1 Customer Churn Analysis & Predictive Modeling for Syria Tel

1.1 Project Overview

Syria Tel is a telecommunication company- mobile network- provider in Syria, founded in 2000. Using the DataSet holding Syria Tel Customer Churn information available on Kaggle, this project aims to build a best in class Machine Learning Algorithm, that can predict which and how many customers will churn based on the information available on the dataset.

1.2 Business Understanding

As important to Telecommunications companies as it is to earn new customers to their services, is the need to retain current customers and preventing them from going to competitors. The act of leaving customers or loss of customers are referred to in this industry as "Churn", from a business perspective. The business would like to understand exactly what factors or situations contribute to churning, and most importantly, post identification of those factors, define precises strategic initiatives to retain customers. This project, therefore aims to help the business first in identifying the attributes and factors that cause the churn, and in turn, building models that can help the business predict it, so that in fact strategic business initiatives can be outlined for solution.

1.2.1 Business Modeling Objectives

1. Building a model than can predict who will churn with a high level of accuracy
2. Identifying important attributes or features that are key in predicting customer churn

1.2.2 Important Model Success Considerations

We are testing for churn. If a customer churns it means churn is positive. A negative is a no, the customer did not churn. What will be more important for this problem are a False Negatives, mening that our model labeled a customer as "not going to churn" when actually churned.

Recall therefore is an important metric in evaluating our model under False Negatives. Recall pertains to the rate at which the model makes correct predictions about customer churning. Aided by a C Matrix- the goal is to minimize false negatives. Failure to identify a customer who is about to churn is more costly from a business persepective, than wrongly classyging a non-churning customer. A good successful model therefore should have an 85% recall at the very least. Precision and accuracy are also metrics to have in mind.

2 EDA - Loading and Understanding the DataSet

In [1]:
```
#install imblearn library
!pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in /Users/jonax/opt/ana
conda3/envs/learn-env/lib/python3.8/site-packages (0.7.0)
Requirement already satisfied: scikit-learn>=0.23 in /Users/jonax/opt/a
naconda3/envs/learn-env/lib/python3.8/site-packages (from imbalanced-le
arn) (0.23.2)
Requirement already satisfied: joblib>=0.11 in /Users/jonax/opt/anacond
a3/envs/learn-env/lib/python3.8/site-packages (from imbalanced-learn)
(0.17.0)
Requirement already satisfied: scipy>=0.19.1 in /Users/jonax/opt/anacon
da3/envs/learn-env/lib/python3.8/site-packages (from imbalanced-learn)
(1.5.2)
Requirement already satisfied: numpy>=1.13.3 in /Users/jonax/opt/anacon
da3/envs/learn-env/lib/python3.8/site-packages (from imbalanced-learn)
(1.18.5)
Requirement already satisfied: threadpoolctl>=2.0.0 in /Users/jonax/op
t/anaconda3/envs/learn-env/lib/python3.8/site-packages (from scikit-lea
rn>=0.23->imbalanced-learn) (2.1.0)
```

In [2]:
```
#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import classification_report, confusion_matrix, Conf
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import RFECV
from sklearn.pipeline import Pipeline

%matplotlib inline
```

In [3]:
```
#loading DataSet first for preview and understanding
customer_df= pd.read_csv('Data/Customer_churn.csv')
customer_df.head()
```

Out[3]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	tota ev calls
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	9
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	10
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	11
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	8
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	12

5 rows × 21 columns

In [4]:
```
#Understanding database shape
customer_df.shape
```

Out[4]: (3333, 21)

In [5]:
```
#Understanding database information on nulls and data types
customer_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
```

From the above we can conclude that of the 3333 rows and 21 columns , there are non-null values in each of the columns. We can change some value columns such as area code , from integer to object data type. And, we can check further.

In [6]:
```
# convert area code from integer to string
customer_df['area code'] = customer_df['area code'].astype(object)
customer_df['area code'].dtype
```

Out[6]:
```
dtype('O')
```

In [7]:
```
#Checking for missing values
customer_df.isna().sum()
```

Out[7]:
```
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
```

From the above, this database does not have missing values.

In [8]:
```
#checking for duplicate numbers using phone numbers
customer_df.duplicated(subset='phone number').value_counts()
```

Out[8]:
```
False    3333
dtype: int64
```

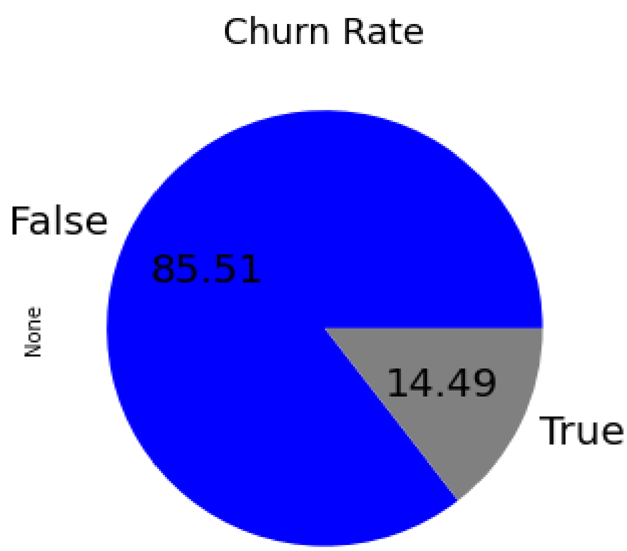
```
From the above we can conclude the database has no duplications in phone
numbers.
```

3 EDA- Analysis & Statistics

3.1 Churn Discovery

In [9]:
```
# Discover churn and vizualize it
customer_df['churn'].value_counts()

#chart
fig, ax = plt.subplots(figsize=(10,5))
customer_df.groupby('churn').size().plot(kind='pie', autopct='%.2f', text
ax.set_title('Churn Rate', fontsize=18)
```

