.98	
...	...	...	...	...	...	...	...	...	...	
2799	AZ	192	415	no	yes	36	156.2	77	26.55	
2800	WV	68	415	no	no	0	231.1	57	39.29	
2801	RI	28	510	no	no	0	180.8	109	30.74	
2802	CT	184	510	yes	no	0	213.8	105	36.35	
2803	TN	74	415	no	yes	25	234.4	113	39.85	

2804 rows × 20 columns

In [1505]:
```
#Drop state because it has too many categorical variables
df3.drop(columns=['state'], inplace=True)
```

In [1506]:
```
#confirm if state has been removed
df3.head()
```

Out[1506]:

	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	tot ev call
0	128	415	no	yes	25	265.1	110	45.07	197.4	9
1	107	415	no	yes	26	161.6	123	27.47	195.5	10
2	137	415	no	no	0	243.4	114	41.38	121.2	11
3	75	415	yes	no	0	166.7	113	28.34	148.3	12
4	118	510	yes	no	0	223.4	98	37.98	220.6	10

In [1507]:
```
#converting categorical variables to numbers
df3['international plan'] = df3['international plan'].map({'no': 1,
df3['voice mail plan'] = df3['voice mail plan'].map({'no': 1, 'yes':
# Convert False/True to 1/2
df3['churn'] = df3['churn'].astype(int)
```

In [1508]:
```
#confirming if they have changed to numeric
df3.head()
```

Out[1508]:

	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	tot ev cal
0	128	415	1	2	25	265.1	110	45.07	197.4	9
1	107	415	1	2	26	161.6	123	27.47	195.5	10
2	137	415	1	1	0	243.4	114	41.38	121.2	11
3	75	415	2	1	0	166.7	113	28.34	148.3	12
4	118	510	2	1	0	223.4	98	37.98	220.6	10

4.4.1.3 5.1.2 Splitting data into target and predictors

In [1509]:
```
x=df3.drop("churn",axis=1)
y=df3["churn"]
```

In [1510]:
```
#confirming if churn has been removed
x
```

Out[1510]:

	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes
0	128	415	1	2	25	265.1	110	45.07	197.4
1	107	415	1	2	26	161.6	123	27.47	195.5
2	137	415	1	1	0	243.4	114	41.38	121.2
3	75	415	2	1	0	166.7	113	28.34	148.3
4	118	510	2	1	0	223.4	98	37.98	220.6
...	...	...	...	...	...	...	...	...	...
2799	192	415	1	2	36	156.2	77	26.55	215.5
2800	68	415	1	1	0	231.1	57	39.29	153.4
2801	28	510	1	1	0	180.8	109	30.74	288.8
2802	184	510	2	1	0	213.8	105	36.35	159.6
2803	74	415	1	2	25	234.4	113	39.85	265.9

2804 rows × 18 columns

4.4.1.4 5.1.3 split the data into train,test and split

In [1511]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,ran
```

4.4.1.5 5.1.4 Scalling

In [1512]:
```
##We scale only the features not target
sc = StandardScaler()
x_train_sc = sc.fit_transform(x_train)
x_test_sc = sc.transform(x_test)
```

4.4.1.6 5.1.5 Build the model

In [1513]:
```
model = LogisticRegression()
model.fit (x_train_sc,y_train)
```

Out[1513]:
```
LogisticRegression()
```

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

4.4.1.7 5.1.6 Predict Y

In [1514]:
```
y_predict=model.predict(x_test_sc)
y_predict
```

Out[1514]:
```
array([0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0,
0,
       0, 0, 1, 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, 0, 0, 0, 0, 0, 0,
0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
1,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 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, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
0,
       0, 1, 0, 0, 0, 0, 0, 1, 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, 0, 0, 0, 0, 0, 1,
0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
0,
       1, 0, 0, 0, 0, 1, 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, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
0,
       0, 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, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 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, 1, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
0,
       1, 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, 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, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
0,
       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, 0, 0, 0, 0, 1, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [1515]:
```
##the original
y
```

