Telecom Churn - ML MiniProject

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Business Problem Overview

In the telecom industry, customers are able to choose from multiple service providers and actively switch from one operator to another. In this highly competitive market, the telecommunications industry experiences an average of 15-25% annual churn rate. Given the fact that it costs 5-10 times more to acquire a new customer than to retain an existing one, customer retention has now become even more important than customer acquisition.

For many incumbent operators, retaining high profitable customers is the number one business goal.

To reduce customer churn, telecom companies need to predict which customers are at high risk of churn.

In this project, you will analyse customer-level data of a leading telecom firm, build predictive models to identify customers at high risk of churn and identify the main indicators of churn.

Definitions of Churn

There are various ways to define churn, such as: 1. Revenue-based churn 2.Usage-based churn

For this project, you will use the **usage-based** definition to define churn.

Usage-based churn: Customers who have not done any usage, either incoming or outgoing - in terms of calls, internet etc. over a period of time. A potential shortcoming of this definition is that when the customer has stopped using the services for a while, it may be too late to take any corrective actions to retain them. For e.g., if you define churn based on a ‘two-months zero usage’ period, predicting churn could be useless since by that time the customer would have already switched to another operator.

business objective:

The business objective is to predict the churn in the last (i.e. the ninth) month using the data (features) from the first three months. To do this task well, understanding the typical customer behaviour during churn will be helpful.

Understanding Customer Behaviour During Churn

Customers usually do not decide to switch to another competitor instantly, but rather over a period of time (this is especially applicable to high-value customers). In churn prediction, we assume that there are three phases of customer lifecycle :

The ‘good’ phase: In this phase, the customer is happy with the service and behaves as usual.

The ‘action’ phase: The customer experience starts to sore in this phase, for e.g. he/she gets a compelling offer from a competitor, faces unjust charges, becomes unhappy with service quality etc. In this phase, the customer usually shows different behaviour than the ‘good’ months. Also, it is crucial to identify high-churn-risk customers in this phase, since some corrective actions can be taken at this point (such as matching the competitor’s offer/improving the service quality etc.)

The ‘churn’ phase: In this phase, the customer is said to have churned. You define churn based on this phase. Also, it is important to note that at the time of prediction (i.e. the action months), this data is not available to you for prediction. Thus, after tagging churn as 1/0 based on this phase, you discard all data corresponding to this phase.

In this case, since you are working over a four-month window, the first two months are the ‘good’ phase, the third month is the ‘action’ phase, while the fourth month is the ‘churn’ phase.

Data

The dataset contains customer-level information for a span of four consecutive months - June, July, August and September. The months are encoded as 6, 7, 8 and 9, respectively.

Filename: telecom_churn_data.csv

In [0]:

```
# Ignoring warning messages
import warnings
warnings.filterwarnings('ignore')

# Import the required library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

pd.set_option('display.max_columns',230)
```

In [0]:

```
# reading the input data and preview
churn= pd.read_csv('telecom_churn_data.csv')
churn.head()
```

Out[0]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou
0	7000842753	109	0.0	0.0
1	7001865778	109	0.0	0.0
2	7001625959	109	0.0	0.0
3	7001204172	109	0.0	0.0
4	7000142493	109	0.0	0.0

In [0]:

```
print (churn.shape)
print (churn.info())
churn.describe()
```

```
(99999, 226)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Columns: 226 entries, mobile_number to sep_vbc_3g
dtypes: float64(179), int64(35), object(12)
memory usage: 172.4+ MB
None
```

Out[0]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_
count	9.999900e+04	99999.0	98981.0	989
mean	7.001207e+09	109.0	0.0	
std	6.956694e+05	0.0	0.0	
min	7.000000e+09	109.0	0.0	
25%	7.000606e+09	109.0	0.0	
50%	7.001205e+09	109.0	0.0	
75%	7.001812e+09	109.0	0.0	
max	7.002411e+09	109.0	0.0	

In [0]:

```
print ("The cutomer-level information for each customer is repr
esented by %d features"% (churn.shape[1]))
# getting the unique number of custormers from the data
print ("Unique customers/MSISDN in the data: %d"%len(churn.mobi
le_number.unique()))
```

```
The cutomer-level information for each customer is
represented by 226 features
Unique customers/MSISDN in the data: 99999
```

In [0]:

```
#list of columns
pd.DataFrame(churn.columns)
```

Out[0]:

	0
0	mobile_number
1	circle_id
2	loc_og_t2o_mou
3	std_og_t2o_mou
4	loc_ic_t2o_mou
5	last_date_of_month_6
6	last_date_of_month_7
7	last_date_of_month_8
8	last_date_of_month_9
9	arpu_6
10	arpu_7
11	arpu_8
12	arpu_9
13	onnet_mou_6
14	onnet_mou_7
15	onnet_mou_8
16	onnet_mou_9
17	offnet_mou_6
18	offnet_mou_7
19	offnet_mou_8
20	offnet_mou_9
21	roam_ic_mou_6
22	roam_ic_mou_7
23	roam_ic_mou_8

	0
24	roam_ic_mou_9
25	roam_og_mou_6
26	roam_og_mou_7
27	roam_og_mou_8
28	roam_og_mou_9
29	loc_og_t2t_mou_6
...	...
196	arpu_2g_9
197	night_pck_user_6
198	night_pck_user_7
199	night_pck_user_8
200	night_pck_user_9
201	monthly_2g_6
202	monthly_2g_7
203	monthly_2g_8
204	monthly_2g_9
205	sachet_2g_6
206	sachet_2g_7
207	sachet_2g_8
208	sachet_2g_9
209	monthly_3g_6
210	monthly_3g_7
211	monthly_3g_8
212	monthly_3g_9
213	sachet_3g_6

	0
214	sachet_3g_7
215	sachet_3g_8
216	sachet_3g_9
217	fb_user_6
218	fb_user_7
219	fb_user_8
220	fb_user_9
221	aon
222	aug_vbc_3g
223	jul_vbc_3g
224	jun_vbc_3g
225	sep_vbc_3g

226 rows × 1 columns

Data Cleaning

Custome function Defination for data cleaning

In [0]:

```
def getMissingValues(missingCutoff):
    # Function to retun the columns with more than missingCutof
f% missing values.
    # argument: missingCutoff, % values threshold for missing v
alues
    missing = round(100*(churn.isnull().sum()/churn.shape[0]))
    print("There are {} features having more than {}% missing v
alues/entries".format(len(missing.loc[missing > missingCutoff
]),missingCutoff))
    return missing.loc[missing > missingCutoff]
```

In [0]:

```
def imputeNan(data,imputeColList=False,missingColList=False):
    # Function impute the nan with 0
    # argument: colList, list of columns for which nan is to be
replaced with 0
    if imputeColList:
        for col in [y + s for s in ['_6','_7','_8','_9'] for y
in imputeColList]:
            data[col].fillna(0, inplace=True)
    else:
        for col in missingColList:
            data[col].fillna(0, inplace=True)
```

Handling missing data

Let's check for missing values in the data.

In [0]:

```
# Missing values per column expressed as % of total number of v
alues
getMissingValues(50)
```

```
There are 40 features having more than 50% missing
values/entries
```

Out[0]:

```
date_of_last_rech_data_6      75.0
date_of_last_rech_data_7      74.0
date_of_last_rech_data_8      74.0
date_of_last_rech_data_9      74.0
total_rech_data_6             75.0
total_rech_data_7             74.0
total_rech_data_8             74.0
total_rech_data_9             74.0
max_rech_data_6               75.0
max_rech_data_7               74.0
max_rech_data_8               74.0
max_rech_data_9               74.0
count_rech_2g_6               75.0
count_rech_2g_7               74.0
count_rech_2g_8               74.0
count_rech_2g_9               74.0
count_rech_3g_6               75.0
count_rech_3g_7               74.0
count_rech_3g_8               74.0
count_rech_3g_9               74.0
av_rech_amt_data_6            75.0
av_rech_amt_data_7            74.0
av_rech_amt_data_8            74.0
av_rech_amt_data_9            74.0
arpu_3g_6                     75.0
arpu_3g_7                     74.0
arpu_3g_8                     74.0
arpu_3g_9                     74.0
arpu_2g_6                     75.0
arpu_2g_7                     74.0
arpu_2g_8                     74.0
arpu_2g_9                     74.0
night_pck_user_6              75.0
night_pck_user_7              74.0
night_pck_user_8              74.0
night_pck_user_9              74.0
fb_user_6                     75.0
fb_user_7                     74.0
fb_user_8                     74.0
```

```
fb_user_9                    74.0
dtype: float64
```

Out the these 40 features, many are required and are essential for analysis. The missing values for these features seems to suggest that these customers KPI's did not have any value at that month. We can choose to impute these values with 0 to make enable these features to give value to analysis.

In [0]:

```
# Since av_rech_amt_data_* features are important for getting t
he high-value customers,
#lets impute the missing av_rech_amt_data_* with 0
imputeCol = ['av_rech_amt_data', 'arpu_2g', 'arpu_3g', 'count_r
ech_2g', 'count_rech_3g',
             'max_rech_data', 'total_rech_data','fb_user','nigh
t_pck_user']
imputeNan(churn,imputeCol)
```

In [0]:

```
getMissingValues(50)
```

```
There are 4 features having  more than 50% missing
values/entries
```

Out[0]:

```
date_of_last_rech_data_6    75.0
date_of_last_rech_data_7    74.0
date_of_last_rech_data_8    74.0
date_of_last_rech_data_9    74.0
dtype: float64
```

In [0]:

```
# dropping the columns having more than 50% missing values
missingcol = list(getMissingValues(50).index)
churn.drop(missingcol,axis=1,inplace=True)
churn.shape
```

```
There are 4 features having more than 50% missing
values/entries
```

Out[0]:

```
(99999, 222)
```

In [0]:

```
# Missing values per column expressed as % of total number of v
alues > 5%
getMissingValues(5)
```

```
There are 29 features having more than 5% missing
values/entries
```

Out[0]:

```
onnet_mou_9          8.0
offnet_mou_9         8.0
roam_ic_mou_9        8.0
roam_og_mou_9        8.0
loc_og_t2t_mou_9     8.0
loc_og_t2m_mou_9     8.0
loc_og_t2f_mou_9     8.0
loc_og_t2c_mou_9     8.0
loc_og_mou_9         8.0
std_og_t2t_mou_9     8.0
std_og_t2m_mou_9     8.0
std_og_t2f_mou_9     8.0
std_og_t2c_mou_9     8.0
std_og_mou_9         8.0
isd_og_mou_9         8.0
spl_og_mou_9         8.0
og_others_9          8.0
loc_ic_t2t_mou_9     8.0
loc_ic_t2m_mou_9     8.0
loc_ic_t2f_mou_9     8.0
loc_ic_mou_9         8.0
std_ic_t2t_mou_9     8.0
std_ic_t2m_mou_9     8.0
std_ic_t2f_mou_9     8.0
std_ic_t2o_mou_9     8.0
std_ic_mou_9         8.0
spl_ic_mou_9         8.0
isd_ic_mou_9         8.0
ic_others_9          8.0
dtype: float64
```

Looks like all these features for the month sep(9) are missing together. Let's check.

In [0]:

```
# checking if all these above features go missing together sinc
e they have the same 8% missing values in each feature.
missingcol = list(getMissingValues(5).index)
print ("There are %d customers/MSISDN's having missing values f
or %s together"%(len(churn[churn[missingcol].isnull().all(axis=
1)]),missingcol))
churn[churn[missingcol].isnull().all(axis=1)][missingcol].head
()
```

```
There are 29 features having more than 5% missing
values/entries
There are 7745 customers/MSISDN's having missing v
alues for ['onnet_mou_9', 'offnet_mou_9', 'roam_ic
_mou_9', 'roam_og_mou_9', 'loc_og_t2t_mou_9', 'loc
_og_t2m_mou_9', 'loc_og_t2f_mou_9', 'loc_og_t2c_mo
u_9', 'loc_og_mou_9', 'std_og_t2t_mou_9', 'std_og_
t2m_mou_9', 'std_og_t2f_mou_9', 'std_og_t2c_mou_
9', 'std_og_mou_9', 'isd_og_mou_9', 'spl_og_mou_
9', 'og_others_9', 'loc_ic_t2t_mou_9', 'loc_ic_t2m
_mou_9', 'loc_ic_t2f_mou_9', 'loc_ic_mou_9', 'std_
ic_t2t_mou_9', 'std_ic_t2m_mou_9', 'std_ic_t2f_mou
_9', 'std_ic_t2o_mou_9', 'std_ic_mou_9', 'spl_ic_m
ou_9', 'isd_ic_mou_9', 'ic_others_9'] together
```

Out[0]:

	onnet_mou_9	offnet_mou_9	roam_ic_mou_9	roam_og_mo
0	NaN	NaN	NaN	
7	NaN	NaN	NaN	
29	NaN	NaN	NaN	
32	NaN	NaN	NaN	
35	NaN	NaN	NaN	

Yes, It looks like for **7745 Customers** all these features are empty together without any value. We can choose to impute these values with 0 also.

In [0]:

```
imputeNan(churn,missingColList=missingcol)
```

In [0]:

```
churn=churn[~churn[missingcol].isnull().all(axis=1)]
churn.shape
```

Out[0]:

```
(99999, 222)
```

In [0]:

```
# Missing values per column expressed as % of total number of v
alues
getMissingValues(2)
```

```
There are 89 features having more than 2% missing
values/entries
```

Out[0]:

```
onnet_mou_6           4.0
onnet_mou_7           4.0
onnet_mou_8           5.0
offnet_mou_6          4.0
offnet_mou_7          4.0
offnet_mou_8          5.0
roam_ic_mou_6         4.0
roam_ic_mou_7         4.0
roam_ic_mou_8         5.0
roam_og_mou_6         4.0
roam_og_mou_7         4.0
roam_og_mou_8         5.0
loc_og_t2t_mou_6      4.0
loc_og_t2t_mou_7      4.0
loc_og_t2t_mou_8      5.0
loc_og_t2m_mou_6      4.0
loc_og_t2m_mou_7      4.0
loc_og_t2m_mou_8      5.0
loc_og_t2f_mou_6      4.0
loc_og_t2f_mou_7      4.0
loc_og_t2f_mou_8      5.0
loc_og_t2c_mou_6      4.0
loc_og_t2c_mou_7      4.0
loc_og_t2c_mou_8      5.0
loc_og_mou_6          4.0
loc_og_mou_7          4.0
loc_og_mou_8          5.0
std_og_t2t_mou_6      4.0
std_og_t2t_mou_7      4.0
std_og_t2t_mou_8      5.0
                     ...
loc_ic_t2f_mou_8      5.0
loc_ic_mou_6          4.0
loc_ic_mou_7          4.0
loc_ic_mou_8          5.0
std_ic_t2t_mou_6      4.0
std_ic_t2t_mou_7      4.0
std_ic_t2t_mou_8      5.0
std_ic_t2m_mou_6      4.0
```

```
std_ic_t2m_mou_7        4.0
std_ic_t2m_mou_8        5.0
std_ic_t2f_mou_6        4.0
std_ic_t2f_mou_7        4.0
std_ic_t2f_mou_8        5.0
std_ic_t2o_mou_6        4.0
std_ic_t2o_mou_7        4.0
std_ic_t2o_mou_8        5.0
std_ic_mou_6            4.0
std_ic_mou_7            4.0
std_ic_mou_8            5.0
spl_ic_mou_6            4.0
spl_ic_mou_7            4.0
spl_ic_mou_8            5.0
isd_ic_mou_6            4.0
isd_ic_mou_7            4.0
isd_ic_mou_8            5.0
ic_others_6             4.0
ic_others_7             4.0
ic_others_8             5.0
date_of_last_rech_8     4.0
date_of_last_rech_9     5.0
Length: 89, dtype: float64
```

In [0]:

```
missingcol = list(getMissingValues(2).index)
print ("There are %d customers/MSISDN's having missing values f
or %s together"%(len(churn[churn[missingcol].isnull().all(axis=
1)]),missingcol))
churn[churn[missingcol].isnull().all(axis=1)][missingcol].head
()
```

```
There are 89 features having more than 2% missing
values/entries
There are 381 customers/MSISDN's having missing va
lues for ['onnet_mou_6', 'onnet_mou_7', 'onnet_mou
_8', 'offnet_mou_6', 'offnet_mou_7', 'offnet_mou_
8', 'roam_ic_mou_6', 'roam_ic_mou_7', 'roam_ic_mou
_8', 'roam_og_mou_6', 'roam_og_mou_7', 'roam_og_mo
u_8', 'loc_og_t2t_mou_6', 'loc_og_t2t_mou_7', 'loc
_og_t2t_mou_8', 'loc_og_t2m_mou_6', 'loc_og_t2m_mo
u_7', 'loc_og_t2m_mou_8', 'loc_og_t2f_mou_6', 'loc
_og_t2f_mou_7', 'loc_og_t2f_mou_8', 'loc_og_t2c_mo
u_6', 'loc_og_t2c_mou_7', 'loc_og_t2c_mou_8', 'loc
_og_mou_6', 'loc_og_mou_7', 'loc_og_mou_8', 'std_o
g_t2t_mou_6', 'std_og_t2t_mou_7', 'std_og_t2t_mou_
8', 'std_og_t2m_mou_6', 'std_og_t2m_mou_7', 'std_o
g_t2m_mou_8', 'std_og_t2f_mou_6', 'std_og_t2f_mou_
7', 'std_og_t2f_mou_8', 'std_og_t2c_mou_6', 'std_o
g_t2c_mou_7', 'std_og_t2c_mou_8', 'std_og_mou_6',
'std_og_mou_7', 'std_og_mou_8', 'isd_og_mou_6', 'i
sd_og_mou_7', 'isd_og_mou_8', 'spl_og_mou_6', 'spl
_og_mou_7', 'spl_og_mou_8', 'og_others_6', 'og_oth
ers_7', 'og_others_8', 'loc_ic_t2t_mou_6', 'loc_ic
_t2t_mou_7', 'loc_ic_t2t_mou_8', 'loc_ic_t2m_mou_
6', 'loc_ic_t2m_mou_7', 'loc_ic_t2m_mou_8', 'loc_i
c_t2f_mou_6', 'loc_ic_t2f_mou_7', 'loc_ic_t2f_mou_
8', 'loc_ic_mou_6', 'loc_ic_mou_7', 'loc_ic_mou_
8', 'std_ic_t2t_mou_6', 'std_ic_t2t_mou_7', 'std_i
c_t2t_mou_8', 'std_ic_t2m_mou_6', 'std_ic_t2m_mou_
7', 'std_ic_t2m_mou_8', 'std_ic_t2f_mou_6', 'std_i
c_t2f_mou_7', 'std_ic_t2f_mou_8', 'std_ic_t2o_mou_
6', 'std_ic_t2o_mou_7', 'std_ic_t2o_mou_8', 'std_i
c_mou_6', 'std_ic_mou_7', 'std_ic_mou_8', 'spl_ic_
mou_6', 'spl_ic_mou_7', 'spl_ic_mou_8', 'isd_ic_mo
u_6', 'isd_ic_mou_7', 'isd_ic_mou_8', 'ic_others_
6', 'ic_others_7', 'ic_others_8', 'date_of_last_re
ch_8', 'date_of_last_rech_9'] together
```

Out[0]:

	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_
202	NaN	NaN	NaN	Na
275	NaN	NaN	NaN	Na
687	NaN	NaN	NaN	Na
1206	NaN	NaN	NaN	Na
1232	NaN	NaN	NaN	Na

Yes, It looks like there are **381 Customers** for whom **all** these features are without any value. Let's drop these customers from the data.

In [0]:

```
churn=churn[~churn[missingcol].isnull().all(axis=1)]
churn.shape
```

Out[0]:

```
(99618, 222)
```

In [0]:

```
# For other customers where these missing values are spread ou
t, let's impute them with zero.

missingcol.remove('date_of_last_rech_8')
missingcol.remove('date_of_last_rech_9')
imputeNan(churn,missingColList=missingcol)
```

In [0]:

```
# Missing values per column expressed as % of total number of v
alues
getMissingValues(0)
```

```
There are 9 features having more than 0% missing v
alues/entries
```

Out[0]:

```
loc_og_t2o_mou          1.0
std_og_t2o_mou          1.0
loc_ic_t2o_mou          1.0
last_date_of_month_8    1.0
last_date_of_month_9    1.0
date_of_last_rech_6     1.0
date_of_last_rech_7     1.0
date_of_last_rech_8     3.0
date_of_last_rech_9     4.0
dtype: float64
```

In [0]:

```
col = ['loc_og_t2o_mou','std_og_t2o_mou','loc_ic_t2o_mou','last
_date_of_month_7','last_date_of_month_8','last_date_of_month_9'
, 'date_of_last_rech_7', 'date_of_last_rech_8', 'date_of_last_r
ech_9']
for c in col:
    print("Unique values in column %s are %s" % (c,churn[c].uni
que()))
```

```
Unique values in column loc_og_t2o_mou are [ 0. na
n]
Unique values in column std_og_t2o_mou are [ 0. na
n]
Unique values in column loc_ic_t2o_mou are [ 0. na
n]
Unique values in column last_date_of_month_7 are
['7/31/2014' nan]
Unique values in column last_date_of_month_8 are
['8/31/2014' nan]
Unique values in column last_date_of_month_9 are
['9/30/2014' nan]
Unique values in column date_of_last_rech_7 are
['7/16/2014' '7/31/2014' '7/24/2014' '7/28/2014'
'7/17/2014' '7/25/2014'
 '7/23/2014' '7/5/2014' '7/10/2014' '7/22/2014'
'7/30/2014' '7/3/2014'
 '7/7/2014' '7/29/2014' '7/27/2014' '7/19/2014'
'7/14/2014' '7/20/2014'
 '7/4/2014' '7/12/2014' nan '7/26/2014' '7/11/201
4' '7/6/2014' '7/21/2014'
 '7/13/2014' '7/15/2014' '7/18/2014' '7/9/2014'
'7/2/2014' '7/8/2014'
 '7/1/2014']
Unique values in column date_of_last_rech_8 are
['8/8/2014' '8/28/2014' '8/14/2014' '8/31/2014'
'8/9/2014' '8/24/2014'
 '8/26/2014' '8/30/2014' '8/29/2014' '8/27/2014'
'8/21/2014' '8/10/2014'
 '8/25/2014' '8/19/2014' '8/22/2014' '8/2/2014'
'8/13/2014' '8/5/2014'
 '8/18/2014' '8/20/2014' '8/23/2014' '8/12/2014'
'8/11/2014' '8/16/2014'
 '8/15/2014' '8/6/2014' nan '8/17/2014' '8/7/2014'
'8/1/2014' '8/4/2014'
 '8/3/2014']
Unique values in column date_of_last_rech_9 are
['9/28/2014' '9/30/2014' '9/29/2014' '9/20/2014'
'9/6/2014' nan
 '9/21/2014' '9/26/2014' '9/10/2014' '9/24/2014'
```

```
'9/16/2014' '9/27/2014'
 '9/25/2014' '9/12/2014' '9/17/2014' '9/15/2014'
'9/8/2014' '9/23/2014'
 '9/11/2014' '9/22/2014' '9/9/2014' '9/19/2014'
'9/7/2014' '9/1/2014'
 '9/2/2014' '9/13/2014' '9/3/2014' '9/18/2014' '9/
14/2014' '9/5/2014'
 '9/4/2014']
```

In [0]:

```
#Some of these features take only one value. Lets impute their
 missing values in these features with the mode
col = ['loc_og_t2o_mou','std_og_t2o_mou','loc_ic_t2o_mou','last
_date_of_month_7','last_date_of_month_8','last_date_of_month_9'
]
for c in col:
    print(churn[c].value_counts())
    churn[c].fillna(churn[c].mode()[0], inplace=True)
print("All the above features take only one value. Lets impute
 the missing values in these features with the mode")
```

```
0.0    98981
Name: loc_og_t2o_mou, dtype: int64
0.0    98981
Name: std_og_t2o_mou, dtype: int64
0.0    98981
Name: loc_ic_t2o_mou, dtype: int64
7/31/2014    99300
Name: last_date_of_month_7, dtype: int64
8/31/2014    98867
Name: last_date_of_month_8, dtype: int64
9/30/2014    98321
Name: last_date_of_month_9, dtype: int64
All the above features take only one value. Lets i
mpute the missing values in these features with th
e mode
```

In [0]:

```
# Missing values per column expressed as % of total number of v
alues
getMissingValues(0)
```

```
There are 4 features having more than 0% missing v
alues/entries
```

Out[0]:

```
date_of_last_rech_6    1.0
date_of_last_rech_7    1.0
date_of_last_rech_8    3.0
date_of_last_rech_9    4.0
dtype: float64
```

In [0]:

```
# All these features are missing together
missingcol = list(getMissingValues(0).index)
print ("There are %d rows in total having missing values for th
ese  variables."%(len(churn[churn[missingcol].isnull().all(axis=
1)])))
```

```
There are 4 features having more than 0% missing v
alues/entries
There are 22 rows in total having missing values f
or these variables.
```

In [0]:

```
churn[churn['date_of_last_rech_6'].isnull()]['date_of_last_rech_6'] = '6/30/2014'
churn[churn['date_of_last_rech_7'].isnull()]['date_of_last_rech_7'] = '7/31/2014'
churn[churn['date_of_last_rech_8'].isnull()]['date_of_last_rech_8'] = '8/31/2014'
churn[churn['date_of_last_rech_9'].isnull()]['date_of_last_rech_9'] = '9/30/2014'
```

Let's look for columns having all values as 0.

In [0]:

```
zero_columns=churn.columns[(churn == 0).all()]
print ("There are {} features which has only 0 as values. These features are \n{}".format(len(zero_columns),zero_columns))
```

```
There are 11 features which has only 0 as values.
These features are
Index(['loc_og_t2o_mou', 'std_og_t2o_mou', 'loc_ic_t2o_mou',
       'std_og_t2c_mou_6', 'std_og_t2c_mou_7', 'std_og_t2c_mou_8',
       'std_og_t2c_mou_9', 'std_ic_t2o_mou_6', 'std_ic_t2o_mou_7',
       'std_ic_t2o_mou_8', 'std_ic_t2o_mou_9'],
      dtype='object')
```

In [0]:

```
# Let's remove these columns as well. All take a single value '0'.
churn.drop(zero_columns,axis=1,inplace=True)
```

In [0]:

```
# Percentage of data left after removing the missing values.
print("Percentage of data remaining after treating missing valu
es: {}%".format(round(churn.shape[0]/99999 *100,2)))
print ("Number of customers: {}".format(churn.shape[0]))
print ("Number of features: {}".format(churn.shape[1]))
```

```
Percentage of data remaining after treating missin
g values: 99.62%
Number of customers: 99618
Number of features: 211
```

Fixing data types and columns names

Let's check for data types of the different columns.

