SYRIA TELECOMMUNICATIOS PROJECT

BUSINESS UNDERSTANDING

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.

Data Preparation

1. Importing libraries

In [62]:
```
#Importing libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
#libraries for statistics
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
#libraries for evaluation
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import (recall_score,
                             precision_score,
                             f1_score,
                             classification_report,
                             roc_auc_score)

from sklearn.metrics import confusion_matrix

from imblearn.over_sampling import SMOTE #SMOTE technique to deal with unbalanced da
from sklearn.metrics import accuracy_score,f1_score,recall_score,precision_score,con
from sklearn.preprocessing import MinMaxScaler # to scale the numeric features
from scipy import stats

#===== Statistic Testing =====#
from scipy import stats
from scipy.stats import f_oneway
from scipy.stats import ttest_ind
from scipy.stats import chi2_contingency

#=====Feature Selection =====#
from sklearn.feature_selection import mutual_info_classif
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif

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

2. **Importing Data**

In [63]:
```
df=pd.read_csv("bigml_59c28831336c6604c800002a.csv")
df
```

Out[63]:

	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 calls	c
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	
...	...	...	...	...	...	...	...	...	...	...	...	...	
3328	AZ	192	415	414-4276	no	yes	36	156.2	77	26.55	...	126	
3329	WV	68	415	370-3271	no	no	0	231.1	57	39.29	...	55	
3330	RI	28	510	328-8230	no	no	0	180.8	109	30.74	...	58	
3331	CT	184	510	364-6381	yes	no	0	213.8	105	36.35	...	84	
3332	TN	74	415	400-4344	no	yes	25	234.4	113	39.85	...	82	

3333 rows × 21 columns

*

3. **Data Understanding**

In [64]:
```
#creating a function for checking information on our data
# checking data info
def info_data(data):
    missing_values= data.isnull().sum()
    missing_perce= (missing_values/len(data)*100)
    data_type = data.dtypes
    num_unique = data.nunique()
    print (f'Number of Rows,Columns {data.shape}')
    print (f'Number of Duplicated Values {data.duplicated().sum()}')


    return pd.DataFrame ({'Missing_value' : missing_values,
                          'Percent_missing_%' : missing_perce,
                          'Data_type' : data_type,
                          'Number of Unique' : num_unique}).sort_values('Percent_mis
```

Checking for outliers

Type *Markdown* and LaTeX: α^2

In [65]:
```
#creating a function for checking outliers in our data
def outlier(df,column):
    q1=df[column].quantile(0.25)
    q3=df[column].quantile(0.75)
    iql=q3-q1
    lower = q1 - (1.5*iqr)
    upper = q3 + (1.5*iqr)
    outlier_list=df[column].apply(lambda x:'outlier' if x<lower or x>upper else 'not
    print (f' outlier lower limit : {lower} \n outlier upper limit : {upper}')
    return outlier_list
```

Data Inspection

In [66]:
```
#checking the top 5 rows
df.head()
```

Out[66]:

	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 calls	to e char
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.

5 rows × 21 columns

In [67]:
```
#checking information on our data
info_data(df)
```

```
Number of Rows,Columns (3333, 21)
Number of Duplicated Values 0
```

Out[67]:

	Missing_value	Percent_missing_%	Data_type	Number of Unique
state	0	0.0	object	51
total eve calls	0	0.0	int64	123
customer service calls	0	0.0	int64	10
total intl charge	0	0.0	float64	162
total intl calls	0	0.0	int64	21
total intl minutes	0	0.0	float64	162
total night charge	0	0.0	float64	933
total night calls	0	0.0	int64	120
total night minutes	0	0.0	float64	1591
total eve charge	0	0.0	float64	1440
total eve minutes	0	0.0	float64	1611
account length	0	0.0	int64	212
total day charge	0	0.0	float64	1667
total day calls	0	0.0	int64	119
total day minutes	0	0.0	float64	1667
number vmail messages	0	0.0	int64	46
voice mail plan	0	0.0	object	2
international plan	0	0.0	object	2
phone number	0	0.0	object	3333
area code	0	0.0	int64	3
churn	0	0.0	bool	2

In [68]:
```
#checking for unique values
df.nunique()
```

Out[68]:
```
state                       51
account length             212
area code                    3
phone number              3333
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
```

In [69]:
```
#printing a list of the unique values
for x in df.columns :
    print (f'===== {x} =====')
    print (f'{df[x].unique()}')
    print()
```

```
===== state =====
['KS' 'OH' 'NJ' 'OK' 'AL' 'MA' 'MO' 'LA' 'WV' 'IN' 'RI' 'IA' 'MT' 'NY'
 'ID' 'VT' 'VA' 'TX' 'FL' 'CO' 'AZ' 'SC' 'NE' 'WY' 'HI' 'IL' 'NH' 'GA'
 'AK' 'MD' 'AR' 'WI' 'OR' 'MI' 'DE' 'UT' 'CA' 'MN' 'SD' 'NC' 'WA' 'NM'
 'NV' 'DC' 'KY' 'ME' 'MS' 'TN' 'PA' 'CT' 'ND']