Out[1515]:
```
0       0
1       0
2       0
3       0
4       0
       ..
2799    0
2800    0
2801    0
2802    0
2803    0
Name: churn, Length: 2804, dtype: int32
```

4.4.1.8 5.1.7 The accuracy

In [1516]:
```
##We can check the model accuracy and round off to the nearest 4
round(accuracy_score(y_test,y_predict),4) *100
```

Out[1516]:
```
88.59
```

In [1517]:
```
confusion_matrix(y_test,y_predict)
```

Out[1517]:
```
array([[474,  14],
       [ 50,  23]], dtype=int64)
```

Dbservation;

- 474 is a true positive
- 23 is a true negative
- 14 is a false positive
- 50 is a false negative

4.4.2 5.1.8 Logistic regression(with balanced class)/SMOTE Technique

In [1518]:
```
# call SMOTE
smote = SMOTE(random_state=42)
```

In [1519]:

```
# Apply SMOTE to the training data
x_train_smote, y_train_smote = smote.fit_resample(x_train, y_train)

# Check the new class distribution
print('Class distribution after SMOTE:')
print(pd.Series(y_train_smote).value_counts())
```

```
Class distribution after SMOTE:
churn
0    2011
1    2011
Name: count, dtype: int64
```

Observation: The class is balanced

4.4.2.1 5.2.1 Build and Evaluate a Model After Addressing Imbalance

In [1520]:

```
# call the Logistic Regression model
smote_model = LogisticRegression()
```

In [1521]:

```
# Train the model on the SMOTE data
smote_model.fit(x_train_smote, y_train_smote)
```

Out[1521]:

```
LogisticRegression()
```

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

In [1522]:

```
# Make predictions
y_pred_smote = smote_model.predict(x_test)
```

In [1523]:

```
# Accuracy
accuracy_smote = accuracy_score(y_test, y_pred_smote)
print(f'SMOTE Model Accuracy: {accuracy_smote:.4f}')
```

```
SMOTE Model Accuracy: 0.6809
```

In [1524]:

```
# Classification Report
print('SMOTE Model Classification Report:')
print(classification_report(y_test, y_pred_smote))
```

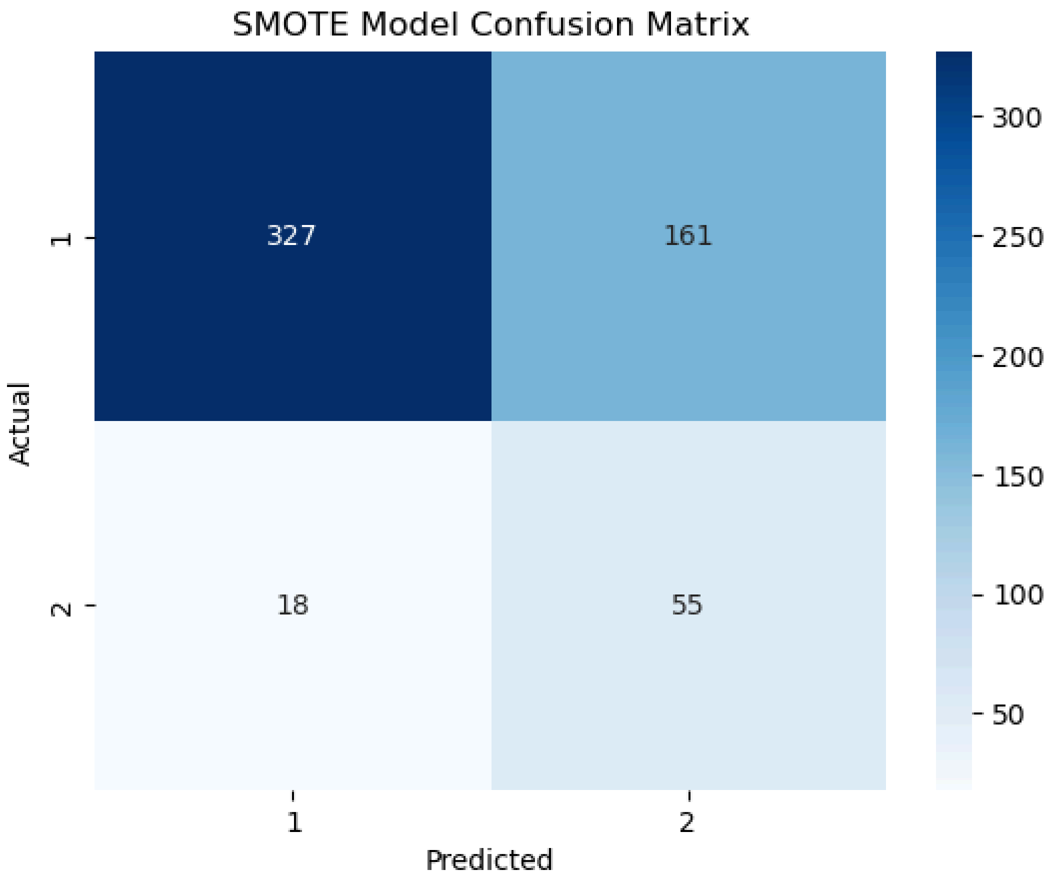
```
SMOTE Model Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.67      0.79       488
           1       0.25      0.75      0.38        73

    accuracy                           0.68       561
   macro avg       0.60      0.71      0.58       561
weighted avg       0.86      0.68      0.73       561
```