In [0]:

```
churn.reset_index(inplace=True,drop=True)
# list of all columns which store date
date_columns = list(churn.filter(regex='date').columns)
date_columns
```

Out[0]:

```
['last_date_of_month_6',
 'last_date_of_month_7',
 'last_date_of_month_8',
 'last_date_of_month_9',
 'date_of_last_rech_6',
 'date_of_last_rech_7',
 'date_of_last_rech_8',
 'date_of_last_rech_9']
```

In [0]:

```
# Converting dtype of date columns to datetime
for col in date_columns:
    churn[col] = pd.to_datetime(churn[col], format='%m/%d/%Y')
```

In [0]:

```
churn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99618 entries, 0 to 99617
Columns: 211 entries, mobile_number to sep_vbc_3g
dtypes: datetime64[ns](8), float64(168), int64(35)
memory usage: 160.4 MB
```

There are some monthly features which are not in the standard naming (_6,_7,_8,_9)

In [0]:

```
# renaming columns,
#'jun_vbc_3g' : 'vbc_3g_6'
#'jul_vbc_3g' : 'vbc_3g_7'
#'aug_vbc_3g' : 'vbc_3g_8'
#'sep_vbc_3g' : 'vbc_3g_9'
churn.rename(columns={'jun_vbc_3g' : 'vbc_3g_6', 'jul_vbc_3g' : 'vbc_3g_7', 'aug_vbc_3g' : 'vbc_3g_8',
                      'sep_vbc_3g' : 'vbc_3g_9'}, inplace=True)
```

Creating new feature: 'vol_data_mb_6', 'vol_data_mb_7', 'vol_data_mb_8', 'vol_data_mb_9'

These will store the total data volume (= vol_2g*mb* + *vol_3gmb*) used by user.

In [0]:

```
#Creating new feature: 'vol_data_mb_6', 'vol_data_mb_7', 'vol_d
ata_mb_8', 'vol_data_mb_9',
for i in range(6,10):
    churn['vol_data_mb_'+str(i)] = (churn['vol_2g_mb_'+str(i)]+
churn['vol_3g_mb_'+str(i)]).astype(int)
```

Filter high-value customers

Defining high-value customers as follows:

Those who have recharged with an amount more than or equal to X, where X is the 70th percentile of the average recharge amount in the first two months (the good phase).

In [0]:

```
rechcol = churn.filter(regex=('count')).columns
churn[rechcol].head()
```

Out[0]:

	count_rech_2g_6	count_rech_2g_7	count_rech_2g_8	count
0	0.0	0.0	0.0	
1	0.0	1.0	2.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
4	1.0	0.0	0.0	

Creating new feature:
avg_rech_amt_6,avg_rech_amt_7,avg_rech_amt_8,avg_rech_amt_9

These will store the average recharge value for each customer for every month

In [0]:

```
# Creating new feature: avg_rech_amt_6,avg_rech_amt_7,avg_rech_amt_8,avg_rech_amt_9
for i in range(6,10):
    churn['avg_rech_amt_'+str(i)] = round(churn['total_rech_amt_'+str(i)]/churn['total_rech_num_'+str(i)]+1,2)
```

In [0]:

```
imputeNan(churn,missingColList=['avg_rech_amt_6','avg_rech_amt_7','avg_rech_amt_8','avg_rech_amt_9'])
```

Creating new feature:
total_rech_num_data_6,total_rech_num_data_7,total_rech_num_data_8,total_r

These will store the total number of data recharge (=count_rech_2g + count_rech_3g) for each month.

In [0]:

```
#Creating new feature: total_rech_num_data_6,total_rech_num_data_7,total_rech_num_data_8,total_rech_num_data_9
for i in range(6,10):
    churn['total_rech_num_data_'+str(i)] = (churn['count_rech_2g_'+str(i)]+churn['count_rech_3g_'+str(i)]).astype(int)
```

Creating new feature:
total_rech_amt_data_6,total_rech_amt_data_7,total_rech_amt_data_8,total_rec

These will store the total amount of data recharge (=total_rech_num_data * av_rech_amt_data) for each month.

In [0]:

```
#Creating new feature: total_rech_amt_data_6,total_rech_amt_data_7,total_rech_amt_data_8,total_rech_amt_data_9
for i in range(6,10):
    churn['total_rech_amt_data_'+str(i)] = churn['total_rech_num_data_'+str(i)]*churn['av_rech_amt_data_'+str(i)]
```

Creating new feature:
total_month_rech_6,total_month_rech_7,total_month_rech_8,total_month_rech

These will store the total recharge amount (= total_rech_amt + total_rech_amt_data) for each customer, for each month.

In [0]:

```
#Creating new feature: total_mon_rech_6,total_mon_rech_7,total_
mon_rech_8,total_mon_rech_9
for i in range(6,10):
    churn['total_month_rech_'+str(i)] = churn['total_rech_amt_'
+str(i)]+churn['total_rech_amt_data_'+str(i)]
churn.filter(regex=('total_month_rech')).head()
```

Out[0]:

	total_month_rech_6	total_month_rech_7	total_month_rech_8
0	614.0	504.0	504.0
1	74.0	538.0	383.0
2	168.0	315.0	116.0
3	230.0	310.0	601.0
4	252.0	350.0	287.0

In [0]:

```
# calculating the avegare of first two months (good phase) tota
l monthly recharge amount
avg_goodPhase =(churn.total_month_rech_6 + churn.total_month_re
ch_7)/2
# finding the cutoff which is the 70th percentile of the good p
hase average recharge amounts
hv_cutoff= np.percentile(avg_goodPhase,70)
# Filtering the users whose good phase avg. recharge amount >=
 to the cutoff of 70th percentile.
hv_users = churn[avg_goodPhase >=  hv_cutoff]
hv_users.reset_index(inplace=True,drop=True)

print("Number of High-Value Customers in the Dataset: %d\n"% le
n(hv_users))
print("Percentage High-value users in data :
{}%".format(round( len(hv_users)/churn.shape[0]*100),2))
```

```
Number of High-Value Customers in the Dataset: 299
06

Percentage High-value users in data : 30%
```

Tagging Churners

Now tag the churned customers (churn=1, else 0) based on the fourth month as follows:

Those who have not made any calls (either incoming or outgoing) AND have not used mobile internet even once in the churn phase. The attributes we need to use to tag churners are:

- total_ic_mou_9
- total_og_mou_9
- vol_2g_mb_9
- vol_3g_mb_9

In [0]:

```
def getChurnStatus(data,churnPhaseMonth=9):
    # Function to tag customers as churners (churn=1, else 0) b
ased on 'vol_2g_mb_','vol_3g_mb_','total_ic_mou_','total_og_mou
_'
    #argument: churnPhaseMonth, indicating the month number to
 be used to define churn (default= 9)
    churn_features= ['vol_2g_mb_','vol_3g_mb_','total_ic_mou_',
'total_og_mou_']
    flag = ~data[[s + str(churnPhaseMonth) for s in churn_featu
res ]].any(axis=1)
    flag = flag.map({True:1, False:0})
    return flag
```

In [0]:

```
hv_users['churn'] = getChurnStatus(hv_users,9)
print("There are {} users tagged as churners out of {} High-Val
ue Customers.".format(len(hv_users[hv_users.churn == 1]),hv_use
rs.shape[0]))
print("High-value Churn Percentage : {}%".format(round(len(hv_u
sers[hv_users.churn == 1])/hv_users.shape[0] *100,2)))
```

```
There are 2418 users tagged as churners out of 299
06 High-Value Customers.
High-value Churn Percentage : 8.09%
```

There are just **8.09% churn** cases.
This indicated an **highly imbalanced** data set where the churn cases are the minority(8.14%) as opposed to the non-churners who are the majority(91.91)

Data Analysis

Define few methods to aid in plotting graphs

In [0]:

```
# Function to plot the histogram with labels
# https://stackoverflow.com/questions/6352740/matplotlib-label-each-bin
def plot_hist(dataset,col,binsize):
    fig, ax = plt.subplots(figsize=(20,4))
    counts, bins, patches = ax.hist(dataset[col],bins=range(0,dataset[col].max(),round(binsize)), facecolor='lightgreen', edgecolor='gray')

    # Set the ticks to be at the edges of the bins.
    ax.set_xticks(bins)
    bin_centers = 0.5 * np.diff(bins) + bins[:-1]
    for count, x in zip(counts, bin_centers):
        # Label the percentages
        percent = '%0.0f%%' % (100 * float(count) / counts.sum())
        ax.annotate(percent, xy=(x,0.2), xycoords=('data', 'axes fraction'),
        xytext=(0, -32), textcoords='offset points', va='top', ha='center')

    ax.set_xlabel(col.upper())
    ax.set_ylabel('Count')
    # Give ourselves some more room at the bottom of the plot
    #plt.subplots_adjust(bottom=0.15)
    plt.show()
```

In [0]:

```
def plot_avgMonthlyCalls(pltType,data,calltype,colList):
    # style
    plt.style.use('seaborn-darkgrid')
    # create a color palette
    palette = plt.get_cmap('Set1')

    if pltType == 'multi':
        #Create dataframe after grouping on AON with colList fe
atures
        total_call_mou = pd.DataFrame(data.groupby('aon_bin',as
_index=False)[colList].mean())
        total_call_mou['aon_bin']=pd.to_numeric(total_call_mou[ 'a
on_bin'])
        total_call_mou
        # multiple line plot
        num=0
        fig, ax = plt.subplots(figsize=(15,8))
        for column in total_call_mou.drop('aon_bin', axis=1):
            num+=1
            ax.plot(total_call_mou['aon_bin']                    ,
total_call_mou[    column],    marker='',    color=palette(num),
linewidth=2, alpha=0.9, label=column)

        ## Add legend
        plt.legend(loc=2, ncol=2)
        ax.set_xticks(total_call_mou['aon_bin'])

        # Add titles
        plt.title("Avg.Monthly "+calltype+" MOU  V/S AON", loc=
'left', fontsize=12, fontweight=0, color='orange')
        plt.xlabel("Aon (years)")
        plt.ylabel("Avg. Monthly "+calltype+" MOU")
    elif pltType == 'single':
        fig, ax = plt.subplots(figsize=(8,4))
        ax.plot(data[colList].mean())
        ax.set_xticklabels(['Jun','Jul','Aug','Sep'])

        # Add titles
```

```
        plt.title("Avg. "+calltype+" MOU V/S Month", loc='lef
t', fontsize=12, fontweight=0, color='orange')
        plt.xlabel("Month")
        plt.ylabel("Avg. "+calltype+" MOU")

    plt.show()
```

In [0]:

```
def plot_byChurnMou(colList,calltype):
    fig, ax = plt.subplots(figsize=(7,4))
    df=hv_users.groupby(['churn'])[colList].mean().T
    plt.plot(df)
    ax.set_xticklabels(['Jun','Jul','Aug','Sep'])
    ## Add legend
    plt.legend(['Non-Churn', 'Churn'])
    # Add titles
    plt.title("Avg. "+calltype+" MOU  V/S Month", loc='left', f
ontsize=12, fontweight=0, color='orange')
    plt.xlabel("Month")
    plt.ylabel("Avg. "+calltype+" MOU")
```

In [0]:

```
def plot_byChurn(data,col):
    # per month churn vs Non-Churn
    fig, ax = plt.subplots(figsize=(7,4))
    colList=list(data.filter(regex=(col)).columns)
    colList = colList[:3]
    plt.plot(hv_users.groupby('churn')[colList].mean().T)
    ax.set_xticklabels(['Jun','Jul','Aug','Sep'])
    ## Add legend
    plt.legend(['Non-Churn', 'Churn'])
    # Add titles
    plt.title( str(col) +" V/S Month", loc='left', fontsize=12,
fontweight=0, color='orange')
    plt.xlabel("Month")
    plt.ylabel(col)
    plt.show()
    # Numeric stats for per month churn vs Non-Churn
    return hv_users.groupby('churn')[colList].mean()
```

In [0]:

```
# Filtering the common monthly columns for each month
comcol = hv_users.filter(regex ='_6').columns
monthlycol = [item.strip('_6') for item in comcol]
monthlycol
```

Out[0]:

```
['last_date_of_month',
 'arpu',
 'onnet_mou',
 'offnet_mou',
 'roam_ic_mou',
 'roam_og_mou',
 'loc_og_t2t_mou',
 'loc_og_t2m_mou',
 'loc_og_t2f_mou',
 'loc_og_t2c_mou',
 'loc_og_mou',
 'std_og_t2t_mou',
 'std_og_t2m_mou',
 'std_og_t2f_mou',
 'std_og_mou',
 'isd_og_mou',
 'spl_og_mou',
 'og_others',
 'total_og_mou',
 'loc_ic_t2t_mou',
 'loc_ic_t2m_mou',
 'loc_ic_t2f_mou',
 'loc_ic_mou',
 'std_ic_t2t_mou',
 'std_ic_t2m_mou',
 'std_ic_t2f_mou',
 'std_ic_mou',
 'total_ic_mou',
 'spl_ic_mou',
 'isd_ic_mou',
 'ic_others',
 'total_rech_num',
 'total_rech_amt',
 'max_rech_amt',
 'date_of_last_rech',
 'last_day_rch_amt',
 'total_rech_data',
 'max_rech_data',
 'count_rech_2g',
```

```
 'count_rech_3g',
 'av_rech_amt_data',
 'vol_2g_mb',
 'vol_3g_mb',
 'arpu_3g',
 'arpu_2g',
 'night_pck_user',
 'monthly_2g',
 'sachet_2g',
 'monthly_3g',
 'sachet_3g',
 'fb_user',
 'vbc_3g',
 'vol_data_mb',
 'avg_rech_amt',
 'total_rech_num_data',
 'total_rech_amt_data',
 'total_month_rech']
```

In [0]:

```
# getting the number of monthly columns and profile columns
print ("Total number of columns in data :", hv_users.shape[1] )
print ("Number of columns for each month : ",len(monthlycol))
print ("Total monthly columns among the orignal columns (%d*4):
%d"%(len(monthlycol), len(monthlycol) * 4))
print ("Columns other than monthly columns :", hv_users.shape[1
] - (len(monthlycol) * 4))
```

```
Total number of columns in data : 232
Number of columns for each month :  57
Total monthly columns among the orignal columns (5
7*4): 228
Columns other than monthly columns : 4
```

In [0]:

```
# Lets remove all the attributes corresponding to the churn pha
se (all attributes having ‘ _9’, etc. in their names).
col_9List = hv_users.filter(regex=('_9')).columns
hv_users.drop(col_9List,axis=1,inplace=True)
```

In [0]:

```
# list of all the monthly columns 6,7,8,9
allmonthlycol = [x + s for s in ['_6','_7','_8'] for x in month
lycol]
allmonthlycol
```

Out[0]:

```
['last_date_of_month_6',
 'arpu_6',
 'onnet_mou_6',
 'offnet_mou_6',
 'roam_ic_mou_6',
 'roam_og_mou_6',
 'loc_og_t2t_mou_6',
 'loc_og_t2m_mou_6',
 'loc_og_t2f_mou_6',
 'loc_og_t2c_mou_6',
 'loc_og_mou_6',
 'std_og_t2t_mou_6',
 'std_og_t2m_mou_6',
 'std_og_t2f_mou_6',
 'std_og_mou_6',
 'isd_og_mou_6',
 'spl_og_mou_6',
 'og_others_6',
 'total_og_mou_6',
 'loc_ic_t2t_mou_6',
 'loc_ic_t2m_mou_6',
 'loc_ic_t2f_mou_6',
 'loc_ic_mou_6',
 'std_ic_t2t_mou_6',
 'std_ic_t2m_mou_6',
 'std_ic_t2f_mou_6',
 'std_ic_mou_6',
 'total_ic_mou_6',
 'spl_ic_mou_6',
 'isd_ic_mou_6',
 'ic_others_6',
 'total_rech_num_6',
 'total_rech_amt_6',
 'max_rech_amt_6',
 'date_of_last_rech_6',
 'last_day_rch_amt_6',
 'total_rech_data_6',
 'max_rech_data_6',
 'count_rech_2g_6',
```

```
'count_rech_3g_6',
'av_rech_amt_data_6',
'vol_2g_mb_6',
'vol_3g_mb_6',
'arpu_3g_6',
'arpu_2g_6',
'night_pck_user_6',
'monthly_2g_6',
'sachet_2g_6',
'monthly_3g_6',
'sachet_3g_6',
'fb_user_6',
'vbc_3g_6',
'vol_data_mb_6',
'avg_rech_amt_6',
'total_rech_num_data_6',
'total_rech_amt_data_6',
'total_month_rech_6',
'last_date_of_month_7',
'arpu_7',
'onnet_mou_7',
'offnet_mou_7',
'roam_ic_mou_7',
'roam_og_mou_7',
'loc_og_t2t_mou_7',
'loc_og_t2m_mou_7',
'loc_og_t2f_mou_7',
'loc_og_t2c_mou_7',
'loc_og_mou_7',
'std_og_t2t_mou_7',
'std_og_t2m_mou_7',
'std_og_t2f_mou_7',
'std_og_mou_7',
'isd_og_mou_7',
'spl_og_mou_7',
'og_others_7',
'total_og_mou_7',
'loc_ic_t2t_mou_7',
'loc_ic_t2m_mou_7',
'loc_ic_t2f_mou_7',
'loc_ic_mou_7',
```

```
    'std_ic_t2t_mou_7',
    'std_ic_t2m_mou_7',
    'std_ic_t2f_mou_7',
    'std_ic_mou_7',
    'total_ic_mou_7',
    'spl_ic_mou_7',
    'isd_ic_mou_7',
    'ic_others_7',
    'total_rech_num_7',
    'total_rech_amt_7',
    'max_rech_amt_7',
    'date_of_last_rech_7',
    'last_day_rch_amt_7',
    'total_rech_data_7',
    'max_rech_data_7',
    'count_rech_2g_7',
    'count_rech_3g_7',
    'av_rech_amt_data_7',
    'vol_2g_mb_7',
    'vol_3g_mb_7',
    'arpu_3g_7',
    'arpu_2g_7',
    'night_pck_user_7',
    'monthly_2g_7',
    'sachet_2g_7',
    'monthly_3g_7',
    'sachet_3g_7',
    'fb_user_7',
    'vbc_3g_7',
    'vol_data_mb_7',
    'avg_rech_amt_7',
    'total_rech_num_data_7',
    'total_rech_amt_data_7',
    'total_month_rech_7',
    'last_date_of_month_8',
    'arpu_8',
    'onnet_mou_8',
    'offnet_mou_8',
    'roam_ic_mou_8',
    'roam_og_mou_8',
    'loc_og_t2t_mou_8',
```

```
    'loc_og_t2m_mou_8',
    'loc_og_t2f_mou_8',
    'loc_og_t2c_mou_8',
    'loc_og_mou_8',
    'std_og_t2t_mou_8',
    'std_og_t2m_mou_8',
    'std_og_t2f_mou_8',
    'std_og_mou_8',
    'isd_og_mou_8',
    'spl_og_mou_8',
    'og_others_8',
    'total_og_mou_8',
    'loc_ic_t2t_mou_8',
    'loc_ic_t2m_mou_8',
    'loc_ic_t2f_mou_8',
    'loc_ic_mou_8',
    'std_ic_t2t_mou_8',
    'std_ic_t2m_mou_8',
    'std_ic_t2f_mou_8',
    'std_ic_mou_8',
    'total_ic_mou_8',
    'spl_ic_mou_8',
    'isd_ic_mou_8',
    'ic_others_8',
    'total_rech_num_8',
    'total_rech_amt_8',
    'max_rech_amt_8',
    'date_of_last_rech_8',
    'last_day_rch_amt_8',
    'total_rech_data_8',
    'max_rech_data_8',
    'count_rech_2g_8',
    'count_rech_3g_8',
    'av_rech_amt_data_8',
    'vol_2g_mb_8',
    'vol_3g_mb_8',
    'arpu_3g_8',
    'arpu_2g_8',
    'night_pck_user_8',
    'monthly_2g_8',
    'sachet_2g_8',
```

```
 'monthly_3g_8',
 'sachet_3g_8',
 'fb_user_8',
 'vbc_3g_8',
 'vol_data_mb_8',
 'avg_rech_amt_8',
 'total_rech_num_data_8',
 'total_rech_amt_data_8',
 'total_month_rech_8']
```

In [0]:

```
# list of column which are not monthly columns
nonmonthlycol = [col for col in hv_users.columns if col not in
allmonthlycol]
nonmonthlycol
```

Out[0]:

```
['mobile_number', 'circle_id', 'aon', 'churn']
```

Feature: circle_id

In [0]:

```
# Getting the distinct circle_id's in the data
hv_users.circle_id.value_counts()
```

Out[0]:

```
109    29906
Name: circle_id, dtype: int64
```

Looks like the data at hand is only for a single **circle_id 109.**
We can remove this feature going forward as it is not contributing to analysis and model building.

In [0]:

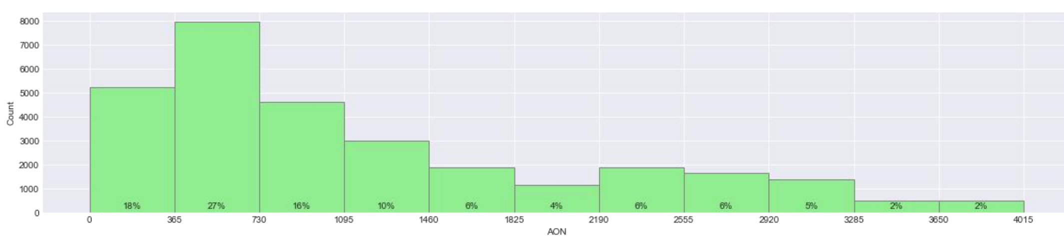
```
hv_users.drop('circle_id',axis=1,inplace=True)
```

Feature: aon

In [0]:

```
# Customers distribution of the age on network
print(hv_users.aon.describe())
plot_hist(hv_users,'aon',365)
```

```
count    29906.000000
mean      1209.062396
std        957.342718
min        180.000000
25%        460.000000
50%        846.000000
75%       1755.000000
max       4321.000000
Name: aon, dtype: float64
```



- **Minimun Age** on network is 180 days.
- **Average age** on network for customers is 1200 days (3.2 years).
- 27% of the **HV users are in their 2nd year** with the network.
- Almost 71% users have Age on network **less than 4 years.**
- 15% users are with the network from **over 7 years.**

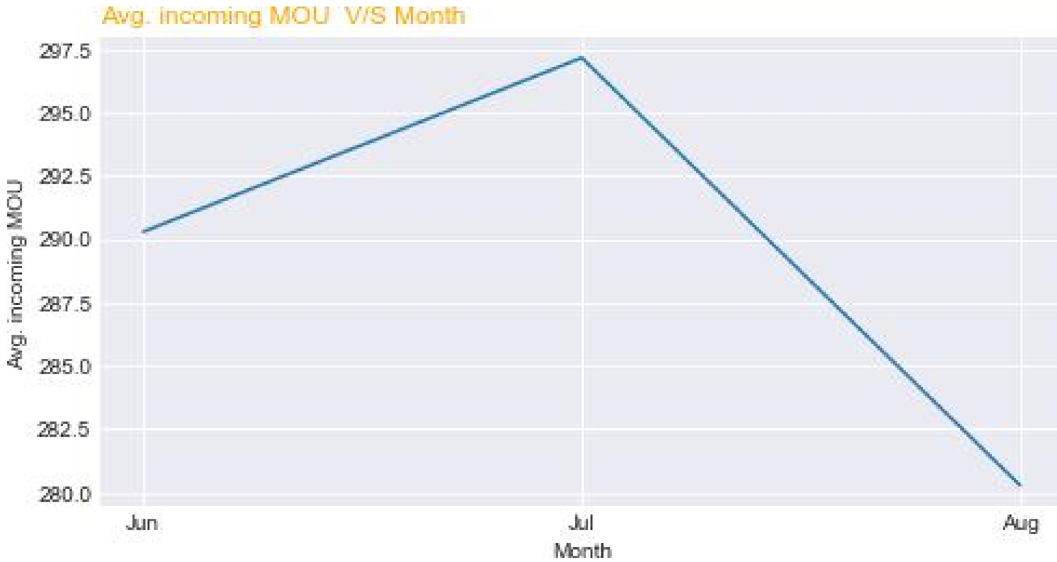
In [0]:

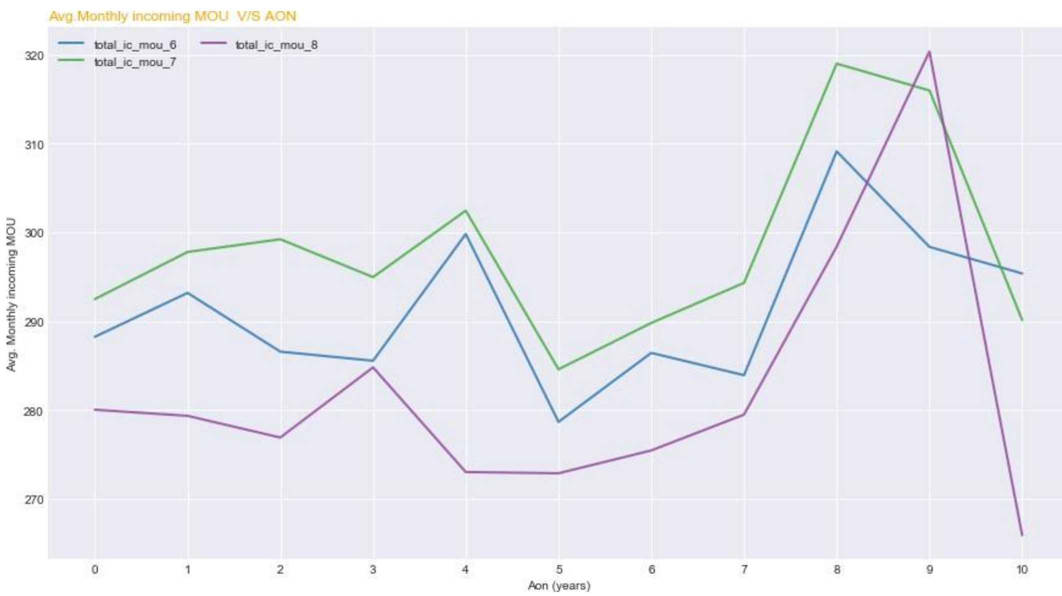
```
#Create Derived categorical variable
hv_users['aon_bin'] = pd.cut(churn['aon'], range(0,churn['aon']
.max(),365), labels=range(0,int(round(churn['aon'].max()/365))-
1))
```