Out[9]:
```
Text(0.5, 1.0, 'Churn Rate')
```



We see that there is and imbalance in the churn rate. with approx 86% False and 14% True (they churn). Let's look at some stats and the distributions of statistics in the database

3.1.1 Call and churn discovery

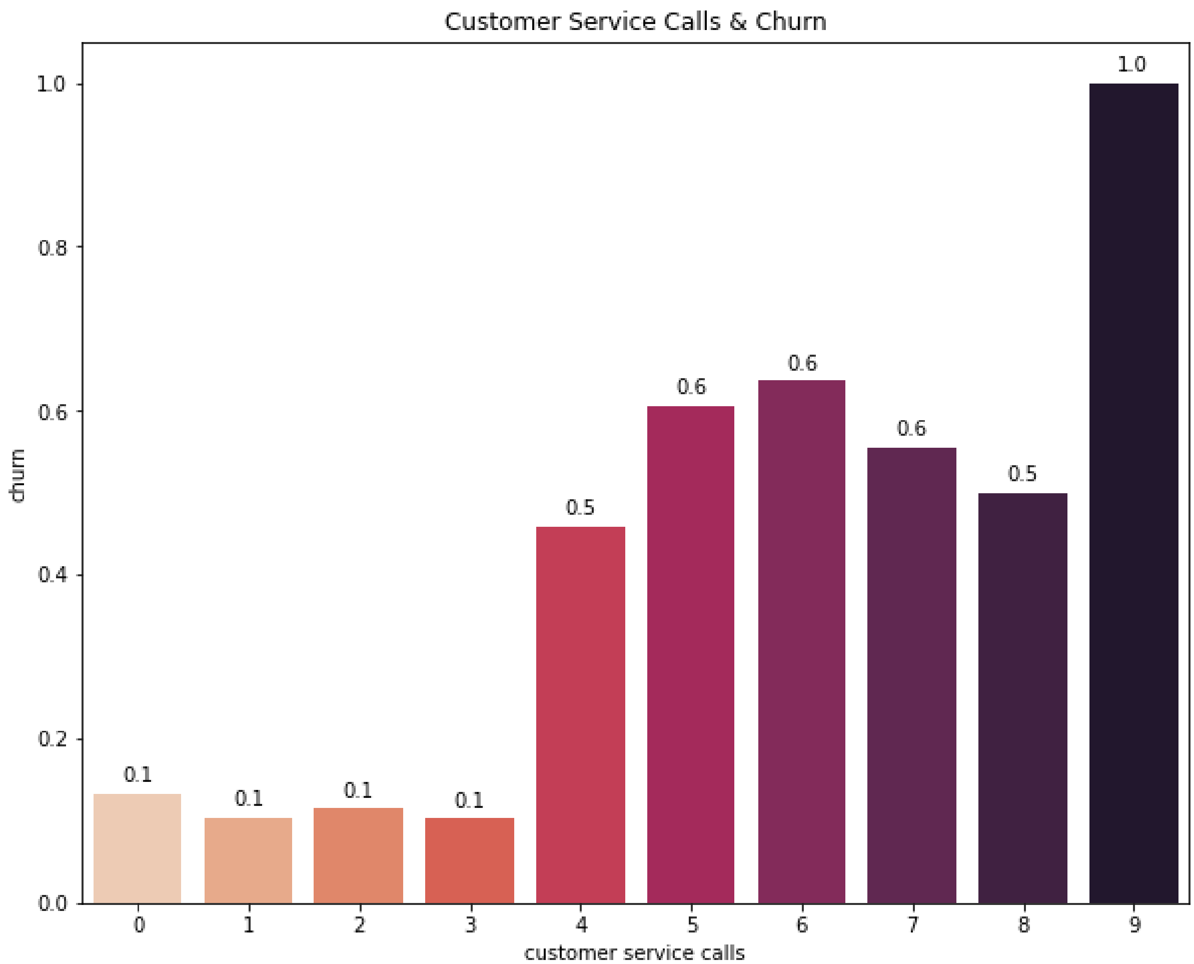
We can look at the number of calls that make at which point customers will churn.

In [20]:
```
churn_call = customer_df.groupby('customer service calls')['churn'].agg([
churn_call
```

Out[20]:

	count
customer service calls	
0	697
1	1181
2	759
3	429
4	166
5	66
6	22
7	9
8	2
9	2

In [24]:
```
plt.figure(figsize=(10, 8))
splot = sns.barplot(x='customer service calls', y='churn',
                    data=customer_df, palette='rocket_r', ci=None)
# Add annotations to bars
for p in splot.patches:
    splot.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
plt.title('Customer Service Calls & Churn')
plt.show()
```