In [1525]:

```
# Confusion Matrix
cm_smote = confusion_matrix(y_test, y_pred_smote)
sns.heatmap(cm_smote, annot=True, fmt='d', cmap='Blues', xticklabels
plt.title('SMOTE Model Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



4.5 5.2 DECISION TREE

In [1526]:
```
##Loading the dataset
df4=pd.read_csv("Ashley_cleaned_bigml.csv")
df4
```

Out[1526]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	mi
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	OK	75	415	yes	no	0	166.7	113	28.34	
4	AL	118	510	yes	no	0	223.4	98	37.98	
...	...	...	...	...	...	...	...	...	...	
2799	AZ	192	415	no	yes	36	156.2	77	26.55	
2800	WV	68	415	no	no	0	231.1	57	39.29	
2801	RI	28	510	no	no	0	180.8	109	30.74	
2802	CT	184	510	yes	no	0	213.8	105	36.35	
2803	TN	74	415	no	yes	25	234.4	113	39.85	

2804 rows × 20 columns

4.5.0.1 5.2.1 Preprocessing

In [1527]:
```
df4 = pd.read_csv("Ashley_cleaned_bigml.csv", dtype={"international
df4
```

Out[1527]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	mi
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	OK	75	415	yes	no	0	166.7	113	28.34	
4	AL	118	510	yes	no	0	223.4	98	37.98	
...	...	...	...	...	...	...	...	...	...	
2799	AZ	192	415	no	yes	36	156.2	77	26.55	
2800	WV	68	415	no	no	0	231.1	57	39.29	
2801	RI	28	510	no	no	0	180.8	109	30.74	
2802	CT	184	510	yes	no	0	213.8	105	36.35	
2803	TN	74	415	no	yes	25	234.4	113	39.85	

2804 rows × 20 columns

In [1528]:
```
#Drop state because it has too many categorical variables
df4.drop(columns=['state'], inplace=True)
```

In [1529]:
```
#confirm if state has been removed
df4.head()
```

Out[1529]:

	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	tot ev call
0	128	415	no	yes	25	265.1	110	45.07	197.4	9
1	107	415	no	yes	26	161.6	123	27.47	195.5	10
2	137	415	no	no	0	243.4	114	41.38	121.2	11
3	75	415	yes	no	0	166.7	113	28.34	148.3	12
4	118	510	yes	no	0	223.4	98	37.98	220.6	10

In [1530]:
```
#converting categorical variables to numbers
df4['international plan'] = df4['international plan'].map({'no': 1,
df4['voice mail plan'] = df4['voice mail plan'].map({'no': 1, 'yes':
# Convert False/True to 1/2
df4['churn'] = df4['churn'].astype(int)
```

In [1531]:
```
#confirming if they have changed to numeric
df4.head()
```

Out[1531]:

	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	tot ev call
0	128	415	1	2	25	265.1	110	45.07	197.4	9
1	107	415	1	2	26	161.6	123	27.47	195.5	10
2	137	415	1	1	0	243.4	114	41.38	121.2	11
3	75	415	2	1	0	166.7	113	28.34	148.3	12
4	118	510	2	1	0	223.4	98	37.98	220.6	10

4.5.0.2 5.2.2 Divide target and predictor

In [1532]:
```
#divide target and predictor
x = df4.drop("churn", axis=1)
y = df4["churn"]
```

In [1533]:
```
x
```

Out[1533]:

	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes
0	128	415	1	2	25	265.1	110	45.07	197.4
1	107	415	1	2	26	161.6	123	27.47	195.5
2	137	415	1	1	0	243.4	114	41.38	121.2
3	75	415	2	1	0	166.7	113	28.34	148.3
4	118	510	2	1	0	223.4	98	37.98	220.6
...	...	...	...	...	...	...	...	...	...
2799	192	415	1	2	36	156.2	77	26.55	215.5
2800	68	415	1	1	0	231.1	57	39.29	153.4
2801	28	510	1	1	0	180.8	109	30.74	288.8
2802	184	510	2	1	0	213.8	105	36.35	159.6
2803	74	415	1	2	25	234.4	113	39.85	265.9

2804 rows × 18 columns

4.5.0.3 5.2.3 Split dataset into train and test

In [1534]:
```
#split dataset into train and test
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=.
```

4.5.0.4 5.2.4 Cheking Shape

In [1535]:
```
print(x_train.shape,x_test.shape)
print(y_train.shape, y_test.shape)
```