Incoming VS month VS AON

In [0]:

```
# Plotting Avg. total monthly incoming MOU vs AON
ic_col = hv_users.filter(regex ='total_ic_mou').columns
plot_avgMonthlyCalls('single',hv_users,calltype='incoming',colL
ist=ic_col)
plot_avgMonthlyCalls('multi',hv_users,calltype='incoming',colLi
st=ic_col)
```


Avg. incoming MOU V/S Month
Avg. incoming MOU
297.5
295.0
292.5
290.0
287.5
285.0
282.5
280.0
Jun
Jul
Aug
Month


Avg.Monthly incoming MOU V/S AON
total_ic_mou_6
total_ic_mou_7
total_ic_mou_8
Avg. Monthly incoming MOU
320
310
300
290
280
270
0
1
2
3
4
5
6
7
8
9
10
Aon (years)

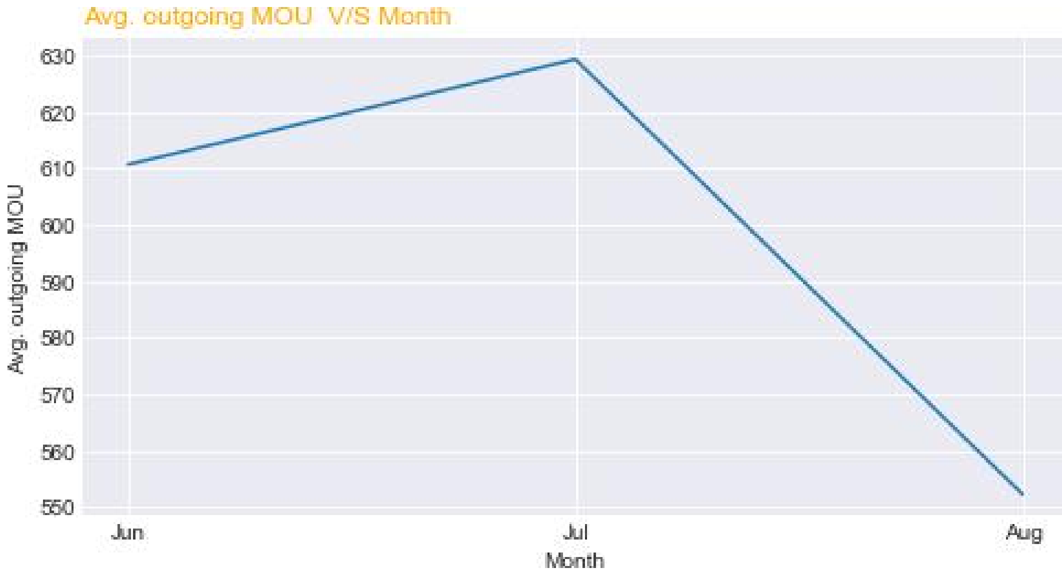
It is evident from the plot that,

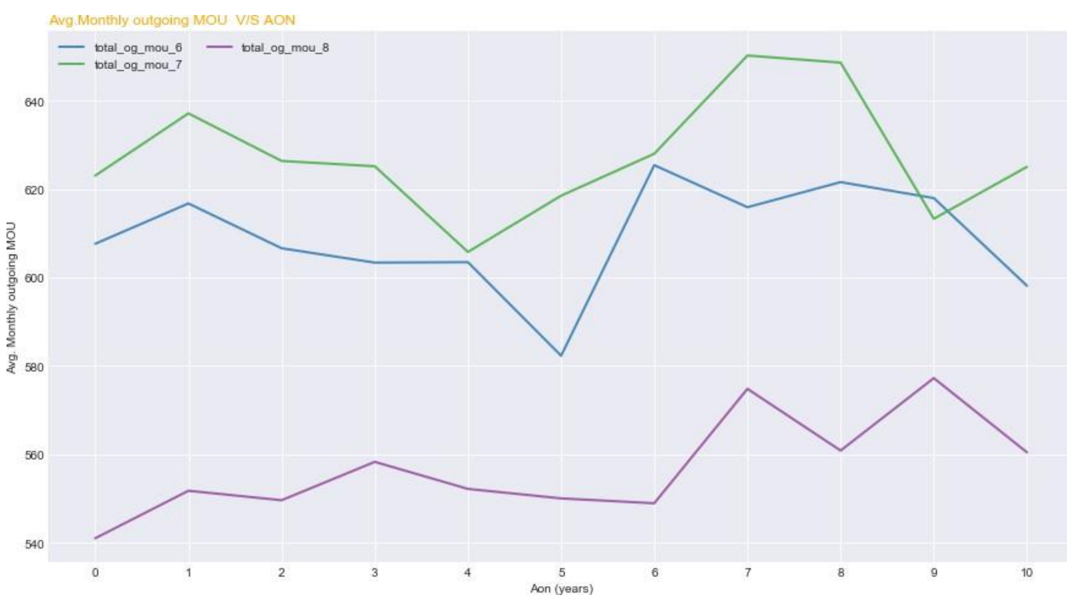
- The more a customer stays on with the operator(AON), more are the total monthly incoming MOU.
- Total Incoming MOU avg. for Jul(_7) are more than the previous Jun(_6) for customers in all AON bands.
- Total Incoming MOU avg. for Aug(_8) cease to increace, infact it shows a decline compared to Jul(_7).
- Total Incoming MOU avg. for Sep(_9) is well below the first months(jun _6) avg.
- Althought the Total incoming mou avg inceases from jun to july, it drop little from aug and reduces lower than that for jun.

Outgoing VS month VS AON

In [0]:

```
# Plotting Avg. total monthly outgoing MOU vs AON
og_col = hv_users.filter(regex ='total_og_mou').columns
plot_avgMonthlyCalls('single',hv_users,calltype='outgoing',colL
ist=og_col)
plot_avgMonthlyCalls('multi',hv_users,calltype='outgoing',colLi
st=og_col)
```


Avg. outgoing MOU V/S Month
Avg. outgoing MOU
630
620
610
600
590
580
570
560
550
Jun
Jul
Aug
Month


Avg.Monthly outgoing MOU V/S AON
total_og_mou_6
total_og_mou_7
total_og_mou_8
Avg. Monthly outgoing MOU
640
620
600
580
560
540
0
1
2
3
4
5
6
7
8
9
10
Aon (years)

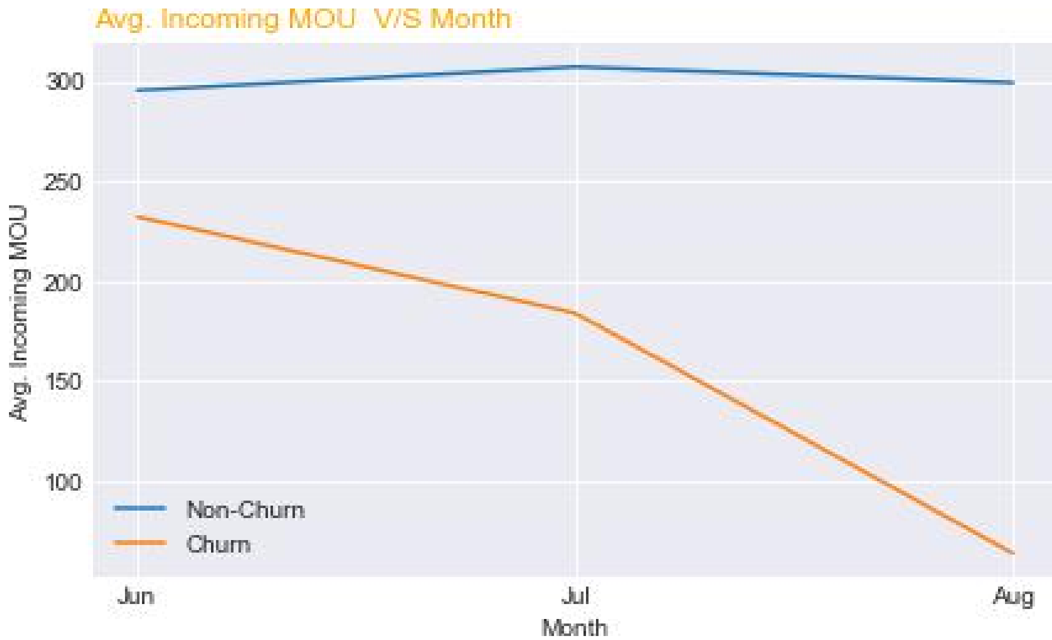
What is the above plot saying ?

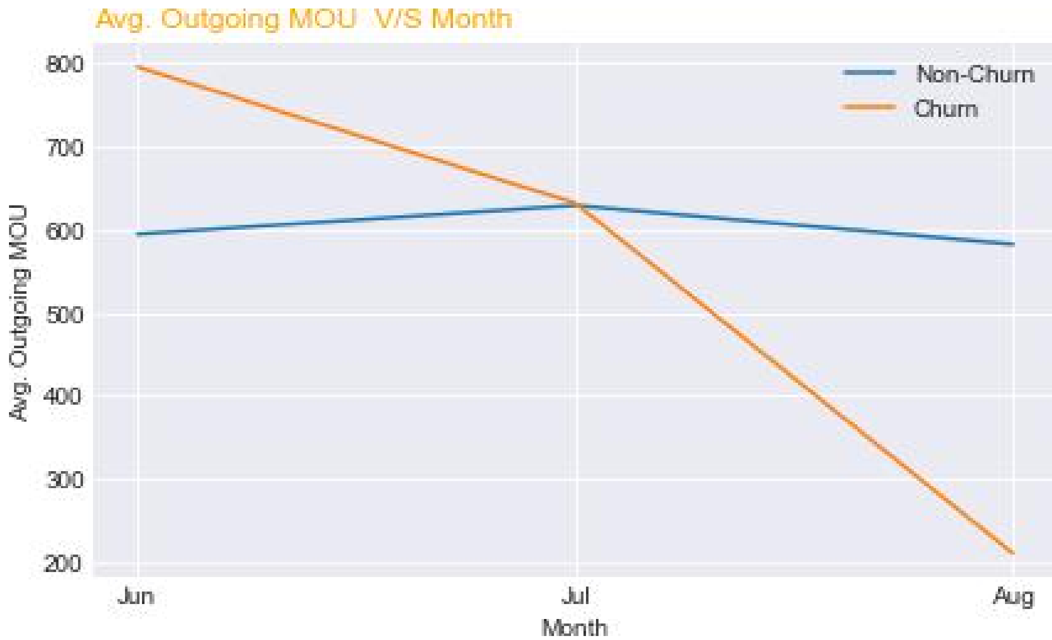
- Overall, the Avg. total outgoing usage reduces with the increasing age on network.
- Total Outgoing MOU avg. for Jul(_7) are more than the previous Jun(_6) for customers in all AON bands, except in the AON band between 7 - 8 years where it is almost simillar.
- Total outgoing MOU avg. for Aug(_8) cease to increace, infact it shows a significant decline compared to Jul(_7).
- Total outgoing MOU avg. for Sep(_9) is the lowest of all 4 months.
- The Avg. outgoing usage reduces drastically for customers in the AON band between 7 - 8 years.

Incoming/Outgoing MOU VS Churn

In [0]:

```
ic_col = ['total_ic_mou_6','total_ic_mou_7','total_ic_mou_8']
og_col = ['total_og_mou_6','total_og_mou_7','total_og_mou_8']
plot_byChurnMou(ic_col,'Incoming')
plot_byChurnMou(og_col,'Outgoing')
```


Avg. Incoming MOU V/S Month
Avg. Incoming MOU
300
250
200
150
100
Non-Churn
Churn
Jun
Jul
Aug
Month



It can be observed,

- Churners Avg. Incoming/Outgoing MOU's **drops drastically after the 2nd month,Jul.**
- While the non-churners Avg. MOU's remains consistant and stable with each month.
- Therefore, users MOU is a key feature to predict churn.

Let's also see this trend in terms of actual numbers.

In [0]:

```
# Avg.Incoming MOU per month churn vs Non-Churn
hv_users.groupby(['churn'])['total_ic_mou_6','total_ic_mou_7',
'total_ic_mou_8'].mean()
```

Out[0]:

churn	total_ic_mou_6	total_ic_mou_7	total_ic_mou_8
0	295.401726	307.108317	299.319664
1	232.221162	183.978888	63.813168

In [0]:

```
# Avg. Outgoing MOU per month churn vs Non-Churn
hv_users.groupby(['churn'])['total_og_mou_6','total_og_mou_7',
'total_og_mou_8'].mean()
```

Out[0]:

churn	total_og_mou_6	total_og_mou_7	total_og_mou_8
0	594.414582	629.096568	582.380539
1	795.591038	631.859433	210.659326

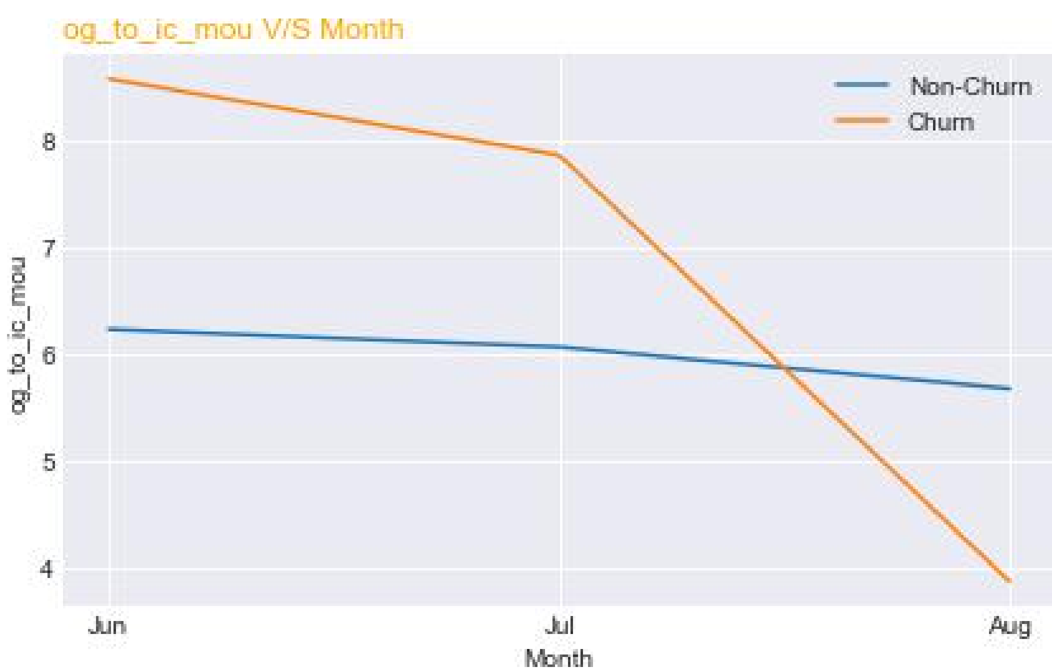
Create new feature: og_to_ic_mou_6, og_to_ic_mou_7, og_to_ic_mou_8 These features will hold the **ratio** (=total_og*mou / total_icmou*) for each month. These features will combine both incoming and outgoing informations and should be a **better predictor of churn.**

In [0]:

```
#Creating new feature: og_to_ic_mou_6, og_to_ic_mou_7, og_to_ic_mou_8
# adding 1 to denominator to avoid dividing by 0 and getting nan values.
for i in range(6,9):
    hv_users['og_to_ic_mou_'+str(i)] = (hv_users['total_og_mou_'+str(i)])/(hv_users['total_ic_mou_'+str(i)]+1)
```

In [0]:

```
plot_byChurn(hv_users,'og_to_ic_mou')
```



Out[0]:

churn	og_to_ic_mou_6	og_to_ic_mou_7	og_to_ic_mou_8
0	6.235602	6.067952	5.678424
1	8.580257	7.865938	3.870145

- Outgoing to incoming mou remains drops significantly for churners from month Jul(6) to Aug(7).
- While it remains almost consistent for the non-churners.

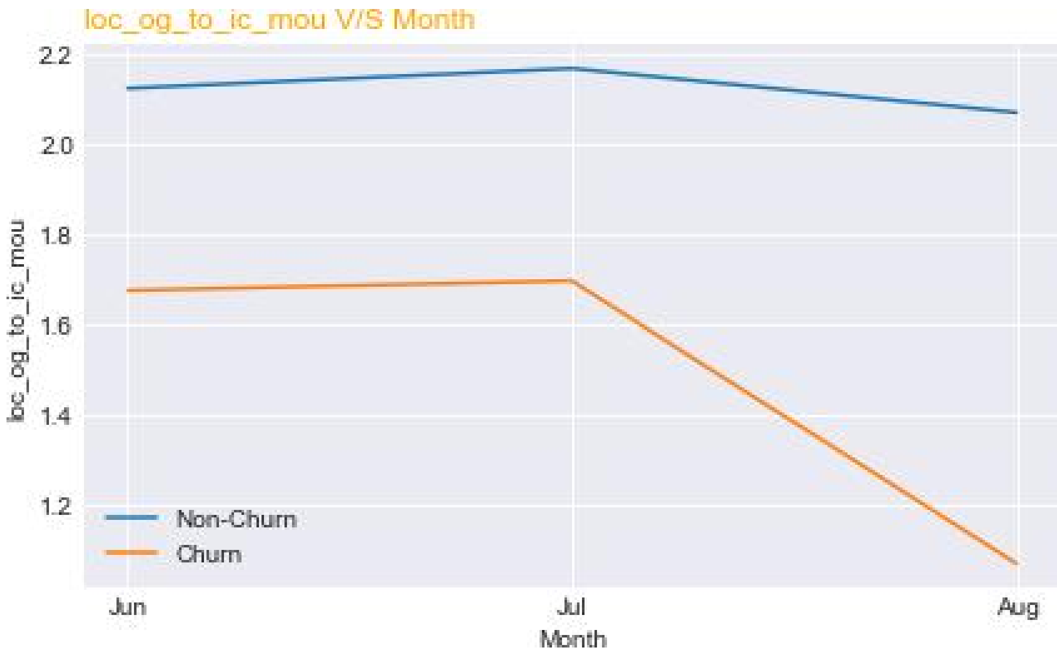
Create new feature: loc_og_to_ic_mou_6, loc_og_to_ic_mou_7, loc_og_to_ic_mou_8 These features will hold the **ratio** (=loc_og*mou / loc_icmou*) for each month. These features will combine the local calls, both incoming and outgoing informations and should be a **better predictor of churn.**

In [0]:

```
#Create new feature: loc_og_to_ic_mou_6, loc_og_to_ic_mou_7, lo
c_og_to_ic_mou_8
# adding 1 to denominator to avoid dividing by 0 and getting na
n values.
for i in range(6,9):
    hv_users['loc_og_to_ic_mou_'+str(i)] = (hv_users['loc_og_mo
u_'+str(i)])/(hv_users['loc_ic_mou_'+str(i)]+1)
```

In [0]:

```
plot_byChurn(hv_users,'loc_og_to_ic_mou')
```



Out[0]:

churn	loc_og_to_ic_mou_6	loc_og_to_ic_mou_7	loc_og_to_ic_
0	2.124471	2.168763	2.
1	1.675413	1.696809	1.

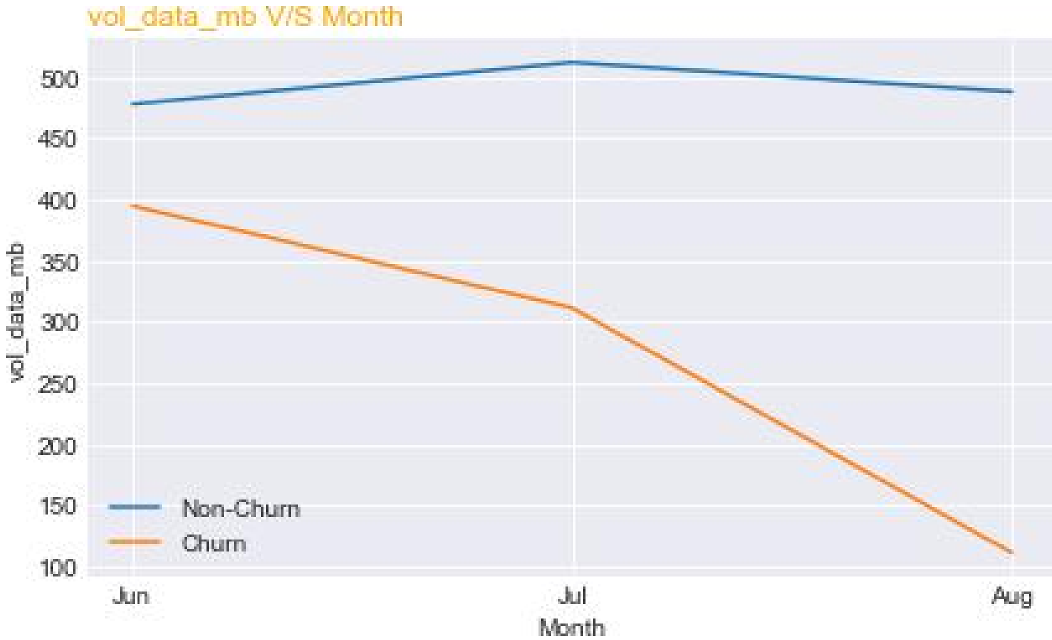
It can be observed that,

- The local outgoing to incoming call mou ratio is genrally low for churners right from the begining of the good phase.
- local mou pattern for the non-churners remains almost constant through out the 3 months.
- The churners genrally show a low loc mou ratio but it drops dramatically after the 2nd month.
- This might suggest that people who are not making/reciving much local calls during their tenure are more likely to churn.

Total data volume VS Churn

In [0]:

```
plot_byChurn(hv_users,'vol_data_mb')
```



Out[0]:

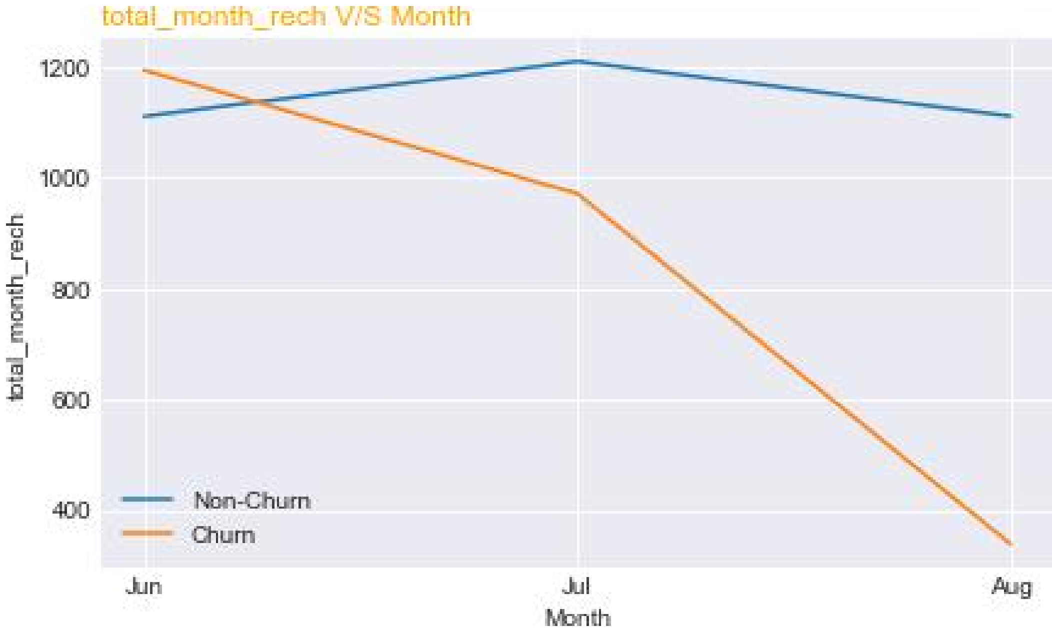
churn	vol_data_mb_6	vol_data_mb_7	vol_data_mb_8
0	478.037762	512.164072	488.389661
1	394.949545	311.507444	111.469396

- The volume of data mb used drops significantly for churners from month Jul(6) to Aug(7).
- While it remains almost consistent for the non-churners.