===== account length =====
[128 107 137  84  75 118 121 147 117 141  65  74 168  95  62 161  85  93
  76  73  77 130 111 132 174  57  54  20  49 142 172  12  72  36  78 136
 149  98 135  34 160  64  59 119  97  52  60  10  96  87  81  68 125 116
  38  40  43 113 126 150 138 162  90  50  82 144  46  70  55 106  94 155
  80 104  99 120 108 122 157 103  63 112  41 193  61  92 131 163  91 127
 110 140  83 145  56 151 139   6 115 146 185 148  32  25 179  67  19 170
 164  51 208  53 105  66  86  35  88 123  45 100 215  22  33 114  24 101
 143  48  71 167  89 199 166 158 196 209  16  39 173 129  44  79  31 124
  37 159 194 154  21 133 224  58  11 109 102 165  18  30 176  47 190 152
  26  69 186 171  28 153 169  13  27   3  42 189 156 134 243  23   1 205
 200   5   9 178 181 182 217 177 210  29 180   2  17   7 212 232 192 195
 197 225 184 191 201  15 183 202   8 175   4 188 204 221]
```

Explanatory Data Analysis

In [70]:
```
# Remove customer number feature it is contact information on the client and adds no
# Recheck dataframe
df.drop(['phone number'],axis=1,inplace=True)
df.head()
```

Out[70]:

	state	account length	area code	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
0	KS	128	415	no	yes	25	265.1	110	45.07	197.4	99	16.78
1	OH	107	415	no	yes	26	161.6	123	27.47	195.5	103	16.62
2	NJ	137	415	no	no	0	243.4	114	41.38	121.2	110	10.30
3	OH	84	408	yes	no	0	299.4	71	50.90	61.9	88	5.26
4	OK	75	415	yes	no	0	166.7	113	28.34	148.3	122	12.61

In [71]:
```
#copying our dataframe to a new dataframe
df_new=df.copy()
```

Feature Types

- Continuous features are numeric values with an infinite number of possible values
- Categorical features are values that have a finite number of categories/groups
- This step seperates all of the useful features in the dataset so that they can be analyzed accordingly ahead of modeling.

Continuous Features:

- 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

In [72]:
```
# Create numeric & categorical lists
numeric_cols = ['account length','number vmail messages','total day minutes','total 
                'total eve minutes','total eve calls','total eve charge','total nigh
                'total night charge','total intl minutes','total intl calls','total 
categoric_cols = ['state','area code','international plan','voice mail plan']
```

In [73]:
```
#checking description of  data
df[numeric_cols].describe()
```

Out[73]:

	account length	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	t
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333
mean	101.064806	8.099010	179.775098	100.435644	30.562307	200.980348	100.114311	17
std	39.822106	13.688365	54.467389	20.069084	9.259435	50.713844	19.922625	4
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	(
25%	74.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.000000	14
50%	101.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.000000	17
75%	127.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.000000	20
max	243.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.000000	30

'Churn' and 'SeniorCitizen' are features with boolean data types. The symmetry of these two properties does not, therefore, need to be known. In light of the details in point. After this part, the 'SeniorCitizen' characteristic will be examined. Because the difference between the mean and median is less than 15%, the 'tenure' and'monthlyCharges' distributions tend to be symmetrical. "TotalCharges" has an uneven distribution because the mean and median values diverge by a significant amount.

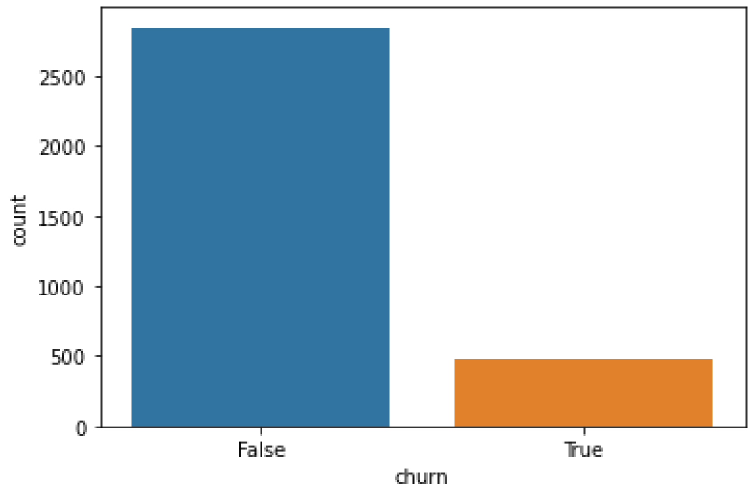
Identifying Dependent Variable

- The churn column will be used as our dependent variable
- Churn indicates if a customer has terminated their contract with SyriaTel. True indicates they have terminated and false indicates they have not and have and have an account.

In [74]:
```
#checking values in the churn column
print(df_new['churn'].value_counts())
sns.countplot(data=df, x='churn')
```

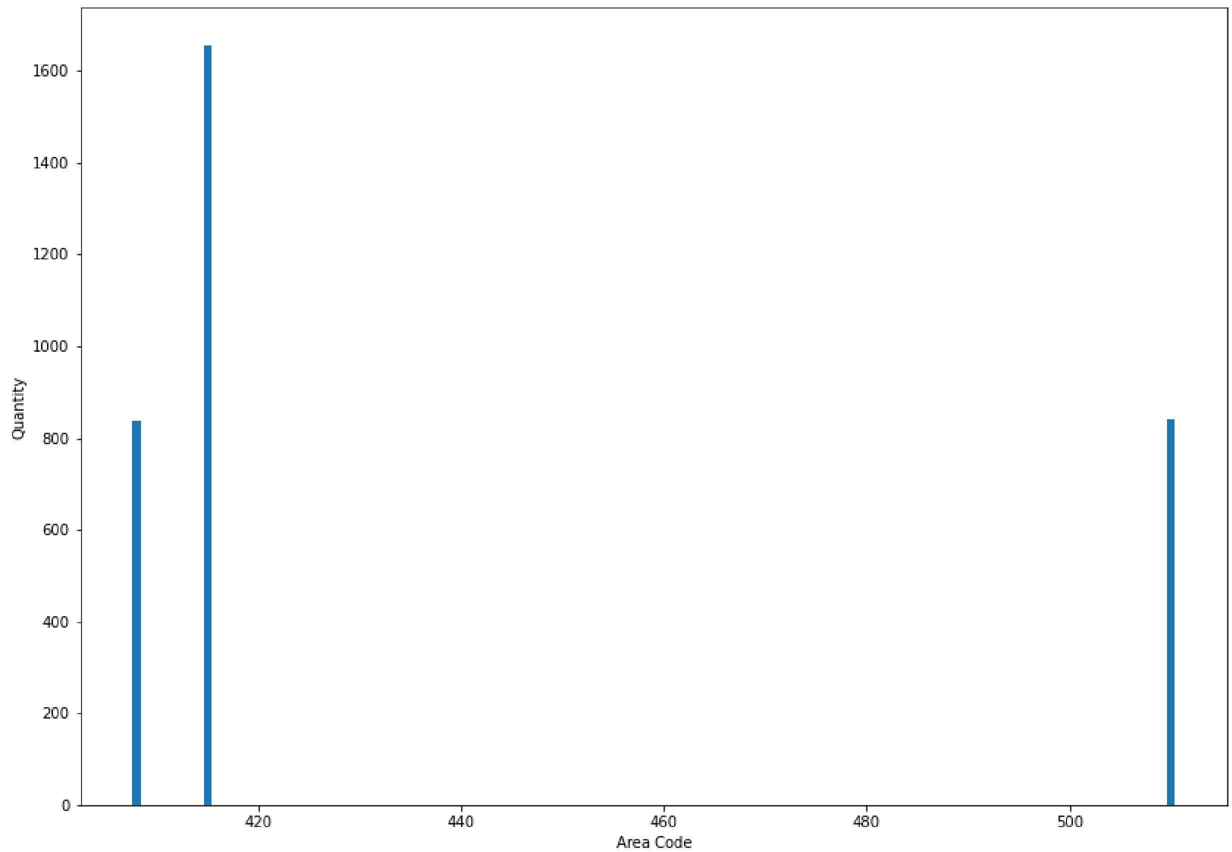
```
False    2850
True      483
Name: churn, dtype: int64
```

Out[74]:
```
<AxesSubplot:xlabel='churn', ylabel='count'>
```



Of the 3,333 customers in the dataset, 483 have terminated their contract with SyriaTel. That is 14.5% of customers lost.

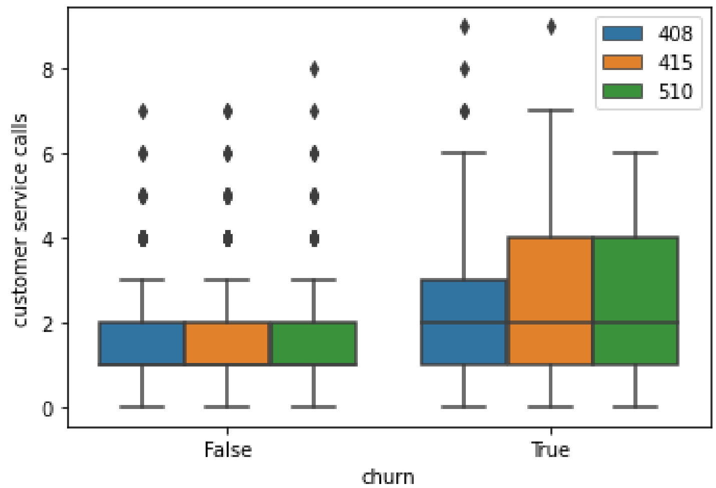
In [75]:
```
#Analyzing Area Code

area = df['area code'].value_counts()

transaction = area.index
quantity = area.values

# Plotting bar graph
plt.figure(figsize=(14,10))
plt.bar(transaction, quantity)
#plt.title('Distribution of Area Codes')
plt.xlabel("Area Code")
plt.ylabel("Quantity")


plt.show()
```



Half of the customers have the area code 415. One fourth of customers have the area code 510 and another fourth have the area code 408.

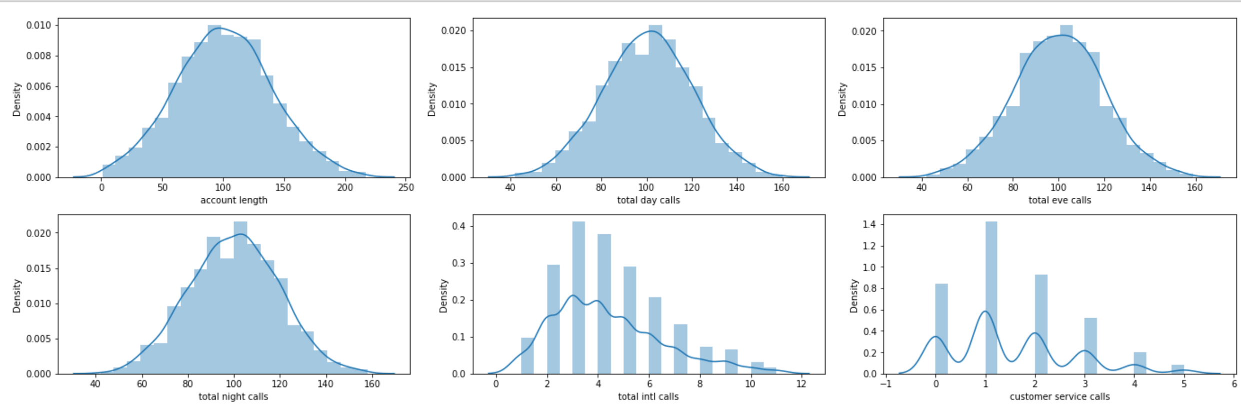
In [76]:
```
# Boxplot to see areas in relation to the churn column