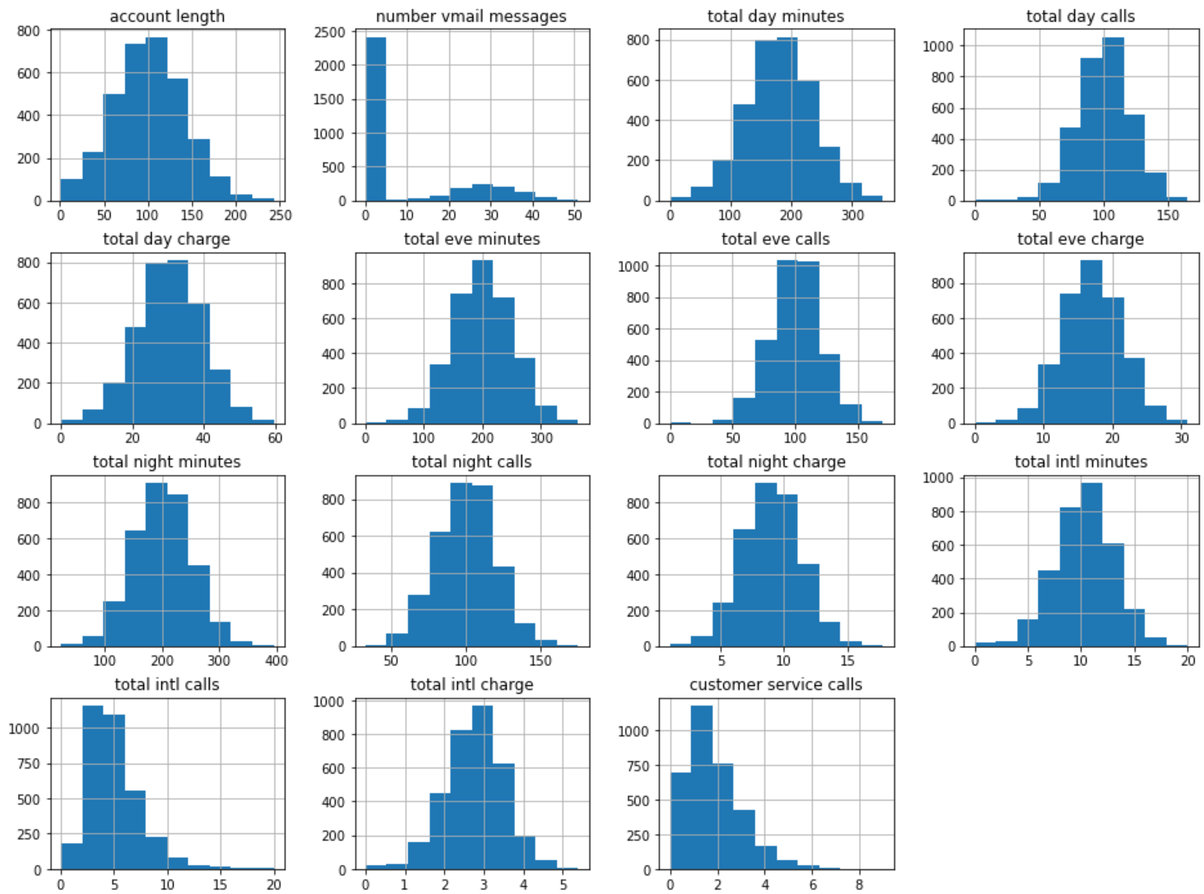
It takes about 4 calls, for customers to start churning, after that the probability of churning is above 50%

In [22]:
```
# summary of statistics
customer_df.describe()
```

Out[22]:

	account length	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total ev calls
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.00000
mean	101.064806	8.099010	179.775098	100.435644	30.562307	200.980348	100.11431
std	39.822106	13.688365	54.467389	20.069084	9.259435	50.713844	19.92262
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	74.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.00000
50%	101.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.00000
75%	127.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.00000
max	243.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.00000

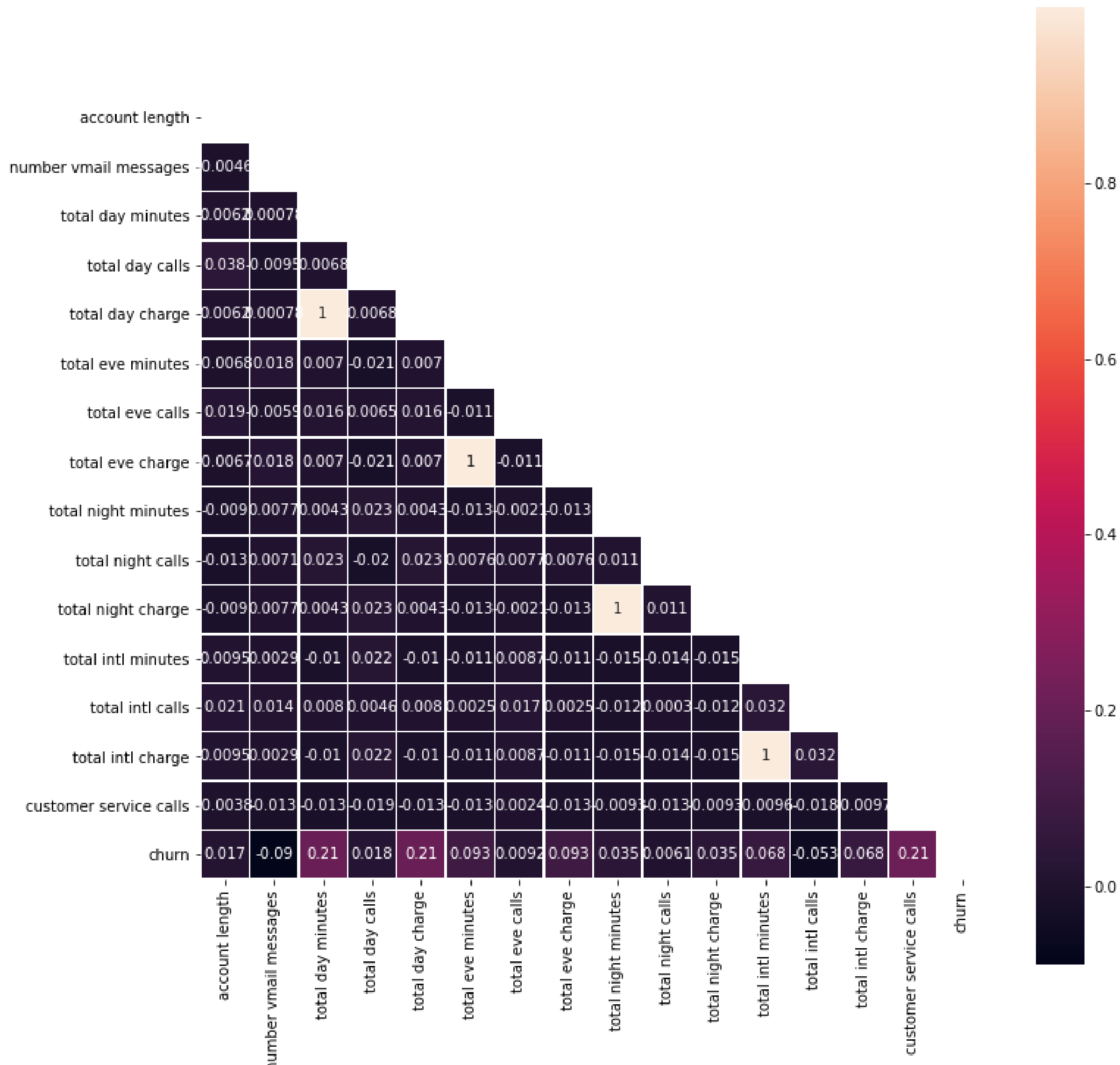
In [26]:
```
customer_df.drop(columns='churn').hist(figsize=(16,12));
```