Total monthly rech VS Churn

In [0]:

```
plot_byChurn(hv_users,'total_month_rech')
```



Out[0]:

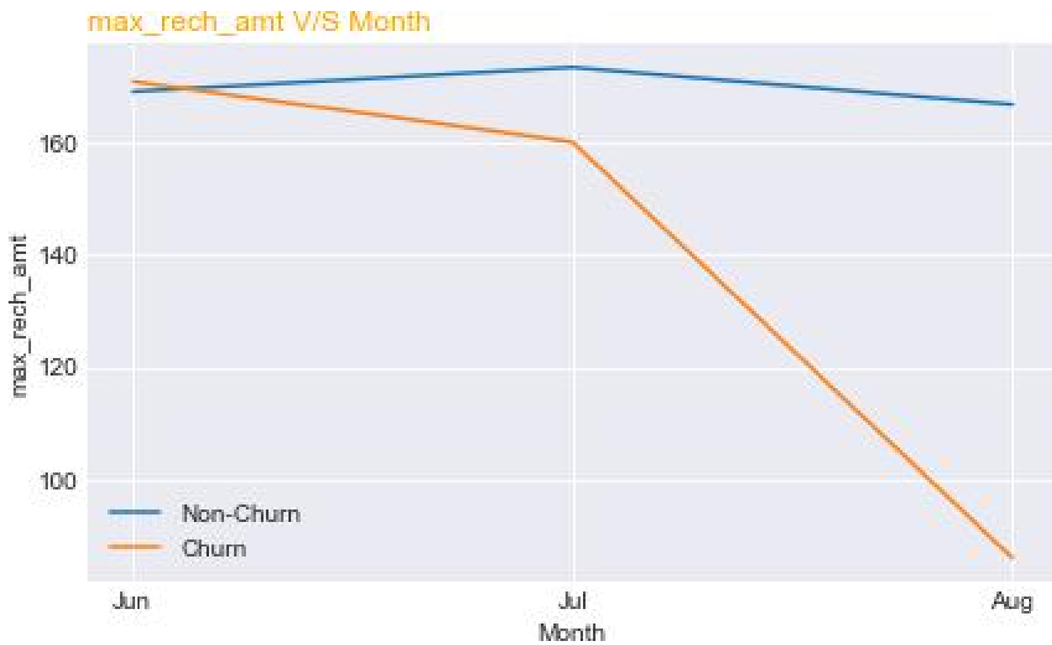
	total_month_rech_6	total_month_rech_7	total_month_re
churn			
0	1111.439977	1210.362853	1111.75
1	1194.747593	971.802758	339.27

- total monthly rech amount also drops significantly for churners from month Jul(6) to Aug(7).
- While it remains almost consistent for the non-churners.

max_rech_amt VS Churn

In [0]:

```
plot_byChurn(hv_users,'max_rech_amt')
```



Out[0]:

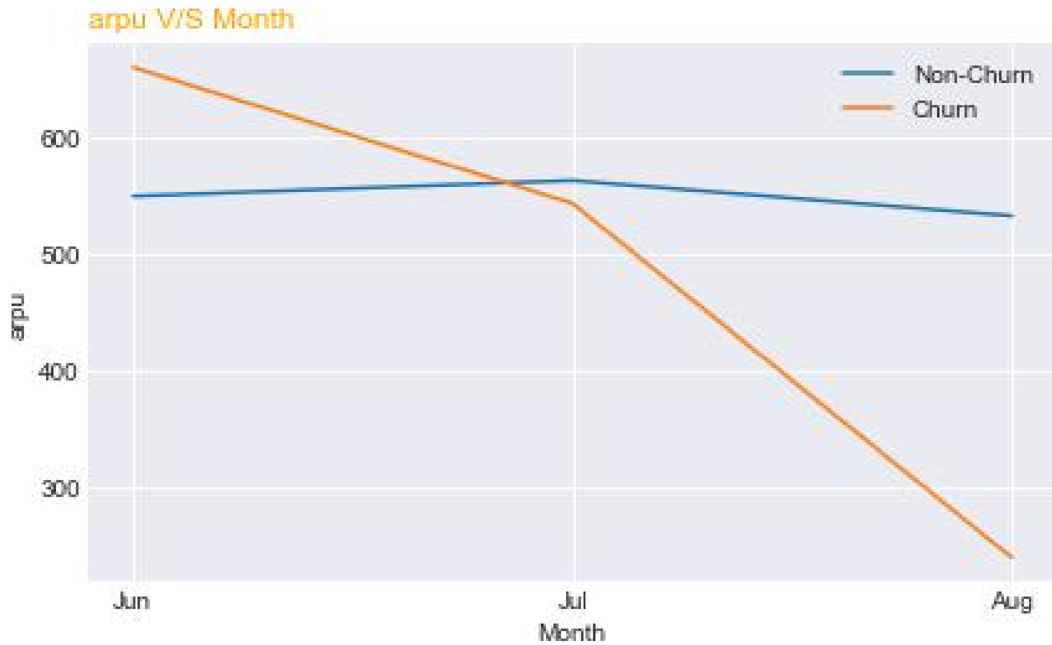
churn	max_rech_amt_6	max_rech_amt_7	max_rech_amt_8
0	169.160943	173.437282	166.865250
1	170.930108	160.152192	86.026468

- maximum recharge amount also drops significantly for churners from month Jul(6) to Aug(7).
- While it remains almost consistent for the non-churners.

arpu VS Churn

In [0]:

```
plot_byChurn(hv_users,'arpu')
```



Out[0]:

	arpu_6	arpu_7	arpu_8
churn			
0	549.843524	563.190828	533.052496
1	660.695411	543.722952	238.631887

- Average revenue per user,arpu also drops significantly for churners from month Jul(6) to Aug(7).
- While it remains almost consistent for the non-churners.

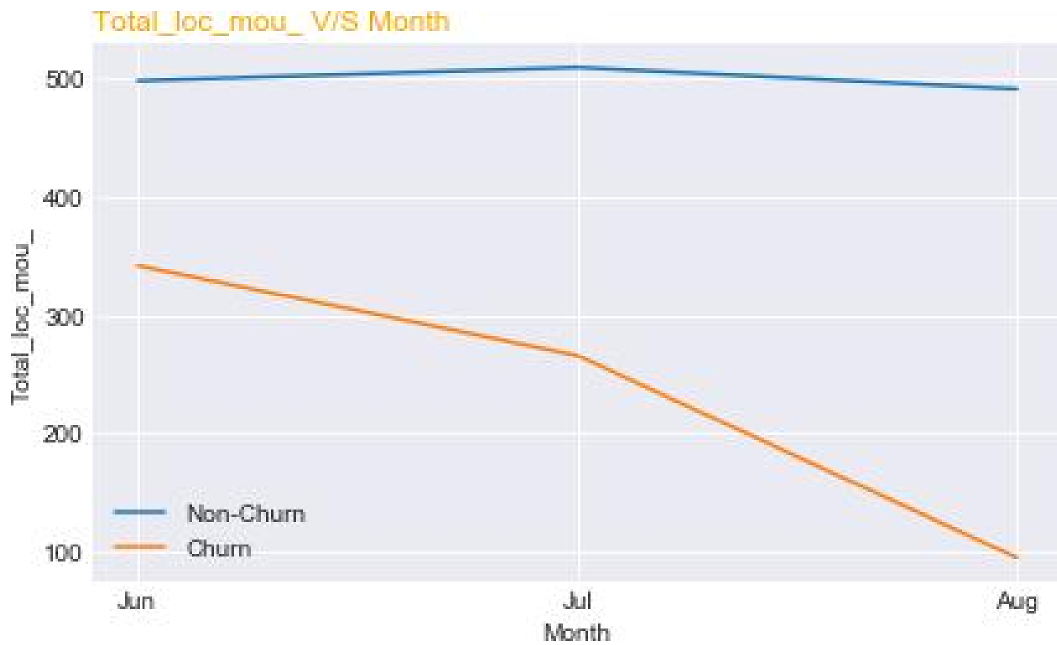
Create new feature: Total_loc_mou_6, Total_loc_mou_7, Total_loc_mou_8
These features will hold the **Total MOU** (=loc_og_mou+loc_ic_mou) for each month.
Using this we will find if the loc MOU (both incoming and outgoing) drops or increaces as the months goes by.
This informations should be a **better predictor of churn.**

In [0]:

```
#Create new feature: Total_loc_mou_6,Total_loc_mou_7,lTotal_loc_mou_8
for i in range(6,9):
    hv_users['Total_loc_mou_'+str(i)] = (hv_users['loc_og_mou_'+str(i)])+(hv_users['loc_ic_mou_'+str(i)])
```

In [0]:

```
plot_byChurn(hv_users,'Total_loc_mou_')
```



Out[0]:

churn	Total_loc_mou_6	Total_loc_mou_7	Total_loc_mou_8
0	498.548969	509.835211	491.705600
1	342.113462	266.025666	94.701154

It can be observed that,

- The Total local call mou is genrally low for churners right from the begining of the good phase.
- local mou pattern for the non-churners remains almost constant through out the 3 months.
- The churners genrally show a low total loc mou but it drops dramatically after the 2nd month.
- This might suggest that people who are not making/reciving much local calls during their tenure are more likely to churn.

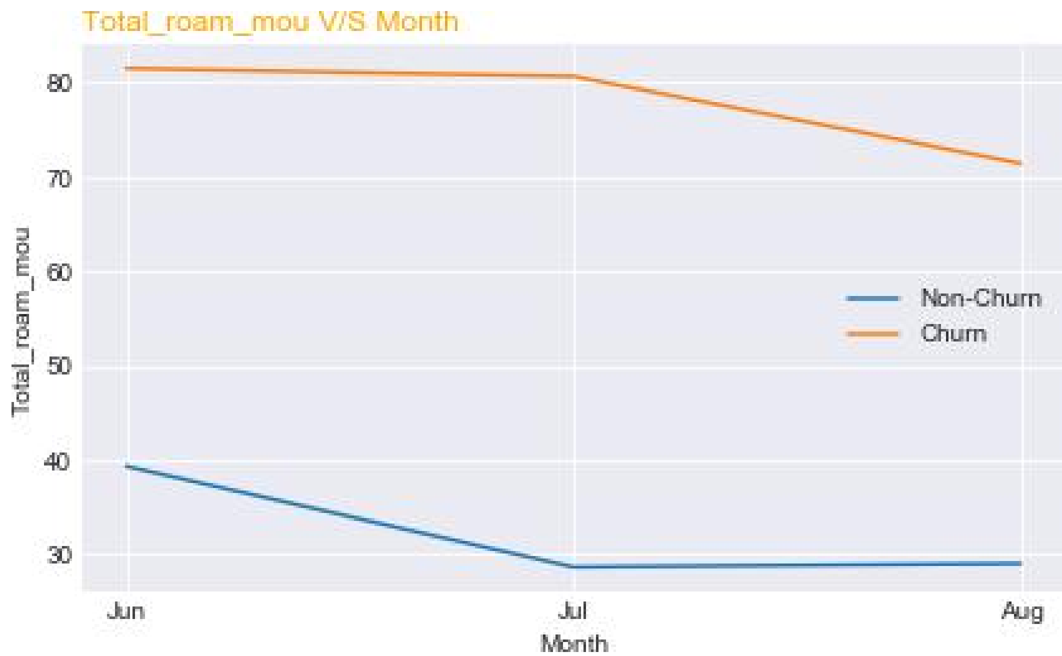
Create new feature:
Total_roam_mou_6,Total_roam_mou_7,Total_roam_mou_8
These features will hold the **Total roaming MOU** (=roam_ic_mou+roam_og_mou) for each month.
Using this we will find if the roam MOU (both incoming and outgoing) drops or increaces as the months goes by.
This informations should be a **better predictor of churn.**

In [0]:

```
#Create new feature: Total_roam_mou_6,Total_roam_mou_7,Total_roam_mou_8
for i in range(6,9):
    hv_users['Total_roam_mou_'+str(i)] = (hv_users['roam_ic_mou_'+str(i)])+(hv_users['roam_og_mou_'+str(i)])
```

In [0]:

```
plot_byChurn(hv_users,'Total_roam_mou')
```



Out[0]:

churn	Total_roam_mou_6	Total_roam_mou_7	Total_roam_mou
0	39.360033	28.643301	29.0167
1	81.504156	80.651973	71.4436

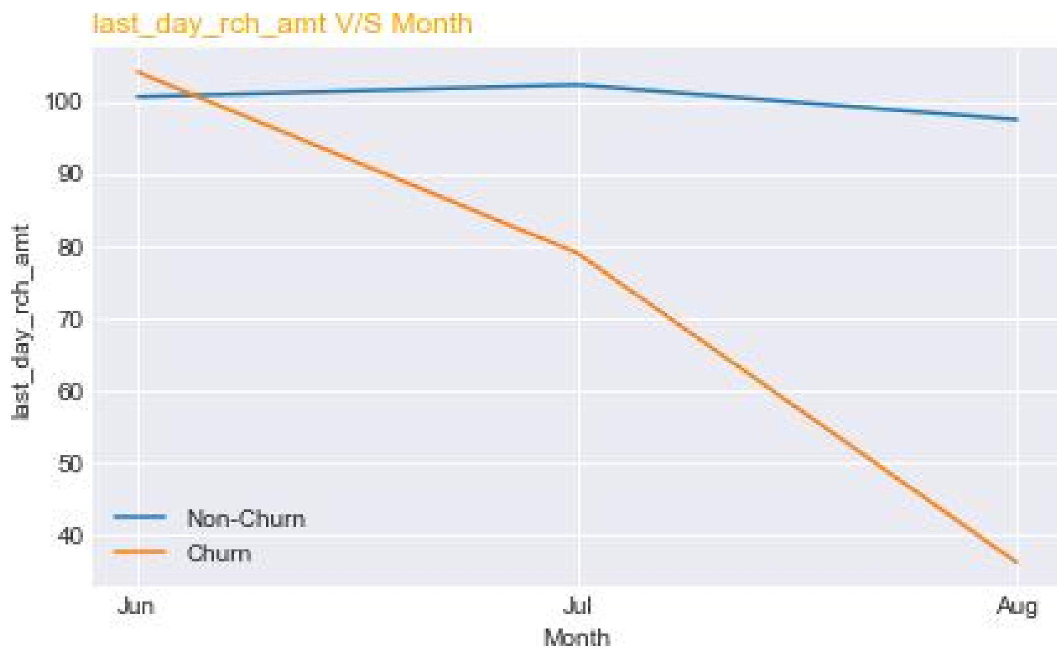
It can be observed that,

- Surprisingly, the roaming usage of churners is way higher than those of non-churners across all months
- People who are making/reciving more roaming calls during their tenure are more likely to churn.
- This might suggest that the operators roaming tariffs are higher than what are offered by its competitor, thus forming one of the reasons of churn.

last_day_rch_amt VS Churn

In [0]:

```
plot_byChurn(hv_users,'last_day_rch_amt')
```



Out[0]:

	last_day_rch_amt_6	last_day_rch_amt_7	last_day_rch_a
churn			
0	100.657232	102.318284	97.45
1	104.085194	78.956989	35.95

- The avg. last recharge amount for churners is less than half the amount of that of the non-churners.
- Suggesting, as the recharge amount reduces for a customer its chances to churn increases.

Modeling

In [0]:

```
import sklearn.preprocessing
from sklearn import metrics
from sklearn.metrics import classification_report,confusion_mat
rix
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
```

In [0]:

```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate
= False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(6, 6))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_
score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rat
e]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return fpr, tpr, thresholds
```

In [0]:

```
def getModelMetrics(actual_churn=False,pred_churn=False):

    confusion = metrics.confusion_matrix(actual_churn, pred_chu
rn)

    TP = confusion[1,1] # true positive
    TN = confusion[0,0] # true negatives
    FP = confusion[0,1] # false positives
    FN = confusion[1,0] # false negatives

    print("Roc_auc_score : {}".format(metrics.roc_auc_score(act
ual_churn,pred_churn)))
    # Let's see the sensitivity of our logistic regression mode
l
    print('Sensitivity/Recall : {}'.format(TP / float(TP+FN)))
    # Let us calculate specificity
    print('Specificity: {}'.format(TN / float(TN+FP)))
    # Calculate false postive rate - predicting churn when cust
omer does not have churned
    print('False Positive Rate: {}'.format(FP/ float(TN+FP)))
    # positive predictive value
    print('Positive predictive value: {}'.format(TP / float(TP+
FP)))
    # Negative predictive value
    print('Negative Predictive value: {}'.format(TN / float(TN+
FN)))
    # sklearn precision score value
    print('sklearn precision score value: {}'.format(metrics.pr
ecision_score(actual_churn, pred_churn )))
```

In [0]:

```
def predictChurnWithProb(model,X,y,prob):
    # Funtion to predict the churn using the input probability
 cut-off
    # Input arguments: model instance, x and y to predict using
model and cut-off probability

    # predict
    pred_probs = model.predict_proba(X)[:,1]

    y_df= pd.DataFrame({'churn':y, 'churn_Prob':pred_probs})
    # Creating new column 'predicted' with 1 if Churn_Prob>0.5
 else 0
    y_df['final_predicted'] = y_df.churn_Prob.map( lambda x: 1
if x > prob else 0)
    # Let's see the head
    getModelMetrics(y_df.churn,y_df.final_predicted)
    return y_df
```

In [0]:

```
def findOptimalCutoff(df):
    #Function to find the optimal cutoff for classifing as chur
n/non-churn
    # Let's create columns with different probability cutoffs
    numbers = [float(x)/10 for x in range(10)]
    for i in numbers:
        df[i] = df.churn_Prob.map( lambda x: 1 if x > i else 0)
    #print(df.head())

    # Now let's calculate accuracy sensitivity and specificity
 for various probability cutoffs.
    cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sen
si','speci'])
    from sklearn.metrics import confusion_matrix

    # TP = confusion[1,1] # true positive
    # TN = confusion[0,0] # true negatives
    # FP = confusion[0,1] # false positives
    # FN = confusion[1,0] # false negatives

    num = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
    for i in num:
        cm1 = metrics.confusion_matrix(df.churn, df[i]  )
        total1=sum(sum(cm1))
        accuracy = (cm1[0,0]+cm1[1,1])/total1

        speci = cm1[0,0]/(cm1[0,0]+cm1[0,1])
        sensi = cm1[1,1]/(cm1[1,0]+cm1[1,1])
        cutoff_df.loc[i] =[ i ,accuracy,sensi,speci]
    print(cutoff_df)
    # Let's plot accuracy sensitivity and specificity for vario
us probabilities.
    cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'
])
    plt.show()
```

In [0]:

```
def modelfit(alg, X_train, y_train, performCV=True, cv_folds=5
):
    #Fit the algorithm on the data
    alg.fit(X_train, y_train)

    #Predict training set:
    dtrain_predictions = alg.predict(X_train)
    dtrain_predprob = alg.predict_proba(X_train)[:,1]

    #Perform cross-validation:
    if performCV:
        cv_score = cross_val_score(alg, X_train, y_train, cv=cv
_folds, scoring='roc_auc')

    #Print model report:
    print ("\nModel Report")
    print ("Accuracy : %.4g" % metrics.roc_auc_score(y_train, d
train_predictions))
    print ("Recall/Sensitivity : %.4g" % metrics.recall_score(y
_train, dtrain_predictions))
    print ("AUC Score (Train): %f" % metrics.roc_auc_score(y_tr
ain, dtrain_predprob))

    if performCV:
        print ("CV Score : Mean - %.7g | Std - %.7g | Min - %.7
g | Max - %.7g" % (np.mean(cv_score),np.std(cv_score),np.min(cv
_score),np.max(cv_score)))
```

In [0]:

```
# creating copy of the final hv_user dataframe
hv_users_PCA = hv_users.copy()
# removing the columns not required for modeling
hv_users_PCA.drop(['mobile_number', 'aon_bin'], axis=1, inplace
=True)
```

In [0]:

```
# removing the datatime columns before PCA
dateTimeCols = list(hv_users_PCA.select_dtypes(include=['dateti
me64']).columns)
print(dateTimeCols)
hv_users_PCA.drop(dateTimeCols, axis=1, inplace=True)
```

```
['last_date_of_month_6', 'last_date_of_month_7',
'last_date_of_month_8', 'date_of_last_rech_6', 'da
te_of_last_rech_7', 'date_of_last_rech_8']
```

In [0]:

```
from sklearn.model_selection import train_test_split

#putting features variables in X
X = hv_users_PCA.drop(['churn'], axis=1)

#putting response variables in Y
y = hv_users_PCA['churn']

# Splitting the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X,y, train_
size=0.7,test_size=0.3,random_state=100)
```

In [0]:

```
#Rescaling the features before PCA as it is sensitive to the sc
ales of the features
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

In [0]:

```
# fitting and transforming the scaler on train
X_train = scaler.fit_transform(X_train)
# transforming the train using the already fit scaler
X_test = scaler.transform(X_test)
```

Handling class imbalance.

Standard classifier algorithms like Decision Tree and Logistic Regression have a bias towards classes which have number of instances. They tend to only predict the majority class data. The features of the minority class are treated as noise and are often ignored. Thus, there is a high probability of misclassification of the minority class as compared to the majority class.

Informed Over Sampling: Synthetic Minority Over-sampling Technique

This technique is followed to avoid overfitting which occurs when exact replicas of minority instances are added to the main dataset. A subset of data is taken from the minority class as an example and then new synthetic similar instances are created. These synthetic instances are then added to the original dataset. The new dataset is used as a sample to train the classification models.

Advantages

- Mitigates the problem of overfitting caused by random oversampling as synthetic examples are generated rather than replication of instances
- No loss of useful information

In [0]:

```
print("Before OverSampling, counts of label '1': {}".format(sum
(y_train==1)))
print("Before OverSampling, counts of label '0': {}
\n".format( sum(y_train==0)))
print("Before OverSampling, churn event rate : {}% \n".format(r
ound(sum(y_train==1)/len(y_train)*100,2)))
```

```
Before OverSampling, counts of label '1': 1700
Before OverSampling, counts of label '0': 19234

Before OverSampling, churn event rate : 8.12%
```

In [0]:

```
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=12, ratio = 1)
X_train_res, y_train_res = sm.fit_sample(X_train, y_train)
```

In [0]:

```
print('After OverSampling, the shape of train_X: {}'.format(X_t
rain_res.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(
y_train_res.shape))

print("After OverSampling, counts of label '1': {}".format(sum(
y_train_res==1)))
print("After OverSampling, counts of label '0': {}".format(sum(
y_train_res==0)))
print("After OverSampling, churn event rate : {}% \n".format(ro
und(sum(y_train_res==1)/len(y_train_res)*100,2)))
```

```
After OverSampling, the shape of train_X: (38468,
178)
After OverSampling, the shape of train_y: (38468,)

After OverSampling, counts of label '1': 19234
After OverSampling, counts of label '0': 19234
After OverSampling, churn event rate : 50.0%
```

In [0]:

```
#Improting the PCA module
from sklearn.decomposition import PCA
pca = PCA(svd_solver='randomized', random_state=42)
```

In [0]:

```
#Doing the PCA on the train data
pca.fit(X_train_res)
```

Out[0]:

```
PCA(copy=True, iterated_power='auto', n_components
=None, random_state=42,
  svd_solver='randomized', tol=0.0, whiten=False)
```

we'll let PCA select the number of components basen on a variance cutoff we provide

In [0]:

```
# let PCA select the number of components basen on a variance c
utoff
#pca_again = PCA(0.9)
```

In [0]:

```
#df_train_pca2 = pca_again.fit_transform(X_train_res)
#df_train_pca2.shape
# we see that PCA selected 12 components
```

In [0]:

```
#X_train_pca = pca_again.fit_transform(X_train_res)
#X_train_pca.shape
```

In [0]:

```
#Applying selected components to the test data - 50 components
#X_test_pca = pca_again.transform(X_test)
#X_test_pca.shape
```

Looking at the screeplot to assess the number of needed principal components

In [0]:

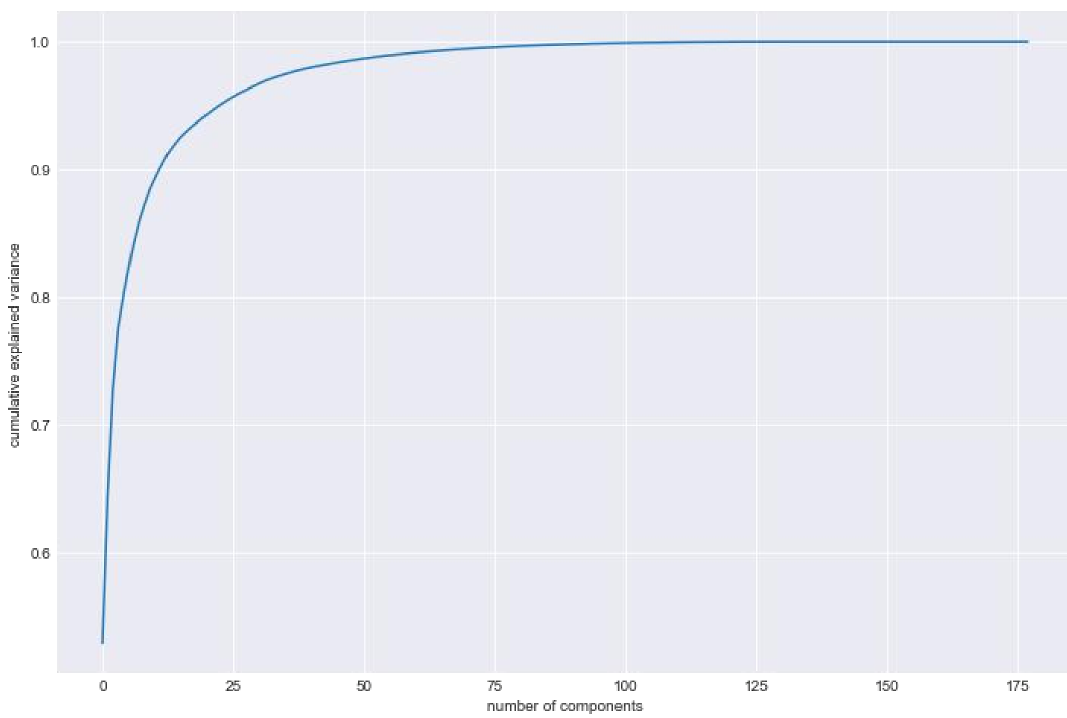
```
pca.explained_variance_ratio_[:50]
```

Out[0]:

```
array([0.52913894, 0.1166657 , 0.0816683 , 0.04689
798, 0.02584179,
       0.02237079, 0.01964869, 0.01659088, 0.01321
824, 0.01176983,
       0.00898743, 0.00843637, 0.0076714 , 0.00612
81 , 0.0054974 ,
       0.00498053, 0.0039488 , 0.00364592, 0.00345
993, 0.00334175,
       0.00313343, 0.00308146, 0.00300552, 0.00267
775, 0.00263377,
       0.00239202, 0.00232195, 0.00216938, 0.00211
813, 0.00207988,
       0.00192842, 0.00182302, 0.00161634, 0.00134
886, 0.00132756,
       0.00129843, 0.00119413, 0.00118133, 0.00103
869, 0.00092527,
       0.00087023, 0.00080434, 0.00080033, 0.00074
551, 0.00073027,
       0.00071356, 0.00065167, 0.00064958, 0.00062
886, 0.00060785])
```

In [0]:

```
#Making the screeplot - plotting the cumulative variance agains
t the number of components
%matplotlib inline
fig = plt.figure(figsize = (12,8))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
plt.show()
```



Looks like 50 components are enough to describe 95% of the variance in the dataset

- We'll choose 50 components for our modeling

In [0]:

```
#Using incremental PCA for efficiency - saves a lot of time on
 larger datasets
from sklearn.decomposition import IncrementalPCA
pca_final = IncrementalPCA(n_components=35)
```

In [0]:

```
X_train_pca = pca_final.fit_transform(X_train_res)
X_train_pca.shape
```

Out[0]:

```
(38468, 35)
```

In [0]:

```
#creating correlation matrix for the principal components
corrmat = np.corrcoef(X_train_pca.transpose())
# 1s -> 0s in diagonals
corrmat_nodiag = corrmat - np.diagflat(corrmat.diagonal())
print("max corr:",corrmat_nodiag.max(), ", min corr: ", corrmat
_nodiag.min(),)
# we see that correlations are indeed very close to 0
```

```
max corr: 0.009724118403007406 , min corr:  -0.013
984397043002297
```

Indeed - there is no correlation between any two components! We effectively have removed multicollinearity from our situation, and our models will be much more stable

In [0]:

```
#Applying selected components to the test data - 50 components
X_test_pca = pca_final.transform(X_test)
X_test_pca.shape
```

Out[0]:

```
(8972, 35)
```

For the prediction of churn customers we will be fitting variety of models and select one which is the best predictor of churn. Models trained are,

```
1. Logistic Regression
2. Decision Tree
3. Random Forest
4. Boosting models - Gradient Boosting Classifier and XG
Boost Classifier
5. SVM
```

1. Logistic Regression

Applying Logistic Regression on our principal components

In [0]:

```
#Training the model on the train data
from sklearn.linear_model import LogisticRegression
from sklearn import metrics

lr0 = LogisticRegression(class_weight='balanced')
```

In [0]:

```
modelfit(lr0, X_train_pca, y_train_res)
```

```
Model Report
Accuracy : 0.827
Recall/Sensitivity : 0.8417
AUC Score (Train): 0.899923
CV Score : Mean - 0.8990912 | Std - 0.002043271 |
Min - 0.8965521 | Max - 0.9027379
```

In [0]:

```
# predictions on Test data
pred_probs_test = lr0.predict(X_test_pca)
getModelMetrics(y_test,pred_probs_test)
```

```
Roc_auc_score : 0.8176059484622296
Sensitivity/Recall : 0.8203342618384402
Specificity: 0.8148776350860188
False Positive Rate: 0.1851223649139811
Positive predictive value: 0.27822390174775624
Negative Predictive value: 0.9811816192560175
sklearn precision score value: 0.27822390174775624
```

In [0]:

```
print("Accuracy : {}".format(metrics.accuracy_score(y_test,pred
_probs_test)))
print("Recall : {}".format(metrics.recall_score(y_test,pred_pro
bs_test)))
print("Precision : {}".format(metrics.precision_score(y_test,pr
ed_probs_test)))
```

```
Accuracy : 0.81531431119037
Recall : 0.8203342618384402
Precision : 0.27822390174775624
```

In [0]:

```
#Making prediction on the test data
pred_probs_train = lr0.predict_proba(X_train_pca)[:,1]
print("roc_auc_score(Train) {:2.2}".format(metrics.roc_auc_scor
e(y_train_res, pred_probs_train)))
```

```
roc_auc_score(Train) 0.9
```

In [0]:

```
cut_off_prob=0.5
y_train_df = predictChurnWithProb(lr0,X_train_pca,y_train_res,c
ut_off_prob)
y_train_df.head()
```

```
Roc_auc_score : 0.8269730685244878
Sensitivity/Recall : 0.8416865966517625
Specificity: 0.8122595403972133
False Positive Rate: 0.18774045960278674
Positive predictive value: 0.8176262626262626
Negative Predictive value: 0.8368866509535033
sklearn precision score value: 0.8176262626262626
```

Out[0]:

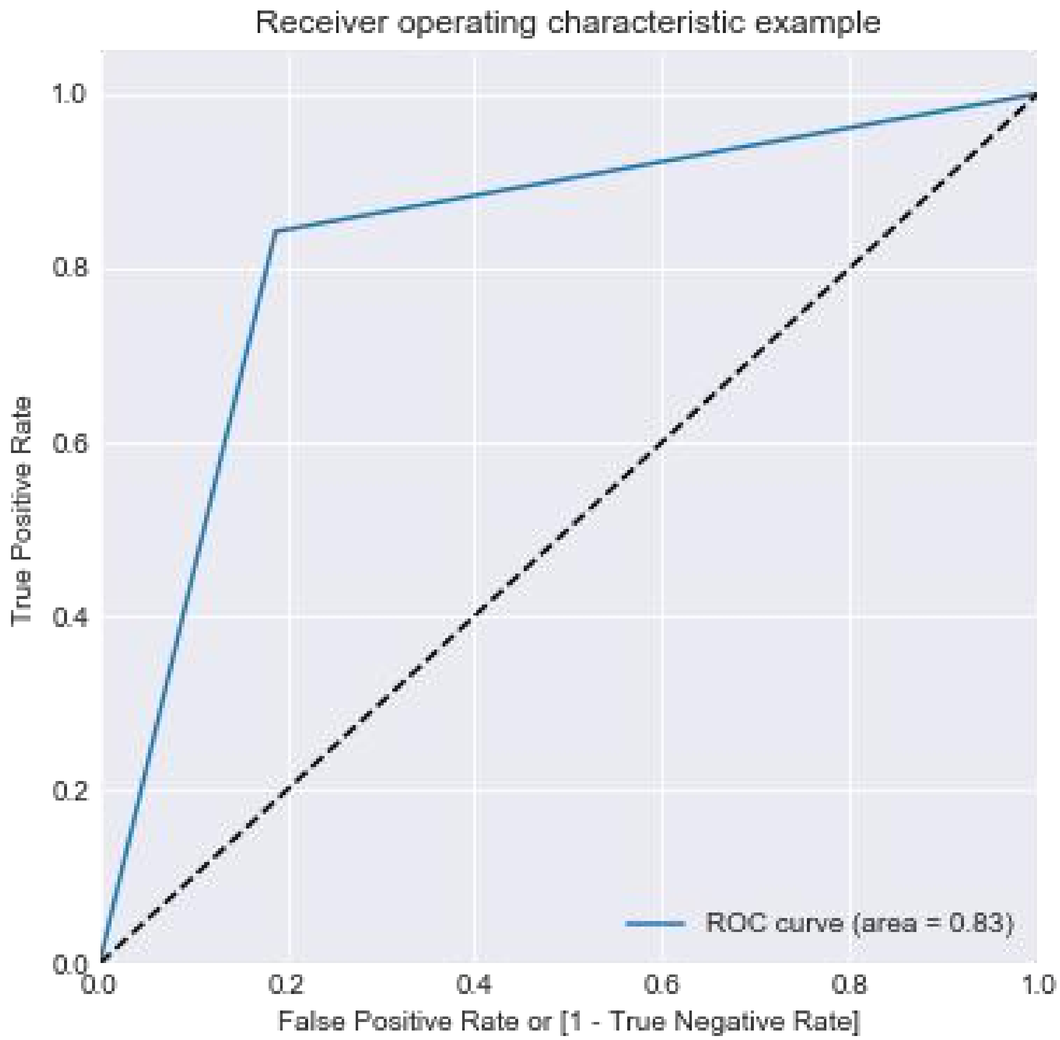
	churn	churn_Prob	final_predicted
0	0	0.721737	1
1	0	0.008855	0
2	0	0.124703	0
3	0	0.022144	0
4	0	0.839913	1

Plotting the ROC Curve : An ROC curve demonstrates several things:

- It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).
- The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.
- The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.

In [0]:

```
draw_roc(y_train_df.churn, y_train_df.final_predicted)
```



Out[0]:

```
(array([0.        , 0.18774046, 1.        ]),
 array([0.       , 0.8416866, 1.       ]),
 array([2, 1, 0]))
```

The roc curve is lying in the top left corner which is a sign of a good fit.

In [0]:

```
#draw_roc(y_pred_final.Churn, y_pred_final.predicted)
print("roc_auc_score : {:2.2f}".format(metrics.roc_auc_score(y_
train_df.churn, y_train_df.final_predicted)))
```

```
roc_auc_score : 0.83
```

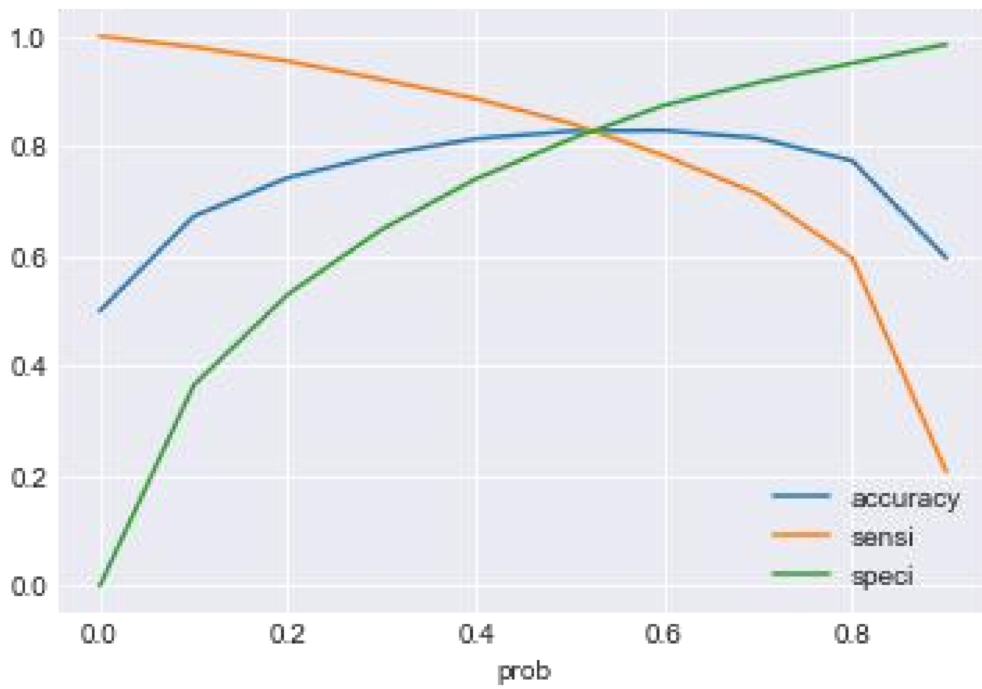
Finding Optimal Cutoff Point

Since recall or sensitivity is a much more important metrics for churn prediction. A trade off between sensitivity(or recall) and specificity is to be considered in doing so. We will try adjusting the probability threshold which shall lead to higher sensitivity or recall rate.

In [0]:

```
# finding cut-off with the right balance of the metrices
# sensitivity vs specificity trade-off
findOptimalCutoff(y_train_df)
```

	prob	accuracy	sensi	speci
0.0	0.0	0.500000	1.000000	0.000000
0.1	0.1	0.672585	0.980087	0.365083
0.2	0.2	0.742383	0.954404	0.530363
0.3	0.3	0.784782	0.920921	0.648643
0.4	0.4	0.813221	0.886191	0.740252
0.5	0.5	0.826973	0.841687	0.812260
0.6	0.6	0.828429	0.782625	0.874233
0.7	0.7	0.814313	0.712956	0.915670
0.8	0.8	0.773526	0.596444	0.950608
0.9	0.9	0.596704	0.208329	0.985079



From the curve above, 0.45 is the optimum point .

Although, other cutoff between 0.4 and 0.6 can also be taken but to keep the test sensitivity/recall significant we choose 0.45. At this point there is a balance of sensitivity, specificity and accuracy.

In [0]:

```
# predicting with the choosen cut-off on train
cut_off_prob = 0.45
predictChurnWithProb(lr0,X_train_pca,y_train_res,cut_off_prob)
```

```
Roc_auc_score : 0.8211500467921389
Sensitivity/Recall : 0.8647707185192888
Specificity: 0.7775293750649891
False Positive Rate: 0.2224706249350109
Positive predictive value: 0.7953806426931905
Negative Predictive value: 0.8518455228981545
sklearn precision score value: 0.7953806426931905
```

Out[0]:

	churn	churn_Prob	final_predicted
0	0	0.721737	1
1	0	0.008855	0
2	0	0.124703	0
3	0	0.022144	0
4	0	0.839913	1
5	1	0.899186	1
6	0	0.571068	1
7	0	0.229033	0
8	0	0.661786	1
9	0	0.223179	0
10	0	0.199185	0
11	0	0.093641	0
12	0	0.891217	1
13	0	0.015225	0
14	0	0.037379	0
15	0	0.356642	0
16	0	0.005017	0
17	0	0.903086	1
18	0	0.596867	1
19	0	0.186214	0
20	0	0.315922	0
21	0	0.078774	0
22	0	0.061154	0
23	0	0.118651	0

	churn	churn_Prob	final_predicted
24	0	0.019983	0
25	0	0.003464	0
26	0	0.837019	1
27	0	0.053939	0
28	0	0.539020	1
29	0	0.075607	0
...	...	...	...
38438	1	0.403947	0
38439	1	0.185400	0
38440	1	0.232411	0
38441	1	0.348306	0
38442	1	0.962795	1
38443	1	0.798656	1
38444	1	0.759494	1
38445	1	0.243256	0
38446	1	0.917228	1
38447	1	0.853177	1
38448	1	0.925624	1
38449	1	0.887905	1
38450	1	0.855468	1
38451	1	0.049835	0
38452	1	0.782620	1
38453	1	0.666634	1
38454	1	0.018943	0
38455	1	0.851814	1

	churn	churn_Prob	final_predicted
38456	1	0.570510	1
38457	1	0.825107	1
38458	1	0.857905	1
38459	1	0.899332	1
38460	1	0.780797	1
38461	1	0.137974	0
38462	1	0.844776	1
38463	1	0.835250	1
38464	1	0.880459	1
38465	1	0.737620	1
38466	1	0.875070	1
38467	1	0.882528	1

38468 rows × 3 columns

Making prediction on test

In [0]:

```
# predicting with the choosen cut-off on test
predictChurnWithProb(lr0,X_test_pca,y_test,cut_off_prob)
```

```
Roc_auc_score : 0.8121194552080092
Sensitivity/Recall : 0.8440111420612814
Specificity: 0.7802277683547371
False Positive Rate: 0.2197722316452629
Positive predictive value: 0.25041322314049586
Negative Predictive value: 0.9829059829059829
sklearn precision score value: 0.25041322314049586
```

Out[0]:

	churn	churn_Prob	final_predicted
4265	0	0.441554	0
29221	0	0.580813	1
974	0	0.392146	0
1602	0	0.307705	0
10225	0	0.158548	0
28358	0	0.114548	0
15763	0	0.052336	0
29075	0	0.369381	0
14665	0	0.325400	0
4719	0	0.093875	0
9377	0	0.017961	0
26496	0	0.566955	1
5736	0	0.500377	1
839	0	0.817273	1
25770	0	0.274642	0
1510	0	0.798745	1
3348	0	0.046528	0
13657	0	0.494611	1
12697	0	0.049432	0
21970	0	0.105374	0
16700	0	0.007342	0
26715	0	0.177941	0
22662	0	0.094731	0
12641	0	0.143756	0

	churn	churn_Prob	final_predicted
22191	1	0.830514	1
15824	0	0.802436	1
27382	0	0.088712	0
9736	0	0.098237	0
6529	0	0.179751	0
29150	0	0.772900	1
...	...	...	...
23991	0	0.016493	0
10635	0	0.042478	0
17808	0	0.124946	0
24525	0	0.496909	1
16215	0	0.085653	0
6607	1	0.871651	1
20000	1	0.914563	1
29679	0	0.264939	0
12048	0	0.462183	1
5658	0	0.804338	1
1434	1	0.542633	1
4636	0	0.342412	0
11718	0	0.219198	0
11078	0	0.025963	0
24499	0	0.338749	0
12817	0	0.594391	1
3762	0	0.780342	1
20886	0	0.499812	1

	churn	churn_Prob	final_predicted
11309	1	0.981163	1
5067	0	0.276158	0
21739	0	0.231329	0
10048	0	0.234242	0
7679	0	0.244752	0
10693	0	0.869202	1
23928	0	0.027859	0
6262	0	0.204097	0
1424	0	0.042646	0
18308	0	0.265107	0
22978	0	0.106384	0
17728	0	0.225277	0

8972 rows × 3 columns

The resulting model, after PCA and logistic regression (with optimal cutoff setting) has a right balance of different metrics score for sensitivity, specificity and Roc Accuracy on the train and test set.

- **train sensitivity :** 86.47%, **train roc auc score :** 82.1%
- **test sensitivity :** 84.40%, **test roc auc score :** 81.21%

2. Decision Tree

Applying Decision Tree Classifier on our principal components with Hyperparameter tuning

In [0]:

```
dt0 = DecisionTreeClassifier(class_weight='balanced',
                             max_features='auto',
                             min_samples_split=100,
                             min_samples_leaf=100,
                             max_depth=6,
                             random_state=10)
modelfit(dt0, X_train_pca, y_train_res)
```

```
Model Report
Accuracy : 0.7737
Recall/Sensitivity : 0.7352
AUC Score (Train): 0.852021
CV Score : Mean - 0.8401263 | Std - 0.005625113 |
Min - 0.8340481 | Max - 0.848167
```

In [0]:

```
# make predictions
pred_probs_test = dt0.predict(X_test_pca)
#Let's check the model metrices.
getModelMetrics(actual_churn=y_test,pred_churn=pred_probs_test)
```

```
Roc_auc_score : 0.728165562337295
Sensitivity/Recall : 0.6476323119777159
Specificity: 0.8086988126968743
False Positive Rate: 0.19130118730312576
Positive predictive value: 0.22749510763209393
Negative Predictive value: 0.9634815242494227
sklearn precision score value: 0.22749510763209393
```

In [0]:

```
# Create the parameter grid based on the results of random sear
ch
param_grid = {
    'max_depth': range(5,15,3),
    'min_samples_leaf': range(100, 400, 50),
    'min_samples_split': range(100, 400, 100),
    'max_features': [8,10,15]
}
# Create a based model
dt = DecisionTreeClassifier(class_weight='balanced',random_stat
e=10)
# Instantiate the grid search model
grid_search = GridSearchCV(estimator = dt, param_grid = param_g
rid,
                          cv = 3, n_jobs = 4,verbose = 1,scorin
g="f1_weighted")
```

In [0]:

```
# Fit the grid search to the data
grid_search.fit(X_train_pca, y_train_res)
```

```
Fitting 3 folds for each of 216 candidates, totall
ing 648 fits

[Parallel(n_jobs=4)]: Using backend LokyBackend wi
th 4 concurrent workers.
[Parallel(n_jobs=4)]:  Done  42 tasks      | elapse
d:    4.8s
[Parallel(n_jobs=4)]:  Done 192 tasks      | elapse
d:   26.8s
[Parallel(n_jobs=4)]:  Done 442 tasks      | elapse
d:  1.1min
[Parallel(n_jobs=4)]:  Done 648 out of 648 | elapse
d:  1.9min finished
```

Out[0]:

```
GridSearchCV(cv=3, error_score='raise-deprecatin
g',
       estimator=DecisionTreeClassifier(class_weig
ht='balanced', criterion='gini',
            max_depth=None, max_features=None, max
_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurit
y_split=None,
            min_samples_leaf=1, min_samples_split=
2,
            min_weight_fraction_leaf=0.0, presort=
False, random_state=10,
            splitter='best'),
       fit_params=None, iid='warn', n_jobs=4,
       param_grid={'max_depth': range(5, 15, 3),
'min_samples_leaf': range(100, 400, 50), 'min_samp
les_split': range(100, 400, 100), 'max_features':
[8, 10, 15]},
       pre_dispatch='2*n_jobs', refit=True, return
_train_score='warn',
       scoring='f1_weighted', verbose=1)
```

In [0]:

```
# printing the optimal accuracy score and hyperparameters
print('We can get recall of',grid_search.best_score_,'using',gr
id_search.best_params_)
```

```
We can get recall of 0.8111386948403967 using {'ma
x_depth': 14, 'max_features': 15, 'min_samples_lea
f': 100, 'min_samples_split': 100}
```

In [0]:

```
# model with the best hyperparameters
dt_final = DecisionTreeClassifier(class_weight='balanced',
                                  max_depth=14,
                                  min_samples_leaf=100,
                                  min_samples_split=100,
                                  max_features=15,
                                  random_state=10)
```

In [0]:

```
modelfit(dt_final,X_train_pca,y_train_res)
```

```
Model Report
Accuracy : 0.8314
Recall/Sensitivity : 0.8248
AUC Score (Train): 0.916653
CV Score : Mean - 0.8923275 | Std - 0.002961782 |
Min - 0.8867514 | Max - 0.8947951
```

In [0]:

```
# make predictions
pred_probs_test = dt_final.predict(X_test_pca)
#Let's check the model metrices.
getModelMetrics(actual_churn=y_test,pred_churn=pred_probs_test)
```

```
Roc_auc_score : 0.7529363664650144
Sensitivity/Recall : 0.6754874651810585
Specificity: 0.8303852677489701
False Positive Rate: 0.1696147322510298
Positive predictive value: 0.2572944297082228
Negative Predictive value: 0.9671229010864965
sklearn precision score value: 0.2572944297082228
```

In [0]:

```
# classification report
print(classification_report(y_test,pred_probs_test))
```

```
              precision    recall  f1-score   supp
ort

           0       0.97      0.83      0.89      8
254
           1       0.26      0.68      0.37
718

   micro avg       0.82      0.82      0.82      8
972
   macro avg       0.61      0.75      0.63      8
972
weighted avg       0.91      0.82      0.85      8
972
```

Even after hyperparameter tuning for the Decision Tree. The recall rate is 67.54% which is not very significant to predict the churn.

Let's see if we can achive a better Recall rate by deciding an optimal cut-off for the model to predict churn.

In [0]:

```
# predicting churn with default cut-off 0.5
cut_off_prob = 0.5
y_train_df = predictChurnWithProb(dt_final,X_train_pca,y_train_
res,cut_off_prob)
y_train_df.head()
```

```
Roc_auc_score : 0.8313663304564833
Sensitivity/Recall : 0.8248414266403244
Specificity: 0.8378912342726422
False Positive Rate: 0.1621087657273578
Positive predictive value: 0.8357477743243955
Negative Predictive value: 0.8270977675134719
sklearn precision score value: 0.8357477743243955
```

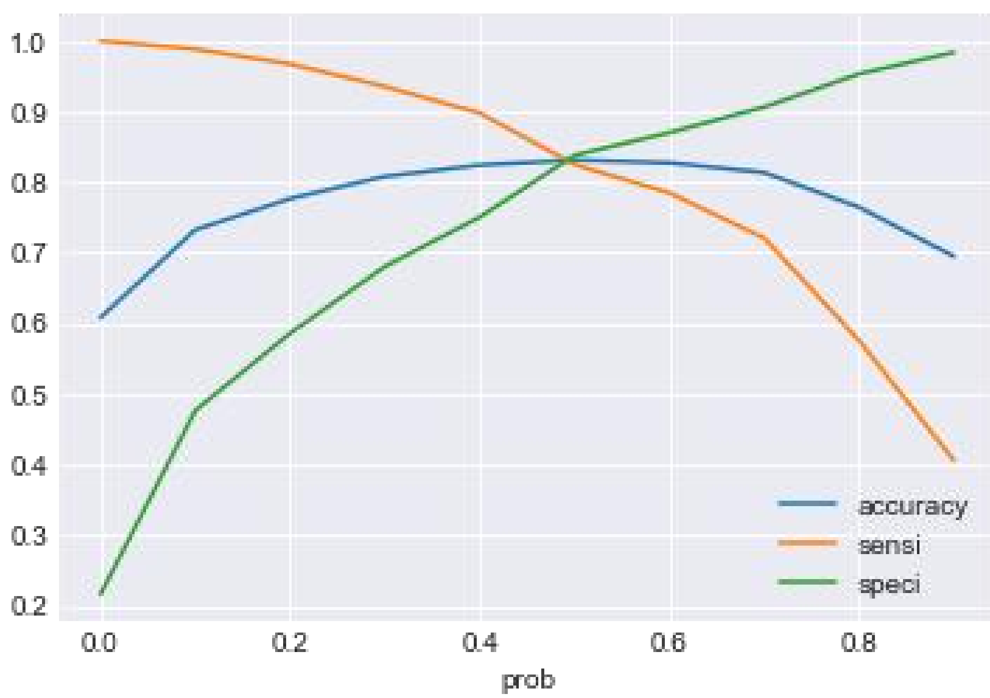
Out[0]:

	churn	churn_Prob	final_predicted
0	0	0.029630	0
1	0	0.000000	0
2	0	0.136054	0
3	0	0.060000	0
4	0	0.753769	1

In [0]:

```
# finding cut-off with the right balance of the metrices
findOptimalCutoff(y_train_df)
```

	prob	accuracy	sensi	speci
0.0	0.0	0.608116	1.000000	0.216232
0.1	0.1	0.732375	0.988302	0.476448
0.2	0.2	0.776542	0.967194	0.585890
0.3	0.3	0.807944	0.935427	0.680462
0.4	0.4	0.824088	0.897889	0.750286
0.5	0.5	0.831366	0.824841	0.837891
0.6	0.6	0.827337	0.784652	0.870022
0.7	0.7	0.813507	0.720755	0.906260
0.8	0.8	0.764454	0.575803	0.953104
0.9	0.9	0.694837	0.406000	0.983675



From the curve above, let'choose 0.4 as the optimum point to make a high enough sensitivity.

In [0]:

```
# predicting churn with cut-off 0.4
cut_off_prob=0.4
y_train_df = predictChurnWithProb(dt_final,X_train_pca,y_train_
res,cut_off_prob)
y_train_df.head()
```

```
Roc_auc_score : 0.824087553291047
Sensitivity/Recall : 0.8978891546220235
Specificity: 0.7502859519600708
False Positive Rate: 0.2497140480399293
Positive predictive value: 0.7824038417976714
Negative Predictive value: 0.8802073802988716
sklearn precision score value: 0.7824038417976714
```

Out[0]:

	churn	churn_Prob	final_predicted
0	0	0.029630	0
1	0	0.000000	0
2	0	0.136054	0
3	0	0.060000	0
4	0	0.753769	1

- At 0.58 cut-off prob. there is a balance of sensitivity , specificity and accuracy.
  Lets see how it performs on test data.

In [0]:

```
#Lets see how it performs on test data.
y_test_df= predictChurnWithProb(dt_final,X_test_pca,y_test,cut_
off_prob)
y_test_df.head()
```

```
Roc_auc_score : 0.765698812021925
Sensitivity/Recall : 0.7813370473537604
Specificity: 0.7500605766900896
False Positive Rate: 0.24993942330991034
Positive predictive value: 0.21379573170731708
Negative Predictive value: 0.9752678008821676
sklearn precision score value: 0.21379573170731708
```

Out[0]:

	churn	churn_Prob	final_predicted
4265	0	0.278846	0
29221	0	0.650000	1
974	0	0.621622	1
1602	0	0.194286	0
10225	0	0.000000	0

- Decision tree after selecting optimal cut-off also is resulting in a model with
  Train Recall : 89.78% and **Train Roc_auc_score : 82.40**
  Test Recall : 78.13% and **Test Roc_auc_score : 76.56**

Random Forest still seems overfitted to the data.

3. Random Forest

Applying Random Forest Classifier on our principal components with Hyperparameter tuning

In [0]:

```
def plot_traintestAcc(score,param):
    scores = score
    # plotting accuracies with max_depth
    plt.figure()
    plt.plot(scores["param_"+param],
    scores["mean_train_score"],
    label="training accuracy")
    plt.plot(scores["param_"+param],
    scores["mean_test_score"],
    label="test accuracy")
    plt.xlabel(param)
    plt.ylabel("f1")
    plt.legend()
    plt.show()
```

Tuning max_depth

In [0]:

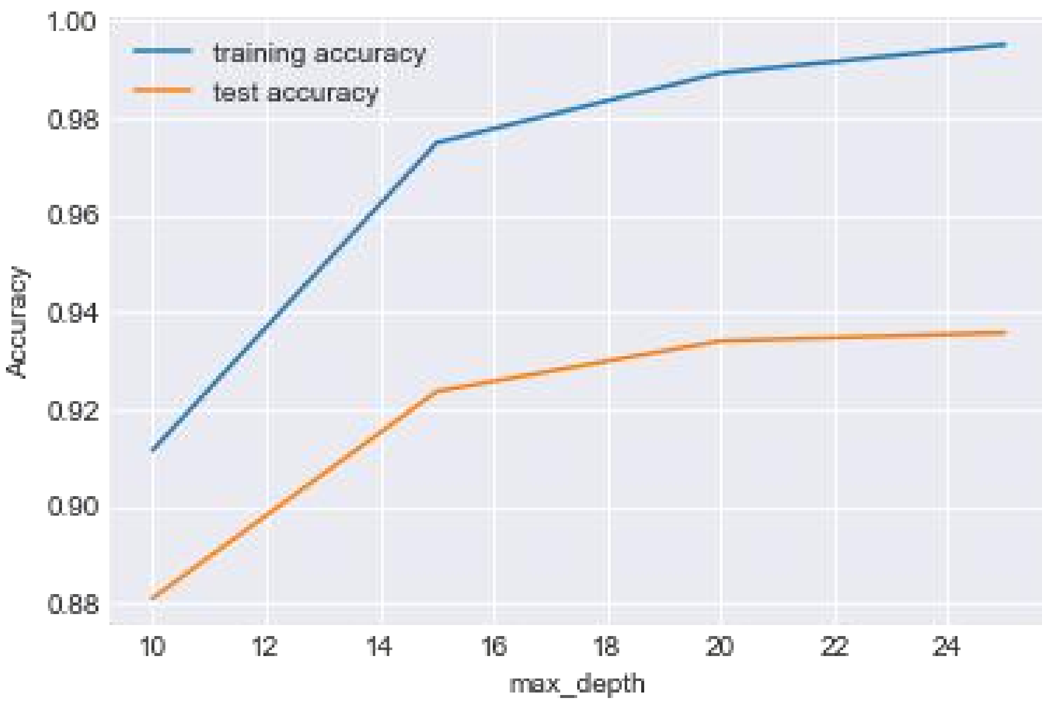
```
parameters = {'max_depth': range(10, 30, 5)}
rf0 = RandomForestClassifier()
rfgs = GridSearchCV(rf0, parameters,
                    cv=5,
                   scoring="f1")
rfgs.fit(X_train_pca,y_train_res)
```

Out[0]:

```
GridSearchCV(cv=5, error_score='raise-deprecatin
g',
       estimator=RandomForestClassifier(bootstrap=
True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', m
ax_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurit
y_split=None,
            min_samples_leaf=1, min_samples_split=
2,
            min_weight_fraction_leaf=0.0, n_estima
tors='warn', n_jobs=None,
            oob_score=False, random_state=None, ve
rbose=0,
            warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'max_depth': range(10, 30, 5)},
pre_dispatch='2*n_jobs',
       refit=True, return_train_score='warn', scor
ing='f1', verbose=0)
```

In [0]:

```
scores = rfgs.cv_results_
# plotting accuracies with max_depth
plt.figure()
plt.plot(scores["param_max_depth"],
         scores["mean_train_score"],
         label="training accuracy")
plt.plot(scores["param_max_depth"],
         scores["mean_test_score"],
         label="test accuracy")
plt.xlabel("max_depth")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Test f1-score almost becomes constant after max_depth=20

Tuning n_estimators

In [0]:

```
parameters = {'n_estimators': range(50, 150, 25)}
rf1 = RandomForestClassifier(max_depth=20,random_state=10)
rfgs = GridSearchCV(rf1, parameters,
                    cv=3,
                   scoring="recall")
```

In [0]:

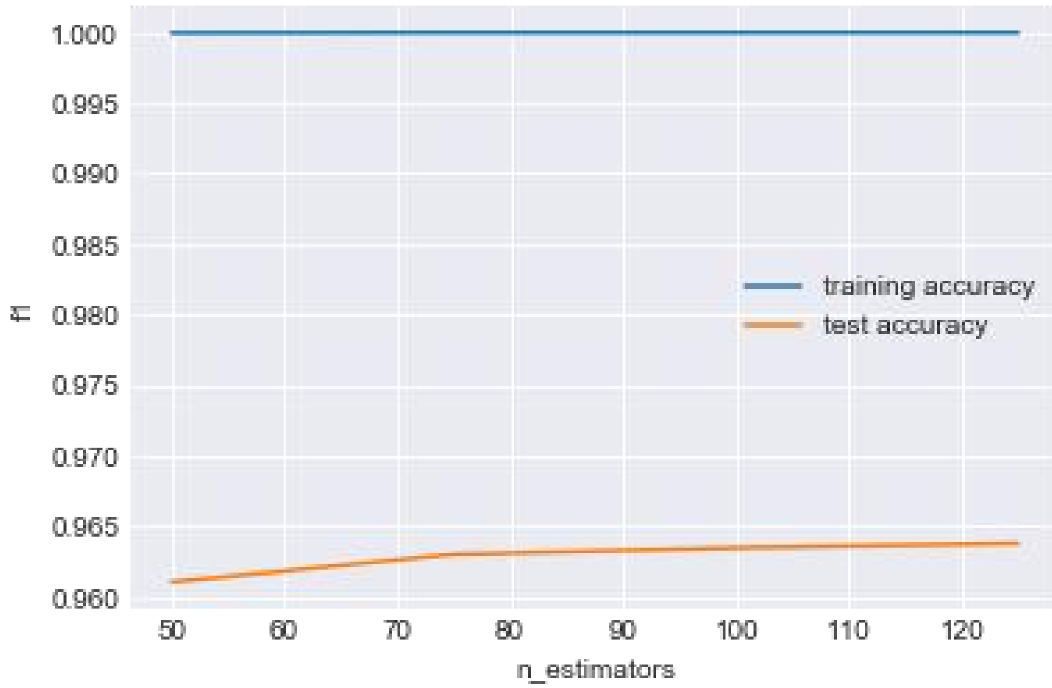
```
rfgs.fit(X_train_pca,y_train_res)
```

Out[0]:

```
GridSearchCV(cv=3, error_score='raise-deprecatin
g',
       estimator=RandomForestClassifier(bootstrap=
True, class_weight=None, criterion='gini',
            max_depth=20, max_features='auto', max
_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurit
y_split=None,
            min_samples_leaf=1, min_samples_split=
2,
            min_weight_fraction_leaf=0.0, n_estima
tors='warn', n_jobs=None,
            oob_score=False, random_state=10, verb
ose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'n_estimators': range(50, 150,
25)},
       pre_dispatch='2*n_jobs', refit=True, return
_train_score='warn',
       scoring='recall', verbose=0)
```

In [0]:

```
plot_traintestAcc(rfgs.cv_results_,'n_estimators')
```



Selecting n_estimators = 80

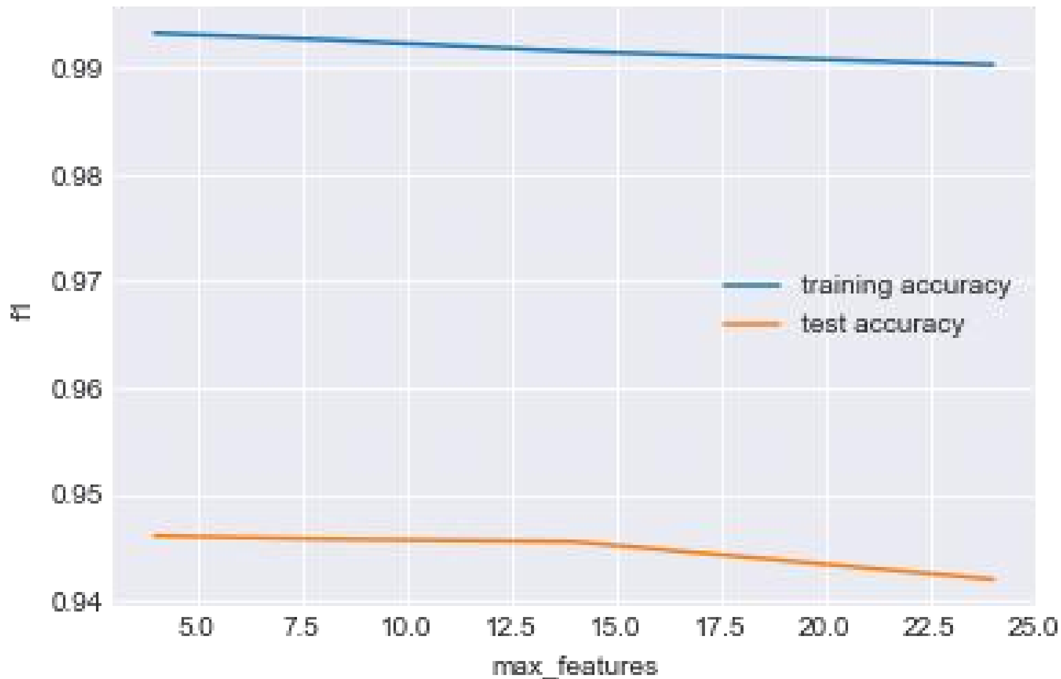
Tuning max_features

In [0]:

```
parameters = {'max_features': [4, 8, 14, 20, 24]}
rf3 = RandomForestClassifier(max_depth=20,n_estimators=80,rando
m_state=10)
rfgs = GridSearchCV(rf3, parameters,
                    cv=5,
                   scoring="f1")
```

In [0]:

```
rfgs.fit(X_train_pca,y_train_res)
plot_traintestAcc(rfgs.cv_results_,'max_features')
```



Selecting max_features = 5

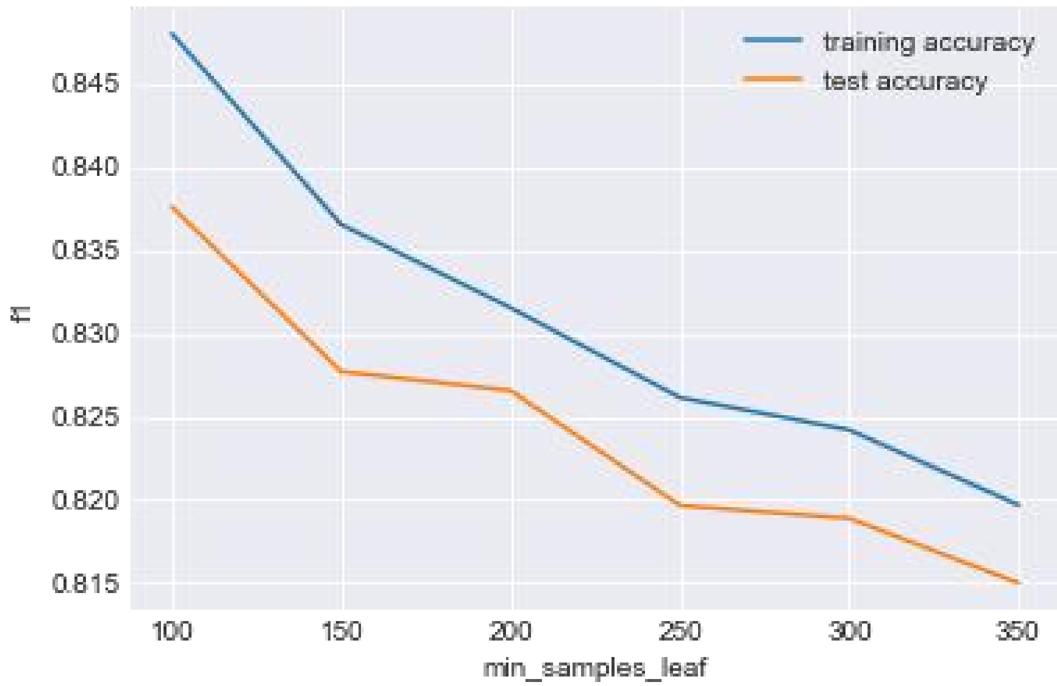
Tuning min_sample_leaf

In [0]:

```
parameters = {'min_samples_leaf': range(100, 400, 50)}
rf4 = RandomForestClassifier(max_depth=20,n_estimators=80,max_f
eatures=5,random_state=10)
rfgs = GridSearchCV(rf4, parameters,
                    cv=3,
                   scoring="f1")
```

In [0]:

```
rfgs.fit(X_train_pca,y_train_res)
plot_traintestAcc(rfgs.cv_results_,'min_samples_leaf')
```



Selecting min_sample_leaf = 100

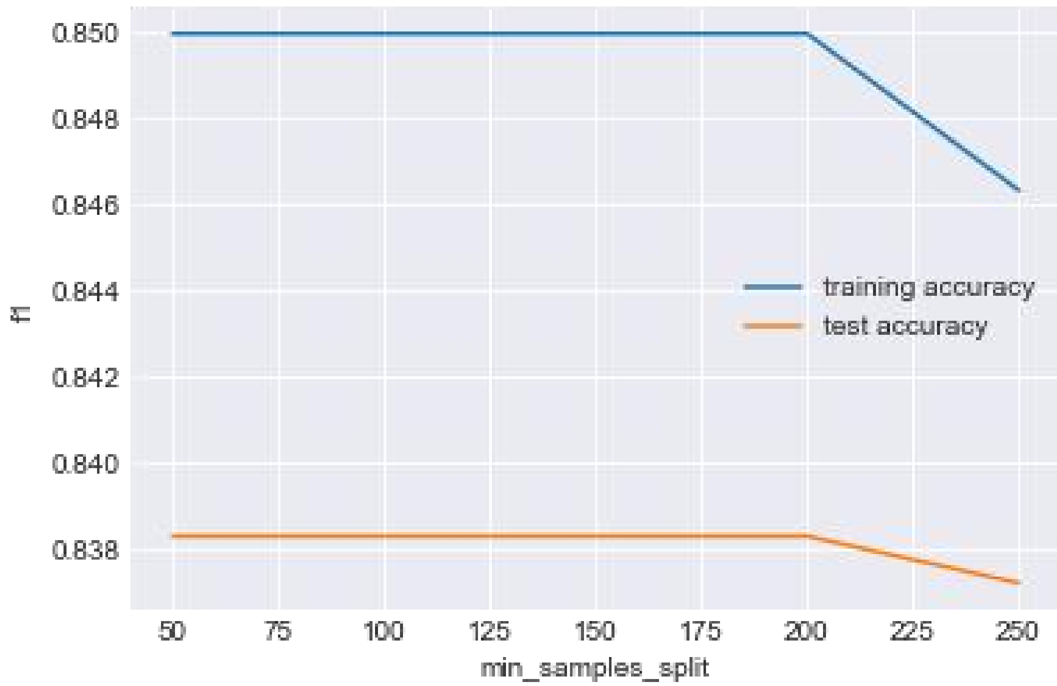
Tuning min_sample_split

In [0]:

```
parameters = {'min_samples_split': range(50, 300, 50)}
rf5 = RandomForestClassifier(max_depth=20,n_estimators=80,max_features=5,min_samples_leaf=100,random_state=10)
rfgs = GridSearchCV(rf5, parameters,
                    cv=3,
                   scoring="f1")
```

In [0]:

```
rfgs.fit(X_train_pca,y_train_res)
plot_traintestAcc(rfgs.cv_results_,'min_samples_split')
```



Selecting min_sample_split = 150

Tunned Random Forest

In [0]:

```
rf_final = RandomForestClassifier(max_depth=20,
                                  n_estimators=80,
                                  max_features=5,
                                  min_samples_leaf=100,
                                  min_samples_split=50,
                                  random_state=10)
```

In [0]:

```
print("Model performance on Train data:")
modelfit(rf_final,X_train_pca,y_train_res)
```

```
Model performance on Train data:

Model Report
Accuracy : 0.8563
Recall/Sensitivity : 0.8529
AUC Score (Train): 0.935241
CV Score : Mean - 0.9177793 | Std - 0.003183345 |
Min - 0.9123647 | Max - 0.9210403
```

In [0]:

```
# predict on test data
predictions = rf_final.predict(X_test_pca)
```

In [0]:

```
print("Model performance on Test data:")
getModelMetrics(y_test,predictions)
```

```
Model performance on Test data:
Roc_auc_score : 0.7930275048545721
Sensitivity/Recall : 0.733983286908078
Specificity: 0.8520717228010661
False Positive Rate: 0.14792827719893384
Positive predictive value: 0.301487414187643
Negative Predictive value: 0.9735603543743079
sklearn precision score value: 0.301487414187643
```

After hyperparameter tuning for the random forest. The Recall rate(Test) is 73.39%.

Let's see if we can achive a better Recall rate by deciding an optimal cut-off for the model to predict churn.

In [0]:

```
# predicting churn with default cut-off 0.5
cut_off_prob=0.5
y_train_df = predictChurnWithProb(rf_final,X_train_pca,y_train_
res,cut_off_prob)
y_train_df.head()
```

```
Roc_auc_score : 0.8562701466153686
Sensitivity/Recall : 0.8529167099927212
Specificity: 0.859623583238016
False Positive Rate: 0.14037641676198398
Positive predictive value: 0.8586757393352525
Negative Predictive value: 0.8538966069307442
sklearn precision score value: 0.8586757393352525
```

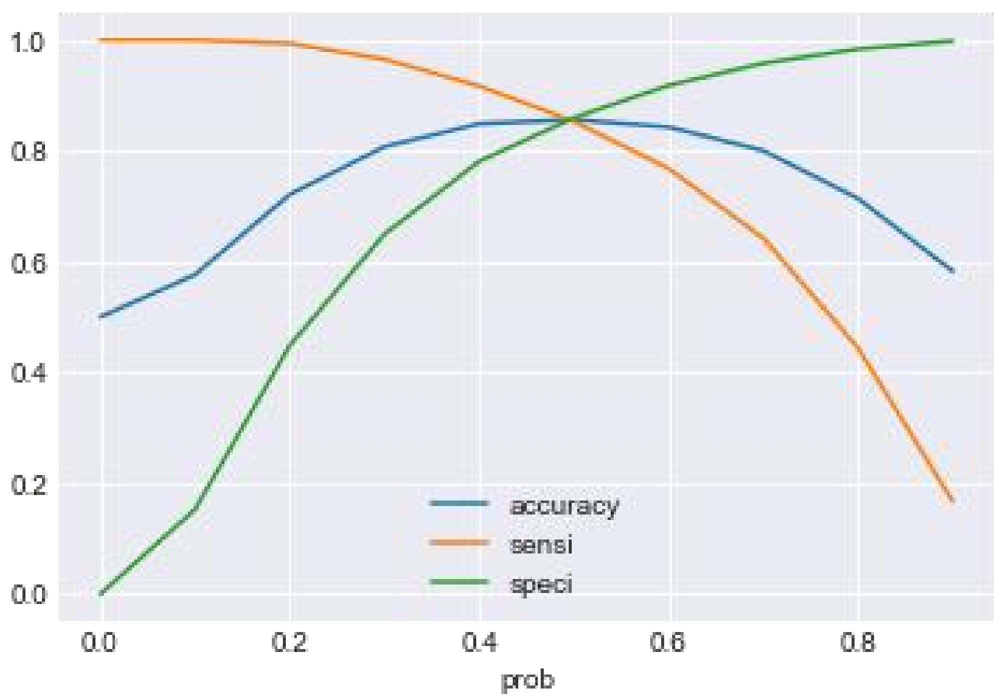
Out[0]:

	churn	churn_Prob	final_predicted
0	0	0.444901	0
1	0	0.049022	0
2	0	0.256567	0
3	0	0.322113	0
4	0	0.810293	1

In [0]:

```
# finding cut-off with the right balance of the metrices
findOptimalCutoff(y_train_df)
```

	prob	accuracy	sensi	speci
0.0	0.0	0.500000	1.000000	0.000000
0.1	0.1	0.576479	1.000000	0.152958
0.2	0.2	0.721223	0.993657	0.448789
0.3	0.3	0.807450	0.965218	0.649683
0.4	0.4	0.848887	0.916866	0.780909
0.5	0.5	0.856270	0.852917	0.859624
0.6	0.6	0.842934	0.767859	0.918010
0.7	0.7	0.800198	0.642456	0.957939
0.8	0.8	0.713866	0.444057	0.983675
0.9	0.9	0.582510	0.166944	0.998076



From the curve above, 0.45 is the optimal point with high enough sensitivity.

In [0]:

```
cut_off_prob=0.45
predictChurnWithProb(rf_final,X_train_pca,y_train_res,cut_off_p
rob)
```

```
Roc_auc_score : 0.856062181553499
Sensitivity/Recall : 0.887074971404804
Specificity: 0.825049391702194
False Positive Rate: 0.17495060829780598
Positive predictive value: 0.8352670485142214
Negative Predictive value: 0.8796075605565101
sklearn precision score value: 0.8352670485142214
```

Out[0]:

	churn	churn_Prob	final_predicted
0	0	0.444901	0
1	0	0.049022	0
2	0	0.256567	0
3	0	0.322113	0
4	0	0.810293	1
5	1	0.850090	1
6	0	0.488889	1
7	0	0.332927	0
8	0	0.704854	1
9	0	0.317052	0
10	0	0.261258	0
11	0	0.129544	0
12	0	0.770292	1
13	0	0.082885	0
14	0	0.330386	0
15	0	0.235159	0
16	0	0.108748	0
17	0	0.685094	1
18	0	0.326117	0
19	0	0.218403	0
20	0	0.310555	0
21	0	0.151782	0
22	0	0.222902	0
23	0	0.135109	0

	churn	churn_Prob	final_predicted
24	0	0.104727	0
25	0	0.064229	0
26	0	0.862799	1
27	0	0.118279	0
28	0	0.533856	1
29	0	0.320238	0
...	...	...	...
38438	1	0.534468	1
38439	1	0.284825	0
38440	1	0.330109	0
38441	1	0.411416	0
38442	1	0.949969	1
38443	1	0.735951	1
38444	1	0.684696	1
38445	1	0.347447	0
38446	1	0.811077	1
38447	1	0.890849	1
38448	1	0.959835	1
38449	1	0.945332	1
38450	1	0.874784	1
38451	1	0.235528	0
38452	1	0.748061	1
38453	1	0.720683	1
38454	1	0.193370	0
38455	1	0.846281	1

	churn	churn_Prob	final_predicted
38456	1	0.628897	1
38457	1	0.814505	1
38458	1	0.865145	1
38459	1	0.653116	1
38460	1	0.838058	1
38461	1	0.415795	0
38462	1	0.812341	1
38463	1	0.672480	1
38464	1	0.924164	1
38465	1	0.831023	1
38466	1	0.867714	1
38467	1	0.913246	1

38468 rows × 3 columns

Making prediction on test

In [0]:

```
y_test_df= predictChurnWithProb(rf_final,X_test_pca,y_test,cut_
off_prob)
y_test_df.head()
```

```
Roc_auc_score : 0.7965333597013485
Sensitivity/Recall : 0.775766016713092
Specificity: 0.8173007026896051
False Positive Rate: 0.18269929731039497
Positive predictive value: 0.26973365617433415
Negative Predictive value: 0.9766903141740263
sklearn precision score value: 0.26973365617433415
```

Out[0]:

	churn	churn_Prob	final_predicted
4265	0	0.454218	1
29221	0	0.379705	0
974	0	0.606964	1
1602	0	0.382579	0
10225	0	0.223496	0

- Random Forest after selecting optimal cut-off also is resulting in a model with
  Train Recall : 88.70% and **Train Roc_auc_score : 85.60**
  Test Recall : 77.57% and **Test Roc_auc_score : 79.65**

4. Boosting models

4.1 Gradiant boosting Classifier

Applying Gradiant boosting Classifier on our principal components with Hyperparameter tuning

In [0]:

```
from sklearn.ensemble import GradientBoostingClassifier  #GBM a
lgorithm
# Fitting the default GradientBoostingClassifier
gbm0 = GradientBoostingClassifier(random_state=10)
modelfit(gbm0, X_train_pca, y_train_res)
```

```
Model Report
Accuracy : 0.855
Recall/Sensitivity : 0.8629
AUC Score (Train): 0.927984
CV Score : Mean - 0.9207933 | Std - 0.005012221 |
Min - 0.91091 | Max - 0.9247451
```

In [0]:

```
# Hyperparameter tuning for n_estimators
param_test1 = {'n_estimators':range(20,150,10)}
gsearch1         =          GridSearchCV(estimator          =
GradientBoostingClassifier(                learning_rate=0.1,
min_samples_split=500,min_samples_leaf=50,ma
x_depth=8,max_features='sqrt',subsample=0.8,random_state=10),
param_grid = param_test1, scoring='f1',n_jobs=4,iid=False, cv=3
)
```

Out[0]:

```
GridSearchCV(cv=3, error_score='raise-deprecatin
g',
       estimator=GradientBoostingClassifier(criter
ion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance',
max_depth=8,
              max_features='sqrt', max_leaf_nodes=
None,
              min_impurity_decrease=0.0, min_impur
ity_split=None,
              min_samples_leaf=50, min_sa...
subsample=0.8, tol=0.0001, validation_fraction=0.
1,
              verbose=0, warm_start=False),
       fit_params=None, iid=False, n_jobs=4,
       param_grid={'n_estimators': range(20, 150,
10)},
       pre_dispatch='2*n_jobs', refit=True, return
_train_score='warn',
       scoring='f1', verbose=0)
```

In [0]:

```
gsearch1.best_params_, gsearch1.best_score_
```

Out[0]:

```
({'n_estimators': 140}, 0.9044472209849493)
```

In [0]:

```
# Hyperparameter tuning for max_depth and min_sample_split
param_test2 = {'max_depth':range(5,16,2), 'min_samples_split':r
ange(200,1001,200)}
gsearch2 = GridSearchCV(estimator =
GradientBoostingClassifier( learning_rate=0.1,
n_estimators=140, max_features='sqrt', subsa mple=0.8,
random_state=10),
param_grid = param_test2, scoring='f1',n_jobs=4,iid=False, cv=3
)
```

Out[0]:

```
GridSearchCV(cv=3, error_score='raise-deprecatin
g',
       estimator=GradientBoostingClassifier(criter
ion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance',
max_depth=3,
              max_features='sqrt', max_leaf_nodes=
None,
              min_impurity_decrease=0.0, min_impur
ity_split=None,
              min_samples_leaf=1, min_sam...
subsample=0.8, tol=0.0001, validation_fraction=0.
1,
              verbose=0, warm_start=False),
       fit_params=None, iid=False, n_jobs=4,
       param_grid={'max_depth': range(5, 16, 2),
'min_samples_split': range(200, 1001, 200)},
       pre_dispatch='2*n_jobs', refit=True, return
_train_score='warn',
       scoring='f1', verbose=0)
```

In [0]:

```
gsearch2.best_params_, gsearch2.best_score_
```

Out[0]:

```
({'max_depth': 15, 'min_samples_split': 200}, 0.94
73969277033908)
```

In [0]:

```
# Hyperparameter tuning for min_sample_leaf
param_test3 = {'min_samples_leaf':range(30,71,10)}
gsearch3 = GridSearchCV(estimator =
GradientBoostingClassifier( learning_rate=0.1,
n_estimators=140,max_depth=15,min_samples_sp lit=200,
max_features='sqrt', subsample=0.8, random_state=10), param_grid
= param_test3, scoring='f1',n_jobs=4,iid=False, cv=3
)
```

Out[0]:

```
GridSearchCV(cv=3, error_score='raise-deprecatin
g',
       estimator=GradientBoostingClassifier(criter
ion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance',
max_depth=15,
              max_features='sqrt', max_leaf_nodes=
None,
              min_impurity_decrease=0.0, min_impur
ity_split=None,
              min_samples_leaf=1, min_sa...      s
ubsample=0.8, tol=0.0001, validation_fraction=0.1,
              verbose=0, warm_start=False),
       fit_params=None, iid=False, n_jobs=4,
       param_grid={'min_samples_leaf': range(30, 7
1, 10)},
       pre_dispatch='2*n_jobs', refit=True, return
_train_score='warn',
       scoring='f1', verbose=0)
```

In [0]:

```
gsearch3.best_params_, gsearch3.best_score_
```

Out[0]:

```
({'min_samples_leaf': 30}, 0.9462537622463577)
```

In [0]:

```
# Hyperparameter tuning for max_features
param_test4 = {'max_features':range(7,20,2)}
gsearch4 = GridSearchCV(estimator = GradientBoostingClassifier( learning_rate=0.1, n_estimators=140,max_depth=15, min_samples_s plit=200, min_samples_leaf=30, subsample=0.8, random_state=10), param_grid = param_test4, scoring='f1',n_jobs=4,iid=False, cv=3 )
```

Out[0]:

```
GridSearchCV(cv=3, error_score='raise-deprecatin
g',
       estimator=GradientBoostingClassifier(criter
ion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance',
max_depth=15,
              max_features=None, max_leaf_nodes=No
ne,
              min_impurity_decrease=0.0, min_impur
ity_split=None,
              min_samples_leaf=30, min_sam...
subsample=0.8, tol=0.0001, validation_fraction=0.
1,
              verbose=0, warm_start=False),
       fit_params=None, iid=False, n_jobs=4,
       param_grid={'max_features': range(7, 20,
2)},
       pre_dispatch='2*n_jobs', refit=True, return
_train_score='warn',
       scoring='f1', verbose=0)
```

In [0]:

```
gsearch4.best_params_, gsearch4.best_score_
```

Out[0]:

```
({'max_features': 15}, 0.948871024643215)
```

Tunned GradientBoostingClassifier

In [0]:

```
# Tunned GradientBoostingClassifier
gbm_final = GradientBoostingClassifier(learning_rate=0.1, n_estimators=140,max_features=15,max_depth=15, min_samples_split=200, min_samples_leaf=40, subsample=0.8, random_state=10)
modelfit(gbm_final, X_train_pca, y_train_res)
```

```
Model Report
Accuracy : 0.9993
Recall/Sensitivity : 0.9999
AUC Score (Train): 1.000000
CV Score : Mean - 0.9878881 | Std - 0.001470339 |
Min - 0.9855792 | Max - 0.9894773
```

In [0]:

```
# predictions on Test data
dtest_predictions = gbm_final.predict(X_test_pca)
```

In [0]:

```
# model Performance on test data
getModelMetrics(y_test,dtest_predictions)
```

```
Roc_auc_score : 0.7737007231446693
Sensitivity/Recall : 0.6093333333333333
Specificity: 0.9380681129560053
False Positive Rate: 0.06193188704399467
Positive predictive value: 0.47210743801652894
Negative Predictive value: 0.9635254574878626
sklearn precision score value: 0.47210743801652894
```

Let's see if we can achive a better Recall rate by deciding an optimal cut-off for the model to predict churn.