sns.boxplot(data=df,x="churn",y="customer service calls",hue="area code")
plt.legend(loc='upper right')
```

Out[76]: <matplotlib.legend.Legend at 0x21dcb89b2b0>



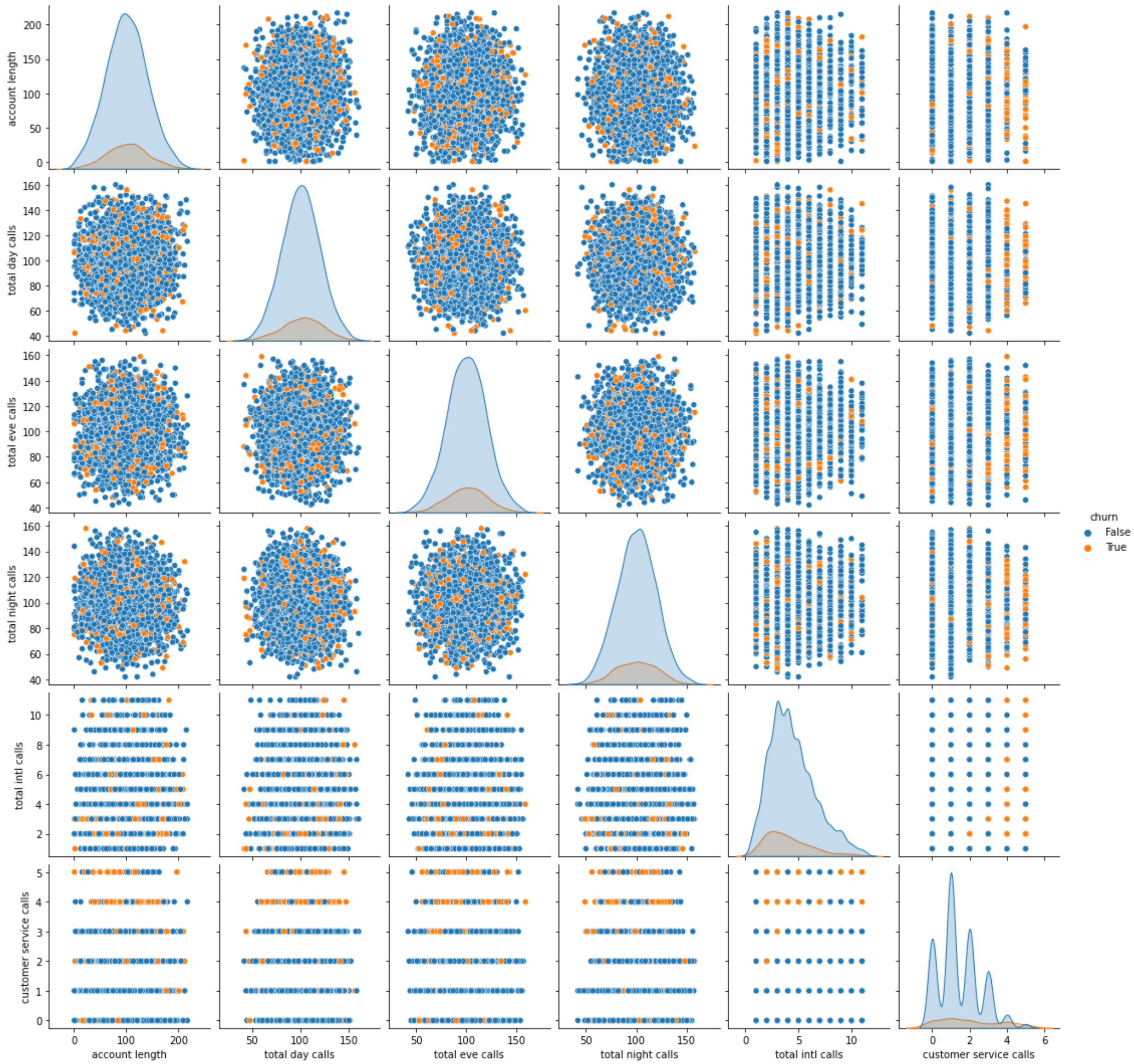
Checking the Distribution Curve of Numeric features

In [87]:
```
#plotting distribution curves
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]);
```



All features seem to have a normal distribution apart from customer servoce calls, whereeas totoal international call seeto be skewed to the right but still has normal distribution

In [89]:
```
#pair plot for numeric feutures
data_temp = df[["account length", "total day calls", "total eve calls", "total night
                "total intl calls", "customer service calls", "churn"]]