```
(1962, 18) (842, 18)
(1962,) (842,)
```

4.5.0.5 5.2.5 Modeling

In [1536]:
```
#modeling
model = DecisionTreeClassifier(max_depth=2, criterion='entropy')
#train
model.fit(x_train, y_train)
```

Out[1536]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=2)
```

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

4.5.0.6 5.2.6 Predict the first index

In [1537]:
```
#predict the first index
y_pred = model.predict(x_test)
y_pred[0]
```

Out[1537]:
```
0
```

In [1538]:
```
#The original value of the first index
y[0]
```

Out[1538]:
```
0
```

4.5.0.7 5.2.7 Accuracy

In [1539]:
```
#accuracy
print(f"The accuracy score is {accuracy_score(y_test, y_pred)*100}",
```

```
The accuracy score is 90.02375296912113 %
```

4.5.0.8 5.2.8 Confusion matrix

In [1540]:
```
#confusion matrix
print(confusion_matrix(y_test, y_pred))
```

```
[[723  21]
 [ 63  35]]
```

Observation:

- 708 is a true positive
- 61 is a true negative

- 37 is a false negative
- 36 is a false positive

4.5.0.9 5.2.9 Report

In [1541]:

```
#report
print(classification_report(y_test, y_pred))
```

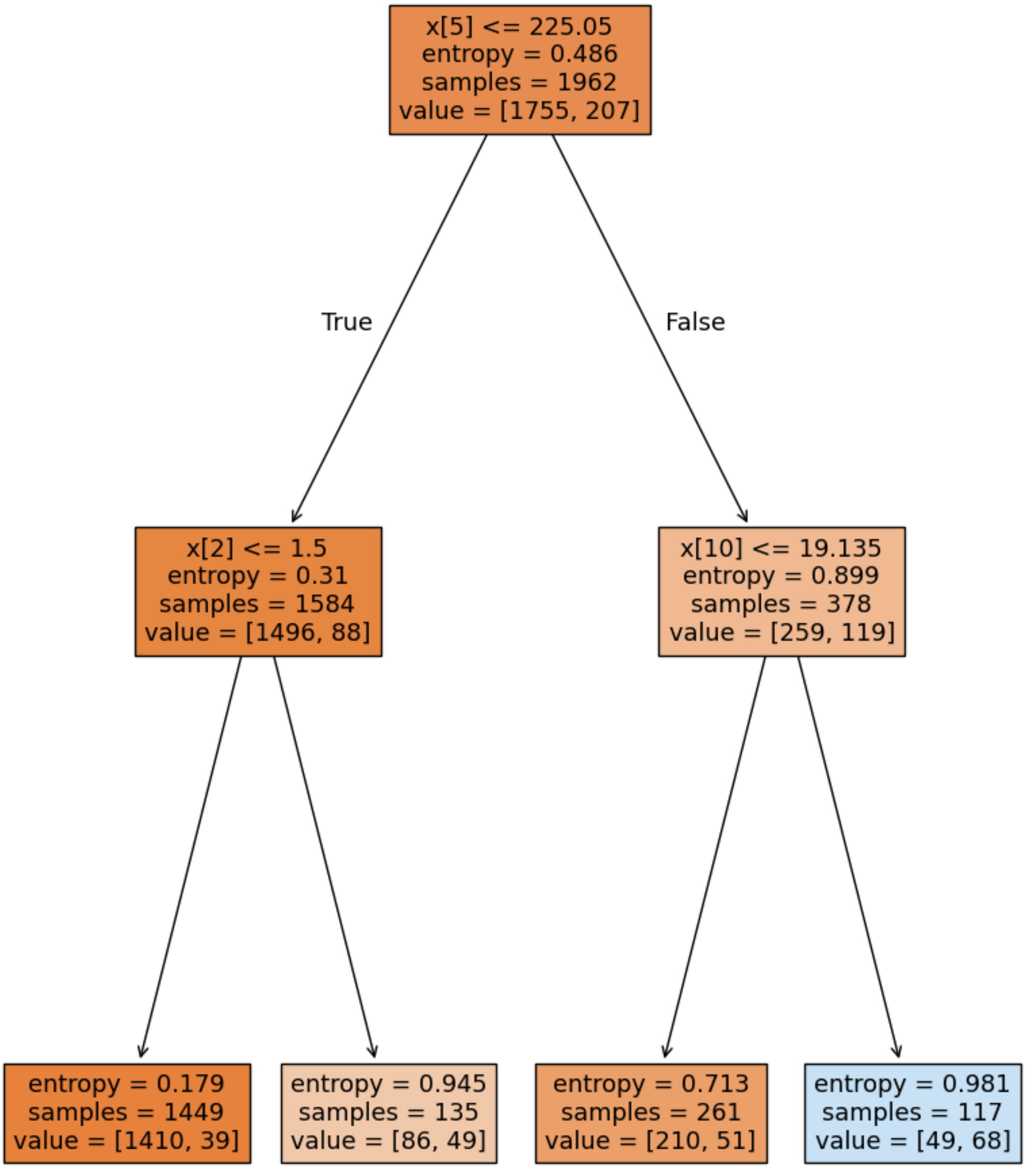
```
              precision    recall  f1-score   support

           0       0.92      0.97      0.95       744
           1       0.62      0.36      0.45        98

    accuracy                           0.90       842
   macro avg       0.77      0.66      0.70       842
weighted avg       0.89      0.90      0.89       842
```

In [1542]:

```
#visualizations
plt.figure(figsize= (10,15))
tree.plot_tree(model, filled= True)
plt.show()
```



5 6 EVALUATION

Decision tree is the best model to use because it has an accuracy of 94% compared to logistic with an accuracy of 68%