In [0]:

```
# predicting churn with default cut-off 0.5
cut_off_prob=0.5
y_train_df = predictChurnWithProb(gbm_final,X_train_pca,y_train
_res,cut_off_prob)
y_train_df.head()
```

```
Roc_auc_score : 0.9993267388264541
Sensitivity/Recall : 0.999896421357916
Specificity: 0.998757056294992
False Positive Rate: 0.0012429437050080273
Positive predictive value: 0.9987584708499302
Negative Predictive value: 0.9998963032094157
sklearn precision score value: 0.9987584708499302
```

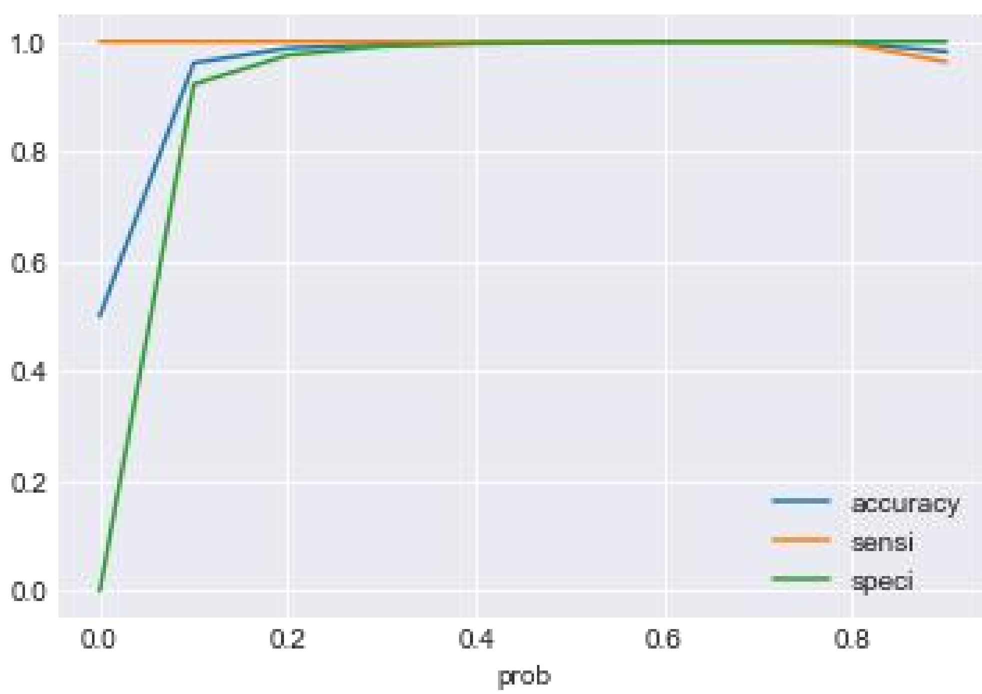
Out[0]:

	churn	churn_Prob	final_predicted
0	0	0.011598	0
1	0	0.011000	0
2	0	0.003578	0
3	0	0.001710	0
4	0	0.007876	0

In [0]:

```
findOptimalCutoff(y_train_df)
```

	prob	accuracy	sensi	speci
0.0	0.0	0.500000	1.000000	0.000000
0.1	0.1	0.961080	1.000000	0.922161
0.2	0.2	0.987648	1.000000	0.975296
0.3	0.3	0.995727	1.000000	0.991455
0.4	0.4	0.998265	1.000000	0.996530
0.5	0.5	0.999327	0.999896	0.998757
0.6	0.6	0.999819	0.999896	0.999741
0.7	0.7	0.999560	0.999171	0.999948
0.8	0.8	0.997669	0.995339	1.000000
0.9	0.9	0.981589	0.963178	1.000000



In [0]:

```
cut_off_prob=0.1
predictChurnWithProb(gbm_final,X_train_pca,y_train_res,cut_off_
prob)
```

```
Roc_auc_score : 0.9610803252369362
Sensitivity/Recall : 1.0
Specificity: 0.9221606504738723
False Positive Rate: 0.07783934952612771
Positive predictive value: 0.9277820488179896
Negative Predictive value: 1.0
sklearn precision score value: 0.9277820488179896
```

Out[0]:

	churn	churn_Prob	final_predicted
0	0	0.011598	0
1	0	0.011000	0
2	0	0.003578	0
3	0	0.001710	0
4	0	0.007876	0
5	0	0.001648	0
6	0	0.006995	0
7	0	0.002105	0
8	0	0.010358	0
9	0	0.026526	0
10	0	0.001252	0
11	0	0.018584	0
12	0	0.013920	0
13	0	0.001008	0
14	0	0.001505	0
15	0	0.245177	1
16	0	0.012880	0
17	0	0.001025	0
18	1	0.950928	1
19	0	0.004259	0
20	0	0.039999	0
21	0	0.017715	0
22	0	0.001496	0
23	0	0.010652	0

	churn	churn_Prob	final_predicted
24	0	0.011837	0
25	0	0.006522	0
26	0	0.077716	0
27	0	0.000903	0
28	0	0.002216	0
29	1	0.951201	1
...	...	...	...
38588	1	0.973245	1
38589	1	0.987559	1
38590	1	0.971137	1
38591	1	0.997203	1
38592	1	0.981624	1
38593	1	0.984498	1
38594	1	0.941370	1
38595	1	0.974639	1
38596	1	0.939837	1
38597	1	0.993428	1
38598	1	0.971813	1
38599	1	0.972294	1
38600	1	0.960860	1
38601	1	0.946815	1
38602	1	0.987669	1
38603	1	0.993360	1
38604	1	0.972699	1
38605	1	0.992266	1

	churn	churn_Prob	final_predicted
38606	1	0.966117	1
38607	1	0.963315	1
38608	1	0.966413	1
38609	1	0.969283	1
38610	1	0.995360	1
38611	1	0.993922	1
38612	1	0.984670	1
38613	1	0.991916	1
38614	1	0.985088	1
38615	1	0.953084	1
38616	1	0.957874	1
38617	1	0.987987	1

38618 rows × 3 columns

Making prediction on test

In [0]:

```
y_test_df= predictChurnWithProb(gbm_final,X_test_pca,y_test,cut
_off_prob)
y_test_df.head()
```

```
Roc_auc_score : 0.8083746616571729
Sensitivity/Recall : 0.7986666666666666
Specificity: 0.8180826566476791
False Positive Rate: 0.18191734335232093
Positive predictive value: 0.28523809523809524
Negative Predictive value: 0.9781191131720041
sklearn precision score value: 0.28523809523809524
```

Out[0]:

	churn	churn_Prob	final_predicted
6102	1	0.385472	1
2539	1	0.594508	1
21576	0	0.659457	1
19574	0	0.017321	0
12804	1	0.199207	1

This model is litrally over-fitting the Training data with a lower performance on the Test data.

4.2 XGBoost Classifier

Applying XGBoost Classifier on our principal components with Hyperparameter tuning

In [0]:

```
import xgboost as xgb
from xgboost.sklearn import XGBClassifier
# Fitting the XGBClassifier
xgb1 = XGBClassifier(learning_rate =0.1,
                     n_estimators=1000,
                     max_depth=5,
                     min_child_weight=1,
                     gamma=0,
                     subsample=0.8,
                     colsample_bytree=0.8,
                     objective= 'binary:logistic',
                     nthread=4,
                     scale_pos_weight=1,
                     seed=27)
```

In [0]:

```
# Model fit and performance on Train data
modelfit(xgb1, X_train_pca, y_train_res)
```

```
Model Report
Accuracy : 0.9984
Recall/Sensitivity : 0.9998
AUC Score (Train): 0.999992
CV Score : Mean - 0.986411 | Std - 0.001289096 | M
in - 0.9845676 | Max - 0.9879032
```

In [0]:

```
# Hyperparameter tunning for the XGBClassifer
param_test1 = {'max_depth':range(3,10,2),'min_child_weight':ran
ge(1,6,2)}
gsearch1 = GridSearchCV(estimator = XGBClassifier( learning_rat
e =0.1, n_estimators=140, max_depth=5,
 min_child_weight=1, gamma=0, subsample=0.8, colsample_bytree=
0.8,
 objective= 'binary:logistic', nthread=4, scale_pos_weight=1, s
eed=27),
 param_grid = param_test1, scoring='f1',n_jobs=4,iid=False, cv=
3)
gsearch1.fit(X_train_pca, y_train_res)
```

Out[0]:

```
GridSearchCV(cv=3, error_score='raise-deprecatin
g',
       estimator=XGBClassifier(base_score=0.5, boo
ster='gbtree', colsample_bylevel=1,
       colsample_bytree=0.8, gamma=0, learning_rat
e=0.1, max_delta_step=0,
       max_depth=5, min_child_weight=1, missing=No
ne, n_estimators=140,
       n_jobs=1, nthread=4, objective='binary:logi
stic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight
=1, seed=27, silent=True,
       subsample=0.8),
       fit_params=None, iid=False, n_jobs=4,
       param_grid={'max_depth': range(3, 10, 2),
'min_child_weight': range(1, 6, 2)},
       pre_dispatch='2*n_jobs', refit=True, return
_train_score='warn',
       scoring='f1', verbose=0)
```

In [0]:

```
gsearch1.best_params_, gsearch1.best_score_
```

Out[0]:

```
({'max_depth': 9, 'min_child_weight': 1}, 0.943964
5819371795)
```

In [0]:

```
# Some more hyperparameter tunning for the XGBClassifer
param_test2 = param_test3 = {'gamma':[i/10.0 for i in range(0,5
)]}
gsearch2 = GridSearchCV(estimator = XGBClassifier( learning_rat
e=0.1, n_estimators=140, max_depth=9,
 min_child_weight=1, gamma=0, subsample=0.8, colsample_bytree=
0.8,
 objective= 'binary:logistic', nthread=4, scale_pos_weight=1,se
ed=27),
 param_grid = param_test2, scoring='f1',n_jobs=4,iid=False, cv=
3)
gsearch2.fit(X_train_pca, y_train_res)
```

Out[0]:

```
GridSearchCV(cv=3, error_score='raise-deprecatin
g',
       estimator=XGBClassifier(base_score=0.5, boo
ster='gbtree', colsample_bylevel=1,
       colsample_bytree=0.8, gamma=0, learning_rat
e=0.1, max_delta_step=0,
       max_depth=9, min_child_weight=1, missing=No
ne, n_estimators=140,
       n_jobs=1, nthread=4, objective='binary:logi
stic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight
=1, seed=27, silent=True,
       subsample=0.8),
       fit_params=None, iid=False, n_jobs=4,
       param_grid={'gamma': [0.0, 0.1, 0.2, 0.3,
0.4]},
       pre_dispatch='2*n_jobs', refit=True, return
_train_score='warn',
       scoring='f1', verbose=0)
```

In [0]:

```
gsearch2.best_params_, gsearch2.best_score_
```

Out[0]:

```
({'gamma': 0.4}, 0.9457184144858951)
```

In [0]:

```
# Final XGBClassifier
xgb2 = XGBClassifier( learning_rate=0.1, n_estimators=140, max_
depth=9,
 min_child_weight=1, gamma=0, subsample=0.8, colsample_bytree=
0.8,
 objective= 'binary:logistic', nthread=4, scale_pos_weight=1,se
ed=27)
```

In [0]:

```
# Fit Train data
modelfit(xgb2, X_train_pca, y_train_res)
```

```
Model Report
Accuracy : 0.9957
Recall/Sensitivity : 0.9989
AUC Score (Train): 0.999932
CV Score : Mean - 0.9865434 | Std - 0.00116304 | M
in - 0.9844505 | Max - 0.9876063
```

In [0]:

```
# Prediction on Test data
dtest_predictions = xgb2.predict(X_test_pca)
```

In [0]:

```
# Model evaluation on Test data
getModelMetrics(y_test,dtest_predictions)
```

```
Roc_auc_score : 0.7698830040803134
Sensitivity/Recall : 0.6093333333333333
Specificity: 0.9304326748272936
False Positive Rate: 0.06956732517270633
Positive predictive value: 0.443258971871968894
Negative Predictive value: 0.9632371392722711
sklearn precision score value: 0.443258971871968894
```

Let's see if we can achive a better Recall rate by deciding an optimal cut-off for the model to predict churn.

In [0]:

```
# predicting churn with default cut-off 0.5
cut_off_prob=0.5
y_train_df = predictChurnWithProb(xgb2,X_train_pca,y_train_res,
cut_off_prob)
y_train_df.head()
```

```
Roc_auc_score : 0.9957014863535139
Sensitivity/Recall : 0.998912424258118
Specificity: 0.9924905484489098
False Positive Rate: 0.007509451551090165
Positive predictive value: 0.9925384654968353
Negative Predictive value: 0.9989053948397185
sklearn precision score value: 0.9925384654968353
```

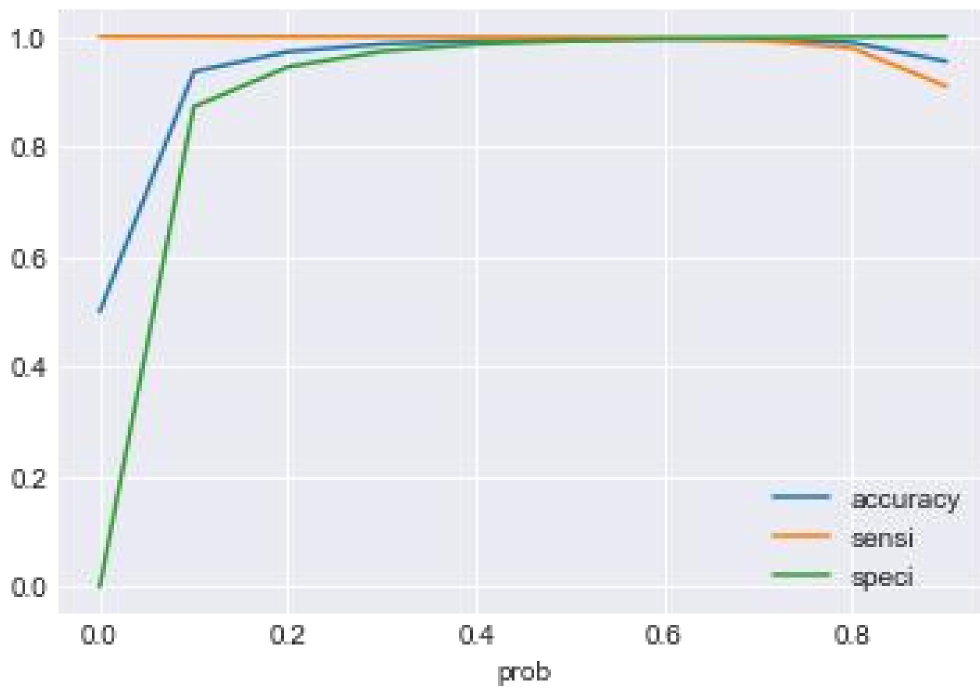
Out[0]:

	churn	churn_Prob	final_predicted
0	0	0.019957	0
1	0	0.038398	0
2	0	0.011305	0
3	0	0.001261	0
4	0	0.007864	0

In [0]:

```
# Finding optimal cut-off probability
findOptimalCutoff(y_train_df)
```

	prob	accuracy	sensi	speci
0.0	0.0	0.500000	1.000000	0.000000
0.1	0.1	0.936247	1.000000	0.872495
0.2	0.2	0.972422	0.999948	0.944896
0.3	0.3	0.986509	0.999845	0.973173
0.4	0.4	0.992749	0.999430	0.986069
0.5	0.5	0.995701	0.998912	0.992491
0.6	0.6	0.996452	0.997255	0.995650
0.7	0.7	0.995960	0.993785	0.998136
0.8	0.8	0.989228	0.979025	0.999430
0.9	0.9	0.954995	0.910042	0.999948



In [0]:

```
# Selecting 0.2 as cut-off in an attempt to improve recall rate
cut_off_prob=0.2
predictChurnWithProb(xgb2,X_train_pca,y_train_res,cut_off_prob)
```

```
Roc_auc_score : 0.9724221865451345
Sensitivity/Recall : 0.999948210678958
Specificity: 0.9448961624113108
False Positive Rate: 0.05510383758868921
Positive predictive value: 0.9477714510111919
Negative Predictive value: 0.9999451934670612
sklearn precision score value: 0.9477714510111919
```

Out[0]:

	churn	churn_Prob	final_predicted
0	0	0.019957	0
1	0	0.038398	0
2	0	0.011305	0
3	0	0.001261	0
4	0	0.007864	0
5	0	0.001282	0
6	0	0.007701	0
7	0	0.001516	0
8	0	0.015800	0
9	0	0.064789	0
10	0	0.000980	0
11	0	0.029394	0
12	0	0.024576	0
13	0	0.004004	0
14	0	0.003187	0
15	0	0.402674	1
16	0	0.006232	0
17	0	0.000303	0
18	1	0.980244	1
19	0	0.041522	0
20	0	0.052871	0
21	0	0.018956	0
22	0	0.001825	0
23	0	0.027170	0

	churn	churn_Prob	final_predicted
24	0	0.048708	0
25	0	0.004883	0
26	0	0.242904	1
27	0	0.000962	0
28	0	0.003758	0
29	1	0.959402	1
...	...	...	...
38588	1	0.949357	1
38589	1	0.973867	1
38590	1	0.964059	1
38591	1	0.995076	1
38592	1	0.974398	1
38593	1	0.974471	1
38594	1	0.957504	1
38595	1	0.960306	1
38596	1	0.917728	1
38597	1	0.988934	1
38598	1	0.945910	1
38599	1	0.972980	1
38600	1	0.934352	1
38601	1	0.936245	1
38602	1	0.978287	1
38603	1	0.983333	1
38604	1	0.957746	1
38605	1	0.983645	1

	churn	churn_Prob	final_predicted
38606	1	0.963211	1
38607	1	0.906144	1
38608	1	0.927316	1
38609	1	0.896737	1
38610	1	0.991899	1
38611	1	0.990023	1
38612	1	0.979150	1
38613	1	0.994571	1
38614	1	0.976706	1
38615	1	0.940262	1
38616	1	0.914186	1
38617	1	0.958143	1

38618 rows × 3 columns

Making prediction on test

In [0]:

```
y_test_df= predictChurnWithProb(xgb2,X_test_pca,y_test,cut_off_
prob)
y_test_df.head()
```

```
Roc_auc_score : 0.8075846160061407
Sensitivity/Recall : 0.7613333333333333
Specificity: 0.853835898678948
False Positive Rate: 0.14616410132105198
Positive predictive value: 0.321328081035453
Negative Predictive value: 0.9752214839424141
sklearn precision score value: 0.321328081035453
```

Out[0]:

	churn	churn_Prob	final_predicted
6102	1	0.196229	0
2539	1	0.659716	1
21576	0	0.613718	1
19574	0	0.046244	0
12804	1	0.074333	0

5. SVM

Using linear kernal

In [0]:

```
# instantiate an object of class SVC()
# note that we are using cost C=1
svm0 = SVC(C = 1)
```

In [0]:

```
# fit
svm0.fit(X_train_pca, y_train_res)

# predict on train
y_pred = svm0.predict(X_train_pca)
getModelMetrics(y_train_res,y_pred)
```

```
Roc_auc_score : 0.8133513569720288
Sensitivity/Recall : 0.7991057502339607
Specificity: 0.8275969637100967
False Positive Rate: 0.1724030362899033
Positive predictive value: 0.8225409397409825
Negative Predictive value: 0.8046709129511678
sklearn precision score value: 0.8225409397409825
```

In [0]:

```
# Predict on test
y_pred = svm0.predict(X_test_pca)
getModelMetrics(y_test,y_pred)
```

```
Roc_auc_score : 0.803768108916091
Sensitivity/Recall : 0.7813333333333333
Specificity: 0.8262028844988486
False Positive Rate: 0.17379711550115137
Positive predictive value: 0.2900990099009901
Negative Predictive value: 0.9765076636585016
sklearn precision score value: 0.2900990099009901
```

Hyperparameter tuning for linear kernal

Let's see if we can tune the hyperparameters of SVM and get a better Sensitivity score.

In [0]:

```
# specify range of parameters (C) as a list
params = {"C": [0.1, 1, 10, 100, 1000]}

svm1 = SVC()

# set up grid search scheme
# note that we are still using the 5 fold CV scheme
model_cv = GridSearchCV(estimator = svm1, param_grid = params,
                        scoring= 'f1',
                        cv = 5,
                        verbose = 1,
                        n_jobs=4,
                       return_train_score=True)
model_cv.fit(X_train_pca, y_train_res)
```

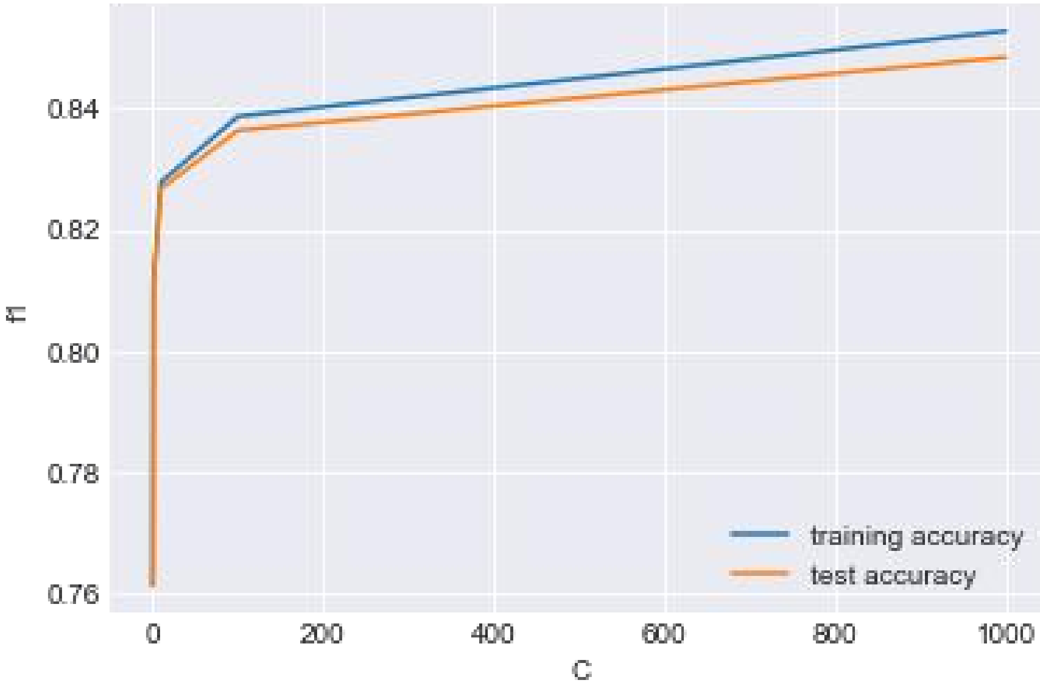
```
Fitting 5 folds for each of 5 candidates, totallin
g 25 fits

[Parallel(n_jobs=4)]: Using backend LokyBackend wi
th 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  25 out of  25 | elapse
d: 19.0min finished
```

Out[0]:

```
GridSearchCV(cv=5, error_score='raise-deprecatin
g',
       estimator=SVC(C=1.0, cache_size=200, class_
weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma
='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, ra
ndom_state=None,
  shrinking=True, tol=0.001, verbose=False),
       fit_params=None, iid='warn', n_jobs=4,
       param_grid={'C': [0.1, 1, 10, 100, 1000]},
pre_dispatch='2*n_jobs',
       refit=True, return_train_score=True, scorin
g='f1', verbose=1)
```

In [0]:

```
plot_traintestAcc(model_cv.cv_results_,'C')
```



In [0]:

```
model_cv.best_params_
```

Out[0]:

```
{'C': 1000}
```

In [0]:

```
svm_final = SVC(C = 1000)
# fit
svm_final.fit(X_train_pca, y_train_res)
```

In [0]:

```
# predict
y_pred = svm_final.predict(X_test_pca)
```

In [0]:

```
getModelMetrics(y_test,y_pred)
```

```
Roc_auc_score : 0.8262503938916494
Sensitivity/Recall : 0.784
Specificity: 0.868500787783299
False Positive Rate: 0.131499212216701
Positive predictive value: 0.3514644351464435
Negative Predictive value: 0.9778930131004366
sklearn precision score value: 0.3514644351464435
```

Using non-linear kernal

In [0]:

```
svm_k = SVC(C = 1000, kernel='rbf')
svm_k.fit(X_train_pca, y_train_res)
```

Out[0]:

```
SVC(C=1000, cache_size=200, class_weight=None, coe
f0=0.0,
  decision_function_shape='ovr', degree=3, gamma
='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, ra
ndom_state=None,
  shrinking=True, tol=0.001, verbose=False)
```

In [0]:

```
y_pred = svm_k.predict(X_test_pca)
```

In [0]:

```
getModelMetrics(y_test,y_pred)
```

```
Roc_auc_score : 0.8262503938916494
Sensitivity/Recall : 0.784
Specificity: 0.868500787783299
False Positive Rate: 0.131499212216701
Positive predictive value: 0.3514644351464435
Negative Predictive value: 0.9778930131004366
sklearn precision score value: 0.3514644351464435
```

Recall Score: 78%

Now that we have a variety of models used to predict the churn for the telecom. Let's caompare and decide a model of choice for this problem of churn prediction.

Final Choice of Model

Recall is the most important business metric for the telecom churn problem. The company would like to identify most customers at risk of churning, even if there are many customers that are misclassified as churn. The cost to the company of churning is much higher than having a few false positives.

Model/Metrics	Train	Test
Logistic Regression (cut-off = 0.45)		
Roc_auc_score	82.11%	81.21%
Sensitivity/Recall	86.48%	84.40%
Specificity	77.75%	78.02%
precision	79.54%	25.04%
DecisionTree (cut-off = 0.4)		
Roc_auc_score	82.41%	76.57%
Sensitivity/Recall	89.79%	78.13%
Specificity	75.03%	75%
precision	78.24%	21.38%
Random Forest (cut-off = 0.45)		
Roc_auc_score	85.60%	96.53%
Sensitivity/Recall	88.70%	77.57%
Specificity	82.50%	81.73%
precision	83.52%	26.97%
GBC		
Roc_auc_score	96.11%	80.84%
Sensitivity/Recall	100.00%	79.87%
Specificity	92.21%	81.81%
precision	92.78%	28.52%
XGB (cut-off = 0.2)		
Roc_auc_score	97.24%	80.76%
Sensitivity/Recall	99.99%	76.13%
Specificity	94.49%	85.38%
precision	94.78%	32.13%

Model/Metrics	Train	Test
SVM (linear C = 1000)		
Roc_auc_score	81.33%	82.62%
Sensitivity/Recall	79.91%	78.40%
Specificity	82.75%	86.85%
precision	82.25%	35.14%

Overall, the **Logistic Regression** model with probability cut-off = 0.45, performs best. It achieved the **best recall accuracy of 84.4%** for test data. Also the overall accuracy and specificity is consistent for Test and train data, thus avoiding overfitting. The precision is compromised in this effort but the business objective to predict Churn customers is most accuratety captured by it.

Next, Linear SVM which achives a recall rate of 78.40%, a slightly better precision of 35.14% and a balanced overall accuracy on train and test.

From the Tree Family, the Decision Tree overfitted the data slightly while obtaining 78.13% recall accuracy on test data. The Random Forest avoided overfitting but obtained only 77.57% recall accuracy on test data.

Among the Bossting Methods, Gradient Boosting Classifer (GBC) achived 81.81% recall rate and XGBoost Classifier achived 76.13% but both tend to overfit the training data.

Identifying relevant churn features.

We will use an instance of Random Forest classifier to identify the features most relevant to churn.

Random Forest for churn driver features

In [0]:

```
# Create the parameter grid based on the results of random sear
ch
param_grid = {
    'max_depth': [8,10,12],
    'min_samples_leaf': range(100, 400, 200),
    'min_samples_split': range(200, 500, 200),
    'n_estimators': [100,200, 300],
    'max_features': [12, 15, 20]
}
# Create a based model
rf = RandomForestClassifier()
# Instantiate the grid search model
grid_search = GridSearchCV(estimator = rf, param_grid = param_g
rid,
                          cv = 3, n_jobs = 4,verbose = 1)
```

In [0]:

```
# Fit the grid search to the data
grid_search.fit(X_train_res, y_train_res)
```

```
Fitting 3 folds for each of 108 candidates, totall
ing 324 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend w
ith 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elaps
ed:  8.6min
[Parallel(n_jobs=-1)]: Done 192 tasks      | elaps
ed: 46.6min
[Parallel(n_jobs=-1)]: Done 324 out of 324 | elaps
ed: 82.8min finished
```

Out[0]:

```
GridSearchCV(cv=3, error_score='raise-deprecatin
g',
       estimator=RandomForestClassifier(bootstrap=
True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', m
ax_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurit
y_split=None,
            min_samples_leaf=1, min_samples_split=
2,
            min_weight_fraction_leaf=0.0, n_estima
tors='warn', n_jobs=None,
            oob_score=False, random_state=None, ve
rbose=0,
            warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'max_depth': [8, 10, 12], 'min_
samples_leaf': range(100, 400, 200), 'min_samples_
split': range(200, 500, 200), 'n_estimators': [10
0, 200, 300], 'max_features': [12, 15, 20]},
       pre_dispatch='2*n_jobs', refit=True, return
_train_score='warn',
       scoring=None, verbose=1)
```

In [0]:

```
# printing the optimal accuracy score and hyperparameters
print('We can get accuracy of',grid_search.best_score_,'using',
grid_search.best_params_)
```

```
We can get accuracy of 0.8936765239007717 using
{'max_depth': 12, 'max_features': 20, 'min_samples
_leaf': 100, 'min_samples_split': 200, 'n_estimato
rs': 300}
```

In [0]:

```
rf = RandomForestClassifier(max_depth=12,
                            max_features=20,
                            min_samples_leaf=100,
                            min_samples_split=200,
                            n_estimators=300,
                            random_state=10)
```

In [0]:

```
rf.fit(X_train_res, y_train_res)
```

Out[0]:

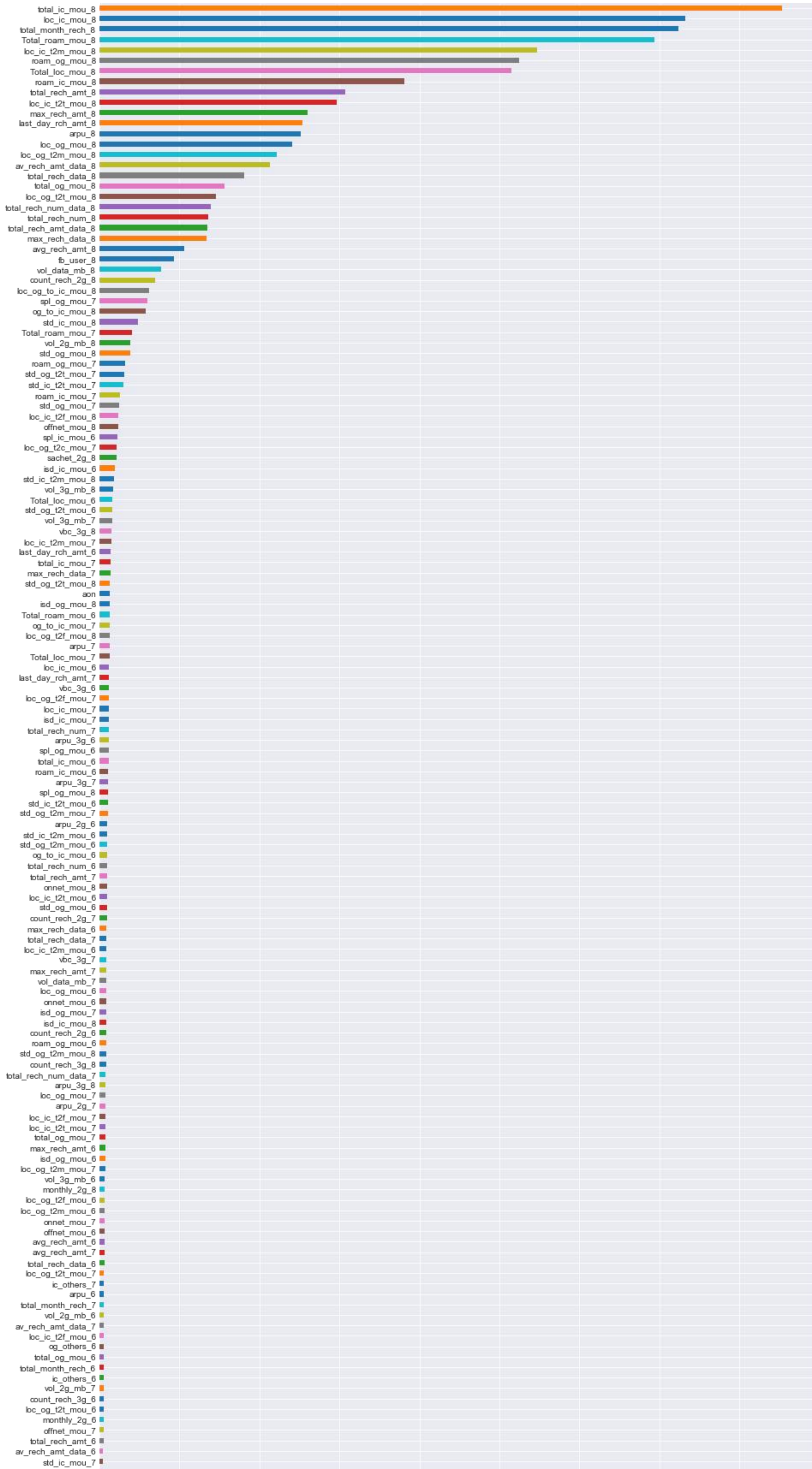
```
RandomForestClassifier(bootstrap=True, class_weigh
t=None, criterion='gini',
             max_depth=12, max_features=20, max_lea
f_nodes=None,
             min_impurity_decrease=0.0, min_impurit
y_split=None,
             min_samples_leaf=100, min_samples_spli
t=200,
             min_weight_fraction_leaf=0.0, n_estima
tors=300, n_jobs=None,
             oob_score=False, random_state=10, verb
ose=0, warm_start=False)
```

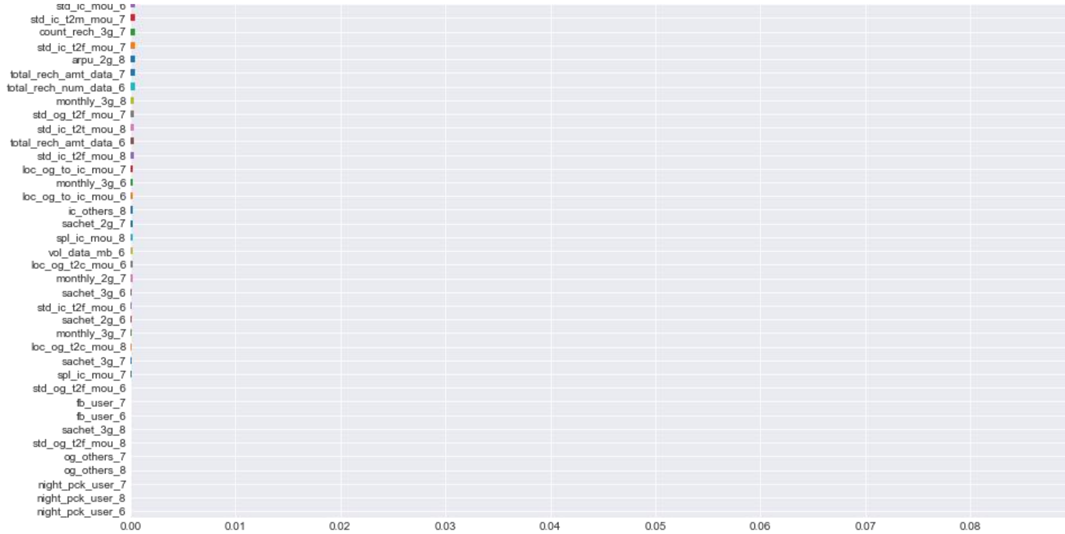
In [0]:

```
plt.figure(figsize=(15,40))
feat_importances = pd.Series(rf.feature_importances_, index=X.c
olumns)
feat_importances.nlargest(len(X.columns)).sort_values().plot(ki
nd='barh', align='center')
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x112eea
358>
```


total_ic_mou_8
loc_ic_mou_8
total_month_rech_8
Total_roam_mou_8
loc_ic_t2m_mou_8
roam_og_mou_8
Total_loc_mou_8
roam_ic_mou_8
total_rech_amt_8
loc_ic_t2t_mou_8
max_rech_amt_8
last_day_rch_amt_8
arpu_8
loc_og_mou_8
loc_og_t2m_mou_8
av_rech_amt_data_8
total_rech_data_8
total_og_mou_8
loc_og_t2t_mou_8
total_rech_num_data_8
total_rech_num_8
total_rech_amt_data_8
max_rech_data_8
avg_rech_amt_8
fb_user_8
vol_data_mb_8
count_rech_2g_8
loc_og_to_ic_mou_8
spl_og_mou_7
og_to_ic_mou_8
std_ic_mou_8
Total_roam_mou_7
vol_2g_mb_8
std_og_mou_8
roam_og_mou_7
std_og_t2t_mou_7
std_ic_t2t_mou_7
roam_ic_mou_7
std_og_mou_7
loc_ic_t2f_mou_8
offnet_mou_8
spl_ic_mou_6
loc_og_t2c_mou_7
sachet_2g_8
isd_ic_mou_6
std_ic_t2m_mou_8
vol_3g_mb_8
Total_loc_mou_6
std_og_t2t_mou_6
vol_3g_mb_7
vbc_3g_8
loc_ic_t2m_mou_7
last_day_rch_amt_6
total_ic_mou_7
max_rech_data_7
std_og_t2t_mou_8
aon
isd_og_mou_8
Total_roam_mou_6
og_to_ic_mou_7
loc_og_t2f_mou_8
arpu_7
Total_loc_mou_7
loc_ic_mou_6
last_day_rch_amt_7
vbc_3g_6
loc_og_t2f_mou_7
loc_ic_mou_7
isd_ic_mou_7
total_rech_num_7
arpu_3g_6
spl_og_mou_6
total_ic_mou_6
roam_ic_mou_6
arpu_3g_7
spl_og_mou_8
std_ic_t2t_mou_6
std_og_t2m_mou_7
arpu_2g_6
std_ic_t2m_mou_6
std_og_t2m_mou_6
og_to_ic_mou_6
total_rech_num_6
total_rech_amt_7
onnet_mou_8
loc_ic_t2t_mou_6
std_og_mou_6
count_rech_2g_7
max_rech_data_6
total_rech_data_7
loc_ic_t2m_mou_6
vbc_3g_7
max_rech_amt_7
vol_data_mb_7
loc_og_mou_6
onnet_mou_6
isd_og_mou_7
isd_ic_mou_8
count_rech_2g_6
roam_og_mou_6
std_og_t2m_mou_8
count_rech_3g_8
total_rech_num_data_7
arpu_3g_8
loc_og_mou_7
arpu_2g_7
loc_ic_t2f_mou_7
loc_ic_t2t_mou_7
total_og_mou_7
max_rech_amt_6
isd_og_mou_6
loc_og_t2m_mou_7
vol_3g_mb_6
monthly_2g_8
loc_og_t2f_mou_6
loc_og_t2m_mou_6
onnet_mou_7
offnet_mou_6
avg_rech_amt_6
avg_rech_amt_7
total_rech_data_6
loc_og_t2t_mou_7
ic_others_7
arpu_6
total_month_rech_7
vol_2g_mb_6
av_rech_amt_data_7
loc_ic_t2f_mou_6
og_others_6
total_og_mou_6
total_month_rech_6
ic_others_6
vol_2g_mb_7
count_rech_3g_6
loc_og_t2t_mou_6
monthly_2g_6
offnet_mou_7
total_rech_amt_6
av_rech_amt_data_6
std_ic_mou_7



Some of the top main predictiors of churn are the monthly KPI features for the action phase (3rd month August).

the graph above suggest that the top 25 features ranked in order of importance as produced by our RandomForest implementation are the features that belong to month 8 i.e., the action month. Hence, it is clear that what happens in the action phase has a direct impact on the customer churn of high value customers. Specifically, these features are as follows:

1. **total_ic_mou_8** -- *Total incoming minutes of usage in month 8*
2. **loc_ic_mou_8** -- *local incoming minutes of usage in month 8*
3. **total_month_rech_8** -- *Total month recharge amount in month 8*
4. **total_roam_mou_8** -- *Total incoming+outgoing roaming minutes of usage in month 8*
5. **loc_ic_t2m_mou_8** -- *local incoming calls to another operator minutes of usage in month 8*
6. **roam_og_mou_8** -- *outgoing roaming calls minutes of usage in month 8*
7. **Total_loc_mou_8** -- *Total local minutes of usage in month 8*
8. **roam_ic_mou_8** -- *incoming roaming calls minutes of usage in month 8*
9. **total_rech_amt_8** -- *total recharge amount in month 8*
10. **loc_ic_t2t_mou_8** -- *local incoming calls from same operator minutes of usage in month 8*
11. **max_rech_amt_8** -- *maximum recharge amount in month 8*
12. **last_day_rch_amt_8** -- *last (most recent) recharge amount in month 8*
13. **arpu_8** -- *average revenue per user in month 8*
14. **loc_og_mou_8** -- *local outgoing calls minutes of usage in month 8*
15. **loc_og_t2n_mou_8** -- *local outgoing calls minutes of usage to other operator mobile in month 8*
16. **av_rech_amt_data_8** -- *average recharge amount for mobile data in month 8*
17. **total_rech_data_8** -- *total data recharge (MB) in month 8*
18. **total_og_t2t_mou_8** -- *total outgoing calls from same operator minutes of usage in month 8*
19. **total_rech_num_8** -- *total number of recharges done in the month 8*
20. **total_rech_amt_data_8** -- *total recharge amount for data in month 8*
21. **max_rech_data_8** -- *maximum data recharge (MB) in month 8*
22. **avg_rech_amt_8** -- *average recharge amount in month 8*

23. **fb_user_8** -- *services of Facebook and similar social networking sites for month 8*
24. **vol_data_mb_8** -- *volume of data (MB) consumed for month 8*
25. **count_rech_2g_8** -- *Number of 2g data recharge in month 8*
26. **loc_og_to_ic_mou_8** -- *local outgoing to incoming mou ratio for month of 8*
27. **spl_og_mou_7** -- *Special outgoing call for the month of 7*

Local calls Mou's be it incoming or outgoing have a very important role for churn predictions. Reduction in these KPI's forms a clear indicator of churn.

Overall, drop in any of these indicator KPI is a signal that the customer is not actively engaging in the services offered by the Network operator and thus may choose to churn in the near future.

Next, we will look at some of the stratergic steps which can be taken to retain these predicted churners.

Strategies to manage customer churn

It is a fact that it costs 5-10 times more to acquire a new customer than to retain an existing one, customer retention has now become even more important than customer acquisition.

For many incumbent operators, retaining high profitable customers is the number one business goal.

Monitoring Drop in usage

Customer churn seems to be well predicted by drop in usage.

Aside from using the Machine Learning model for predicting churn, the telecom company should pay close attention to drop in MoU, ARPU and data usage (2g and 3g) month over month. If feasible, the company should track these numbers week over week. Since billing cycles are typically monthly, a drop in usage numbers will give the company time to react when tracked at weekly level.

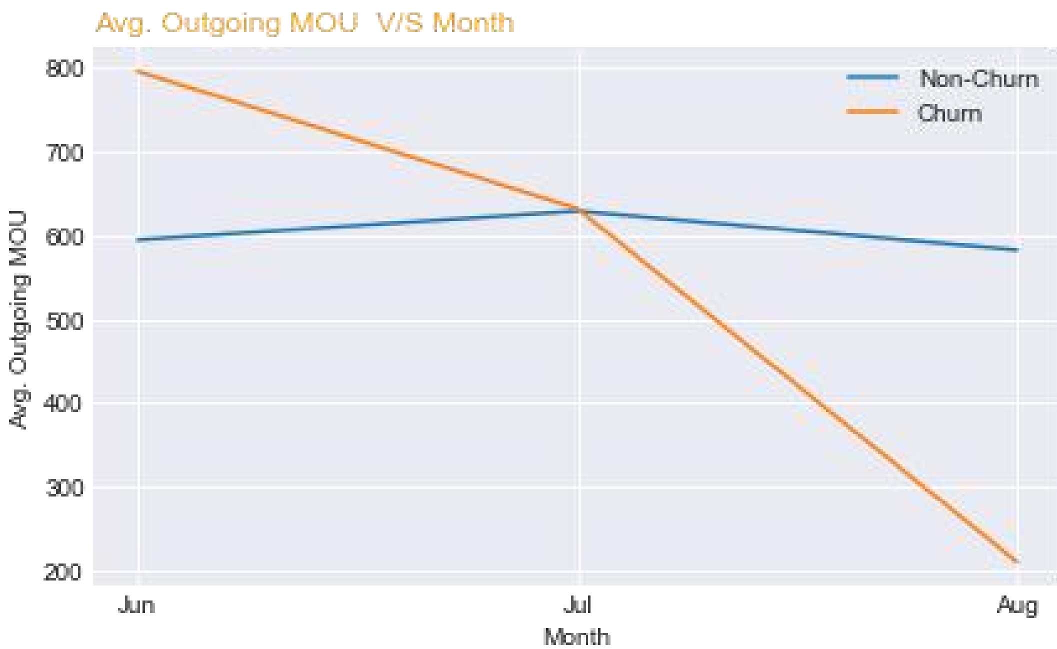
Contact these customers proactively to find out what's affecting their experience. Perhaps, offer them coupons or other incentives to continue to use the services, while the company fixes the issues reported.

Marketing team must come up with campaigns which targets these high-value to-be churner.

Improving Outgoing services

In [0]:

```
# Outgoing Mou
plot_byChurnMou(og_col,'Outgoing')
```



- Initially, churner's outgoing usage was more than that of non-churners. Gradually they dropped there outgoing usage. May be these customers din't like the outgoing services offered to them or may be the call tariffs seemed expensive to them or may be the overall call quality, network coverage was not liked my them. This could be further investigated by the network service provider.

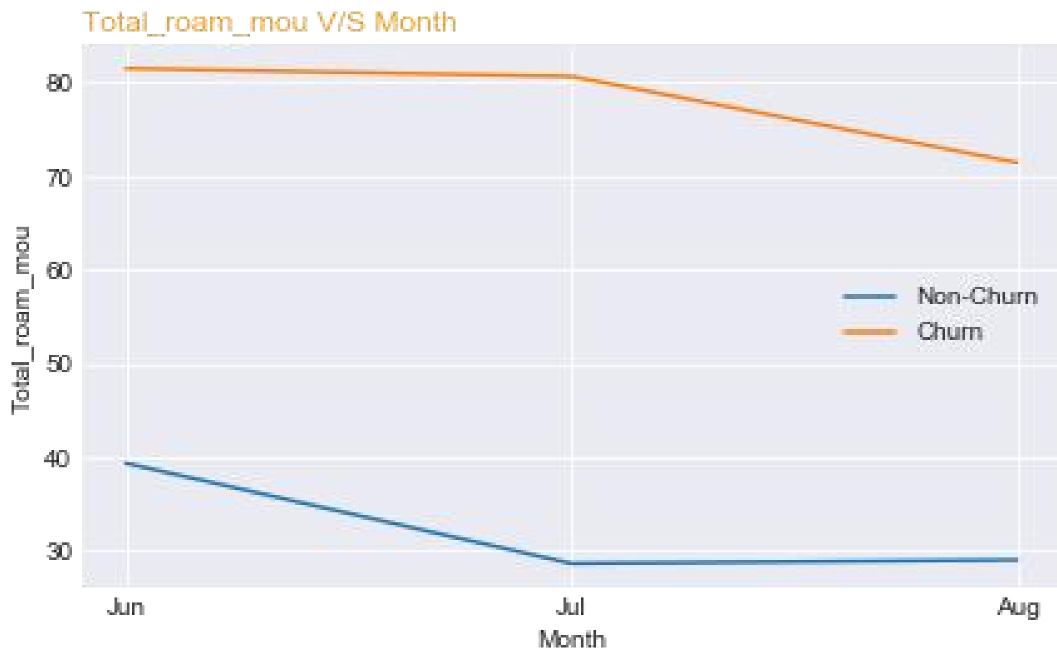
Stratergy suggestions,

- The Network operators must futher investigate their outgoing tariffs, plans and campaigns.
- Might be that the outgoing tariffs offered to it's customer are less competitive to the outgoing tariffs of their competitor.
- New campaigns which targets the customers with high outgoing usage be rolled out.Like,
    - Discounted outgoing rates during particular hours of the day for these customers.
    - For every X mou, grant customer with some % of X free mou.
    - Investigate and if need be revise the outgoing tarrifs to make it competitive.
    - Free monthly outgoing mou's depending on the users past roaming mou usage.

Improving Roaming services

In [0]:

```
plot_byChurn(hv_users,'Total_roam_mou')
```



Out[0]:

churn	Total_roam_mou_6	Total_roam_mou_7	Total_roam_mou
0	39.360033	28.643301	29.0167
1	81.504156	80.651973	71.4436

Stratergy suggestions,

- Churners show higher roaming usage than non-churners.
- The Network operators must futher investigate their roaming tariffs, and quality of service.
- Might be that the roaming tariffs offered are less competitive than their competitor.
- It might be that the customer is not getting good quality of service while roaming. In this case, quality of service guarantees with roaming partners and network quality need to be investigated.
- New campaigns which targets the roaming customers can be rolled out. Like,
  - Discounted roaming rates during particular hours of the day.
  - Free monthly roaming mou's depending on the users past roaming mou usage.

In [ ]:

```

```