sns.pairplot(data_temp, hue="churn", height=2.5);
plt.show();
```

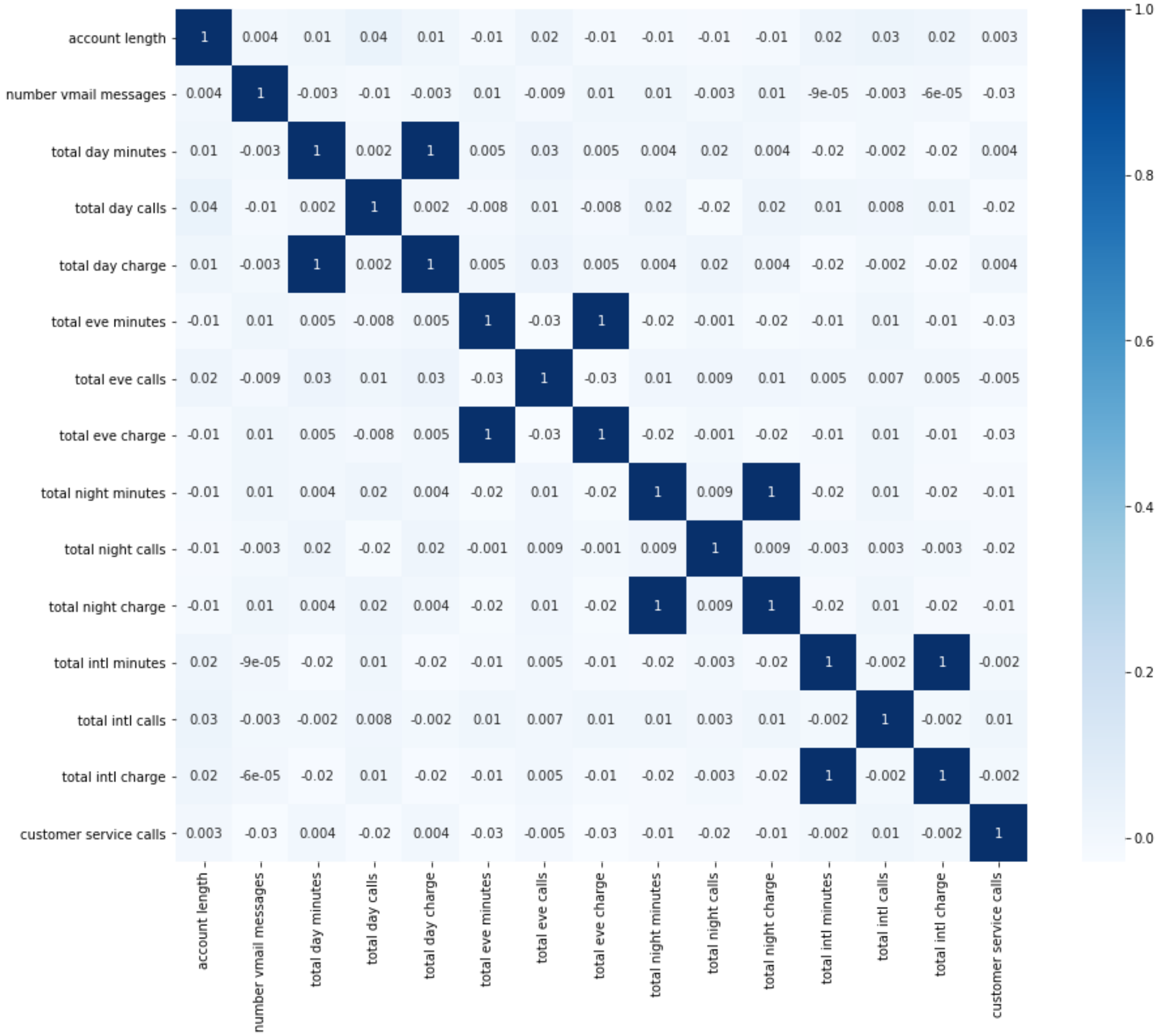


There seems to be a evident relationship between customer service calls and true churn values. After 4 calls, customers are a lot more likely to discontinue their service.

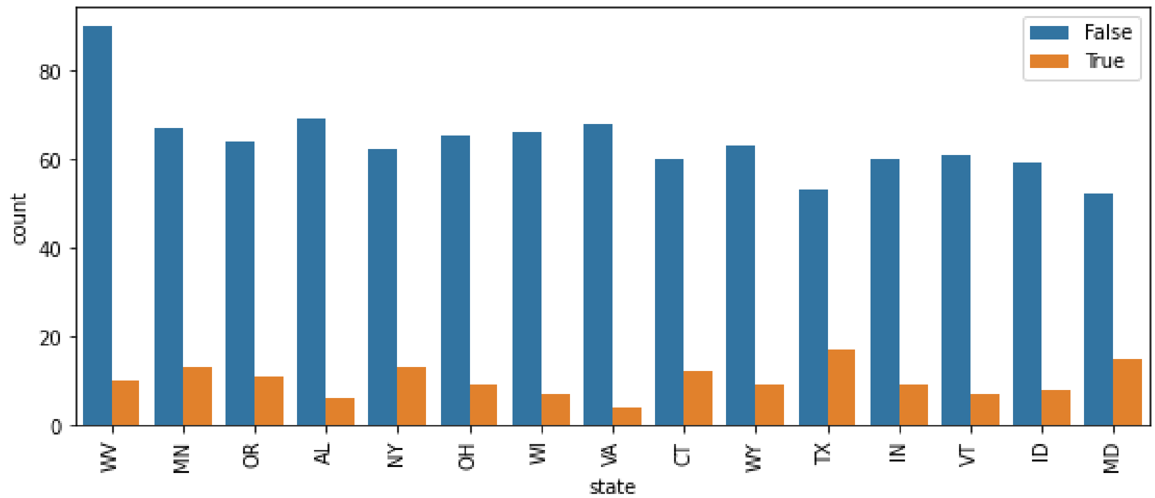
Correlation map between the Numeric features

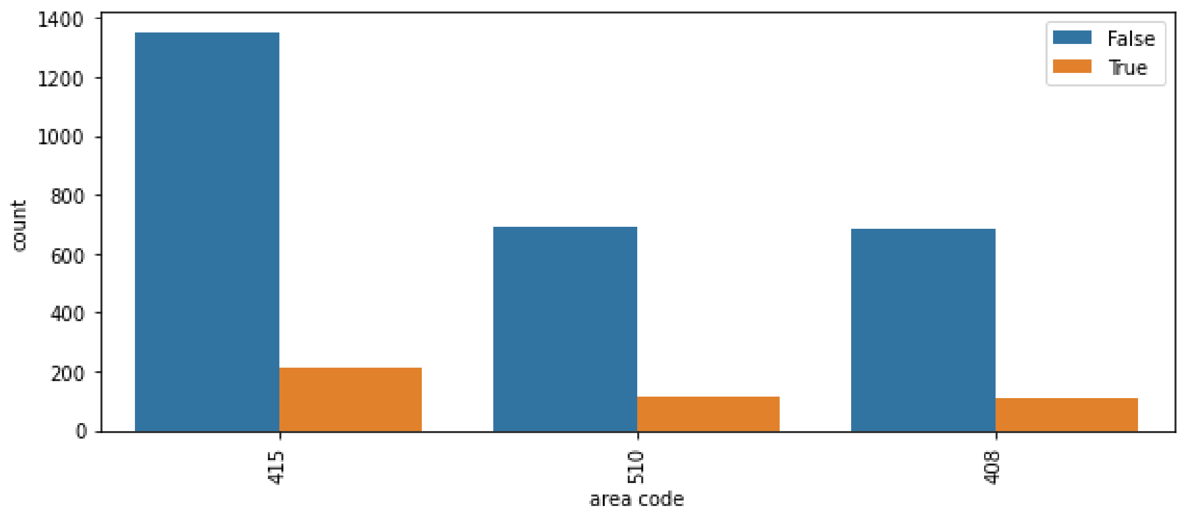
In [93]:
```
#Correlation matrix figure
corr_mat= df[numeric_cols].corr()
plt.subplots(figsize=(15,12))
sns.heatmap(corr_mat, annot=True, cmap='Blues', square=True,fmt='.0g')
```

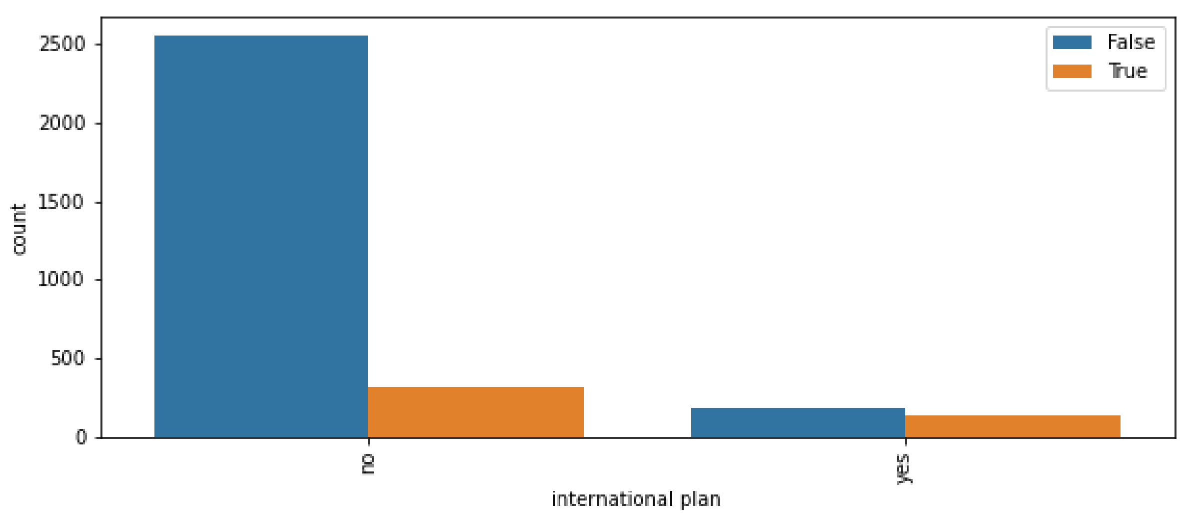
Out[93]: <AxesSubplot:>

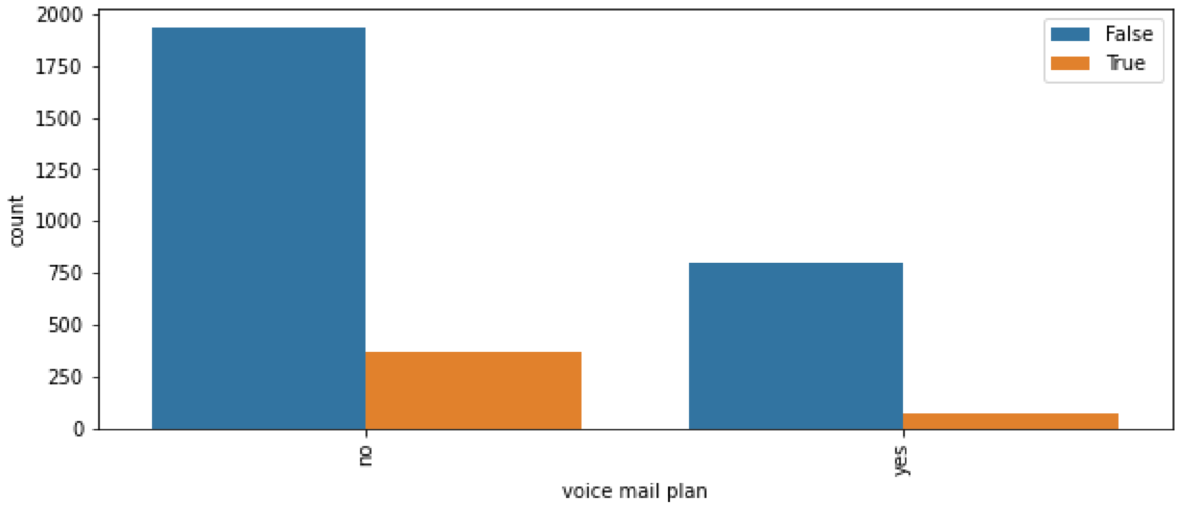


In [94]:
```
#categorical featurs for analysis
for i in categoric_cols:
    plt.figure(figsize=(10,4))
    sns.countplot(x=i, hue="churn", data=df,order= df[i].value_counts().iloc[0:15].i
    plt.xticks(rotation=90)
    plt.legend(loc="upper right")
    plt.show()
```









Detecting outliers

In [95]:

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

def drop_numerical_outliers(df, z_thresh=3):
    # Select columns with numerical data
    numeric_columns = df.select_dtypes(include=np.number)

    # Calculate z-scores for each numeric column
    z_scores = np.abs(stats.zscore(numeric_columns))

    # Create a boolean mask for rows where all z-scores are less than the threshold
    row_mask = np.all(z_scores < z_thresh, axis=1)

    # Drop rows that contain outliers
    df.drop(df.index[~row_mask], inplace=True)

# Call the function to drop numerical outliers
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:  3169
After dropping numerical outliers, length of the dataframe is:  3127
```

In [96]:

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

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

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

Transforming "Churn" Feature's Rows into 0s and 1s

In [97]:

```
#checking for number of values
reduced_df['churn'].value_counts()
#convertting churn columns to 0 and 1
reduced_df['churn'] = reduced_df['churn'].map({True: 1, False: 0}).astype('int')
#checking our data frame
reduced_df.head()
```

Out[97]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day calls	total day charge	total eve calls	total eve charge	total night calls	total night charge	tot ir cal
0	KS	128	415	no	yes	25	110	45.07	99	16.78	91	11.01	
1	OH	107	415	no	yes	26	123	27.47	103	16.62	103	11.45	
2	NJ	137	415	no	no	0	114	41.38	110	10.30	104	7.32	
3	OH	84	408	yes	no	0	71	50.90	88	5.26	89	8.86	
4	OK	75	415	yes	no	0	113	28.34	122	12.61	121	8.41	

One Hot Encoding

Changing the categorical values to numeric values to be used in modelling

In [98]:

```
dummy_df_state = pd.get_dummies(reduced_df["state"], dtype=np.int64, prefix="state_i
dummy_df_area_code = pd.get_dummies(reduced_df["area code"], dtype=np.int64, prefix=
dummy_df_international_plan = pd.get_dummies(reduced_df["international plan"], dtype
dummy_df_voice_mail_plan = pd.get_dummies(reduced_df["voice mail plan"], dtype=np.in

reduced_df = pd.concat([reduced_df, dummy_df_state, dummy_df_area_code, dummy_df_int
reduced_df = reduced_df.loc[:, ~reduced_df.columns.duplicated()]
reduced_df = reduced_df.drop(['state', 'area code', 'international plan', 'voice mai

reduced_df.head()
```

Out[98]:

	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	...	state_is_VT	state_
0	128	25	110	45.07	99	16.78	91	11.01	3	2.70	...	0	
1	107	26	123	27.47	103	16.62	103	11.45	3	3.70	...	0	
2	137	0	114	41.38	110	10.30	104	7.32	5	3.29	...	0	
3	84	0	71	50.90	88	5.26	89	8.86	7	1.78	...	0	
4	75	0	113	28.34	122	12.61	121	8.41	3	2.73	...	0	

5 rows × 68 columns

Scaling numerical Values

In [101]:
```
from sklearn.preprocessing import MinMaxScaler

# Create an instance of MinMaxScaler
transformer = MinMaxScaler()

# Function to perform scaling using the transformer
def scaling(columns):
    return transformer.fit_transform(reduced_df[columns].values.reshape(-1, 1))

numeric_columns = reduced_df.select_dtypes(include=[np.number]).columns

for column in numeric_columns:
    reduced_df[column] = scaling(column)

reduced_df.head()
```

Out[101]:

	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
0	0.587963	0.520833	0.586207	0.773038	0.487179	0.484801	0.422414	0.644461	0.222222	0.474178
1	0.490741	0.541667	0.698276	0.448015	0.521368	0.478484	0.525862	0.677395	0.222222	0.708920
2	0.629630	0.000000	0.620690	0.704894	0.581197	0.228977	0.534483	0.368263	0.444444	0.612676
3	0.384259	0.000000	0.250000	0.880702	0.393162	0.030004	0.405172	0.483533	0.666667	0.258216
4	0.342593	0.000000	0.612069	0.464081	0.683761	0.320174	0.681034	0.449850	0.222222	0.481221

5 rows × 68 columns

Performing a Train Test Split

In [103]:
```
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

This helps to overcome the overfitting problem posed by random oversampling. It focuses on the feature space to generate new instances with the help of interpolation between the positive instances that lie together.

In [104]:
```
reduced_df.churn.value_counts()
```

Out[104]:
```
0.0    2690
1.0     437
Name: churn, dtype: int64
```

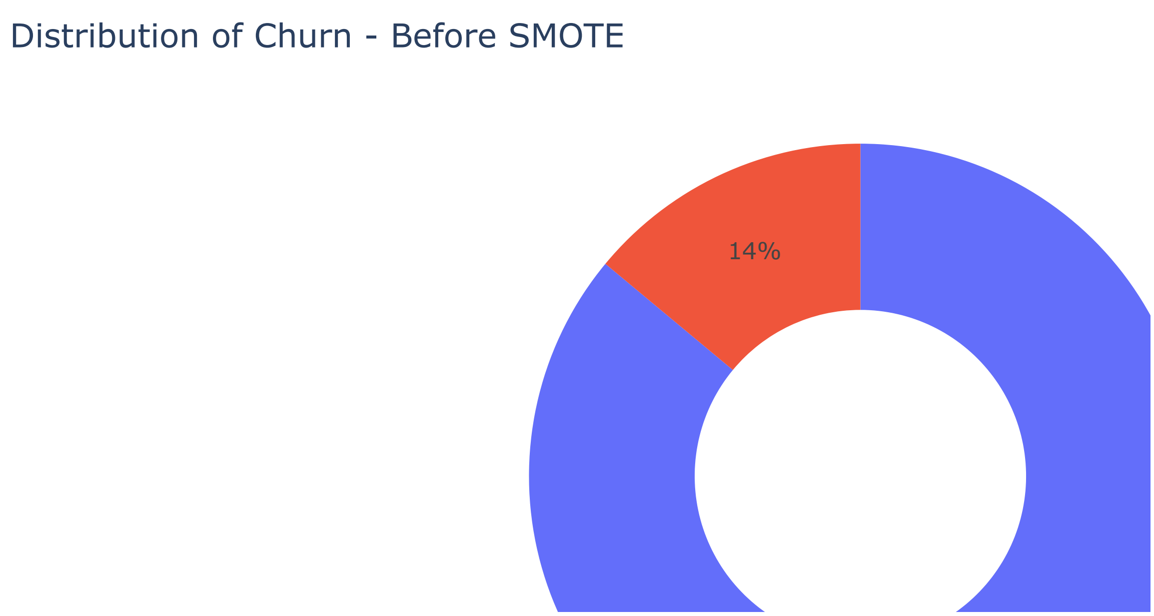
In [105]:
```
sm = SMOTE(k_neighbors=5, random_state=123)
X_train_over, y_train_over = sm.fit_resample(X_train, y_train)
print('Before OverSampling, the shape of X_train: {}'.format(X_train.shape))
print('Before OverSampling, the shape of y_train: {}'.format(y_train.shape))
print('After OverSampling, 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: (2345, 67)
Before OverSampling, the shape of y_train: (2345,)
After OverSampling, the shape of X_train_over: (4030, 67)
After OverSampling, the shape of y_train_over: (4030,)
```

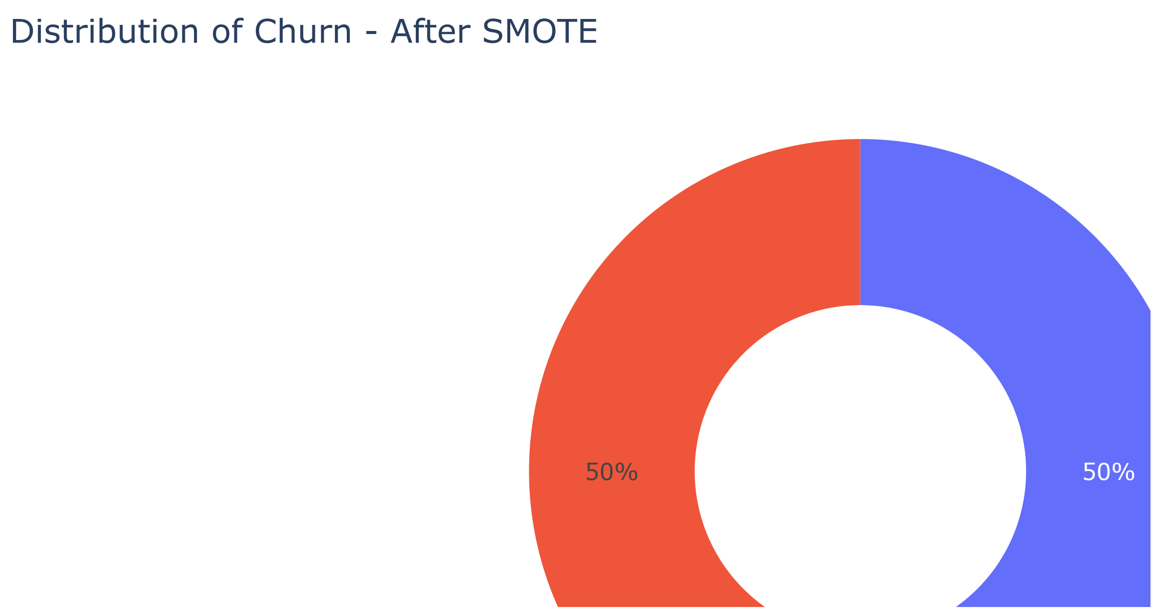
In [106]:
```
#checking the values in y_train_over
y_train_over.value_counts()
```

Out[106]:
```
1.0    2015
0.0    2015
Name: churn, dtype: int64
```

In [107]:
```
import plotly.express as px

#distribution of churn before smote
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()
```



In [109]:
```
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()
```



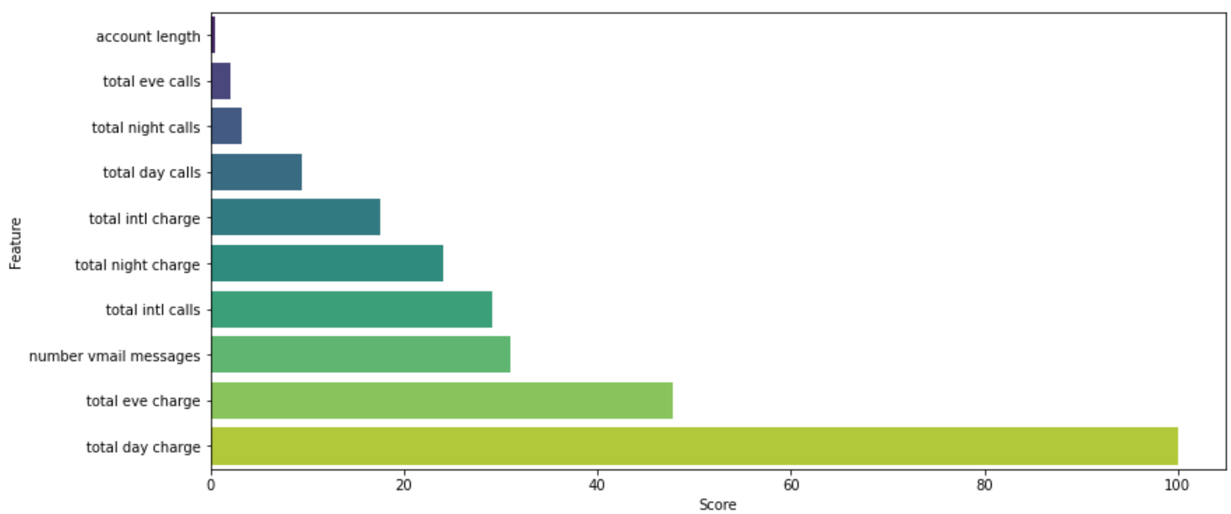
Modeling

Logistic Regression Classifier

- This is a classification algorithm used to predict the probability of a binary outcome based on one or more input variables. It assumes a linear relationship between the input variables and the logodds of the outcome

In [110]:
```
# Object creation, fitting the data & getting predictions
lr= LogisticRegression()
lr.fit(X_train_over,y_train_over)
y_pred = lr.predict(X_test)
```

In [111]:
```
# Checking the important features
feature_importance = abs(lr.coef_[0])
feature_importance = 100.0 * (feature_importance / feature_importance.max())[0:10]