While some distributions are normal approximately. Some are not and scaling and normalization are needed.

3.2 Multivariate Analysis

In [27]:
```
#Heatmap to show correlations
fig, ax = plt.subplots(figsize=(12,12))
multi = np.triu(np.ones_like(customer_df.corr(), dtype=bool))
sns.heatmap(customer_df.corr(), linewidths=0.5, mask=multi, square=True,
```



Noting from the heatmap above four main views:

1) Perfect Correlations spotted: a) total day charge & total day minutes b) total even charge & total eve minutes c) total night charge & total nights minutes d) total international charge & total int. minutes One correlated variable from each of these pairs will have to be dropped from each pair to handle multicollinearity issues.

2) Churn - Weak Positive Correlation with total day minutes, total day charge, and customer service calls have a weak positive correlation with churn.

3) Churn- almost 0 correlations with most of features with exception of point 2 above.

4) Most features have very lo correlations

4 Preparing Data for Machine Learning

4.0.1 Managing Multicolinearity

In [28]:
```
# .75 < multicolinearity pairs
df = customer_df.corr().abs().stack().reset_index().sort_values(0, ascend
df['pairs'] = list(zip(df.level_0, df.level_1))
df.set_index(['pairs'], inplace = True)
df.drop(columns=['level_1', 'level_0'], inplace = True)
df.columns = ['cc']
df.drop_duplicates(inplace=True)
df[(df.cc>.75) & (df.cc<1)]
```

Out[28]:

pairs	cc
(total day charge, total day minutes)	1.000000
(total eve charge, total eve minutes)	1.000000
(total night minutes, total night charge)	0.999999
(total intl charge, total intl minutes)	0.999993

In [29]:
```
# dropping a few columns to address collinearity
customer_df = customer_df.drop(columns = ['total day charge', 'total eve 
customer_df.columns
```

Out[29]:
```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', 'number vmail message
s',
       'total day minutes', 'total day calls', 'total eve minutes',
       'total eve calls', 'total night minutes', 'total night calls',
       'total intl minutes', 'total intl calls', 'customer service call
s',
       'churn'],
      dtype='object')
```

4.0.2 Performing a train-test split

In [30]:
```
#predictor and target variables
y= customer_df['churn']
X= customer_df.drop(columns= ['churn','phone number'])

#splitting data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
```

In [31]:
```
#view into X_train head
X_train.head()
```

Out[31]:

	state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total eve minutes	total eve calls	tot nig minut
1066	KS	117	510	no	yes	25	216.0	140	224.1	69	267
1553	CO	86	415	no	no	0	217.8	93	214.7	95	228
2628	TN	37	415	no	no	0	221.0	126	204.5	110	118
882	FL	130	415	no	no	0	162.8	113	290.3	111	114
984	NV	77	415	no	no	0	142.3	112	306.3	111	196

In [32]:
```
#Transforming categorial variables.Creating dummy variables for the categ
X_train= pd.get_dummies (X_train, drop_first= True)
X_test = pd.get_dummies (X_test, drop_first= True)
X_train.head(3)
```

Out[32]:

	account length	number vmail messages	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	total night calls	total intl minutes	total intl calls	...	state
1066	117	25	216.0	140	224.1	69	267.9	112	11.8	4	...	
1553	86	0	217.8	93	214.7	95	228.7	70	11.3	7	...	
2628	37	0	221.0	126	204.5	110	118.0	98	6.8	3	...	

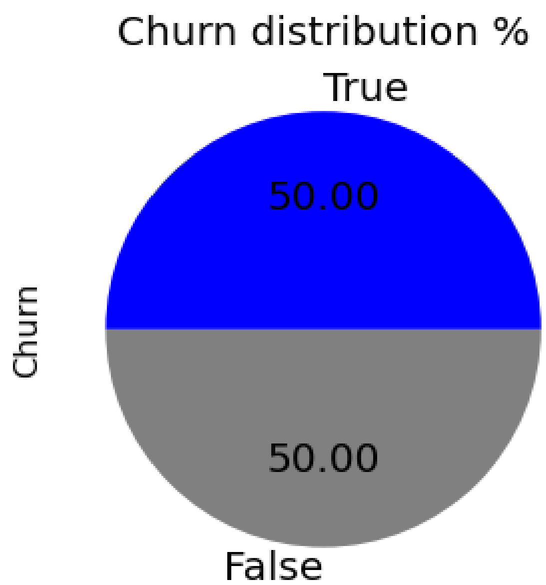
3 rows × 65 columns

4.0.3 SMOTE

SMOTE is used to handle classes imbalance. We are trying to have a 50/50 split on into our training data(unlike what is seen in our Churn discovery entire data set of 86%False-14%True) . Therefore resampling X_train and y_training sets, and fitting SMOTE to these training data.

In [33]:
```
#fitting SMOTE to training data.
smote= SMOTE(random_state=123)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_trai

#looking at the class distribution
print(pd.Series(y_train_resampled).value_counts())

#Visualize it
fig, ax = plt.subplots(figsize=(10, 5))
y_train_resampled.value_counts().plot(kind='pie', autopct='%.2f', textpro
ax.set_ylabel('Churn', fontsize=16)
ax.set_title('Churn distribution %', fontsize=20);
```

```
True     2127
False    2127
Name: churn, dtype: int64
```



In [ ]:

Training sets churn distribution is balanced. Now we can ensure we don't have oversampled or undersampled. I can move forward to modeling the data.

5 Modeling Data

5.0.1 Metric Choice (Precision, Recall, Accuracy)

Choosing to measure Recall as the most appropiate for this kind of problem. False Negatives will cost more than False Positives. Not capturing someone who churned, loosing them as a customer while paying a cost to acquire another customer to replace the lost customer is the highest challenge. If we identified someone as churned, when in fact they didn't and we do however pay to retain that False Positive would be less costly.

5.0.2 Baseline: Logistic Regression

Using 'liblinear', as solver.

In [34]:
```
#creating pipeline
pipe_log = Pipeline(steps=[('scale', StandardScaler()), ('logreg', Logist
pipe_log.fit(X_train_resampled, y_train_resampled)
```

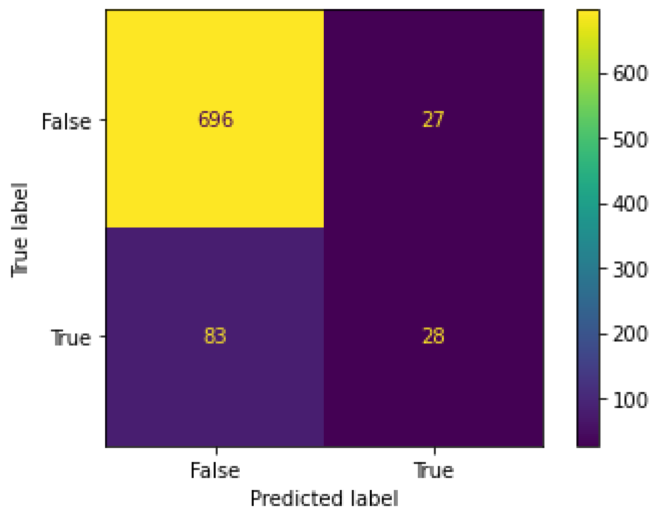
Out[34]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('logreg',
                 LogisticRegression(fit_intercept=False, solver='liblin
ear'))])
```

5.0.2.1 Confusion Matrix and Model Evaluation

In [35]:
```
#evaluating performance function & confusion matrix
def evaluate(model, X_test, y_test):
    y_train_preds = model.predict(X_train_resampled)
    y_test_preds = model.predict(X_test)
    print('Recall_score: ')
    print('Train: ', recall_score(y_train_resampled, y_train_preds))
    print('Test: ', recall_score(y_test, y_test_preds))
    print('\nPrecision_score: ')
    print('Train: ', precision_score(y_train_resampled, y_train_preds))
    print('Test: ', precision_score(y_test, y_test_preds))
    print('\nAccuracy_score: ')
    print('Train: ', accuracy_score(y_train_resampled, y_train_preds))
    print('Test: ', accuracy_score(y_test, y_test_preds))
    cm = confusion_matrix(y_test, y_test_preds, labels=model.classes_)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=mod
    disp.plot();
```

In [36]:
```
#passing the evaluation function
evaluate(pipe_log, X_test, y_test)
```

```
Recall_score:
Train:  0.8556652562294311
Test:  0.2522522522522523

Precision_score:
Train:  0.9494001043296818
Test:  0.509090909090909

Accuracy_score:
Train:  0.9050305594734368
Test:  0.86810551558753
```



There is a large number of false negatives, making the model perform poorly. The model is overfitting performing well on the training data but not on the test data. On test data there is good accuracy at 86%, but recall is extremely low at 25%.

5.1 Decision Tree Model

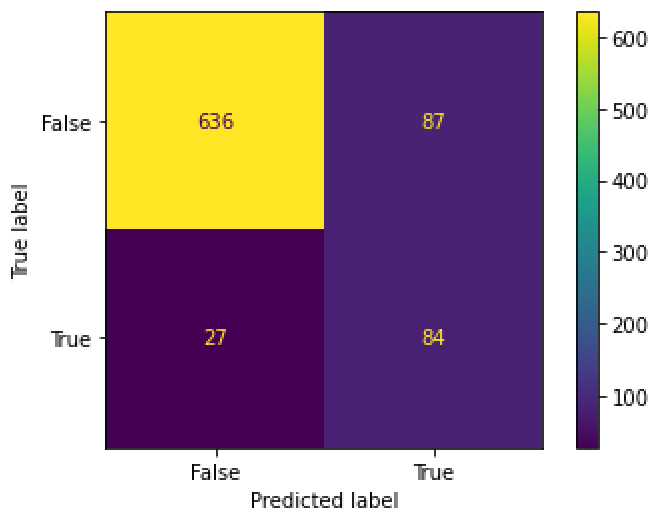
5.1.1 Importing library and scaling data

In [37]:
```
#Bringing Decision tree library from sklearn
from sklearn.tree import DecisionTreeClassifier
# Creating a pipeline
pipe_dt = Pipeline(steps=[('scale', StandardScaler()), ('clf', DecisionTr
pipe_dt.fit(X_train_resampled, y_train_resampled)
```

Out[37]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('clf',
                 DecisionTreeClassifier(criterion='entropy', random_sta
te=42))])
```

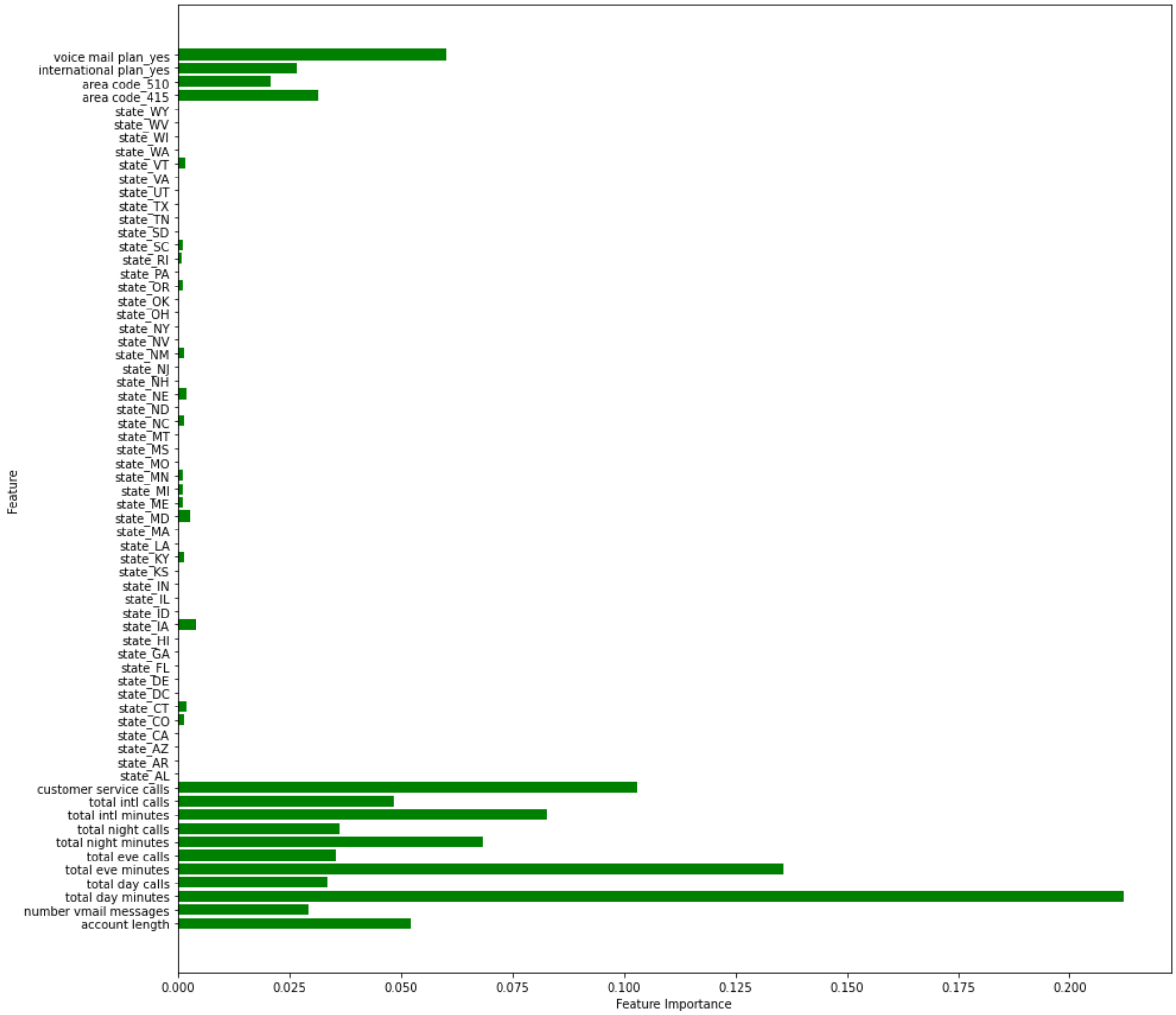
In [38]:
```
#evaluate the performance of the model
evaluate (pipe_dt, X_test, y_test)
```

```
Recall_score:
Train:  1.0
Test:  0.7567567567567568

Precision_score:
Train:  1.0
Test:  0.49122807017543857

Accuracy_score:
Train:  1.0
Test:  0.8633093525179856
```



Clearly the decision tree has a higher performance than the baseline. It is still however overfitting.

In [39]:
```
#Finding out the features that most affect the decision tree for Feature
def plot_feature_importances(pipe, figsize):
    model =pipe.steps[1][1]
    plt.figure(figsize=figsize)
    plt.barh(X_train_resampled.columns, model.feature_importances_, align
    plt.xlabel('Feature Importance')
    plt.ylabel('Feature')

plot_feature_importances(pipe_dt,(15,15))
```



Top 3 features affecting churn include: 1)total day minutes 2) total mins and 3) customer service calls

5.1.2 Recursive Feature

This feature along with cross-validation is used to seelct a subset of features used to build model

In [40]:
```
# feature selection using RFECV
rfecv = RFECV(estimator=DecisionTreeClassifier(random_state=42), scoring=
pipe_dt2 = Pipeline(steps=[('scale', StandardScaler()), ('Feature Selecti
pipe_dt2.fit(X_train_resampled, y_train_resampled)
```

Out[40]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('Feature Selection',
                 RFECV(estimator=DecisionTreeClassifier(random_state=4
2),
                       scoring='recall')),
                ('clf', DecisionTreeClassifier(random_state=42))])
```

In [41]:
```
# optimal number of features selected via cross-validation
print(f'Optimal # features: {rfecv.n_features_}' )
```

```
Optimal # features: 15
```

In [42]:
```
# selected features (assigned a rank of 1)
rfecv_df = pd.DataFrame(rfecv.ranking_,index=X_train_resampled.columns,co
rfecv_df[rfecv_df['Rank'] == 1]
```

Out[42]:

	Rank
account length	1
area code_510	1
area code_415	1
international plan_yes	1
customer service calls	1
total intl calls	1
total intl minutes	1
voice mail plan_yes	1
total night minutes	1
total eve calls	1
total eve minutes	1
number vmail messages	1
total day minutes	1
total day calls	1
total night calls	1

In [43]:
```
# remove columns that are not part of the optimal features
cols = rfecv_df[rfecv_df['Rank'] == 1].index
X_train_resampled = X_train_resampled[cols]
X_test = X_test[cols]
X_train_resampled.head(2)
```

Out[43]:

	account length	area code_510	area code_415	international plan_yes	customer service calls	total intl calls	total intl minutes	voice mail plan_yes	total night minutes	total eve calls
0	117	1	0	0	0	4	11.8	1	267.9	69
1	86	0	1	0	0	7	11.3	0	228.7	95

5.1.3 Hyperparameters testing in Decision Tree Model

In decision treee model the hyperparameters include max_depth, min_samples_leaf, min_sample_split, help the model be better tuned to stop the model from overfitting.

In [44]:
```
#Using Gridsearch for Hyperparameters
# hyperparameter tuning using GridSearchCV
params_dt = {'clf__criterion': ['gini', 'entropy'],
             'clf__max_depth': range(14, 32, 2),
             'clf__min_samples_split' : range(2, 10, 2),
             'clf__min_samples_leaf': [2, 3, 5, 7, 10],
             'clf__max_features': [11, 13, 15]
}

gridsearch_dt = GridSearchCV(pipe_dt, params_dt, cv=4, scoring='recall')
gridsearch_dt.fit(X_train_resampled, y_train_resampled)
```

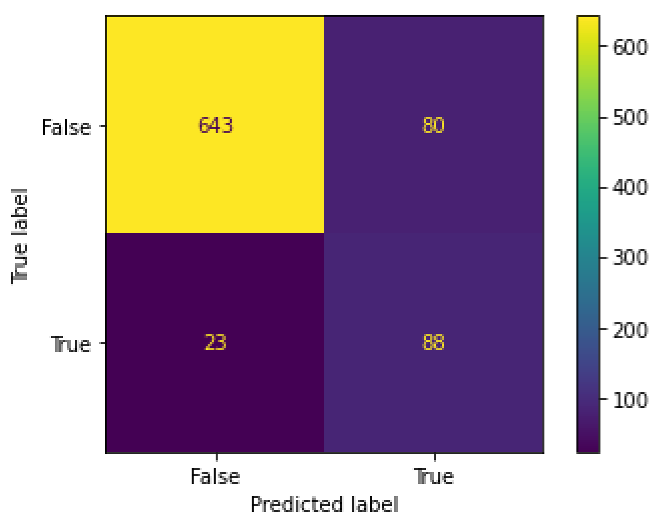
Out[44]:
```
GridSearchCV(cv=4,
             estimator=Pipeline(steps=[('scale', StandardScaler()),
                                       ('clf',
                                        DecisionTreeClassifier(criterio
n='entropy',
                                                               random_s
tate=42))]),
             param_grid={'clf__criterion': ['gini', 'entropy'],
                         'clf__max_depth': range(14, 32, 2),
                         'clf__max_features': [11, 13, 15],
                         'clf__min_samples_leaf': [2, 3, 5, 7, 10],
                         'clf__min_samples_split': range(2, 10, 2)},
             scoring='recall')
```

In [45]:
```
# parameters that gave the best result
print(f'Optimal parameters: {gridsearch_dt.best_params_}')

# Mean cross-validated score of the best_estimator
print(f'Validation recall: {gridsearch_dt.best_score_}')
```

```
Optimal parameters: {'clf__criterion': 'entropy', 'clf__max_depth': 28,
'clf__max_features': 15, 'clf__min_samples_leaf': 2, 'clf__min_samples_
split': 2}
Validation recall: 0.8725937371677781
```

In [46]:
```
# evaluate the performance of the model
evaluate(gridsearch_dt, X_test, y_test)
```

```
Recall_score:
Train:  0.9811941701927598
Test:  0.7927927927927928

Precision_score:
Train:  0.9971333014811276
Test:  0.5238095238095238

Accuracy_score:
Train:  0.9891866478608369
Test:  0.8764988009592326
```



As opposed to the Decision Tree with no hyperparameters, this model has performed much better on recall score. The train and test scores are closer related, and overfitting has been reduced.

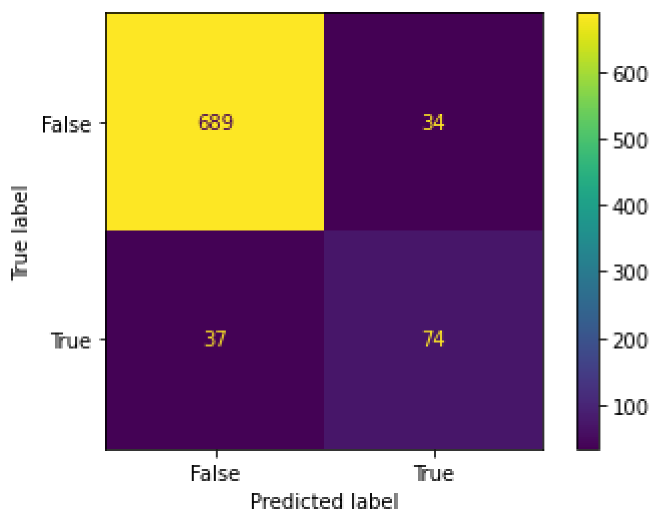
5.2 Random Forest Model

In [47]:
```
#creating a pipeline
pipe_rf= Pipeline(steps=[('scale', StandardScaler()), ('rf', RandomForest
pipe_rf.fit(X_train_resampled, y_train_resampled)
```

Out[47]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('rf', RandomForestClassifier(random_state=42))])
```

In [48]:
```
#evaluate model performance
evaluate(pipe_rf, X_test, y_test)
```

```
Recall_score:
Train:  1.0
Test:  0.6666666666666666

Precision_score:
Train:  1.0
Test:  0.6851851851851852

Accuracy_score:
Train:  1.0
Test:  0.9148681055155875
```



Random forest model has a recall score of 0.66. This is better than the baseline model of 0.25 recall on test data. However, in comparisson with Decision Tree Model with Hyperparameter recall of 0.79, it is not better.

5.2.1 Random Forest with Hyperparameters

In [49]:
```
# hyperparameter tuning using GridSearchCV
params_rf = {'rf__n_estimators': range(400, 800, 200),
             'rf__criterion': ['gini', 'entropy'],
             'rf__max_depth': range(14, 20, 2),
             'rf__min_samples_split': range(3, 4, 7),
             'rf__min_samples_leaf': [5, 7, 12]

}

gridsearch_rf = GridSearchCV(pipe_rf, params_rf, cv=4, scoring='recall')
gridsearch_rf.fit(X_train_resampled, y_train_resampled)
```

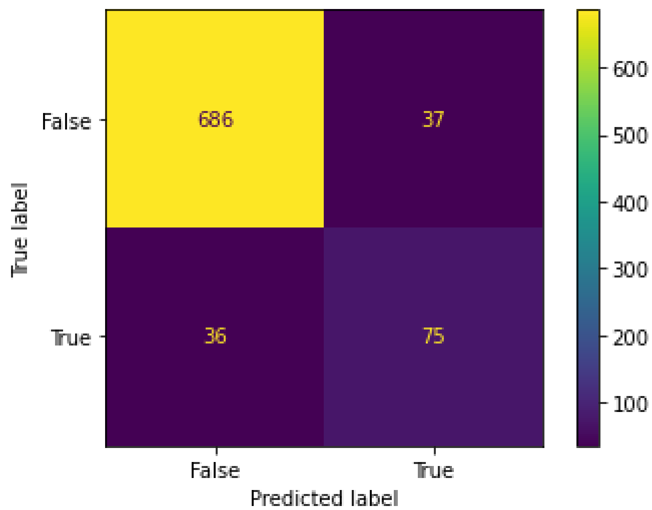
Out[49]:
```
GridSearchCV(cv=4,
             estimator=Pipeline(steps=[('scale', StandardScaler()),
                                       ('rf',
                                        RandomForestClassifier(random_s
tate=42))]),
             param_grid={'rf__criterion': ['gini', 'entropy'],
                         'rf__max_depth': range(14, 20, 2),
                         'rf__min_samples_leaf': [5, 7, 12],
                         'rf__min_samples_split': range(3, 4, 7),
                         'rf__n_estimators': range(400, 800, 200)},
             scoring='recall')
```

In [50]:
```
# parameters that gave the best result
print(f'Optimal parameters: {gridsearch_rf.best_params_}')

# Mean cross-validated score of the best_estimator
print(f'Validation recall: {gridsearch_rf.best_score_}')
```

```
Optimal parameters: {'rf__criterion': 'entropy', 'rf__max_depth': 18,
'rf__min_samples_leaf': 5, 'rf__min_samples_split': 3, 'rf__n_estimator
s': 600}
Validation recall: 0.8702494229925095
```

In [51]:
```
#evaluating the performance
evaluate(gridsearch_rf, X_test, y_test)
```

```
Recall_score:
Train:  0.9619181946403385
Test:  0.6756756756756757

Precision_score:
Train:  0.9898403483309144
Test:  0.6696428571428571

Accuracy_score:
Train:  0.9760225669957687
Test:  0.9124700239808153
```



5.3 Model Finalization

The best model is the Decision Tree with Hyperparameters. This model has the highest recall scores in summary:

Recall scores: Test: 0.7927927927927928

Precision score: Test: 0.5238095238095238

Accuracy score: Test: 0.8764988009592326

Correctly identify a negative 80% of time. /100 , 80 of them identify and mis-identify 20%

6 Business Recommendations & Conclusions

According to our analysis, the most important features in predicting churn are :

1.The total number of minutes that the customer has done during the day

2.The total number of evenining minutes

4.The number of customer calls to customer service

3.The total international minutes in international calls

For Syria tel, customer srvice is a key differentiatior. Syria tel should focus on training programs to enhance this features that mostly need to reduce the number of minutes spent by a customer on the phone. Therefore effective communication training to customer service representatives is a key success factor. When a customer spends or makes 3 or more phone calls to customer service, this is an indication of higher churn. So providing customer incentives provided at the third call will be a recommendation.

6.0.1 Modeling- next steps recommendations & conclusions

The best performing model at a targeted level of 85% is not achieved by best model. There is still some overfitting. An increase in the training data set should reduce the overfitting and improve performance.