Kulle Omer

Phase 3 Project

Self-Paced

SyriaTel Customer Churn

We will be assisting SyriaTel in determining why customers are churning. We will use the data science process of OSEMN which is obtaining the data, scrubbing the data, exploring it, modeling it, and finally interpreting it. This will allow SyriaTel to recognize their customers who are unsatisfied in leaving and give them an opportunity to explore ways to keep them. This is a binary classification since we are determining if a customer stays or leaves SyriaTel.

Obtain Data

In [1]:
```
#importing libraries
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

#Preprocessing
import sklearn
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncode
from sklearn.compose import ColumnTransformer

# Modeling
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
from sklearn.dummy import DummyClassifier
from sklearn.model_selection import train_test_split, cross_val_score, Grid
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier

#Metrics
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score, recall_score, accuracy_score,
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv("file:///Users/kulleomer/Downloads/bigml_59c28831336c6604c
```

Data Cleaning

In [3]:
```
df.info() #creating dataset
```

```
<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 [4]:
```
df.head() #taking a look at it
```

Out[4]:

	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
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

5 rows × 21 columns

In [5]:
```
df.isna().sum() #looking for null values
```

Out[5]:
```
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 [6]:
```
df['churn'] = df['churn'].astype(int) #changing churn values to 0/1
df.head()
```

Out[6]:

	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
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

5 rows × 21 columns

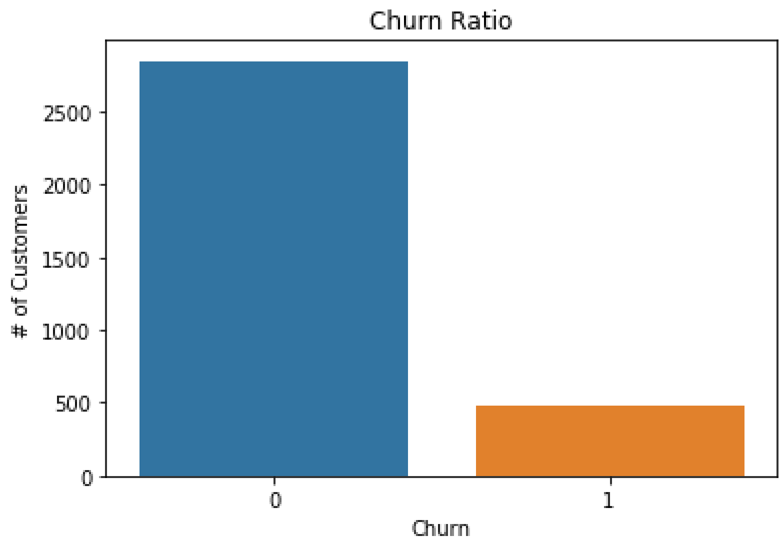
We see that there aren't any null values, however there are some categorical columns that we must convert to numerical down the line. Looks good overall.

Exploratory Data

In [7]:
```
df['churn'].value_counts() #looking at churn values
```

Out[7]:
```
0    2850
1     483
Name: churn, dtype: int64
```

In [8]:
```
sns.countplot(x = 'churn', data = df)
plt.title('Churn Ratio')
plt.xlabel('Churn')
plt.ylabel('# of Customers')
plt.savefig("Ratio of Churn")
```

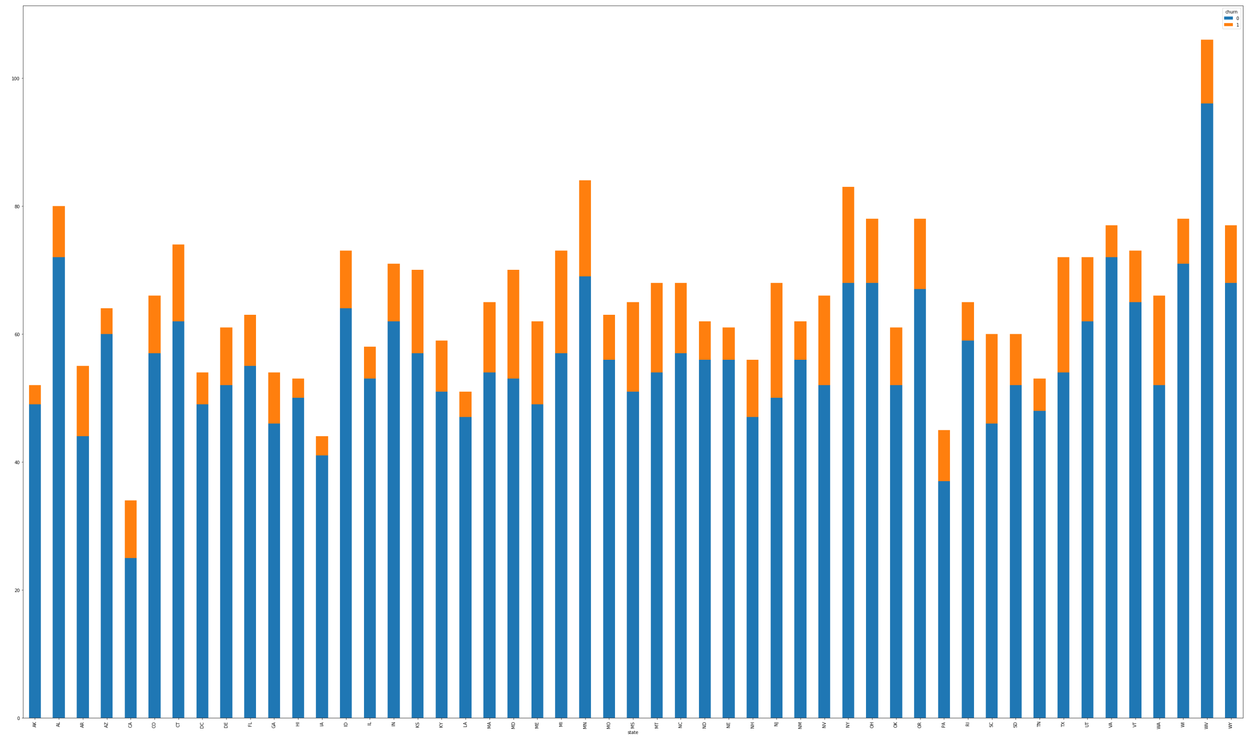


In [9]:
```
Percent_churn = 483/(2850+483)
print(Percent_churn) #percentage of customers churning
```

```
0.14491449144914492
```

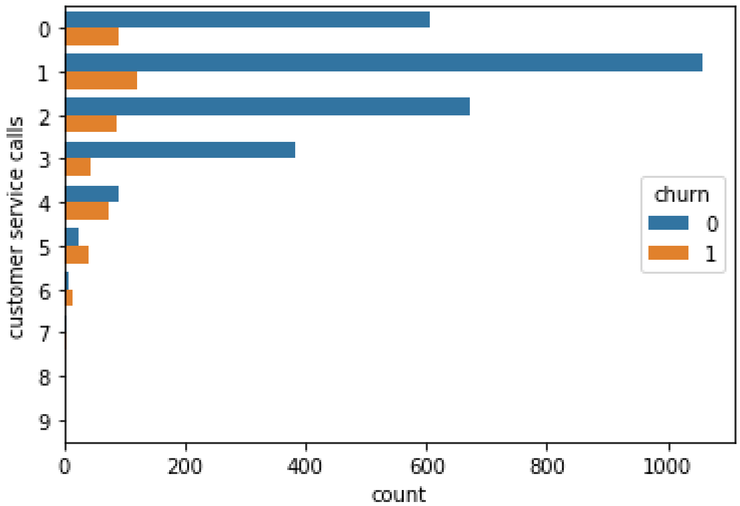
In [10]:
```
"churn"]).size().unstack().plot(kind='bar', stacked=True, figsize=(50,30))
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1b1b55efd0>



In [11]:
```
sns.countplot(y='customer service calls', hue='churn', data=df)
```

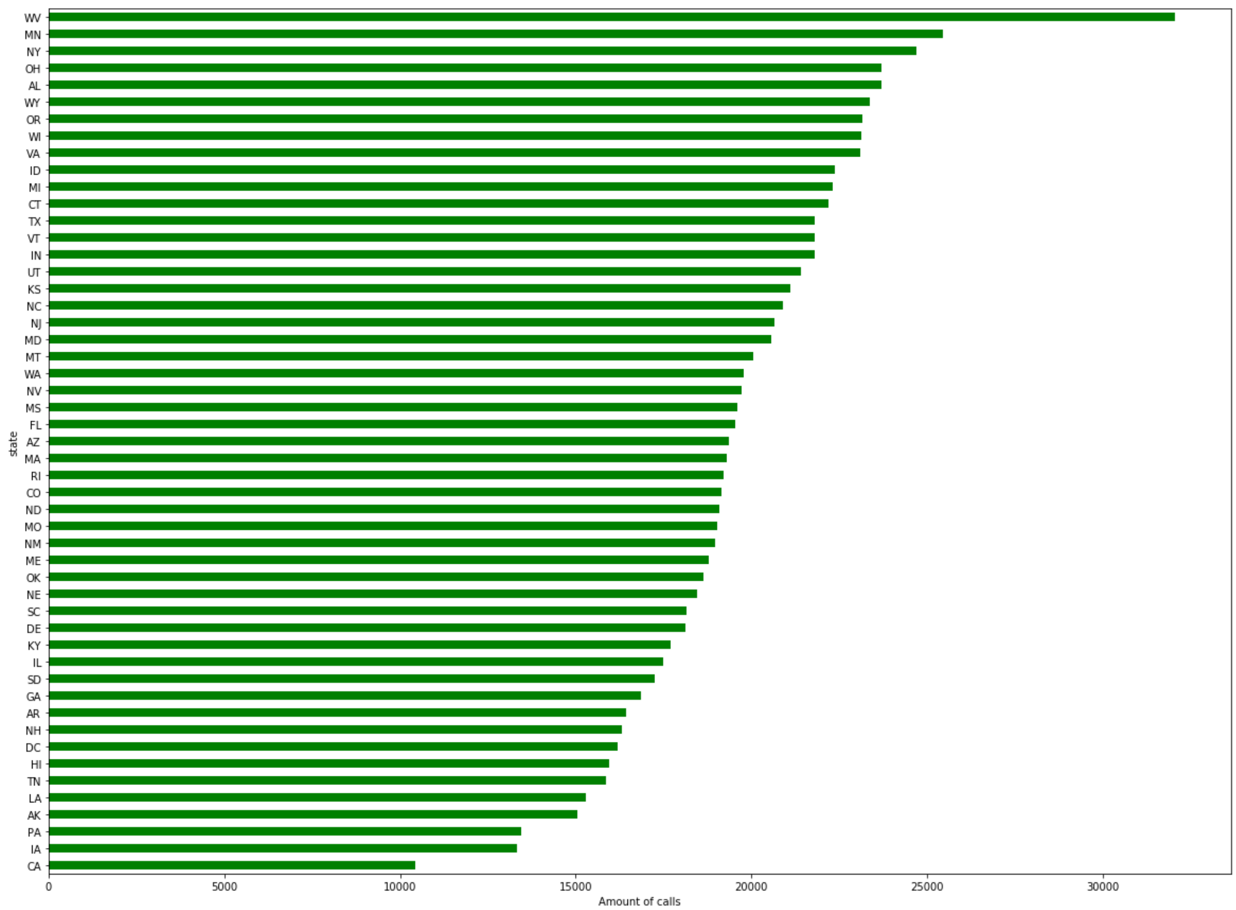
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x103e0fcd0>



In [12]:
```
f['all calls'] = df['total day calls'] + df['total eve calls'] + df['total r
tate_calls = df.groupby('state')['all calls'].sum().sort_values()
rint('State with the minimum amount of calls:\n', state_calls[state_calls ==
rint('State with the maximum amount of calls:\n', state_calls[state_calls ==
lt.xlabel('Amount of calls')
lt.ylabel('State')
tate_calls.plot(kind='barh', x='Amount of calls', y='State', figsize=(20, 15
```

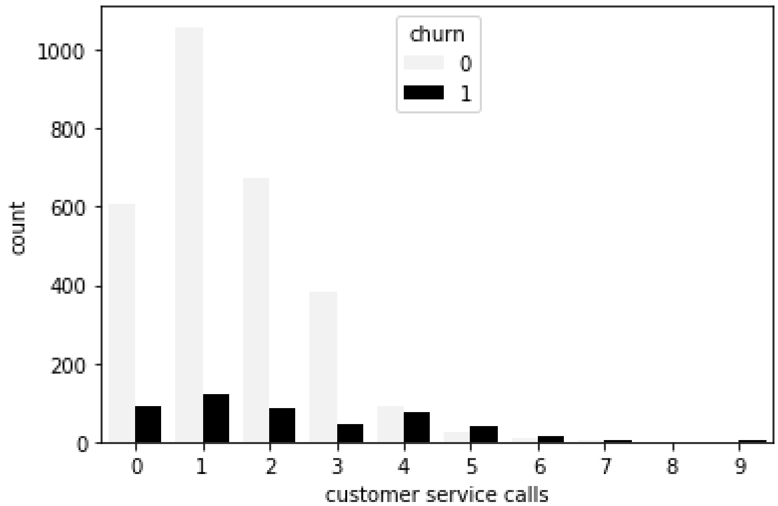
```
State with the minimum amount of calls:
state
CA    10431
Name: all calls, dtype: int64
State with the maximum amount of calls:
state
WV    32055
Name: all calls, dtype: int64
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x1b1e7482d0>



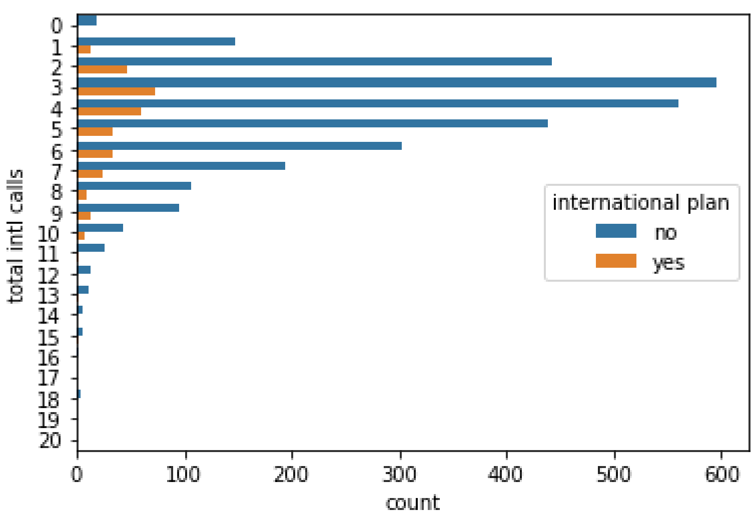
In [13]:
```
sns.countplot(x='customer service calls', hue='churn', data=df, color = 'bla
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x1b1a0e1d50>



In [14]:
```
sns.countplot(y='total intl calls', hue='international plan', data=df)
```

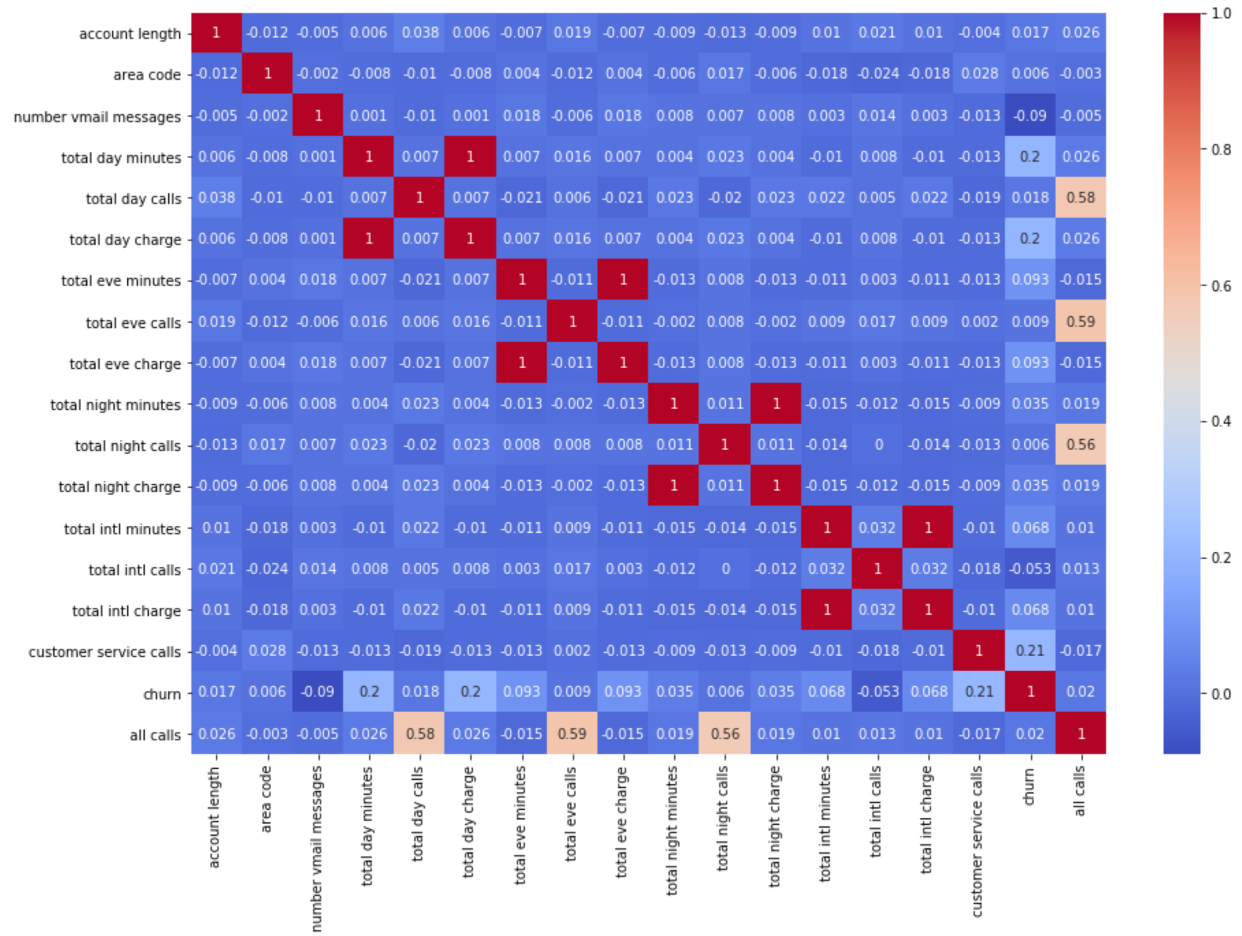
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x1b1a1b5d10>



Our exploratory data gives us a bit of insight of the data. We see that 14% of the customers are churning, and that there is a class imbalance between those churning and not churning. While modeling, SMOTE would probably be a useful tool to fix this.

Preparing for modeling

In [15]:
```
cor = df.corr()
plt.figure(figsize=(15,10))
sns.heatmap(cor.round(3),annot=True,cmap='coolwarm')
plt.show()
df.corr()
#analyzing correlating values
```



Out[15]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls
account length	1.000000	-0.012463	-0.004628	0.006216	0.038470	0.006214	-0.006757	0.019260
area code	-0.012463	1.000000	-0.001994	-0.008264	-0.009646	-0.008264	0.003580	-0.011886
number vmail messages	-0.004628	-0.001994	1.000000	0.000778	-0.009548	0.000776	0.017562	-0.005864
total day minutes	0.006216	-0.008264	0.000778	1.000000	0.006750	1.000000	0.007043	0.015769

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls
total day calls	0.038470	-0.009646	-0.009548	0.006750	1.000000	0.006753	-0.021451	0.006462
total day charge	0.006214	-0.008264	0.000776	1.000000	0.006753	1.000000	0.007050	0.015769
total eve minutes	-0.006757	0.003580	0.017562	0.007043	-0.021451	0.007050	1.000000	-0.011430
total eve calls	0.019260	-0.011886	-0.005864	0.015769	0.006462	0.015769	-0.011430	1.000000
total eve charge	-0.006745	0.003607	0.017578	0.007029	-0.021449	0.007036	1.000000	-0.011423
total night minutes	-0.008955	-0.005825	0.007681	0.004323	0.022938	0.004324	-0.012584	-0.002093
total night calls	-0.013176	0.016522	0.007123	0.022972	-0.019557	0.022972	0.007586	0.007710
total night charge	-0.008960	-0.005845	0.007663	0.004300	0.022927	0.004301	-0.012593	-0.002056
total intl minutes	0.009514	-0.018288	0.002856	-0.010155	0.021565	-0.010157	-0.011035	0.008703
total intl calls	0.020661	-0.024179	0.013957	0.008033	0.004574	0.008032	0.002541	0.017434
total intl charge	0.009546	-0.018395	0.002884	-0.010092	0.021666	-0.010094	-0.011067	0.008674
customer service calls	-0.003796	0.027572	-0.013263	-0.013423	-0.018942	-0.013427	-0.012985	0.002423
churn	0.016541	0.006174	-0.089728	0.205151	0.018459	0.205151	0.092796	0.009233
all calls	0.026157	-0.003119	-0.004925	0.026193	0.577225	0.026195	-0.014850	0.588530

The features that have good correlation with churn are total day charge, customer service calls, total day charge/day plan. We will find out more using machine learning methods.

In [16]:
```
df.dtypes
```

Out[16]:
```
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                        int64
all calls                    int64
dtype: object
```

In [17]:
```
corr_matrix = df.corr()
corr_matrix['churn'].sort_values(ascending=False)
```

Out[17]:
```
churn                     1.000000
customer service calls    0.208750
total day minutes         0.205151
total day charge          0.205151
total eve minutes         0.092796
total eve charge          0.092786
total intl charge         0.068259
total intl minutes        0.068239
total night charge        0.035496
total night minutes       0.035493
all calls                 0.019651
total day calls           0.018459
account length            0.016541
total eve calls           0.009233
area code                 0.006174
total night calls         0.006141
total intl calls         -0.052844
number vmail messages    -0.089728
Name: churn, dtype: float64
```

Customer service calls, total day minutes, total day charge are the features most correlated with churn. Our model will give us more insight regarding this.

In [18]:
```
df = df.drop(['area code', 'state', 'phone number'], axis=1)
#these features are causing noise
#I don't think they are necessary so i will drop them
```

In [19]:
```
#making sure those values are dropped
df.head()
```

Out[19]:

	account length	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	tota nigh minutes
0	128	no	yes	25	265.1	110	45.07	197.4	99	16.78	244.7
1	107	no	yes	26	161.6	123	27.47	195.5	103	16.62	254.4
2	137	no	no	0	243.4	114	41.38	121.2	110	10.30	162.6
3	84	yes	no	0	299.4	71	50.90	61.9	88	5.26	196.9
4	75	yes	no	0	166.7	113	28.34	148.3	122	12.61	186.9

In [20]:
```
#Dealing with spaces between column names
df.columns = [c.replace(' ', '_') for c in df.columns]
```

In [21]:
```
print(df["international_plan"].unique())
print(df["voice_mail_plan"].unique())
print(df["customer_service_calls"].unique())
```

```
['no' 'yes']
['yes' 'no']
[1 0 2 3 4 5 7 9 6 8]
```

In [22]:
```
#changing boolean to int
df['total_day_minutes'] = df['total_day_minutes'].astype(int)
df['total_day_charge'] = df['total_day_charge'].astype(int)
df['total_eve_minutes'] = df['total_eve_minutes'].astype(int)
df['total_eve_charge'] = df['total_eve_charge'].astype(int)
df['total_night_minutes'] = df['total_night_minutes'].astype(int)
df['total_night_charge'] = df['total_night_charge'].astype(int)
df['total_intl_minutes'] = df['total_intl_minutes'].astype(int)
df['total_intl_charge'] = df['total_intl_charge'].astype(int)
```

In [23]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 19 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   account_length          3333 non-null   int64 
 1   international_plan      3333 non-null   object
 2   voice_mail_plan         3333 non-null   object
 3   number_vmail_messages   3333 non-null   int64 
 4   total_day_minutes       3333 non-null   int64 
 5   total_day_calls         3333 non-null   int64 
 6   total_day_charge        3333 non-null   int64 
 7   total_eve_minutes       3333 non-null   int64 
 8   total_eve_calls         3333 non-null   int64 
 9   total_eve_charge        3333 non-null   int64 
 10  total_night_minutes     3333 non-null   int64 
 11  total_night_calls       3333 non-null   int64 
 12  total_night_charge      3333 non-null   int64 
 13  total_intl_minutes      3333 non-null   int64 
 14  total_intl_calls        3333 non-null   int64 
 15  total_intl_charge       3333 non-null   int64 
 16  customer_service_calls  3333 non-null   int64 
 17  churn                   3333 non-null   int64 
 18  all_calls               3333 non-null   int64 
dtypes: int64(17), object(2)
memory usage: 494.9+ KB
```

In [24]:
```
#encoding churn to 0/1
labelencoder = LabelEncoder()
df['churn'] = labelencoder.fit_transform(df['churn'])
```

In [25]:
```
#dropping target variable
X = df.drop(columns= 'churn', axis=1)
y = df['churn']
```

In [26]:
```
#dummying variables(subgrouping)
X
X = pd.get_dummies(X)
X.head()
```

Out[26]:

	account_length	number_vmail_messages	total_day_minutes	total_day_calls	total_day_charge	tot
0	128	25	265	110	45	
1	107	26	161	123	27	
2	137	0	243	114	41	
3	84	0	299	71	50	
4	75	0	166	113	28	

In [27]:
```
#looking over columns
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   account_length          3333 non-null   int64
 1   number_vmail_messages   3333 non-null   int64
 2   total_day_minutes       3333 non-null   int64
 3   total_day_calls         3333 non-null   int64
 4   total_day_charge        3333 non-null   int64
 5   total_eve_minutes       3333 non-null   int64
 6   total_eve_calls         3333 non-null   int64
 7   total_eve_charge        3333 non-null   int64
 8   total_night_minutes     3333 non-null   int64
 9   total_night_calls       3333 non-null   int64
 10  total_night_charge      3333 non-null   int64
 11  total_intl_minutes      3333 non-null   int64
 12  total_intl_calls        3333 non-null   int64
 13  total_intl_charge       3333 non-null   int64
 14  customer_service_calls  3333 non-null   int64
 15  all_calls               3333 non-null   int64
 16  international_plan_no   3333 non-null   uint8
 17  international_plan_yes  3333 non-null   uint8
 18  voice_mail_plan_no      3333 non-null   uint8
 19  voice_mail_plan_yes     3333 non-null   uint8
dtypes: int64(16), uint8(4)
memory usage: 429.8 KB
```

In [28]:
```
/train split
.n, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s
```

Dummy Classifier: using this for my baseline accuracy. It would tell us that we are correct in predicting churn and no churn, and we will use it to compare the future models.

In [29]:
```
dummy = DummyClassifier(strategy='most_frequent')
dummy.fit(X_train, y_train)
baseline_acc = round(dummy.score(X_test, y_test), 2) * 100
print('Baseline Accuracy: {0}%'.format(baseline_acc))
```

```
Baseline Accuracy: 85.0%
```

Model 1: Logistic Regression

In [30]:
```
reating a pipeline with scaling, smote, and the lr model
 = LogisticRegression()
 = Pipeline([('standardscaler', StandardScaler()), ('smote', SMOTE()), ('lr'
itting the model
.fit(X_train, y_train)
```

Out[30]:
```
Pipeline(steps=[('standardscaler', StandardScaler()), ('smote', SMOTE()),
                ('lr', LogisticRegression())])
```

In [31]:
```
#checking accuracy
LR.score(X_test, y_test)
```

Out[31]:
```
0.7901049475262368
```

In [32]:
```
#estimating how well our unseen data is
cross_val_score(LR, X, y)
```

Out[32]:
```
array([0.73913043, 0.77211394, 0.7856072 , 0.76876877, 0.77177177])
```

In [33]:
```
#making predictions
LR_Pred = LR.predict(X_test)
```

In [34]:
```
print(classification_report(y_test, LR_Pred))
```

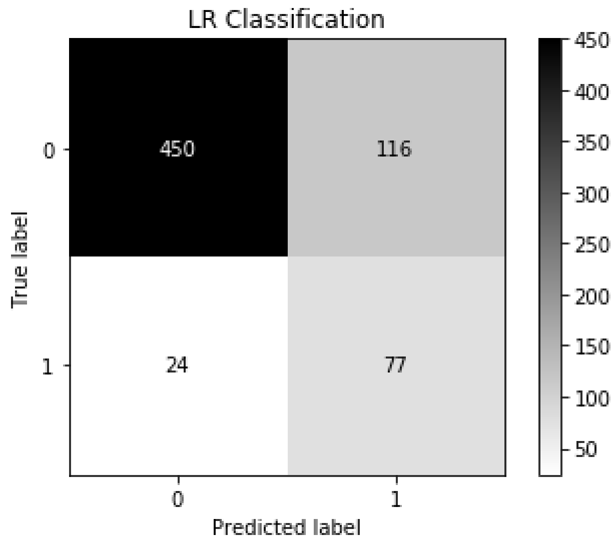
```
              precision    recall  f1-score   support

           0       0.95      0.80      0.87       566
           1       0.40      0.76      0.52       101

    accuracy                           0.79       667
   macro avg       0.67      0.78      0.69       667
weighted avg       0.87      0.79      0.81       667
```

In [35]:
```
plot_confusion_matrix(LR, X_test, y_test, cmap='binary')
plt.title('LR Classification')
```

Out[35]:
```
Text(0.5, 1.0, 'LR Classification')
```



Our logistic regression model was 78% accurate in identifying the true positives(recall) which is about 76%.

Model 2- KNN

In [36]:
```
#creating knn classifier
knn = KNeighborsClassifier()
```

In [37]:
```
line with scaler, smote,
([('standardscaler', StandardScaler()), ('smote', SMOTE()), ('knn', KNeighbo
```

In [38]:
```
#fitting train data
KNN.fit(X_train, y_train)
```

Out[38]:
```
Pipeline(steps=[('standardscaler', StandardScaler()), ('smote', SMOTE()),
                ('knn', KNeighborsClassifier())])
```

In [39]:
```
#creating predictions
KNN_Pred = KNN.predict(X_test)
```

In [40]:
```
print(classification_report(y_test, KNN_Pred))
```

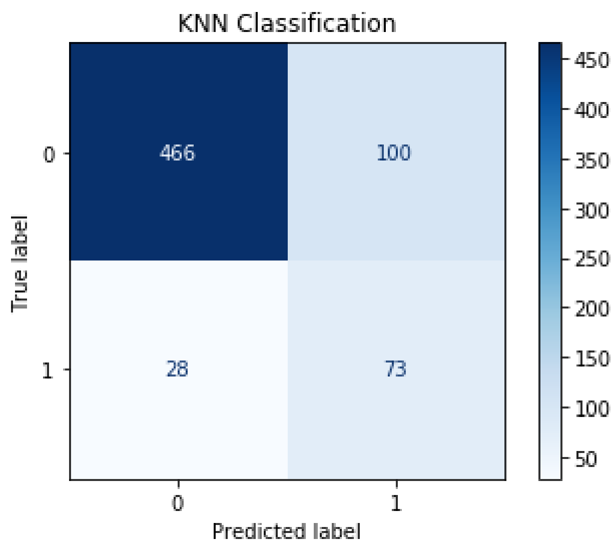
```
              precision    recall  f1-score   support

           0       0.94      0.82      0.88       566
           1       0.42      0.72      0.53       101

    accuracy                           0.81       667
   macro avg       0.68      0.77      0.71       667
weighted avg       0.86      0.81      0.83       667
```

In [41]:
```
plot_confusion_matrix(KNN, X_test, y_test, cmap='Blues')
plt.title('KNN Classification')
```

Out[41]:
```
Text(0.5, 1.0, 'KNN Classification')
```



The KNN model was 80% accurate in identifying the true positives (recall) of 81%.

Model 3- Random Forest

In [42]:
```
#assigning classifier
rfc = RandomForestClassifier()
```

In [43]:
```
#creating pipeline with scaler, smote, classifier
RFC = Pipeline([('standardscaler', StandardScaler()), ('smote', SMOTE()), (
```

In [44]:
```
#fitting training data
RFC.fit(X_train, y_train)
```

Out[44]:
```
Pipeline(steps=[('standardscaler', StandardScaler()), ('smote', SMOTE()),
                ('rfc', RandomForestClassifier())])
```

In [45]:
```
#viewing cross validation score
cross_val_score(RFC, X, y)
```

Out[45]:
```
array([0.94452774, 0.94302849, 0.95052474, 0.95345345, 0.95495495])
```

In [46]:
```
#making predictions
RFC_Pred = RFC.predict(X_test)
```

In [47]:
```
#looking at classification report
print(classification_report(y_test, RFC_Pred))
```

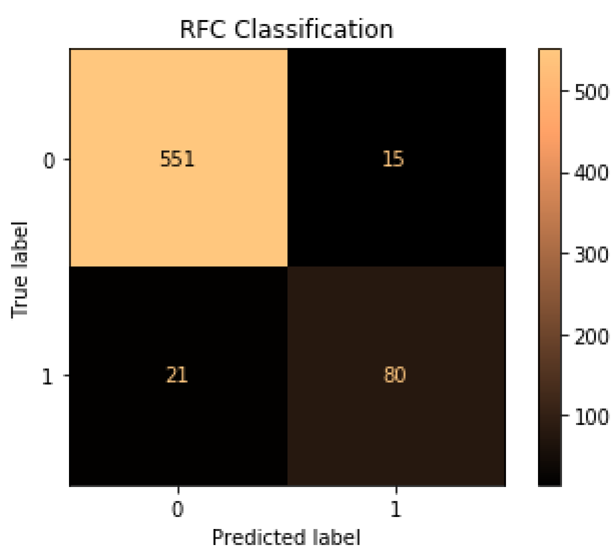
```
              precision    recall  f1-score   support

           0       0.96      0.97      0.97       566
           1       0.84      0.79      0.82       101

    accuracy                           0.95       667
   macro avg       0.90      0.88      0.89       667
weighted avg       0.94      0.95      0.95       667
```

In [48]:
```
plot_confusion_matrix(RFC, X_test, y_test, cmap='copper')
plt.title('RFC Classification')
```

Out[48]:
```
Text(0.5, 1.0, 'RFC Classification')
```



Our random forest model was 95% accurate in identifying our true postives (recall) of 82%

Final Best Model: Random Forest

In [49]:
```
#creating the best model
bestmodel = RandomForestClassifier(criterion='gini')
bestmodel.fit(X_train, y_train)
```

Out[49]:
```
RandomForestClassifier()
```

In [50]:
```
#looking at feature importance
bestmodel.feature_importances_
```

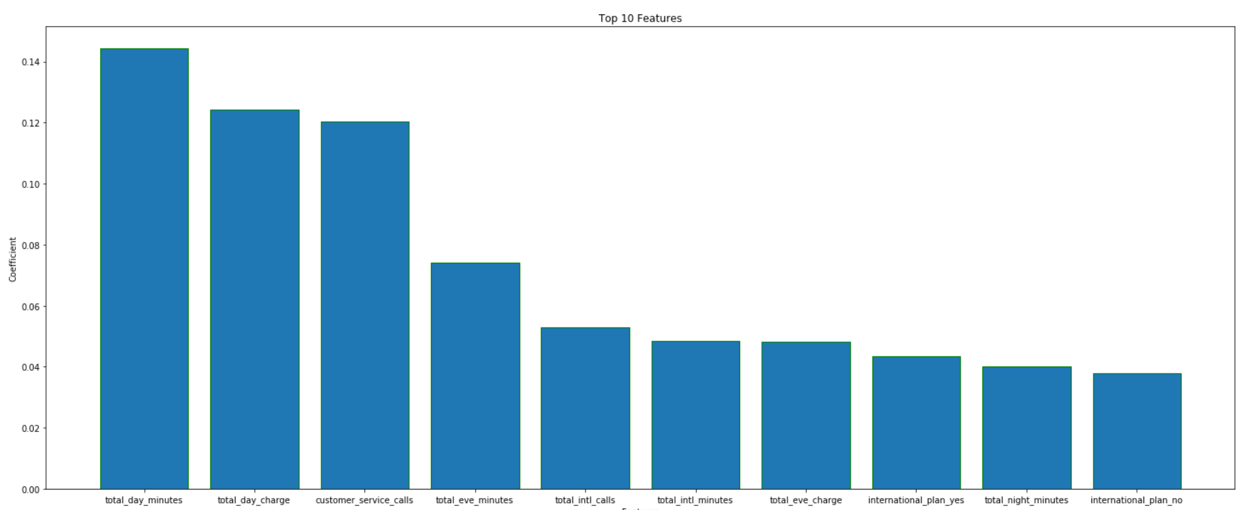
Out[50]:
```
array([0.03385099, 0.02452531, 0.14429217, 0.03638387, 0.12415622,
       0.07414389, 0.03401325, 0.04817144, 0.04010619, 0.0365109 ,
       0.02476625, 0.0484375 , 0.0530417 , 0.01504665, 0.12044864,
       0.03463549, 0.03794183, 0.04349885, 0.01271092, 0.01331794])
```

In [51]:
```
#using pearson coeff for correlation
bm = pd.DataFrame({'Features':X.columns, 'coeff':bestmodel.feature_importan
```

In [52]:
```
#ranking coeff
final_model = bm.sort_values(by='coeff', ascending=False)
```

In [53]:
```
fm1 = final_model.head(10)
plt.figure(figsize=(25,10))
plt.title('Top 10 Features')
plt.xlabel('Features')
plt.ylabel('Coefficient')
plt.bar(fm1['Features'], fm1['coeff'], edgecolor='green')
```

Out[53]: <BarContainer object of 10 artists>



In [54]:
```
finalmodeldf = df
```

In [55]:
```
finalmodeldf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 19 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   account_length          3333 non-null   int64
 1   international_plan      3333 non-null   object
 2   voice_mail_plan         3333 non-null   object
 3   number_vmail_messages   3333 non-null   int64
 4   total_day_minutes       3333 non-null   int64
 5   total_day_calls         3333 non-null   int64
 6   total_day_charge        3333 non-null   int64
 7   total_eve_minutes       3333 non-null   int64
 8   total_eve_calls         3333 non-null   int64
 9   total_eve_charge        3333 non-null   int64
 10  total_night_minutes     3333 non-null   int64
 11  total_night_calls       3333 non-null   int64
 12  total_night_charge      3333 non-null   int64
 13  total_intl_minutes      3333 non-null   int64
 14  total_intl_calls        3333 non-null   int64
 15  total_intl_charge       3333 non-null   int64
 16  customer_service_calls  3333 non-null   int64
 17  churn                   3333 non-null   int64
 18  all_calls               3333 non-null   int64
dtypes: int64(17), object(2)
memory usage: 494.9+ KB
```

In [56]:
```
#chaging target to num variable
labelencoder = LabelEncoder()
finalmodeldf['churn'] = labelencoder.fit_transform(finalmodeldf['churn'])

#create and set features
X = finalmodeldf.drop(columns= 'churn', axis=1)
y = df['churn']

#creating dummies for categorical variables
X = pd.get_dummies(X)
X.head()

#checking the columns
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   account_length          3333 non-null   int64
 1   number_vmail_messages   3333 non-null   int64
 2   total_day_minutes       3333 non-null   int64
 3   total_day_calls         3333 non-null   int64
 4   total_day_charge        3333 non-null   int64
 5   total_eve_minutes       3333 non-null   int64
 6   total_eve_calls         3333 non-null   int64
 7   total_eve_charge        3333 non-null   int64
 8   total_night_minutes     3333 non-null   int64
 9   total_night_calls       3333 non-null   int64
 10  total_night_charge      3333 non-null   int64
 11  total_intl_minutes      3333 non-null   int64
 12  total_intl_calls        3333 non-null   int64
 13  total_intl_charge       3333 non-null   int64
 14  customer_service_calls  3333 non-null   int64
 15  all_calls               3333 non-null   int64
 16  international_plan_no   3333 non-null   uint8
 17  international_plan_yes  3333 non-null   uint8
 18  voice_mail_plan_no      3333 non-null   uint8
 19  voice_mail_plan_yes     3333 non-null   uint8
dtypes: int64(16), uint8(4)
memory usage: 429.8 KB
```

In [57]:
```
# test/train split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra
```

In [58]:
```
# assigning classifier
rfc = RandomForestClassifier(random_state=101)

#applying parameters
params = {
    'max_features': [1, 'sqrt', 'log2'],
    'max_depth': [None, 1, 2, 3, 4, 5],
    'criterion': ['entropy', 'gini']
}

#gridsearch for hyperparameter tuning
grid = GridSearchCV(estimator= rfc, param_grid=params, verbose=1)
```

In [59]:
```
#fitting train data
grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
```

Out[59]:
```
GridSearchCV(estimator=RandomForestClassifier(random_state=101),
             param_grid={'criterion': ['entropy', 'gini'],
                         'max_depth': [None, 1, 2, 3, 4, 5],
                         'max_features': [1, 'sqrt', 'log2']},
             verbose=1)
```

In [60]:
```
#finding best paramaters
rf_best = grid.best_estimator_
```

In [61]:
```
#checking cross validation score
cross_val_score(rf_best, X, y, scoring='f1_micro')
```

Out[61]:
```
array([0.94902549, 0.94602699, 0.96401799, 0.94894895, 0.95645646])
```

In [62]:
```
#classification report
print(classification_report(y_test, rf_best.predict(X_test)))
```

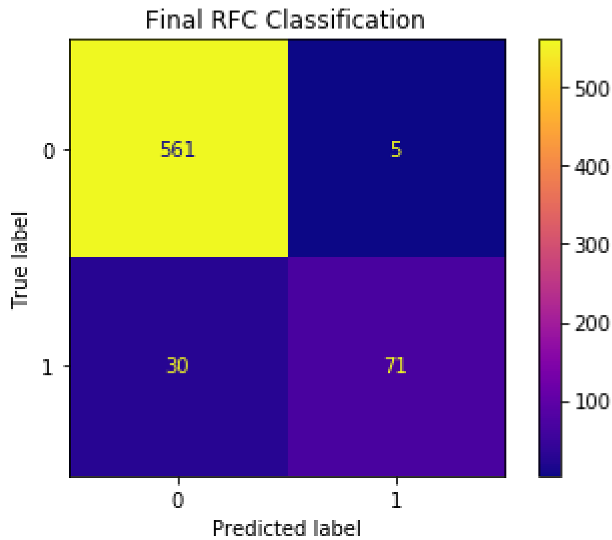
```
              precision    recall  f1-score   support

           0       0.95      0.99      0.97       566
           1       0.93      0.70      0.80       101

    accuracy                           0.95       667
   macro avg       0.94      0.85      0.89       667
weighted avg       0.95      0.95      0.94       667
```

In [63]:
```
#creating confusion matrix
plot_confusion_matrix(rf_best, X_test, y_test, cmap='plasma')
plt.title('Final RFC Classification')
```

Out[63]:
```
Text(0.5, 1.0, 'Final RFC Classification')
```



After hyperparameter tuning, our accuracy stayed the same overall, however we got a higher precision and a lower recall from our original rf model.

Findings/Conclusion

The Random Forest Classifier was 95% accurate in classifying churn of the customer. We also got a recall of 82% (our model correctly identified true positives 82% of the time). However, after implementing hyperparameter tuning, the accuracy stayed the same while the precision increased, and the recall decreased. The f1 scores were close with .82 from the original rf model and .80 from the final one. Our cross validation score was about 95%, which showed us our model performed well and avoided overfitting. We were also successfully able to see an increase in our accuracy from our baseline model to final model in 10%.

Total day minutes, total day charge, and customer service calls seem to be the main reasons why customers are churning. Recommendations we would give to SyriaTel is to work out better plans that are more fitting for customers who make more calls or use their phone more overall. This could be unlimited plans. Also, this could cut down on the number of customers making customer service calls that cause them to churn. We also recommend training customer service staff in dealing with unhappy customers better.