# Sorting indices
sorted_idx = np.argsort(feature_importance)[0:10]

# Creating DataFrame for plotting
df = pd.DataFrame({'Feature': np.array(X.columns)[sorted_idx],
                   'Importance': feature_importance[sorted_idx]})

# Plotting using seaborn
plt.figure(figsize=(13, 6))
sns.barplot(x='Importance', y='Feature', data=df, palette='viridis')
#plt.title ('Top 10 Relative Feature Importance for Logistic Regression Model', )
plt.xlabel('Score')
plt.ylabel('Feature')
plt.show()
```



In [112]:
```
from sklearn.metrics import classification_report

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

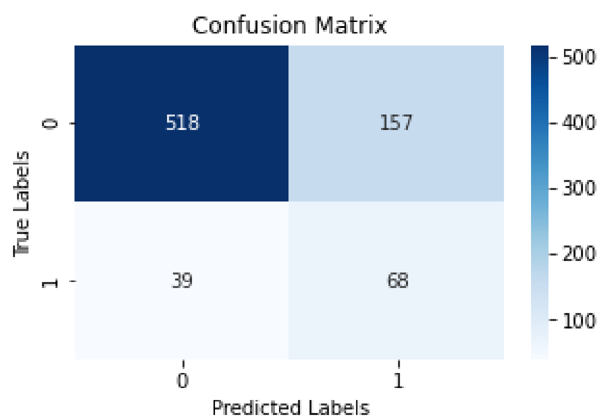
```
              precision    recall  f1-score   support

           0       0.93      0.77      0.84       675
           1       0.30      0.64      0.41       107

    accuracy                           0.75       782
   macro avg       0.62      0.70      0.63       782
weighted avg       0.84      0.75      0.78       782
```

In [113]:
```
#providing classification report for the predicted values
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.93      0.77      0.84       675
         1.0       0.30      0.64      0.41       107

    accuracy                           0.75       782
   macro avg       0.62      0.70      0.63       782
weighted avg       0.84      0.75      0.78       782
```

In [124]:
```
print("LOGISTIC REGRESSION CLASSIFIER MODEL RESULTS  ")
print('Accuracy score for testing set: ',(accuracy_score(y_test,y_pred),5))
print('F1 score for testing set: ',(f1_score(y_test,y_pred),5))
print('Recall score for testing set: ',(recall_score(y_test,y_pred),5))
print('Precision score for testing set: ',(precision_score(y_test,y_pred),5))
cm_lr = confusion_matrix(y_test, y_pred)
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('Conf
ax.xaxis.set_ticklabels(['0', '1']) ; ax.yaxis.set_ticklabels(['0', '1'])
plt.show();
```

```
LOGISTIC REGRESSION CLASSIFIER MODEL RESULTS
Accuracy score for testing set:  (0.7493606138107417, 5)
F1 score for testing set:  (0.4096385542168674, 5)
Recall score for testing set:  (0.6355140186915887, 5)
Precision score for testing set:  (0.3022222222222222, 5)
```



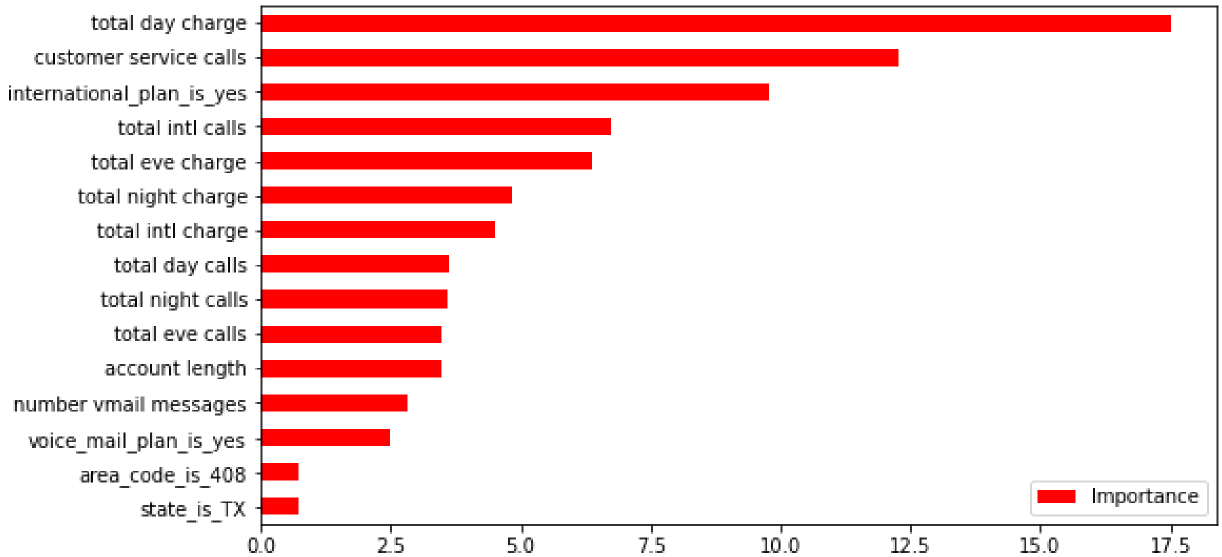
- The top three features in the logistic regression classifier model are total day charge, voicemail message count, and total evening charge. The model's accuracy is decent at 76.5%. With an F1 score of only 50.2%, the test will only be accurate 50% of the time.

RANDOM FOREST CLASSIFIER

- This is an ensemble machine learning algorithm that combines multiple decision trees to make predictions. It is a popular algorithm for both classification and regression tasks. Each decision tree in the random forest is trained on a random subset of the training data, and the final prediction is made by aggregating the predictions of all the individual trees.

In [125]:
```
# Fitting the data and gwtting predictions
rf_model_final = RandomForestClassifier()
rf_model_final.fit(X_train_over,y_train_over)
y_pred_rf = rf_model_final.predict(X_test)
```

In [126]:
```
import matplotlib.pyplot as plt


Importance =pd.DataFrame({"Importance": rf_model_final.feature_importances_*100},ind
Importance.sort_values(by = "Importance", axis = 0, ascending = True).tail(15).plot(

plt.show()
```

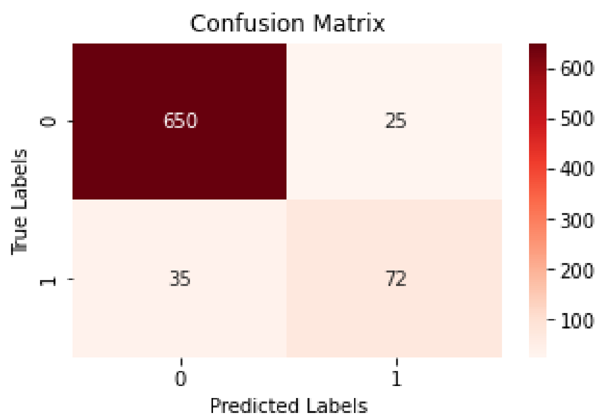


In [127]:
```
print(classification_report(y_test, y_pred_rf, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.95      0.96      0.96       675
           1       0.74      0.67      0.71       107

    accuracy                           0.92       782
   macro avg       0.85      0.82      0.83       782
weighted avg       0.92      0.92      0.92       782
```

In [128]:
```
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('Conf
ax.xaxis.set_ticklabels(['0', '1']) ; ax.yaxis.set_ticklabels(['0', '1'])
plt.show();
```

```
RANDOM FOREST MODEL RESULTS
Accuracy score for testing set:  0.92327
F1 score for testing set:  0.70588
Recall score for testing set:  0.6729
Precision score for testing set:  0.74227
```



