# Syria Tel Customers

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## Overview

Syria Tel is a communications company. A company can expect a certain amount of turnover in custumers. I examined the percentage of turnover and looked at reasons for why a customer may leave.

## Business Problem

It can be more expensive to get new clients versus retaining current clients. The question is what makes a customer leave. Can we predict when a customer is considering changing phone services? What incentive can we give to make them reconsider?

## Data Understanding

The data has been collected from Kaggle. The dataset has the information from 3,333 customers. The dataset has information on the length of account, types of plans, minutes charged, and if they terminated the service.

In [1]:

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

import sklearn.preprocessing as preprocessing
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split


from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline
from sklearn import tree
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, recal
l_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
from sklearn.model_selection import GridSearchCV, cross_val_score
from xgboost import XGBClassifier

np.random.seed(0)

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:

```
pip install -U imbalanced-learn
```

```
Requirement already up-to-date: imbalanced-learn in c:\users\bkcoleman1024\an
aconda3\lib\site-packages (0.8.0)
Requirement already satisfied, skipping upgrade: numpy>=1.13.3 in c:\users\bk
coleman1024\anaconda3\lib\site-packages (from imbalanced-learn) (1.18.5)
Requirement already satisfied, skipping upgrade: scikit-learn>=0.24 in c:\use
rs\bkcoleman1024\anaconda3\lib\site-packages (from imbalanced-learn) (0.24.2)
Requirement already satisfied, skipping upgrade: joblib>=0.11 in c:\users\bkc
oleman1024\anaconda3\lib\site-packages (from imbalanced-learn) (0.16.0)
Requirement already satisfied, skipping upgrade: scipy>=0.19.1 in c:\users\bk
coleman1024\anaconda3\lib\site-packages (from imbalanced-learn) (1.5.0)
Requirement already satisfied, skipping upgrade: threadpoolctl>=2.0.0 in c:\u
sers\bkcoleman1024\anaconda3\lib\site-packages (from scikit-learn>=0.24->imba
lanced-learn) (2.1.0)
Note: you may need to restart the kernel to use updated packages.
```

In [3]:

```
conda install -c conda-forge imbalanced-learn
```

```
Collecting package metadata (current_repodata.json): ...working... done
Solving environment: ...working... done

# All requested packages already installed.


Note: you may need to restart the kernel to use updated packages.
```

In [4]:

```
from imblearn.over_sampling import SMOTE, ADASYN
```

In [5]:

```
telecom = pd.read_csv('telecom.csv')
telecom.head()
```

Out[5]:

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

5 rows × 21 columns

In [6]:

```
telecom.describe()
```

Out[6]:

| | account length | area code | number vmail messages | total day minutes | total day calls | total day charge | total e minut |
|---|---|---|---|---|---|---|---|
| **count** | 3333.000000 | 3333.000000 | 3333.000000 | 3333.000000 | 3333.000000 | 3333.000000 | 3333.000( |
| **mean** | 101.064806 | 437.182418 | 8.099010 | 179.775098 | 100.435644 | 30.562307 | 200.9803 |
| **std** | 39.822106 | 42.371290 | 13.688365 | 54.467389 | 20.069084 | 9.259435 | 50.7138 |
| **min** | 1.000000 | 408.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000( |
| **25%** | 74.000000 | 408.000000 | 0.000000 | 143.700000 | 87.000000 | 24.430000 | 166.600( |
| **50%** | 101.000000 | 415.000000 | 0.000000 | 179.400000 | 101.000000 | 30.500000 | 201.400( |
| **75%** | 127.000000 | 510.000000 | 20.000000 | 216.400000 | 114.000000 | 36.790000 | 235.300( |
| **max** | 243.000000 | 510.000000 | 51.000000 | 350.800000 | 165.000000 | 59.640000 | 363.700( |

In [7]:

```
telecom.shape
```

Out[7]:

```
(3333, 21)
```

In [8]:

```
telecom.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 [9]:

```
#Reformat column names

telecom.columns = [x.lower().replace(' ', '_') for x in telecom.columns]
telecom.head()
```

Out[9]:

| | state | account_length | area_code | phone_number | international_plan | voice_mail_plan | number |
|---|---|---|---|---|---|---|---|
| **0** | KS | 128 | 415 | 382-4657 | no | yes | |
| **1** | OH | 107 | 415 | 371-7191 | no | yes | |
| **2** | NJ | 137 | 415 | 358-1921 | no | no | |
| **3** | OH | 84 | 408 | 375-9999 | yes | no | |
| **4** | OK | 75 | 415 | 330-6626 | yes | no | |

5 rows × 21 columns

In [10]:

```
telecom['churn'].unique()
```

Out[10]:

```
array([False,  True])
```

In [11]:

```
#Number of true and false values in churn

telecom['churn'].value_counts()
```

Out[11]:

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

Out of the 3333 customers 14.49% decided to leave Syria. How can we reduce this turn over rate? Why did these customers decide to leave? What can we do to make them stay? What is the potential cost to get them to stay versus trying to get new customers?

In [12]:

```
#Checking the number of unique area codes

telecom["area_code"].value_counts()
```

Out[12]:

```
415    1655
510     840
408     838
Name: area_code, dtype: int64
```

In [13]:

```
#Broken down by area codes.

print(telecom.groupby(['area_code'])['churn'].mean())
```

```
area_code
408    0.145585
415    0.142598
510    0.148810
Name: churn, dtype: float64
```

Only three area codes are present in this data set.

The phone numbers and area codes won't matter and so I am removing them. I am also removing the states.

In [14]:

```
telecom.drop(columns = 'phone_number', axis=1, inplace = True)
telecom.drop(columns = 'area_code', axis=1, inplace = True)
telecom.drop(columns = 'state', axis=1, inplace = True)
telecom.head()
```

Out[14]:

| | account_length | international_plan | voice_mail_plan | number_vmail_messages | total_day_minute |
|---|---|---|---|---|---|
| **0** | 128 | no | yes | 25 | 265. |
| **1** | 107 | no | yes | 26 | 161. |
| **2** | 137 | no | no | 0 | 243. |
| **3** | 84 | yes | no | 0 | 299. |
| **4** | 75 | yes | no | 0 | 166. |

As I cleaning and examing the data, I am looking closer at the customer service calls.

In [15]:

```
#How many unique values for customer service calls

telecom['customer_service_calls'].value_counts()
```

Out[15]:

```
1    1181
2     759
0     697
3     429
4     166
5      66
6      22
7       9
9       2
8       2
Name: customer_service_calls, dtype: int64
```

In [16]:

```
print(telecom.groupby(['customer_service_calls'])['churn'].mean())
```

```
customer_service_calls
0    0.131994
1    0.103302
2    0.114625
3    0.102564
4    0.457831
5    0.606061
6    0.636364
7    0.555556
8    0.500000
9    1.000000
Name: churn, dtype: float64
```

In [17]:

```
# Change international and voicemail columns to integers

telecom.international_plan.replace(('yes', 'no'), (1,0), inplace = True)
telecom.voice_mail_plan.replace(('yes', 'no'), (1,0), inplace = True)
telecom.head()
```

Out[17]:

| | account_length | international_plan | voice_mail_plan | number_vmail_messages | total_day_minute |
|---|---|---|---|---|---|
| **0** | 128 | 0 | 1 | 25 | 265. |
| **1** | 107 | 0 | 1 | 26 | 161. |
| **2** | 137 | 0 | 0 | 0 | 243. |
| **3** | 84 | 1 | 0 | 0 | 299. |
| **4** | 75 | 1 | 0 | 0 | 166. |

In [18]:

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

In [19]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .25, random_state=42
)
```

# Imbalance

There is an imbalance in our data. If I was to run models without adjusting for this. I will use SMOTE

In [20]:

```
# Previous original class distribution
print('Original class distribution: \n')
print(y.value_counts())
X, y = SMOTE().fit_resample(X, y)
X_train_resampled, y_train_resampled = SMOTE().fit_resample(X_train, y_train)
# Preview synthetic sample class distribution
print('----------------------------------------')
print('Synthetic sample class distribution: \n')
print(pd.Series(y_train_resampled).value_counts())
```

```
Original class distribution:

False    2850
True      483
Name: churn, dtype: int64
----------------------------------------
Synthetic sample class distribution:

True     2141
False    2141
Name: churn, dtype: int64
```

In [21]:

```
telecom.corr()
```

Out[21]:

| | account_length | international_plan | voice_mail_plan | number_vmail_mess |
|---|---|---|---|---|
| **account_length** | 1.000000 | 0.024735 | 0.002918 | -0.0( |
| **international_plan** | 0.024735 | 1.000000 | 0.006006 | 0.0( |
| **voice_mail_plan** | 0.002918 | 0.006006 | 1.000000 | 0.9( |
| **number_vmail_messages** | -0.004628 | 0.008745 | 0.956927 | 1.0( |
| **total_day_minutes** | 0.006216 | 0.049396 | -0.001684 | 0.0( |
| **total_day_calls** | 0.038470 | 0.003755 | -0.011086 | -0.0( |
| **total_day_charge** | 0.006214 | 0.049398 | -0.001686 | 0.0( |
| **total_eve_minutes** | -0.006757 | 0.019100 | 0.021545 | 0.01 |
| **total_eve_calls** | 0.019260 | 0.006114 | -0.006444 | -0.0( |
| **total_eve_charge** | -0.006745 | 0.019106 | 0.021559 | 0.01 |
| **total_night_minutes** | -0.008955 | -0.028905 | 0.006079 | 0.0( |
| **total_night_calls** | -0.013176 | 0.012451 | 0.015553 | 0.0( |
| **total_night_charge** | -0.008960 | -0.028913 | 0.006064 | 0.0( |
| **total_intl_minutes** | 0.009514 | 0.045871 | -0.001318 | 0.0( |
| **total_intl_calls** | 0.020661 | 0.017366 | 0.007618 | 0.01 |
| **total_intl_charge** | 0.009546 | 0.045780 | -0.001276 | 0.0( |
| **customer_service_calls** | -0.003796 | -0.024522 | -0.017824 | -0.01 |
| **churn** | 0.016541 | 0.259852 | -0.102148 | -0.0( |

In [22]:

```
def model(model, X, y):
    model = model
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.25, random_state=
42)

    # Predict on training and test sets
    training_preds = model.predict(X_train)
    test_preds = model.predict(X_test)



    print(model.fit(X_train, y_train))


    print(f"Training recall score: {recall_score(y_train, model.predict(X_train))}")
    print(f"Test recall score: {recall_score(y_test, model.predict(X_test))}")

    print(f"Cross val Score train:  {cross_val_score(model, X_train, y_train, cv=5, scorin
g='recall')}")
    print(f"Cross val Score test:  {cross_val_score(model, X_test, y_test, cv=5, scoring=
'recall')}")

    print(f"Train: {confusion_matrix(y_train, model.predict(X_train))}")
    print(f"Test: {confusion_matrix(y_test, model.predict(X_test))}")
```

In [35]:

```
# Instantiate and fit a DecisionTreeClassifier
tree_clf = DecisionTreeClassifier(criterion='gini', max_depth=5, random_state=42)
tree_clf.fit(X_train_resampled, y_train_resampled)
```

Out[35]:

```
DecisionTreeClassifier(max_depth=5, random_state=42)
```

In [36]:

```
model(tree_clf, X, y)
```

```
DecisionTreeClassifier(max_depth=5, random_state=42)
Training recall score: 0.6934812760055479
Test recall score: 0.7132459970887919
Cross val Score train:  [0.68981481 0.71759259 0.67898383 0.6812933  0.713625
87]
Cross val Score test:  [0.72992701 0.67883212 0.73722628 0.66666667 0.7101449
3]
Train: [[2036   76]
 [ 663 1500]]
Test: [[702  36]
 [197 490]]
```

In [25]:

```
# Feature importance
tree_clf.feature_importances_
```

Out[25]:

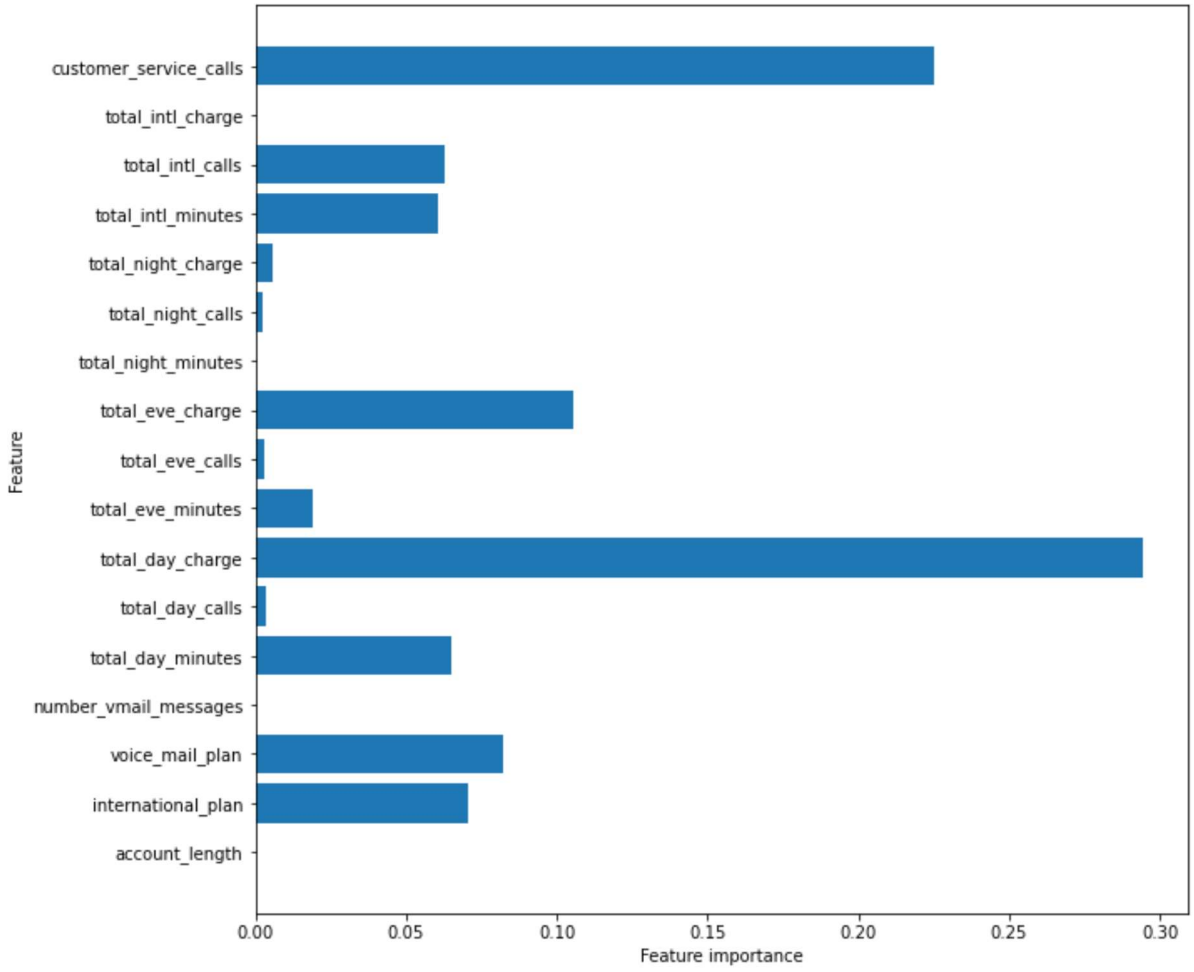
```
array([0.        , 0.07077169, 0.08211828, 0.        , 0.06481112,
       0.00334387, 0.29433311, 0.01921658, 0.00291866, 0.10550907,
       0.        , 0.00272125, 0.00587812, 0.06060958, 0.06275842,
       0.        , 0.22501026])
```

In [26]:

```
def plot_feature_importances(model):
    n_features = X_train.shape[1]
    plt.figure(figsize=(10,10))
    plt.barh(range(n_features), model.feature_importances_, align='center')
    plt.yticks(np.arange(n_features), X_train.columns.values)
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')
```

In [27]:

```
plot_feature_importances(tree_clf)
```



From this chart the following features are th

In [28]:

```
# Instantiate a BaggingClassifier
bagged_tree =  BaggingClassifier(DecisionTreeClassifier(criterion='gini', max_depth=5),
                                 n_estimators=20)
bagged_tree.fit(X_train, y_train)
```

Out[28]:

```
BaggingClassifier(base_estimator=DecisionTreeClassifier(max_depth=5),
                  n_estimators=20)
```

In [29]:

```
model(bagged_tree, X, y)
```

```
BaggingClassifier(base_estimator=DecisionTreeClassifier(max_depth=5),
                  n_estimators=20)
Training recall score: 0.7179842810910773
Test recall score: 0.7365356622998545
Cross val Score train:  [0.69675926 0.72916667 0.69053118 0.70438799 0.715935
33]
Cross val Score test:  [0.70072993 0.71532847 0.73722628 0.72463768 0.7391304
3]
Train: [[2025   87]
 [ 610 1553]]
Test: [[698  40]
 [181 506]]
```

In [31]:

```
# Instantiate and fit a RandomForestClassifier
forest = RandomForestClassifier(n_estimators=100, max_depth= 5)
forest.fit(X_train, y_train)
```

Out[31]:

```
RandomForestClassifier(max_depth=5)
```

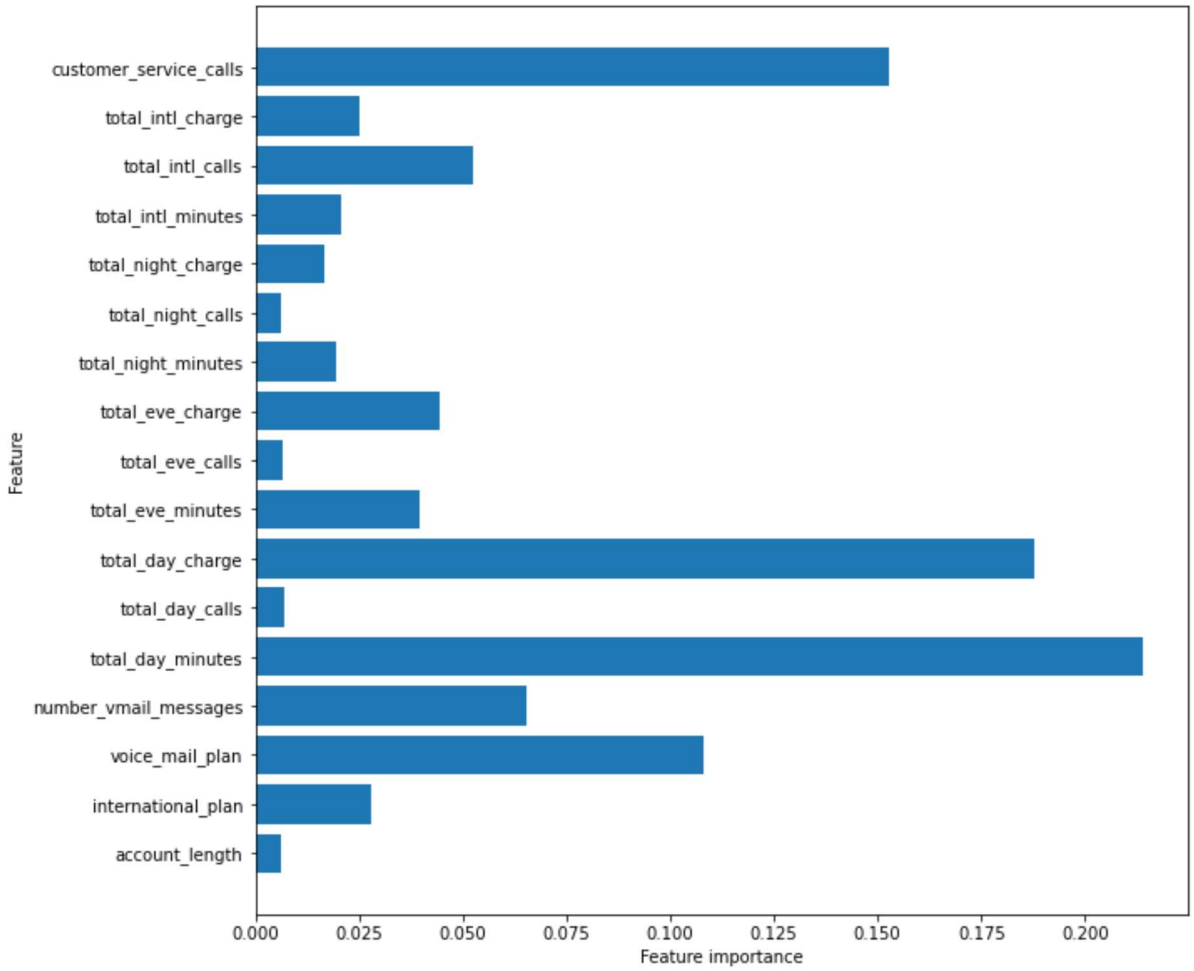
In [32]:

```
model(forest, X, y)
```

```
RandomForestClassifier(max_depth=5)
Training recall score: 0.7484974572353214
Test recall score: 0.7510917030567685
Cross val Score train:  [0.7337963  0.75694444 0.70900693 0.77367206 0.748267
9 ]
Cross val Score test:  [0.71532847 0.72262774 0.67153285 0.72463768 0.7463768
1]
Train: [[1986  126]
 [ 544 1619]]
Test: [[680  58]
 [171 516]]
```

In [33]:

```
plot_feature_importances(forest)
```




Based on this customer service calls, day charges, day minutes, and an international plan have an impact on whether a customer leaves.

Based on the results of this model, there seems to be an overfit.