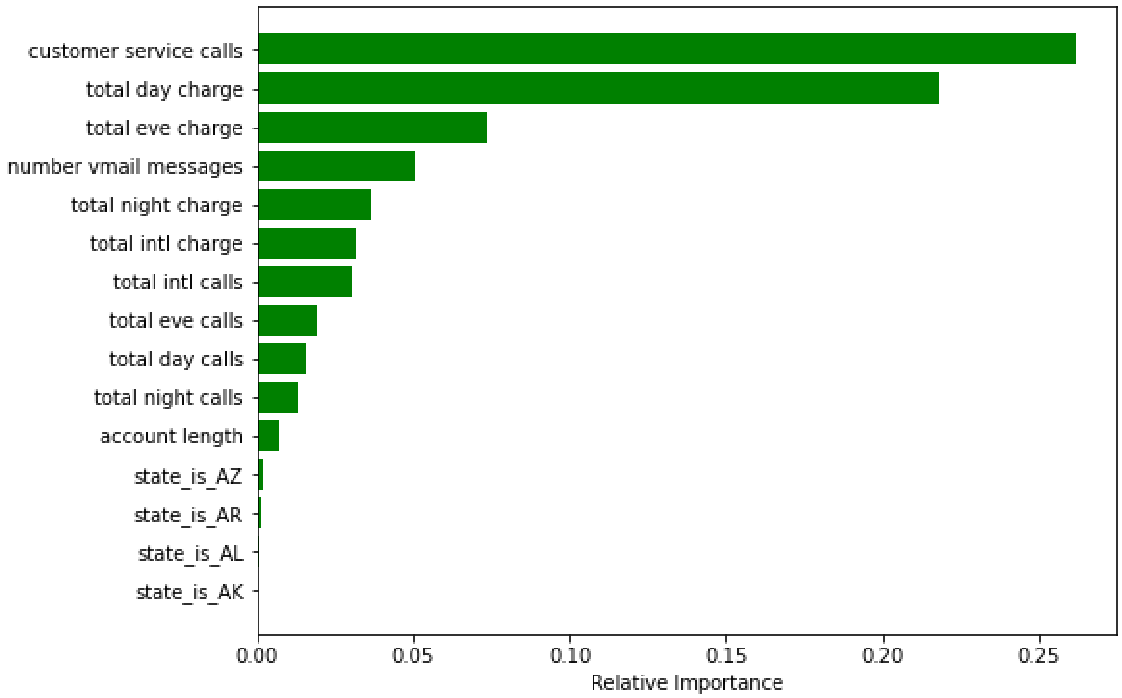
- The top three features in the logistic regression classifier model are total day charge, voicemail message count, and total evening charge. The model's accuracy is decent at 76.5%. With an F1 score of only 50.2%, the test will only be accurate 50% of the time.

Decision Tree classifier

- This is a supervised machine learning algorithm that uses a tree-like model to make predictions. It partitions the input data into subsets based on the values of the input features and assigns a label to each subset based on the majority class within that subset.

In [130]:
```
#  Fitting the data & getting predictions
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train_over,y_train_over)
y_pred_dt = decision_tree.predict(X_test)
```

In [131]:
```
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()
```



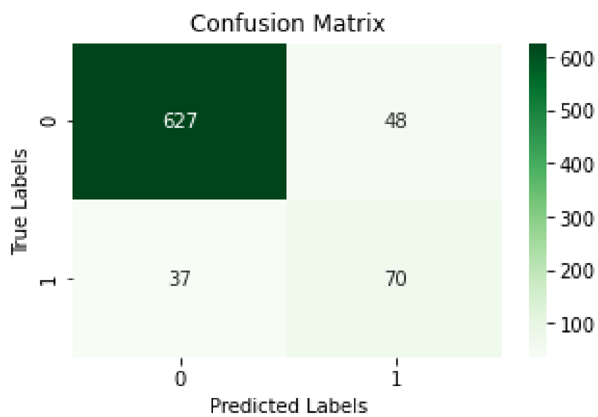
Type *Markdown* and LaTeX: α^2

In [132]:
```
print(classification_report(y_test, y_pred_dt, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.94      0.93      0.94       675
           1       0.59      0.65      0.62       107

    accuracy                           0.89       782
   macro avg       0.77      0.79      0.78       782
weighted avg       0.90      0.89      0.89       782
```

In [133]:
```
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('Conf
ax.xaxis.set_ticklabels(['0', '1']) ; ax.yaxis.set_ticklabels(['0', '1'])
plt.show();
```

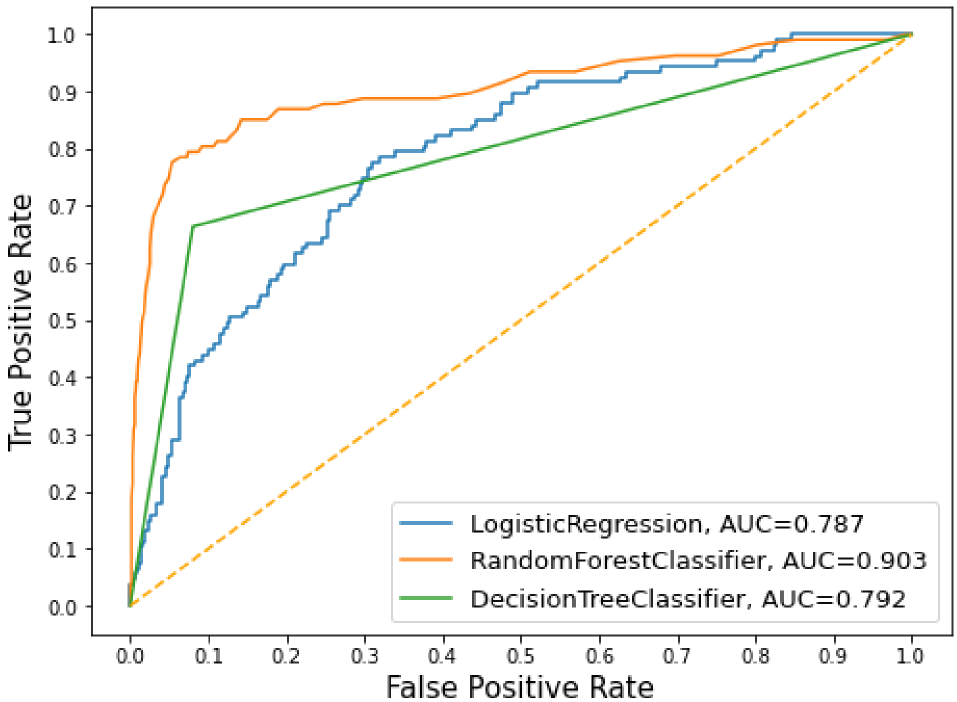
```
 DECISION TREE CLASSIFIER MODEL RESULTS
Accuracy score for testing set:  0.8913
F1 score for testing set:  0.62222
Recall score for testing set:  0.65421
Precision score for testing set:  0.59322
```



Customer service calls total day fee, total evening charge, and decision tree classifier rank as the model's top three drivers. This model's F1 score and accuracy are not as good as model 2's.

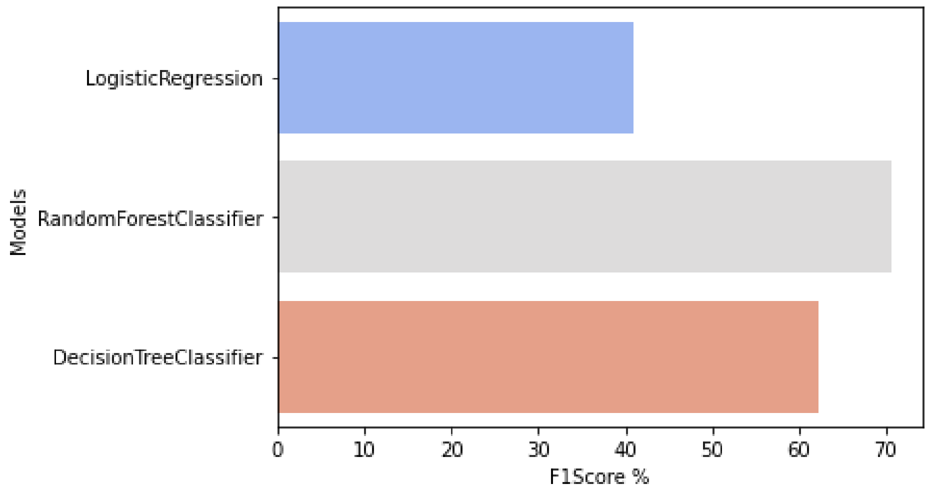
Model Comparison

In [134]:
```
#using ROC curve to compare the models
classifiers = [LogisticRegression(),
               RandomForestClassifier(),
               DecisionTreeClassifier()]


# Define a result table as a DataFrame
result_table = pd.DataFrame(columns=['classifiers', 'fpr','tpr','auc'])

# Train the models and record the results
for cls in classifiers:
    model = cls.fit(X_train_over, y_train_over)
    yproba = model.predict_proba(X_test)[::,1]

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

    result_table = result_table.append({'classifiers':cls.__class__.__name__,
                                        'fpr':fpr,
                                        'tpr':tpr,
                                        'auc':auc}, ignore_index=True)

# Set name of the classifiers as index labels
result_table.set_index('classifiers', inplace=True)

fig = plt.figure(figsize=(8,6))
for i in result_table.index:
    plt.plot(result_table.loc[i]['fpr'],
             result_table.loc[i]['tpr'],
             label="{}, AUC={:.3f}".format(i, result_table.loc[i]['auc']))

plt.plot([0,1], [0,1], color='orange', linestyle='--')

plt.xticks(np.arange(0.0, 1.1, step=0.1))
plt.xlabel("False Positive Rate", fontsize=15)

plt.yticks(np.arange(0.0, 1.1, step=0.1))
plt.ylabel("True Positive Rate", fontsize=15)


plt.legend(prop={'size':13}, loc='lower right')

plt.show()
```



- The ROC curve contrasts our classifier's true positive rate with false positive rate. The best models, in this case the random forest classifier, will have a curve that closely hugs the upper left corner of the graph.

In [135]:
```
#using F1 Score to compare the models
models = [lr,rf_model_final,decision_tree]

result = []
results = pd.DataFrame(columns= ["Models","F1Score"])

for model in models:
    names = model.__class__.__name__
    y_pred = model.predict(X_test)
    precision = f1_score(y_test, y_pred)
    result = pd.DataFrame([[names, precision*100]], columns= ["Models","F1Score"])
    results = results.append(result)


sns.barplot(x= 'F1Score', y = 'Models', data=results, palette="coolwarm")
plt.xlabel('F1Score %');
```



In [136]:
```
results
```

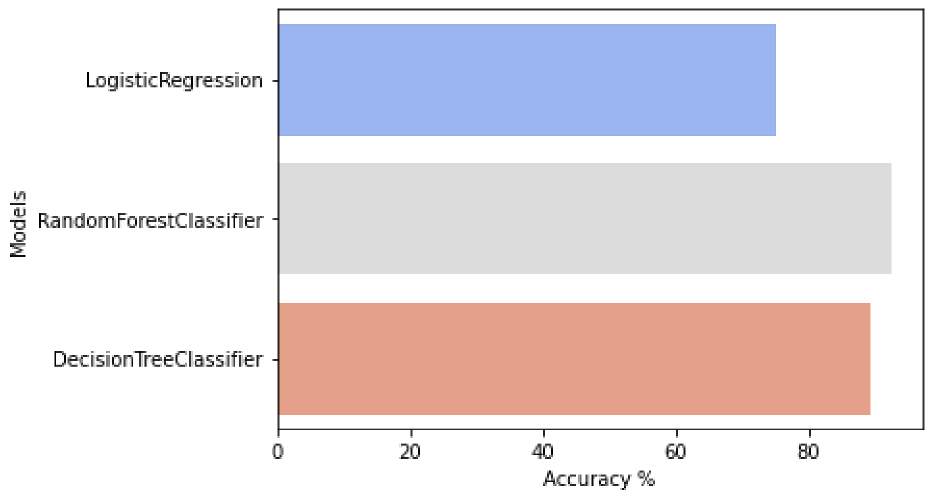
Out[136]:

	Models	F1Score
0	LogisticRegression	40.963855
0	RandomForestClassifier	70.588235
0	DecisionTreeClassifier	62.222222

Model Accuracy

In [137]:
```
models = [lr,rf_model_final,decision_tree]

result = []
results = pd.DataFrame(columns= ["Models","Accuracy"])

for model in models:
    names = model.__class__.__name__
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    result = pd.DataFrame([[names, accuracy*100]], columns= ["Models","Accuracy"])
    results = results.append(result)


sns.barplot(x= 'Accuracy', y = 'Models', data=results, palette="coolwarm")
plt.xlabel('Accuracy %')
;
```

Out[137]: ''



In [138]:
```
results
```

Out[138]:

	Models	Accuracy
0	LogisticRegression	74.936061
0	RandomForestClassifier	92.327366
0	DecisionTreeClassifier	89.130435

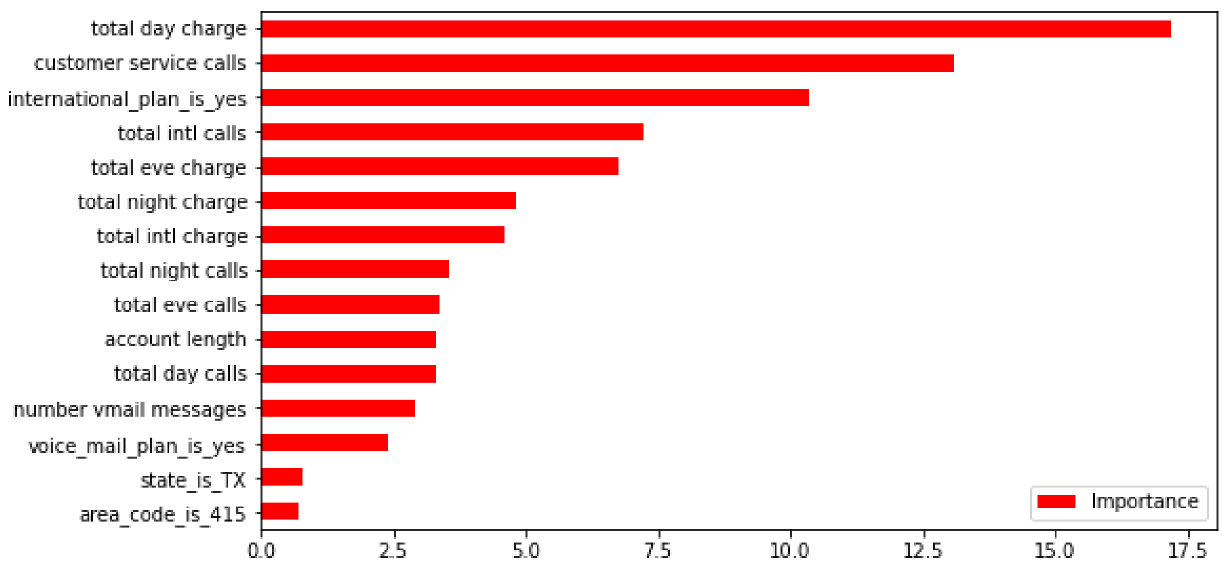
Tuning Of Random Forest Classifier Using HyperParameter

In [146]:
```
#using a 3 fold cross validation technique
rf_params = {"max_depth": [8,15,20],
             "n_estimators":[500,1000],
             "min_samples_split":[5,10,15],
             "criterion":['entropy','gini']}
```

In [*]:
```
from sklearn.model_selection import GridSearchCV

rf_model2 = RandomForestClassifier()
rf_cv_model = GridSearchCV(rf_model2,rf_params,cv=3,n_jobs=-1,verbose=False)
rf_cv_model.fit(X_train_over,y_train_over)
print("Best parameters:"+str(rf_cv_model.best_params_))

#Best parameters:{'criterion': 'entropy', 'max_depth': 20, 'min_samples_split': 5, 'r
```

In [*]:
```
rf_model_final = RandomForestClassifier(max_depth=20,min_samples_split=5,n_estimator
rf_model_final.fit(X_train_over,y_train_over)
y_pred_final = rf_model_final.predict(X_test)
```

In [142]:
```
Importance =pd.DataFrame({"Importance": rf_model_final.feature_importances_*100},ind
Importance.sort_values(by = "Importance", axis = 0, ascending = True).tail(15).plot(
#plt.title("Feature Importance Levels");
plt.show()
```

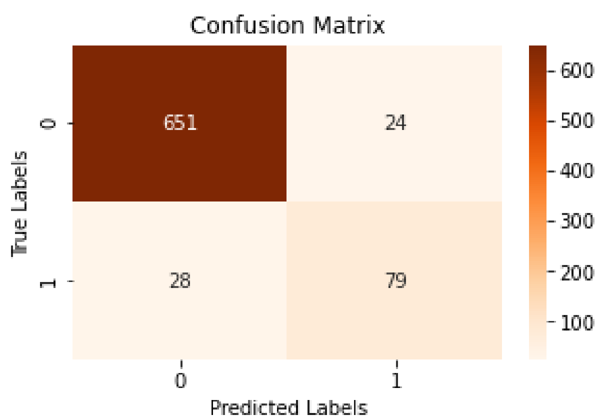


In [143]:
```
print(classification_report(y_test, y_pred_final, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.96      0.96      0.96       675
           1       0.77      0.74      0.75       107

    accuracy                           0.93       782
   macro avg       0.86      0.85      0.86       782
weighted avg       0.93      0.93      0.93       782
```

In [144]:
```
print(" HYPERPARAMETER TUNED RANDOM FOREST MODEL RESULTS ")
print('Accuracy score for testing set: ',round(accuracy_score(y_test,y_pred_final),5
print('F1 score for testing set: ',round(f1_score(y_test,y_pred_final),5))
print('Recall score for testing set: ',round(recall_score(y_test,y_pred_final),5))
print('Precision score for testing set: ',round(precision_score(y_test,y_pred_final)
cm_rf = confusion_matrix(y_test, y_pred_final)
f, ax= plt.subplots(1,1,figsize=(5,3))
sns.heatmap(cm_rf, annot=True, cmap='Oranges', fmt='g', ax=ax);
ax.set_xlabel('Predicted Labels'); ax.set_ylabel('True Labels') ; ax.set_title('Conf
ax.xaxis.set_ticklabels(['0', '1']) ; ax.yaxis.set_ticklabels(['0', '1'])
plt.show();
```

```
 HYPERPARAMETER TUNED RANDOM FOREST MODEL RESULTS
Accuracy score for testing set:  0.9335
F1 score for testing set:  0.75238
Recall score for testing set:  0.73832
Precision score for testing set:  0.76699
```



In [ ]: