Telecom Churn - ML Group Case Study

By: Nisha Kumar

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.

Filename: telecom_churn_data_v1.csv

In [1]:

```
import pandas as pd
```

** Importing Data

In [2]:

```
churn=pd.read_csv("/Users/nisha/Downloads/telecom_churn_data_v1.csv")
```

In [3]:

```
churn.head()
```

Out[3]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	last_date_of_m
0	7000842753	109	0.0	0.0	0.0	6/3
1	7001865778	109	0.0	0.0	0.0	6/3
2	7001625959	109	0.0	0.0	0.0	6/3
3	7001204172	109	0.0	0.0	0.0	6/3
4	7000142493	109	0.0	0.0	0.0	6/3

5 rows × 226 columns

In [4]:

```
churn.shape
```

Out[4]:

```
(99999, 226)
```

Data Cleaning and Data Preparation

Handling missing data*

** Missing Values more than 50%

In [5]:

```
missing=round(100*churn.isnull().sum()/len(churn),2)
print("Columns with more than 50% missing values: ",len(missing.loc[missing>50
]))
missing.loc[missing>50]
```

```
Columns with more than 50% missing values:  40
```

Out[5]:

```
date_of_last_rech_data_6    74.85
date_of_last_rech_data_7    74.43
date_of_last_rech_data_8    73.66
date_of_last_rech_data_9    74.08
total_rech_data_6           74.85
total_rech_data_7           74.43
total_rech_data_8           73.66
total_rech_data_9           74.08
max_rech_data_6             74.85
max_rech_data_7             74.43
max_rech_data_8             73.66
max_rech_data_9             74.08
count_rech_2g_6             74.85
count_rech_2g_7             74.43
count_rech_2g_8             73.66
count_rech_2g_9             74.08
count_rech_3g_6             74.85
count_rech_3g_7             74.43
count_rech_3g_8             73.66
count_rech_3g_9             74.08
av_rech_amt_data_6          74.85
av_rech_amt_data_7          74.43
av_rech_amt_data_8          73.66
av_rech_amt_data_9          74.08
arpu_3g_6                   74.85
arpu_3g_7                   74.43
arpu_3g_8                   73.66
arpu_3g_9                   74.08
arpu_2g_6                   74.85
arpu_2g_7                   74.43
arpu_2g_8                   73.66
arpu_2g_9                   74.08
night_pck_user_6            74.85
night_pck_user_7            74.43
night_pck_user_8            73.66
night_pck_user_9            74.08
fb_user_6                   74.85
fb_user_7                   74.43
fb_user_8                   73.66
fb_user_9                   74.08
dtype: float64
```

Imputing with 0 for few missing values* 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 [6]:

```
impute0 = ['av_rech_amt_data_6', 'arpu_2g_6', 'arpu_3g_6', 'count_rech_2g_6', 'c
ount_rech_3g_6',
             'max_rech_data_6', 'total_rech_data_6','fb_user_6','night_pck_user_
6','av_rech_amt_data_7', 'arpu_2g_7', 'arpu_3g_7', 'count_rech_2g_7', 'count_rec
h_3g_7',
             'max_rech_data_7', 'total_rech_data_7','fb_user_7','night_pck_user_
7','av_rech_amt_data_8', 'arpu_2g_8', 'arpu_3g_8', 'count_rech_2g_8', 'count_rec
h_3g_8',
             'max_rech_data_8', 'total_rech_data_8','fb_user_8','night_pck_user_
8','av_rech_amt_data_9', 'arpu_2g_9', 'arpu_3g_9', 'count_rech_2g_9', 'count_rec
h_3g_9',
             'max_rech_data_9', 'total_rech_data_9','fb_user_9','night_pck_user_
9']
```

In [7]:

```
for i in impute0:
    churn[i].fillna(0,inplace=True)
```

missing Values more than 50% after 0 imputation***

In [8]:

```
missing=round(100*churn.isnull().sum()/len(churn),2)
missing.loc[missing>50]
```

Out[8]:

```
date_of_last_rech_data_6    74.85
date_of_last_rech_data_7    74.43
date_of_last_rech_data_8    73.66
date_of_last_rech_data_9    74.08
dtype: float64
```

*dropping columns with more than 50% missing values**

In [9]:

```
d=['date_of_last_rech_data_6','date_of_last_rech_data_7','date_of_last_rech_data
_8','date_of_last_rech_data_9']
churn.drop(d,axis=1,inplace=True)
```

missing values more than 2% for columns

In [10]:

```
missing=round(100*churn.isnull().sum()/len(churn),2)
miss=missing.loc[missing>2]
miss=list(miss.index)
print("Total missing values with more tha 3% missing values :",len(miss))
```

```
Total missing values with more tha 3% missing values : 118
```

In [11]:

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

In [12]:

```
churn.shape
```

Out[12]:

```
(99618, 222)
```

*Adding New Features:***

```
total_rechg_data6=total_rech_data_6*av_rech_amt_data_6
1. Total rech_6=total rech_amt_6 +total rechg_data_6
2. Total rech_7=total rech_amt_7 +total rechg_data_7
3. avg rechg for 6 &7 =(Total rech_6+Total rech_7)/2
```

In [13]:

```
churn['rech_data_6_total']=churn['total_rech_data_6']*churn['av_rech_amt_data_6'
]
churn['rech_data_7_total']=churn['total_rech_data_7']*churn['av_rech_amt_data_7'
]
#churn['rech_data_8_total']=churn['total_rech_data_6']*churn['av_rech_amt_data_
6']
```

In [14]:

```
churn['Total rech_6']=churn['rech_data_6_total']+churn['total_rech_amt_6']
churn['Total rech_7']=churn['rech_data_7_total']+churn['total_rech_amt_7']
```

In [15]:

```
churn['avg_amt_6_7']=churn[['Total rech_6','Total rech_7']].mean(axis=1)
```

High profitable customer finding 70th percentile and extracting data with more than 70% percentile avg recharge amount for both data & calling -

In [16]:

```
import numpy as np
amount_70th_percentile = np.percentile(churn['avg_amt_6_7'], 70)
```

In [17]:

```
print(amount_70th_percentile)
```

```
479.5
```

```
    ******Deriving records containing only High profitable customer in a D
ataFrame and resetting index *********
```

In [18]:

```
hvc=churn[churn['avg_amt_6_7']>=amount_70th_percentile]
```

In [19]:

```
hvc.shape
```

Out[19]:

```
(29906, 227)
```

Total Records for High Profitable Customers= 29906**

In [20]:

```
hvc = hvc.reset_index(drop=True)
```

In [21]:

```
hvc.head()
```

Out[21]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	last_date_of_m
0	7000842753	109	0.0	0.0	0.0	6/3
1	7000701601	109	0.0	0.0	0.0	6/3
2	7001524846	109	0.0	0.0	0.0	6/3
3	7002124215	109	0.0	0.0	0.0	6/3
4	7000887461	109	0.0	0.0	0.0	6/3

5 rows × 227 columns

```
    ****finding columns with 0 variance and dropping them as they have not muc
    h significance to show any pattern********
```

In [22]:

```
zero_var=hvc.var()==0
```

In [23]:

```
print(zero_var.sum())
zero_var1=zero_var[zero_var==1].index
print(zero_var1)
```

```
12
Index(['circle_id', '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 [24]:

```
hvc.drop(zero_var1,axis=1,inplace=True)
```

Deriving and adding the churn variable using features: total_ic_mou_9,total_ic_mou_9,vol_2g_mb_9,vol_3g_mb_9

**where : total_ic_mou_9+total_ic_mou_9+vol_2g_mb_9+vol_3g_mb_9==0-> 1 (churned) else : 0: not churned

In [25]:

```
import numpy as np
hvc['churn']=np.where((hvc['total_ic_mou_9']+hvc['total_og_mou_9']+ hvc['vol_2g_
mb_9']+hvc['vol_3g_mb_9']==0),1,0)

#hvc['churn']=hvc.apply(lambda x: 1 if ((x.total_ic_mou_9==0) and x.total_og_mou
_9==0 and x.vol_2g_mb_9==0 and x.vol_3g_mb_9'==0 else 0)
```

In [26]:

```
print("Total Churned Customers: ",hvc['churn'].sum())
```

```
Total Churned Customers:  2418
```

In [27]:

```
print("Total % of Churned Customers: " ,round(100* hvc['churn'].sum()/len(hvc),2
)) # churn %
```

```
Total % of Churned Customers:  8.09
```

We need to drop the above list of last month columns entirely.

In [28]:

```
col_9List = hvc.filter(regex=('_9')).columns
```

In [29]:

```
hvc.drop(col_9List, axis=1, inplace=True)
```

In [30]:

```
hvc.shape
```

Out[30]:

```
(29906, 165)
```

Dropping some more columns*

In [31]:

```
hvc.drop(['mobile_number'], axis=1, inplace = True)
```

In [32]:

```
hvc.drop(['last_date_of_month_6','last_date_of_month_7','last_date_of_month_8'],
axis=1,inplace=True)
```

In [33]:

```
hvc.drop(['date_of_last_rech_6', 'date_of_last_rech_7', 'date_of_last_rech_8'],a
xis=1, inplace=True)
```

In [34]:

```
hvc.head()
```

Out[34]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	off
0	197.385	214.816	213.803	NaN	NaN	0.00	NaN	
1	1069.180	1349.850	3171.480	57.84	54.68	52.29	453.43	
2	378.721	492.223	137.362	413.69	351.03	35.08	94.66	
3	514.453	597.753	637.760	102.41	132.11	85.14	757.93	
4	74.350	193.897	366.966	48.96	50.66	33.58	85.41	

5 rows × 158 columns

In [35]:

```
from fancyimpute import IterativeImputer
```

```
Using TensorFlow backend.
```

In [36]:

```
missing=round(100*hvc.isnull().sum()/len(hvc),2)
miss=missing.loc[missing>3]
miss=list(miss.index)
len(miss)
```

Out[36]:

```
27
```

Using Iterative Imputer to impute columns with more than 3% missing values** Note- Iterative Imputer used only for a chunk of columns as it was making the system very slow and it was done in parts due to performance issues

In [37]:

```
temp=hvc[['total_rech_num_6', 'total_rech_num_7', 'total_rech_num_8']]
```

In [38]:

```
df_columns = temp.columns
ii = IterativeImputer()
dftemp= pd.DataFrame(ii.fit_transform(temp))
dftemp.columns=df_columns
hvc[['total_rech_num_6', 'total_rech_num_7', 'total_rech_num_8']]=dftemp[['total
_rech_num_6', 'total_rech_num_7', 'total_rech_num_8']]
```

In [39]:

```
#for i in list(df_clean.columns):
 # hvc[i]=df_clean[i]
missing=round(100*hvc.isnull().sum()/len(hvc),2)
miss=missing.loc[missing>3]
miss=list(miss.index)
len(miss)
print(miss)
hvc.shape
```

```
['onnet_mou_8', 'offnet_mou_8', 'roam_ic_mou_8', 'roam_og_mou_8', 'l
oc_og_t2t_mou_8', 'loc_og_t2m_mou_8', 'loc_og_t2f_mou_8', 'loc_og_t2
c_mou_8', 'loc_og_mou_8', 'std_og_t2t_mou_8', 'std_og_t2m_mou_8', 's
td_og_t2f_mou_8', 'std_og_mou_8', 'isd_og_mou_8', 'spl_og_mou_8', 'o
g_others_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', 'spl_ic_mou_8', 'isd_ic_mou_8', 'ic_oth
ers_8']
```

Out[39]:

```
(29906, 158)
```

***Iterative Imputation for more columns**

In [40]:

```
temp2=hvc[['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_m
ou_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',
            'loc_ic_t2t_mou_8', 'loc_ic_t2m_mou_8', 'loc_ic_t2f_mou_8', 'loc_ic_m
ou_8', 'std_ic_t2t_mou_8',
            'std_ic_t2m_mou_8', 'std_ic_t2f_mou_8', 'std_ic_mou_8', 'spl_ic_mou_
8', 'isd_ic_mou_8', 'ic_others_8']]
df_columns = temp2.columns
ii = IterativeImputer()
dftemp2= pd.DataFrame(ii.fit_transform(temp2))
dftemp2.columns=df_columns
hvc[['onnet_mou_8', 'offnet_mou_8', 'roam_ic_mou_8', 'roam_og_mou_8', 'loc_og_t2
t_mou_8',
            'loc_og_t2m_mou_8', 'loc_og_t2f_mou_8', 'loc_og_t2c_mou_8', 'loc_og_m
ou_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',
            'loc_ic_t2t_mou_8', 'loc_ic_t2m_mou_8', 'loc_ic_t2f_mou_8', 'loc_ic_m
ou_8', 'std_ic_t2t_mou_8',
            'std_ic_t2m_mou_8', 'std_ic_t2f_mou_8', 'std_ic_mou_8', 'spl_ic_mou_
8', 'isd_ic_mou_8', 'ic_others_8']]=dftemp2[['onnet_mou_8', 'offnet_mou_8', 'roa
m_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_m
ou_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',
            'loc_ic_t2t_mou_8', 'loc_ic_t2m_mou_8', 'loc_ic_t2f_mou_8', 'loc_ic_m
ou_8', 'std_ic_t2t_mou_8',
            'std_ic_t2m_mou_8', 'std_ic_t2f_mou_8', 'std_ic_mou_8', 'spl_ic_mou_
8', 'isd_ic_mou_8', 'ic_others_8']]
```

In [41]:

```
missing=round(100*hvc.isnull().sum()/len(hvc),2)
miss=missing.loc[missing>2]
print("Columns with more than 2-3 % missing Values: ",len(miss))
```

```
Columns with more than 2-3 % missing Values:  0
```

In [42]:

```
hvc.shape
```

Out[42]:

```
(29906, 158)
```

In [ ]:

```

```

In [43]:

```
missing=round(100*hvc.isnull().sum()/len(hvc),2)
miss=missing.loc[missing>0]
print("Remaining columns with missing values i.e more than 0% and less than 3%)
 : ",len(miss))
```

```
Remaining columns with missing values i.e more than 0% and less than
3%) :  54
```

In [44]:

```
hvc_clean=hvc
```

*Using median Technique to impute remaining columns with missing values (less than 3%)**

In [45]:

```
hvc_clean=hvc.fillna(hvc.mean())
missing=round(100*hvc_clean.isnull().sum()/len(hvc_clean),2)
miss=missing.loc[missing>0]
print("Missing values columns : " , len(miss))
```

```
Missing values columns :  0
```

In [46]:

```
hvc_clean.shape
```

Out[46]:

```
(29906, 158)
```

Looking at the problem statement, attributes total_ic_mou_9, total_og_mou_9, vol_2g_mb_9 and vol_3g_mb_9 are used to tag churners. So, it is clearly evident from the problem statement that the individual incoming and outgoing attributes are not used for data analysis. Dropping the individual columns (whose totals are already available like incoming, outgoing, arpu, etc) can help us in better analysis. Also, dropping these individual columns will help in removing the multicollinearity.

In [47]:

```
individual_cols = ['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_ic_t2f_mou_6', 'loc_ic_t2f_mou_7', 'loc_ic_t2f_mou_8',
                   'std_ic_t2t_mou_6', 'std_ic_t2t_mou_7', 'std_ic_t2t_mou_8',
                   'std_ic_t2m_mou_6', 'std_ic_t2m_mou_7', 'std_ic_t2m_mou_8',
                   'std_ic_t2f_mou_6', 'std_ic_t2f_mou_7', 'std_ic_t2f_mou_8',
                   'loc_og_t2t_mou_6', 'loc_og_t2t_mou_7', 'loc_og_t2t_mou_8',
                   'loc_og_t2m_mou_6', 'loc_og_t2m_mou_7', 'loc_og_t2m_mou_8',
                   'loc_og_t2f_mou_6', 'loc_og_t2f_mou_7', 'loc_og_t2f_mou_8',
                   'loc_og_t2c_mou_6', 'loc_og_t2c_mou_7', 'loc_og_t2c_mou_8',
                   'std_og_t2t_mou_6', 'std_og_t2t_mou_7', 'std_og_t2t_mou_8',
                   'std_og_t2m_mou_6', 'std_og_t2m_mou_7', 'std_og_t2m_mou_8',
                   'std_og_t2f_mou_6', 'std_og_t2f_mou_7', 'std_og_t2f_mou_8',
                   'last_day_rch_amt_6', 'last_day_rch_amt_7', 'last_day_rch_amt
_8',
                   'arpu_3g_6', 'arpu_3g_7', 'arpu_3g_8',
                   'arpu_2g_6', 'arpu_2g_7', 'arpu_2g_8',
                   'av_rech_amt_data_6', 'av_rech_amt_data_7', 'av_rech_amt_data
_8']

hvc_clean.drop(individual_cols, axis=1, inplace=True)
```

In [652]:

```
hvc_clean.shape
```

Out[652]:

```
(29906, 107)
```

Variables night_pck_user_6, night_pck_user_7, night_pck_user_8, fb_user_6, fb_user_7 and fb_user_8 are encoded with number 0 and 1. These variables can be considered as Ordered Categorical columns. Also, the datatype of these variables can be converted to integer.Also

In [48]:

```
hvc_final=hvc_clean
```

In [50]:

```
category_list = ['night_pck_user_6', 'night_pck_user_7', 'night_pck_user_8', 'fb
_user_6', 'fb_user_7', 'fb_user_8']

hvc_clean[category_list] = hvc_clean[category_list].astype(int)
```

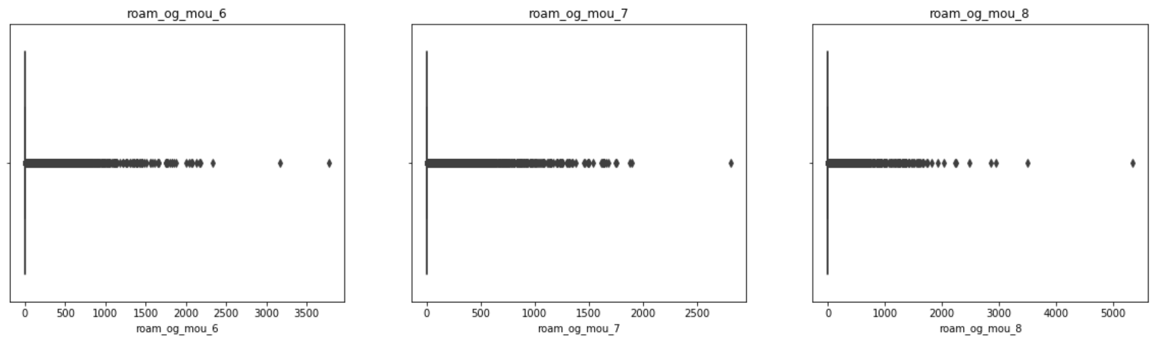
In [51]:

```
plt.figure(figsize=(20, 5))


var = ['max_rech_data_6', 'max_rech_data_7','max_rech_data_8']

for i in enumerate(var[0:3]):
    plt.subplot(1,3,i[0]+1)
    sns.boxplot(x = i[1], data = hvc_clean)
    plt.title(i[1])

    'roam_og_mou_8'
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent cal
l last)
<ipython-input-51-d1334a297fb7> in <module>
----> 1 plt.figure(figsize=(20, 5))
      2
      3
      4 var = ['max_rech_data_6', 'max_rech_data_7','max_rech_data_
8']
      5

NameError: name 'plt' is not defined
```

In [784]:

```
plt.figure(figsize=(20, 5))


var = ['roam_og_mou_6',  'roam_og_mou_7', 'roam_og_mou_8']

for i in enumerate(var[0:3]):
    plt.subplot(1,3,i[0]+1)
    sns.boxplot(x = i[1], data = hvc_clean)
    plt.title(i[1])
```



In [52]:

```
hvc_clean[['roam_og_mou_6',  'roam_og_mou_7', 'roam_og_mou_8']].describe(percent
iles = [0.05,.10,.25,.50,.75,.90,.95,.99])
```

Out[52]:

	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8
count	29906.000000	29906.000000	29906.000000
mean	27.105763	20.545711	20.721445
std	116.299660	96.168645	104.802679
min	0.000000	0.000000	0.000000
5%	0.000000	0.000000	0.000000
10%	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000
90%	50.510000	31.180000	29.025000
95%	145.632500	104.470000	101.117500
99%	531.973500	438.512500	427.106000
max	3775.110000	2812.040000	5337.040000

Correlation Matrix

In [53]:

```
hvc_clean.shape
```

Out[53]:

```
(29906, 107)
```

In [54]:

```
hvc_clean.corr()
```

Out[54]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8
arpu_6	1.000000	0.673890	0.614850	0.336680	0.216372	0.189865
arpu_7	0.673890	1.000000	0.759918	0.210143	0.314374	0.261969
arpu_8	0.614850	0.759918	1.000000	0.149375	0.228362	0.331684
onnet_mou_6	0.336680	0.210143	0.149375	1.000000	0.750729	0.623379
onnet_mou_7	0.216372	0.314374	0.228362	0.750729	1.000000	0.804208
onnet_mou_8	0.189865	0.261969	0.331684	0.623379	0.804208	1.000000
offnet_mou_6	0.503186	0.350875	0.276933	0.083074	0.049301	0.060984
offnet_mou_7	0.341108	0.482936	0.370811	0.032867	0.077852	0.080573
offnet_mou_8	0.291456	0.386513	0.505523	0.034148	0.066843	0.117753
roam_ic_mou_6	0.124468	0.091613	0.086920	0.022285	0.036976	0.050030
roam_ic_mou_7	0.083454	0.091537	0.075989	0.023526	0.006666	0.018601
roam_ic_mou_8	0.091067	0.090747	0.105062	0.043455	0.034607	0.019631
roam_og_mou_6	0.193622	0.132633	0.127220	0.075074	0.080194	0.096236
roam_og_mou_7	0.143380	0.177333	0.139405	0.074509	0.066588	0.082141
roam_og_mou_8	0.125832	0.148654	0.192735	0.072225	0.080985	0.092154
loc_og_mou_6	0.322348	0.211648	0.205902	0.290101	0.198764	0.187931
loc_og_mou_7	0.246894	0.296860	0.258626	0.221321	0.300140	0.251068
loc_og_mou_8	0.227920	0.245504	0.327574	0.187777	0.232229	0.324027
std_og_mou_6	0.380325	0.247334	0.148494	0.625309	0.466829	0.383590
std_og_mou_7	0.230870	0.375422	0.254126	0.447699	0.623831	0.505982
std_og_mou_8	0.185396	0.297237	0.386341	0.371508	0.504859	0.635303
isd_og_mou_6	0.467276	0.417040	0.394498	-0.015336	-0.013289	-0.012673
isd_og_mou_7	0.421577	0.508579	0.437533	-0.015835	-0.014553	-0.013856
isd_og_mou_8	0.414536	0.451791	0.453813	-0.013748	-0.012626	-0.012247
spl_og_mou_6	0.118770	0.065878	0.098316	0.095789	0.059666	0.051958
spl_og_mou_7	0.068735	0.110754	0.121643	0.077070	0.107708	0.077222
spl_og_mou_8	0.046421	0.064293	0.097303	0.082996	0.105796	0.127393
og_others_6	0.052782	0.017213	0.012253	0.053046	0.027321	0.018100
og_others_7	0.024368	0.025880	0.015584	-0.000705	-0.000591	-0.002038
og_others_8	0.015564	0.017519	0.011764	-0.003387	0.002198	-0.001835
...	...	...	...	...	...	...
vol_3g_mb_8	0.084933	0.117680	0.188343	-0.093900	-0.090389	-0.073101
night_pck_user_6	0.014175	-0.003247	-0.006162	-0.000391	-0.005046	-0.000183
night_pck_user_7	-0.004990	0.008788	0.004271	-0.004581	0.008456	0.009328
night_pck_user_8	0.009710	0.018681	0.028719	0.017073	0.035554	0.042438

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8
monthly_2g_6	-0.038854	-0.081154	-0.053042	-0.107206	-0.112395	-0.098526
monthly_2g_7	-0.083853	-0.033438	-0.039188	-0.115068	-0.113961	-0.098440
monthly_2g_8	-0.060908	-0.048144	0.013437	-0.098770	-0.097434	-0.083134
sachet_2g_6	-0.158860	-0.183455	-0.153765	-0.131772	-0.133487	-0.115298
sachet_2g_7	-0.194322	-0.151892	-0.137655	-0.130825	-0.122059	-0.106287
sachet_2g_8	-0.152365	-0.132728	-0.075097	-0.108251	-0.100140	-0.080992
monthly_3g_6	0.176918	0.084529	0.089644	-0.081778	-0.084249	-0.072342
monthly_3g_7	0.081124	0.190621	0.123247	-0.082764	-0.081449	-0.067547
monthly_3g_8	0.103863	0.132428	0.223722	-0.075896	-0.076312	-0.059915
sachet_3g_6	-0.002547	-0.027453	-0.022386	-0.053433	-0.053765	-0.046420
sachet_3g_7	-0.025182	0.010745	-0.002303	-0.045542	-0.050519	-0.038532
sachet_3g_8	-0.017355	0.000923	0.045390	-0.045178	-0.039826	-0.033782
fb_user_6	-0.120347	-0.184654	-0.130863	-0.265405	-0.271157	-0.236517
fb_user_7	-0.197370	-0.117756	-0.102908	-0.275292	-0.269509	-0.235153
fb_user_8	-0.139852	-0.102191	0.007663	-0.233759	-0.222089	-0.187058
aon	0.041272	0.031618	0.070913	-0.051094	-0.058321	-0.036139
aug_vbc_3g	0.058837	0.083545	0.146394	-0.104990	-0.103066	-0.084375
jul_vbc_3g	0.055373	0.102169	0.085114	-0.110913	-0.108839	-0.091661
jun_vbc_3g	0.112206	0.055121	0.073724	-0.102253	-0.106994	-0.083225
sep_vbc_3g	0.045143	0.059089	0.104801	-0.034119	-0.033976	-0.029142
rech_data_6_total	0.089110	-0.013729	-0.004020	-0.098787	-0.101599	-0.086766
rech_data_7_total	-0.023862	0.091538	0.028596	-0.101304	-0.099503	-0.077776
Total rech_6	0.419419	0.230773	0.215430	0.027959	-0.014524	-0.009964
Total rech_7	0.211270	0.419401	0.295716	-0.020083	0.018716	0.022254
avg_amt_6_7	0.368623	0.384910	0.301778	0.004051	0.002871	0.007624
churn	0.065642	-0.011052	-0.159777	0.077764	0.027333	-0.033193

107 rows × 107 columns

In [105]:

```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize = (25, 20))

sns.heatmap(hvc_clean.corr())

plt.show()
```

```
<Figure size 2500x2000 with 2 Axes>
```

*Features with high correlation***

In [55]:

```
corr_matrix = hvc_clean.corr().abs()

#the matrix is symmetric so we need to extract upper triangle matrix without dia
gonal (k = 1)
upper_triangle = (corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).ast
ype(np.bool)))

highly_correlated_features = [column for column in upper_triangle.columns if any
(upper_triangle[column] > 0.80)]
print("List of highly correlated features from the above plot - \n\n", highly_co
rrelated_features)
print("\n\nTotal features with high correlation - ", len(highly_correlated_featu
res))
```

```
List of highly correlated features from the above plot -

 ['onnet_mou_8', 'loc_og_mou_7', 'loc_og_mou_8', 'isd_og_mou_7', 'is
d_og_mou_8', 'total_og_mou_6', 'total_og_mou_7', 'total_og_mou_8',
'loc_ic_mou_7', 'loc_ic_mou_8', 'total_ic_mou_6', 'total_ic_mou_7',
'total_ic_mou_8', 'total_rech_amt_6', 'total_rech_amt_7', 'total_rec
h_amt_8', 'count_rech_2g_6', 'count_rech_2g_7', 'count_rech_2g_8',
'sachet_2g_6', 'sachet_2g_7', 'sachet_2g_8', 'sachet_3g_6', 'sachet_
3g_7', 'sachet_3g_8', 'Total rech_6', 'Total rech_7', 'avg_amt_6_7']


Total features with high correlation -  28
```

Model Building

SMOTE for Class Imbalance

    Deriving Train and Test Data for Model building with PCA

In [56]:

```
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split, GridSearchCV
X= hvc_clean.drop('churn', axis = 1)
y = hvc_clean[['churn']]
df_cols = X.columns
X1=X
y1=y
###################
sm = SMOTE(random_state=12, ratio = 1)
X, y = sm.fit_sample(X, y)
####################
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, test
_size = 0.3)

print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
/Users/nisha/anaconda3/lib/python3.7/site-packages/sklearn/utils/dep
recation.py:144: FutureWarning: The sklearn.neighbors.base module is
deprecated in version 0.22 and will be removed in version 0.24. The
corresponding classes / functions should instead be imported from sk
learn.neighbors. Anything that cannot be imported from sklearn.neigh
bors is now part of the private API.
  warnings.warn(message, FutureWarning)
/Users/nisha/anaconda3/lib/python3.7/site-packages/sklearn/utils/dep
recation.py:144: FutureWarning: The sklearn.ensemble.bagging module
is  deprecated in version 0.22 and will be removed in version 0.24.
The corresponding classes / functions should instead be imported fro
m sklearn.ensemble. Anything that cannot be imported from sklearn.en
semble is now part of the private API.
  warnings.warn(message, FutureWarning)
/Users/nisha/anaconda3/lib/python3.7/site-packages/sklearn/utils/dep
recation.py:144: FutureWarning: The sklearn.ensemble.base module is
deprecated in version 0.22 and will be removed in version 0.24. The
corresponding classes / functions should instead be imported from sk
learn.ensemble. Anything that cannot be imported from sklearn.ensemb
le is now part of the private API.
  warnings.warn(message, FutureWarning)
/Users/nisha/anaconda3/lib/python3.7/site-packages/sklearn/utils/dep
recation.py:144: FutureWarning: The sklearn.ensemble.forest module i
s  deprecated in version 0.22 and will be removed in version 0.24. T
he corresponding classes / functions should instead be imported from
sklearn.ensemble. Anything that cannot be imported from sklearn.ense
mble is now part of the private API.
  warnings.warn(message, FutureWarning)
/Users/nisha/anaconda3/lib/python3.7/site-packages/sklearn/utils/dep
recation.py:144: FutureWarning: The sklearn.utils.testing module is
deprecated in version 0.22 and will be removed in version 0.24. The
corresponding classes / functions should instead be imported from sk
learn.utils. Anything that cannot be imported from sklearn.utils is
now part of the private API.
  warnings.warn(message, FutureWarning)
/Users/nisha/anaconda3/lib/python3.7/site-packages/sklearn/utils/dep
recation.py:144: FutureWarning: The sklearn.metrics.classification m
odule is  deprecated in version 0.22 and will be removed in version
0.24. The corresponding classes / functions should instead be import
ed from sklearn.metrics. Anything that cannot be imported from sklea
rn.metrics is now part of the private API.
  warnings.warn(message, FutureWarning)
/Users/nisha/anaconda3/lib/python3.7/site-packages/sklearn/utils/val
idation.py:760: DataConversionWarning: A column-vector y was passed
when a 1d array was expected. Please change the shape of y to (n_sam
ples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
/Users/nisha/anaconda3/lib/python3.7/site-packages/sklearn/utils/dep
recation.py:87: FutureWarning: Function safe_indexing is deprecated;
safe_indexing is deprecated in version 0.22 and will be removed in v
ersion 0.24.
  warnings.warn(msg, category=FutureWarning)

(38483, 106)
(38483,)
(16493, 106)
(16493,)
```

Test Data and Train data after Class Imbalance for non PCA analysis *

In [57]:

```
X_train_np=pd.DataFrame(X_train)
X_test_np=pd.DataFrame(X_test)

X_train_np.columns=df_cols
X_test_np.columns=df_cols
X_train_np.head()
```

Out[57]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou
0	1821.176000	2018.948000	2014.693	39.360000	73.33000	16.730000	264.7300
1	317.967000	370.947000	546.528	43.910000	27.28000	62.610000	101.6800
2	4.980000	549.687000	0.000	265.901436	273.09219	243.971718	380.9553
3	128.831677	34.545236	0.000	0.000000	0.00000	243.971718	5.6852
4	0.000000	2281.505000	2680.019	265.901436	31.78000	74.280000	380.9553

5 rows × 106 columns

In [58]:

```
X_test_np.head()
```

Out[58]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mo
0	696.450337	457.562286	258.567499	207.236209	214.543462	60.232194	398.514
1	499.946829	294.848224	35.588019	104.540619	117.285273	204.334766	60.601
2	351.471079	507.384328	144.360999	331.773562	622.016320	137.761047	215.006
3	681.953774	459.034941	192.076542	1002.189898	815.287732	65.559705	189.718
4	1049.508653	8.944276	0.000000	458.837107	157.583545	243.971718	1925.545

5 rows × 106 columns

Class Imbalance rectification analysis-SMOTE

In [59]:

```
print('After SMOTE, the shape of train_X: {}'.format(X_train.shape))
print('After SMOTE, the shape of train_y: {} \n'.format(y_train.shape))

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

```
After SMOTE, the shape of train_X: (38483, 106)
After SMOTE, the shape of train_y: (38483,)

After SMOTE, counts of label '1': 19206
After SMOTE, counts of label '0': 19277
After SMOTE, churn event rate : 49.91%
```

Scaling the train and test data

In [60]:

```
## Scaling the train and test data
from sklearn.preprocessing import  StandardScaler,MinMaxScaler
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train )
X_test = scaler.fit_transform(X_test)
```

In [61]:

```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(38483, 106)
(38483,)
(16493, 106)
(16493,)
```

Model Building

In [62]:

```
from sklearn.utils import class_weight
```

Applying PCA

In [63]:

```
from sklearn.decomposition import PCA
```

In [64]:

```
pca = PCA(svd_solver='randomized', random_state=42)
```

In [65]:

```
df_train_pca = pca.fit(X_train)
```

In [67]:

```
pca.components_
```

Out[67]:

```
array([[-4.89022587e-03, -2.50511794e-03,  9.69378829e-05, ...,
         6.67443250e-03,  9.83099398e-03,  1.25726967e-02],
       [-3.61815507e-04,  7.32708468e-03,  1.20529630e-02, ...,
        -1.02672092e-02,  1.09919825e-02,  2.98434794e-04],
       [ 8.11525749e-03, -3.29775301e-03,  5.11425030e-03, ...,
         1.00571994e-02, -1.13694603e-02, -7.45280523e-04],
       ...,
       [ 0.00000000e+00,  7.19172471e-16,  7.09736793e-16, ...,
        -1.93491192e-02,  1.87884557e-01, -5.45415722e-02],
       [ 0.00000000e+00,  4.50569278e-16,  3.16966032e-16, ...,
        -2.30314574e-01, -4.42168570e-02, -2.24891345e-01],
       [ 0.00000000e+00, -1.53279142e-14,  1.00951330e-14, ...,
        -2.29319761e-01, -1.20845150e-01,  3.57059559e-01]])
```

In [68]:

```
pca.explained_variance_ratio_
```

Out[68]:

```
array([5.66837907e-01, 1.19704697e-01, 8.22492957e-02, 4.95273077e-0
2,
       2.26130403e-02, 2.12219586e-02, 1.74750400e-02, 1.22963370e-0
2,
       1.09240245e-02, 7.83153702e-03, 7.59701673e-03, 7.10710946e-0
3,
       6.72818491e-03, 5.34560727e-03, 5.10781548e-03, 4.19099820e-0
3,
       4.05460915e-03, 3.72749497e-03, 3.52939930e-03, 3.18717919e-0
3,
       2.64050086e-03, 2.46598214e-03, 2.42414772e-03, 2.25153894e-0
3,
       2.16486584e-03, 1.99162160e-03, 1.72564352e-03, 1.48471235e-0
3,
       1.43971461e-03, 1.34734424e-03, 1.32330640e-03, 1.23823606e-0
3,
       1.14886829e-03, 1.05455835e-03, 8.82519048e-04, 8.72386531e-0
4,
       7.36250124e-04, 6.63345058e-04, 6.44863749e-04, 6.16886610e-0
4,
       6.02349161e-04, 5.47696522e-04, 5.34156273e-04, 5.10995852e-0
4,
       4.91390294e-04, 4.36866227e-04, 4.17624336e-04, 4.08889245e-0
4,
       3.94413589e-04, 3.77018776e-04, 3.47548386e-04, 3.39239137e-0
4,
       2.87636686e-04, 2.72494377e-04, 2.66469768e-04, 2.56314259e-0
4,
       2.44731622e-04, 2.42464295e-04, 2.33363761e-04, 2.17921553e-0
4,
       2.08206014e-04, 1.90867864e-04, 1.76383245e-04, 1.66370060e-0
4,
       1.58560567e-04, 1.40348875e-04, 1.11338170e-04, 1.11016816e-0
4,
       1.08320622e-04, 9.77655427e-05, 9.10014500e-05, 8.41513650e-0
5,
       7.82887794e-05, 7.30788259e-05, 6.67481054e-05, 6.34172521e-0
5,
       5.06718614e-05, 4.29319142e-05, 4.07631848e-05, 3.83280927e-0
5,
       3.26133540e-05, 3.11421873e-05, 1.03201408e-05, 7.42233005e-0
6,
       5.84596283e-06, 4.25375962e-06, 3.11456268e-06, 2.48833632e-0
6,
       5.00262767e-07, 2.31581771e-07, 7.33191420e-08, 1.94668116e-1
3,
       1.34174545e-13, 1.13734492e-13, 1.77573757e-29, 4.03455096e-3
3,
       4.03455096e-33, 4.03455096e-33, 4.03455096e-33, 4.03455096e-3
3,
       4.03455096e-33, 4.03455096e-33, 4.03455096e-33, 4.03455096e-3
3,
       4.03455096e-33, 2.64935969e-34])
```

Cumulative Variance Explained- n_components derived is 17

In [69]:

```
var_cumu = np.cumsum(pca.explained_variance_ratio_)
```

In [70]:

```
fig = plt.figure(figsize=[12,8])
plt.vlines(x=17, ymax=1, ymin=0, colors="r", linestyles="--")
plt.hlines(y=0.95, xmax=30, xmin=0, colors="g", linestyles="--")
plt.plot(var_cumu)
plt.ylabel("Cumulative variance explained")
plt.show()
```

```
--------------------------------------------------------------------
-------
NameError                                 Traceback (most recent cal
l last)
<ipython-input-70-d29b968c85f2> in <module>
----> 1 fig = plt.figure(figsize=[12,8])
      2 plt.vlines(x=17, ymax=1, ymin=0, colors="r", linestyles="--"
)
      3 plt.hlines(y=0.95, xmax=30, xmin=0, colors="g", linestyles=
"--")
      4 plt.plot(var_cumu)
      5 plt.ylabel("Cumulative variance explained")

NameError: name 'plt' is not defined
```

Incremental PCA*

In [71]:

```
from sklearn.decomposition import IncrementalPCA
```

In [72]:

```
pca_final = IncrementalPCA(n_components=17)
```

In [73]:

```
df_train_pca = pca_final.fit_transform(X_train)
df_train_pca.shape
```

Out[73]:

```
(38483, 17)
```

In [74]:

```
df_test_pca = pca_final.fit_transform(X_test)
df_test_pca.shape
```

Out[74]:

```
(16493, 17)
```

Model-1 -> Logistic Regression

Applying Logistic Regression on our principal components

***using Class_weight="balanced" for class balancing while building model

In [90]:

```
from sklearn.linear_model import LogisticRegression
import sklearn.metrics as metrics
from sklearn.metrics import classification_report,confusion_matrix, accuracy_sco
re
logistic_pca = LogisticRegression(class_weight="balanced")
```

In [91]:

```
#Training the model on the train data
model_pca = logistic_pca.fit(df_train_pca, y_train)
```

In [92]:

```
pred_probs_train1=model_pca.predict(df_train_pca)
```

In [93]:

```
pred_probs_train = model_pca.predict_proba(df_train_pca)[:,1]
pred_probs_train[:5]
```

Out[93]:

```
array([0.04721767, 0.13752496, 0.75748083, 0.86692538, 0.07924185])
```

In [79]:

```
# predictions on Test data
```

In [94]:

```
pred_probs_test1 = model_pca.predict(df_test_pca)
pred_probs_test = model_pca.predict_proba(df_test_pca)[:,1]
pred_probs_test[:10]
```

Out[94]:

```
array([0.72214954, 0.62116989, 0.82122323, 0.68487828, 0.75766312,
       0.80972516, 0.24244965, 0.7275321 , 0.65553895, 0.78447575])
```

In [97]:

```
print ("\nModel Report- Training")
print ("Accuracy : %.4g" % metrics.accuracy_score(y_train, pred_probs_train1))
print ("Recall/Sensitivity : %.4g" % metrics.recall_score(y_train, pred_probs_tr
ain1))
print ("AUC Score (Train): %f" % metrics.roc_auc_score(y_train, pred_probs_train
))
print("Precision : {}".format(metrics.precision_score(y_test,pred_probs_test1)))
```

```
Model Report- Training
Accuracy : 0.7596
Recall/Sensitivity : 0.7853
AUC Score (Train): 0.836468
Precision : 0.7045039234655488
```

In [96]:

```
print ("\nEvaluation Report (Test data)")
print("Accuracy : {}".format(metrics.accuracy_score(y_test,pred_probs_test1)))
print("Recall : {}".format(metrics.recall_score(y_test,pred_probs_test1)))
print("Precision : {}".format(metrics.precision_score(y_test,pred_probs_test1)))
```

```
Evaluation Report (Test data)
Accuracy : 0.7285515066998121
Recall : 0.7913547452306207
Precision : 0.7045039234655488
```

Evaluating the model with cut-off probability as 0.5*

In [98]:

```
predprob=pd.DataFrame({"Churn":y_train,"Probs":pred_probs_train})
```

In [99]:

```
predprob.head()
```

Out[99]:

	Churn	Probs
0	0	0.047218
1	0	0.137525
2	1	0.757481
3	1	0.866925
4	0	0.079242

In [100]:

```
predprob["Train_Predicted"]=predprob.Probs.map(lambda x:1 if x>0.5 else 0)
```

In [101]:

```
predprob.head()
```

Out[101]:

	Churn	Probs	Train_Predicted
0	0	0.047218	0
1	0	0.137525	0
2	1	0.757481	1
3	1	0.866925	1
4	0	0.079242	0

In [687]:

```
print('For 0.5 as cut off probability Accuracy is', metrics.accuracy_score(predp
rob.Churn, predprob.Train_Predicted))
```

```
For 0.5 as cut off probability Accuracy is 0.7615570511654497
```

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

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

In [102]:

```
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=(5, 5))
    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 Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return None
```

In [103]:

```
fpr, tpr, thresholds = metrics.roc_curve( predprob.Churn, predprob.Train_Predict
ed,
                                          drop_intermediate = False )
```

In [104]:

```
draw_roc(predprob.Churn, predprob.Train_Predicted)
```

```
---------------------------------------------------------------------------
-------
NameError                                 Traceback (most recent cal
l last)
<ipython-input-104-3d3cdf78a640> in <module>
----> 1 draw_roc(predprob.Churn, predprob.Train_Predicted)

<ipython-input-102-069ff4f446a6> in draw_roc(actual, probs)
      3                                             drop_intermedi
ate = False )
      4     auc_score = metrics.roc_auc_score( actual, probs )
----> 5     plt.figure(figsize=(5, 5))
      6     plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % a
uc_score )
      7     plt.plot([0, 1], [0, 1], 'k--')

NameError: name 'plt' is not defined
```

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

** 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.

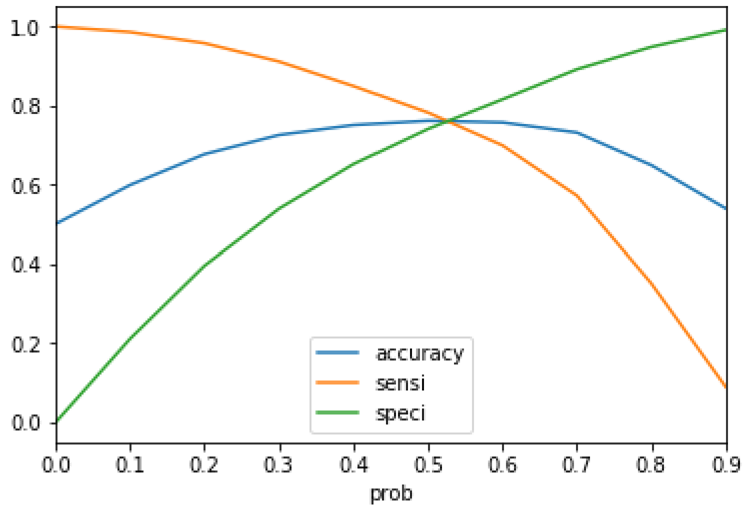
In [691]:

```
def findOptimalCutoff(df):
    #Function to find the optimal cutoff for classifing as churn/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.Probs.map( lambda x: 1 if x > i else 0)
    #print(df.head())

    # Now let's calculate accuracy sensitivity and specificity for various proba
bility cutoffs.
    cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','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 various probabilities.
    cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
    plt.show()
```

In [692]:

```
findOptimalCutoff(predprob)
```

```
     prob  accuracy     sensi     speci
0.0   0.0  0.500689  1.000000  0.000000
0.1   0.1  0.599096  0.985935  0.211189
0.2   0.2  0.677052  0.957858  0.395472
0.3   0.3  0.725515  0.911459  0.539058
0.4   0.4  0.750747  0.849439  0.651782
0.5   0.5  0.761557  0.782126  0.740932
0.6   0.6  0.757399  0.699294  0.815665
0.7   0.7  0.731752  0.572192  0.891751
0.8   0.8  0.649300  0.351048  0.948374
0.9   0.9  0.539823  0.089682  0.991205
```



*From the curve above, 0.52 is the optimum point***

** Operations on Training set with new cut off Probability value of 0.52

In [693]:

```
predprob['Finalpredicted']=predprob.Probs.map(lambda x:1 if x>0.52 else 0)
```

In [694]:

```
predprob.head()
```

Out[694]:

	Churn	Probs	Train_Predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Finalpredi
0	0	0.449957	0	1	1	1	1	1	0	0	0	0	0	
1	1	0.519310	1	1	1	1	1	1	1	0	0	0	0	
2	0	0.291949	0	1	1	1	0	0	0	0	0	0	0	
3	0	0.234129	0	1	1	1	0	0	0	0	0	0	0	
4	0	0.173535	0	1	1	0	0	0	0	0	0	0	0	

In [695]:

```
# Let's check the overall accuracy.
metrics.accuracy_score(predprob.Churn, predprob.Finalpredicted)
print("Training Data Report with cut off probability-0.52")
print("Accuracy : {}".format(metrics.accuracy_score(predprob.Churn, predprob.Fin
alpredicted)))
print("Recall : {}".format(metrics.recall_score(predprob.Churn, predprob.Finalpr
edicted)))
print("Precision : {}".format(metrics.precision_score(predprob.Churn, predprob.F
inalpredicted)))
```

```
Training Data Report with cut off probability-0.52
Accuracy : 0.7602058051607203
Recall : 0.76453186630683
Precision : 0.7584697765420657
```

In [696]:

```
print (classification_report(predprob.Churn, predprob.Finalpredicted))
```

```
              precision    recall  f1-score   support

           0       0.76      0.76      0.76     19215
           1       0.76      0.76      0.76     19268

    accuracy                           0.76     38483
   macro avg       0.76      0.76      0.76     38483
weighted avg       0.76      0.76      0.76     38483
```

*Making prediction on test

In [697]:

```
cutoff_p=0.52
predtest=pd.DataFrame({'Churn':y_test,"Probs":pred_probs_test})
```

In [698]:

```
predtest["Predicted"]=predtest.Probs.map(lambda x:1 if x>0.52 else 0)
```

In [699]:

```
predtest.head()
```

Out[699]:

	Churn	Probs	Predicted
0	0	0.194127	0
1	1	0.560061	1
2	0	0.683013	1
3	1	0.839623	1
4	0	0.011113	0

In [700]:

```
metrics.accuracy_score(predtest.Churn, predtest.Predicted)
```

Out[700]:

```
0.7347359485842478
```

In [365]:

```
print("Classification Report Test Data: " )
print(classification_report(predtest.Churn, predtest.Predicted))
```

```
Classification Report Test Data: 
              precision    recall  f1-score   support

           0       0.73      0.65      0.69      8286
           1       0.68      0.76      0.72      8207

    accuracy                           0.70     16493
   macro avg       0.71      0.70      0.70     16493
weighted avg       0.71      0.70      0.70     16493
```

In [701]:

```
print("Evaluation Report on Test Data cut off probability-0.52")
print("Accuracy : {}".format(metrics.accuracy_score(predtest.Churn,predtest.Pred
icted)))
print("Recall : {}".format(metrics.recall_score(predtest.Churn,predtest.Predicte
d)))
print("Precision : {}".format(metrics.precision_score(predtest.Churn,predtest.Pr
edicted)))
```

```
Evaluation Report on Test Data cut off probability-0.52
Accuracy : 0.7347359485842478
Recall : 0.7838199513381995
Precision : 0.7126424068134056
```

In [774]:

```
from sklearn.metrics import confusion_matrix
print("Confusion Matrix: ")
print(confusion_matrix(predtest.Churn,predtest.Predicted))
```

```
Confusion Matrix:
[[5675 2598]
 [1777 6443]]
```

Model-2 -> Random Forest

In [702]:

```
from sklearn.ensemble import RandomForestClassifier
```

Tuning hyperparameters- n_estimators*

In [ ]:

```
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV

# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'n_estimators': range(50, 800,300)}

# instantiate the model (note we are specifying a max_depth)
rf1 = RandomForestClassifier(max_depth=4, class_weight="balanced")
rfgs = GridSearchCV(rf1, parameters,
                    cv=n_folds, return_train_score=True,
                   scoring="accuracy")
rfgs.fit(df_train_pca, y_train)
```

In [652]:

```
# scores of GridSearch CV
scores = rfgs.cv_results_
pd.DataFrame(scores).head()
```

Out[652]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_estimators	p
0	1.154389	0.029149	0.023435	0.004354	50	{'n_estim
1	8.046226	0.311798	0.134913	0.005352	350	{'n_estim
2	14.987780	0.532380	0.261628	0.015967	650	{'n_estim

3 rows × 21 columns

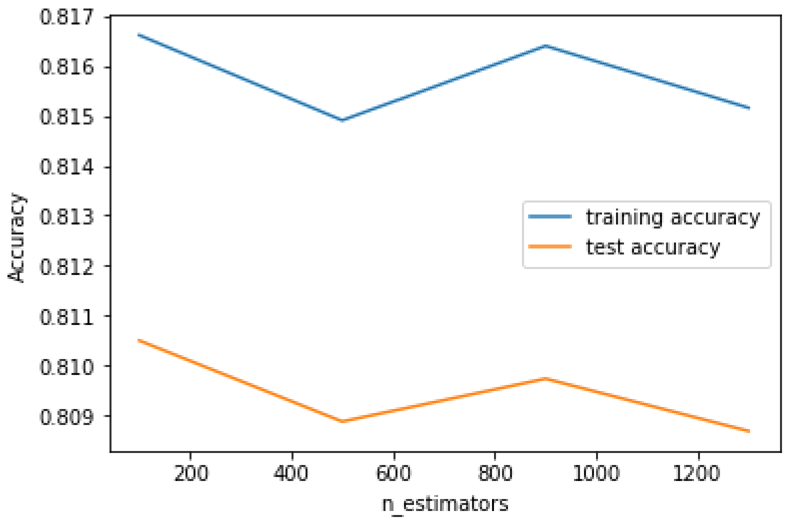
In [653]:

```
print('We can get accuracy of',rfgs.best_score_,'using',rfgs.best_params_)
```

```
We can get accuracy of 0.7485369329609581 using {'n_estimators': 35
0}
```

In [422]:

```
# plotting accuracies with n_estimators
from sklearn.metrics import classification_report,confusion_matrix, accuracy_sco
re
plt.figure()
plt.plot(scores["param_n_estimators"],
         scores["mean_train_score"],
         label="training accuracy")
plt.plot(scores["param_n_estimators"],
         scores["mean_test_score"],
         label="test accuracy")
plt.xlabel("n_estimators")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



HyperTuning Max Depth **

In [423]:

```
# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'max_depth': range(10, 30, 5)}

# instantiate the model (note we are specifying a max_depth)
rf1 = RandomForestClassifier(class_weight="balanced")
rfgs = GridSearchCV(rf1, parameters,
                    cv=n_folds, return_train_score=True,
                   scoring="accuracy")
rfgs.fit(df_train_pca, y_train.values.ravel())
```

Out[423]:

```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_al
pha=0.0,
                                              class_weight='balance
d',
                                              criterion='gini', max_
depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=
0.0,
                                              min_impurity_split=Non
e,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_le
af=0.0,
                                              n_estimators=100, n_jo
bs=None,
                                              oob_score=False,
                                              random_state=None, ver
bose=0,
                                              warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'max_depth': range(10, 30, 5)},
             pre_dispatch='2*n_jobs', refit=True, return_train_score
=True,
             scoring='accuracy', verbose=0)
```

In [424]:

```
# scores of GridSearch CV
scores = rfgs.cv_results_
pd.DataFrame(scores).head()
```

Out[424]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	para
0	3.933134	0.053682	0.059777	0.003125	10	{'max_dep
1	4.503921	0.031481	0.071830	0.004123	15	{'max_dep
2	4.583008	0.056256	0.072929	0.003688	20	{'max_dep
3	4.758910	0.104177	0.090992	0.031049	25	{'max_dep

4 rows × 21 columns

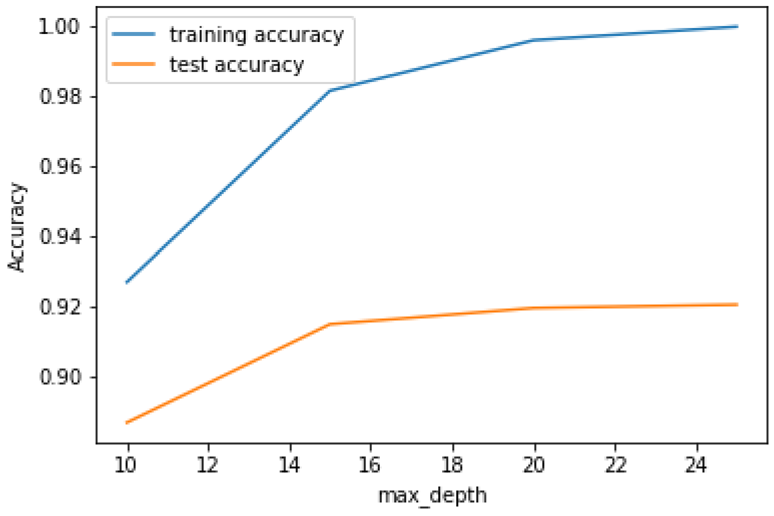
In [425]:

```
print('We can get accuracy of',rfgs.best_score_,'using',rfgs.best_params_)
```

```
We can get accuracy of 0.9206075707451602 using {'max_depth': 25}
```

In [426]:

```
# plotting accuracies with n_estimators
from sklearn.metrics import classification_report,confusion_matrix, accuracy_sco
re
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()
```



In [427]:

```
print('We can get accuracy of',rfgs.best_score_,'using',rfgs.best_params_)
```

```
We can get accuracy of 0.9206075707451602 using {'max_depth': 25}
```

hypertuning max_features***

In [0]:

```
# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'max_features': [3, 8, 13,17]}

# instantiate the model (note we are specifying a max_depth)
rf1 = RandomForestClassifier(max_depth=10, class_weight="balanced")
rfgs = GridSearchCV(rf1, parameters,
                    cv=n_folds, return_train_score=True,
                   scoring="accuracy")
rfgs.fit(df_train_pca, y_train)
```

In [665]:

```
# scores of GridSearch CV
scores = rfgs.cv_results_
pd.DataFrame(scores).head()
```

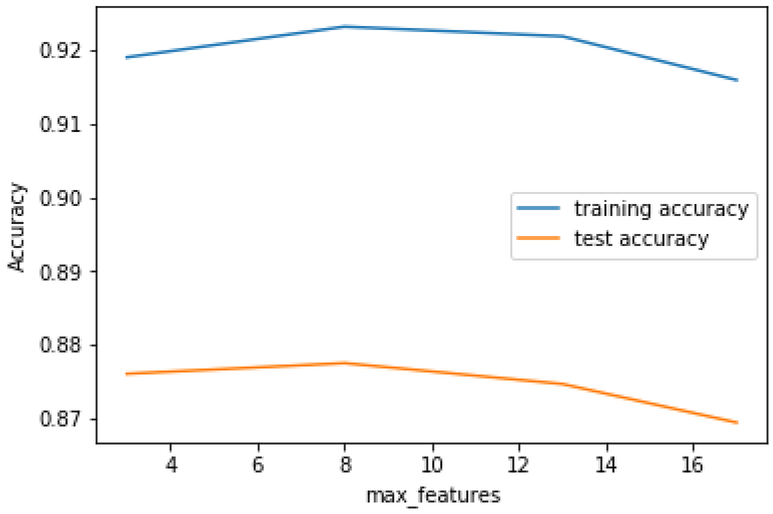
Out[665]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_features	
0	3.413739	0.085685	0.055989	0.002160	3	{'max_fe
1	8.463211	0.338176	0.062273	0.012617	8	{'max_fe
2	15.493625	1.489093	0.062968	0.006723	13	{'max_fe
3	17.467777	1.356815	0.057345	0.008069	17	{'max_fe

4 rows × 21 columns

In [666]:

```
# plotting accuracies with max_features
from sklearn.metrics import classification_report,confusion_matrix, accuracy_sco
re
plt.figure()
plt.plot(scores["param_max_features"],
         scores["mean_train_score"],
         label="training accuracy")
plt.plot(scores["param_max_features"],
         scores["mean_test_score"],
         label="test accuracy")
plt.xlabel("max_features")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



In [667]:

```
print('We can get accuracy of',rfgs.best_score_,'using',rfgs.best_params_)
```

```
We can get accuracy of 0.8775012246325558 using {'max_features': 8}
```

hypertuning hyperparameter Min Samples Leaf

In [433]:

```
# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'min_samples_leaf': range(100, 400, 50)}

# instantiate the model (note we are specifying a max_depth)
rf1 = RandomForestClassifier(max_depth=10, class_weight="balanced")
rfgs = GridSearchCV(rf1, parameters,
                    cv=n_folds, return_train_score=True,
                   scoring="accuracy")
rfgs.fit(df_train_pca, y_train.values.ravel())
```

Out[433]:

```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_al
pha=0.0,
                                              class_weight='balance
d',
                                              criterion='gini', max_
depth=10,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=
0.0,
                                              min_impurity_split=Non
e,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_le
af=0.0,
                                              n_estimators=100, n_jo
bs=None,
                                              oob_score=False,
                                              random_state=None, ver
bose=0,
                                              warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'min_samples_leaf': range(100, 400, 50)},
             pre_dispatch='2*n_jobs', refit=True, return_train_score
=True,
             scoring='accuracy', verbose=0)
```

In [434]:

```
# scores of GridSearch CV
scores = rfgs.cv_results_
pd.DataFrame(scores).head()
```

Out[434]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_min_samples_leaf	
0	3.258261	0.079839	0.065393	0.013718	100	{'m
1	2.964460	0.031697	0.052615	0.003026	150	{'m
2	2.807050	0.058211	0.054392	0.009293	200	{'m
3	2.647471	0.069888	0.050909	0.002653	250	{'m
4	2.571249	0.054979	0.052108	0.004405	300	{'m

5 rows × 21 columns

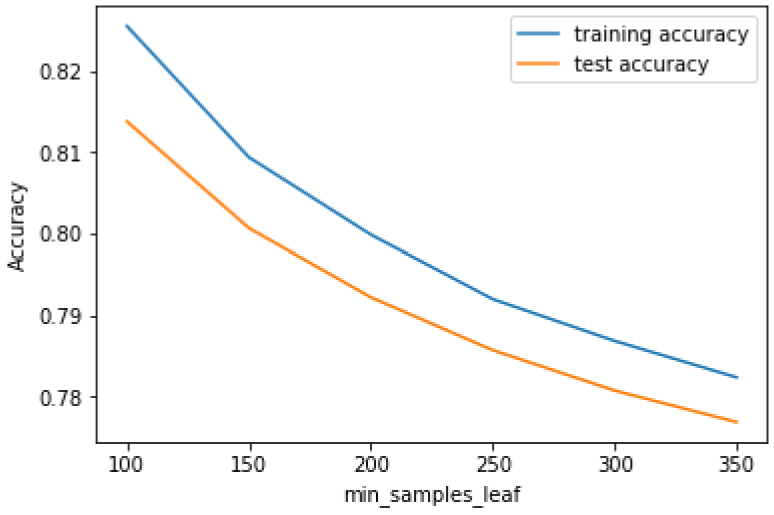
In [436]:

```
print('We can get accuracy of',rfgs.best_score_,'using',rfgs.best_params_)
```

```
We can get accuracy of 0.8137955729694134 using {'min_samples_leaf':
100}
```

In [437]:

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



In [ ]:

```

```

hypertuning hyperparameter Min Samples Split

In [438]:

```
# specify number of folds for k-fold CV
n_folds = 5

# parameters to build the model on
parameters = {'min_samples_split': range(50, 300, 50)}

# instantiate the model (note we are specifying a max_depth)
rf1 = RandomForestClassifier(max_depth=10, class_weight="balanced")
rfgs = GridSearchCV(rf1, parameters,
                    cv=n_folds, return_train_score=True,
                   scoring="accuracy")
rfgs.fit(df_train_pca, y_train.values.ravel())
```

Out[438]:

```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_al
pha=0.0,
                                              class_weight='balance
d',
                                              criterion='gini', max_
depth=10,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=
0.0,
                                              min_impurity_split=Non
e,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_le
af=0.0,
                                              n_estimators=100, n_jo
bs=None,
                                              oob_score=False,
                                              random_state=None, ver
bose=0,
                                              warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'min_samples_split': range(50, 300, 50)},
             pre_dispatch='2*n_jobs', refit=True, return_train_score
=True,
             scoring='accuracy', verbose=0)
```

In [439]:

```
# scores of GridSearch CV
scores = rfgs.cv_results_
pd.DataFrame(scores).head()
```

Out[439]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_min_samples_split	
0	4.058382	0.102550	0.064116	0.005752	50	{'n
1	3.912810	0.068948	0.061389	0.004724	100	{'n
2	3.803410	0.028911	0.058375	0.006574	150	{'n
3	3.759199	0.136453	0.057979	0.006735	200	{'n
4	3.564885	0.057454	0.052718	0.001757	250	{'n

5 rows × 21 columns

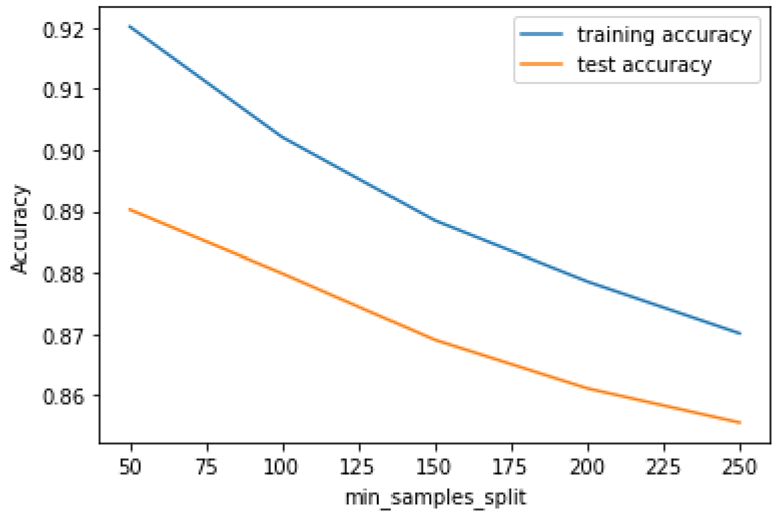
In [440]:

```
print('We can get accuracy of',rfgs.best_score_,'using',rfgs.best_params_)
```

```
We can get accuracy of 0.8723607220081815 using {'min_samples_spli
t': 50}
```

In [0]:

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



In [0]:

```

```

Fitting the final model with the best parameters obtained from grid search.

In [704]:

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(bootstrap=True,class_weight="balanced",
                             max_depth=10,
                             min_samples_leaf=100,
                             min_samples_split=50,
                             max_features=8,
                             n_estimators=350,
                             random_state=10)
```

In [705]:

```
rfc.fit(df_train_pca, y_train)
```

Out[705]:

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight
='balanced',
                       criterion='gini', max_depth=10, max_features=
8,
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split
=None,
                       min_samples_leaf=100, min_samples_split=50,
                       min_weight_fraction_leaf=0.0, n_estimators=35
0,
                       n_jobs=None, oob_score=False, random_state=1
0, verbose=0,
                       warm_start=False)
```

Checking Performance

In [706]:

```
dtrain_predict=rfc.predict(df_train_pca)
dtrain_predprob = rfc.predict_proba(df_train_pca)[:,1]
print("Training Model parameters: ")
print ("Accuracy : %.4g" % metrics.roc_auc_score(y_train, dtrain_predict))
print ("Recall/Sensitivity : %.4g" % metrics.recall_score(y_train, dtrain_predic
t))
print ("AUC Score (Train): %f" % metrics.roc_auc_score(y_train, dtrain_predprob
))
#print("Precision : {}".format(metrics.precision_score(predprob.Churn, predprob.
Finalpredicted)))
```

```
Training Model parameters:
Accuracy : 0.8494
Recall/Sensitivity : 0.8617
AUC Score (Train): 0.927490
```

*** Model Performance on Test Data***

In [709]:

```
predict_test = rfc.predict(df_test_pca)
```

In [710]:

```
print("Model performance on Test data ")
print ("Accuracy : %.4g" % metrics.roc_auc_score(y_test, predict_test))
print ("Recall/Sensitivity : %.4g" % metrics.recall_score(y_test, predict_test))
print ("AUC Score (Train): %f" % metrics.roc_auc_score(y_test, predict_test))
```

```
Model performance on Test data
Accuracy : 0.795
Recall/Sensitivity : 0.853
AUC Score (Train): 0.795009
```

Notes The Model Performs quite satisfactorily in Random Forest as:

```
      1. Accuracy is good in both Training and Test Data sets
      2. Recall/Sensitivity is maintained and is above 85% in both Training
   and Test Data sets
      3. AUC score is satisfactory but there is a variation of 20% between T
  raining and Test which we will try to improve once we define the threshold
  probability and make predictions
```

In [711]:

```
rfpred_train=pd.DataFrame({'Churn':y_train,'Probs':dtrain_predprob})
```

In [712]:

```
rfpred_train.head()
```

Out[712]:

	Churn	Probs
0	0	0.286831
1	1	0.939682
2	0	0.179675
3	0	0.160300
4	0	0.061806

In [713]:

```
rfpred_train['predicted']=rfpred_train.Probs.map(lambda x:1 if x>0.5 else 0)
```

In [714]:

```
rfpred_train.head()
```

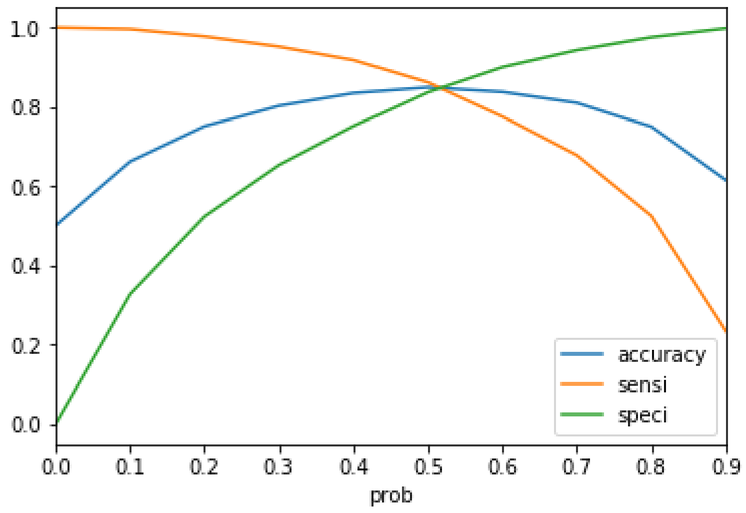
Out[714]:

	Churn	Probs	predicted
0	0	0.286831	0
1	1	0.939682	1
2	0	0.179675	0
3	0	0.160300	0
4	0	0.061806	0

In [715]:

```
findOptimalCutoff(rfpred_train)
```

```
     prob  accuracy     sensi     speci
0.0   0.0  0.500689  1.000000  0.000000
0.1   0.1  0.662240  0.996056  0.327505
0.2   0.2  0.750981  0.977579  0.523757
0.3   0.3  0.802848  0.951889  0.653396
0.4   0.4  0.834732  0.917947  0.751288
0.5   0.5  0.849414  0.861688  0.837106
0.6   0.6  0.837747  0.775535  0.900130
0.7   0.7  0.810280  0.677963  0.942961
0.8   0.8  0.749994  0.525171  0.975436
0.9   0.9  0.615596  0.234326  0.997918
```



In [0]:

```

```

From the curve above, 0.52 is the optimal point with high enough sensitivity.

Fine tuning/Evaluating the model with Threshold probability of 0.52

In [716]:

```
rfpred_train['Finalpredicted']=rfpred_train.Probs.map(lambda x:1 if x>0.52 else
0)
```

In [717]:

```
rfpred_train.head()
```

Out[717]:

	Churn	Probs	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Finalpredicted
0	0	0.286831	0	1	1	1	0	0	0	0	0	0	0	0
1	1	0.939682	1	1	1	1	1	1	1	1	1	1	1	1
2	0	0.179675	0	1	1	0	0	0	0	0	0	0	0	0
3	0	0.160300	0	1	1	0	0	0	0	0	0	0	0	0
4	0	0.061806	0	1	0	0	0	0	0	0	0	0	0	0

In [718]:

```
print (classification_report(rfpred_train.Churn, rfpred_train.Finalpredicted))
```

```
              precision    recall  f1-score   support

           0       0.85      0.85      0.85     19215
           1       0.85      0.85      0.85     19268

    accuracy                           0.85     38483
   macro avg       0.85      0.85      0.85     38483
weighted avg       0.85      0.85      0.85     38483
```

In [719]:

```
rfpred_t =rfc.predict_proba(df_test_pca)[:,1]
```

In [720]:

```
rfpred_test=pd.DataFrame({'Churn':y_test,'Probs':rfpred_t})
```

In [721]:

```
rfpred_test.head()
```

Out[721]:

	Churn	Probs
0	0	0.279869
1	1	0.525919
2	0	0.766447
3	1	0.543565
4	0	0.117195

In [722]:

```
rfpred_test['Predicted']=rfpred_test.Probs.map(lambda x:1 if x>0.52 else 0)
```

In [723]:

```
rfpred_test.head()
```

Out[723]:

	Churn	Probs	Predicted
0	0	0.279869	0
1	1	0.525919	1
2	0	0.766447	1
3	1	0.543565	1
4	0	0.117195	0

In [724]:

```
print (classification_report(rfpred_test.Churn, rfpred_test.Predicted))
```

```
              precision    recall  f1-score   support

           0       0.83      0.75      0.79      8273
           1       0.77      0.84      0.81      8220

    accuracy                           0.80     16493
   macro avg       0.80      0.80      0.80     16493
weighted avg       0.80      0.80      0.80     16493
```

In [725]:

```
print("Training Model parameters: ")
print ("Accuracy : %.4g" % metrics.roc_auc_score(y_train, rfpred_train.Finalpred
icted))
print ("Recall/Sensitivity : %.4g" % metrics.recall_score(y_train, rfpred_train.
Finalpredicted))
print ("AUC Score (Train): %f" % metrics.roc_auc_score(y_train, dtrain_predprob
))
print("Precision : {}".format(metrics.precision_score(y_train, rfpred_train.Fina
lpredicted)))
```

```
Training Model parameters:
Accuracy : 0.8493
Recall/Sensitivity : 0.8468
AUC Score (Train): 0.927490
Precision : 0.8513435950952257
```

In [726]:

```
print("Test Model parameters: ")
print ("Accuracy : %.4g" % metrics.roc_auc_score(y_test, rfpred_test.Predicted))
print ("Recall/Sensitivity : %.4g" % metrics.recall_score(y_test, rfpred_test.Pr
edicted))
print ("AUC Score (Test): %f" % metrics.roc_auc_score(y_test, rfpred_t))
print("Precision : {}".format(metrics.precision_score(y_test, rfpred_test.Predic
ted)))
```

```
Test Model parameters:
Accuracy : 0.7979
Recall/Sensitivity : 0.8438
AUC Score (Test): 0.870826
Precision : 0.7716955941255007
```

In [773]:

```
from sklearn.metrics import confusion_matrix
print("Confusion Matrix: ")
print(confusion_matrix(y_test, rfpred_test.Predicted))
```

```
Confusion Matrix:
[[6221 2052]
 [1284 6936]]
```

*Notes**

```
1. Accuracy of model is good in both Training and Test Data sets
2. Recall/Sensitivity is also good and maintained in both Training and Tes
t Data sets
3. Precison is also good as above 70%
4. AUC score of the model has improved to 84.5% post the threshold Probabi
lity of 0.52
```

Preferred Model Analysis

Logistic Regression: --Accuracy : 0.7347359485842478 --Recall : 0.7838199513381995 --Precision : 0.7126424068134056 **Random Forest:** --Accuracy : 0.7979 --Recall/Sensitivity : 0.8438 --Precision : 0.7716955941255007

Preferred Model/ Winner : Random Forest

1. **Random Forest is the preferred Model as Accuracy of the model is better than Logistic Model**
2. **The Recall/Sensitivity & Precison factors are also better and maintained in Random Forest
3. **The model is not overfitting and is generic as there is no drastic difference between Training and Test Results. So the model performs better on unseen data
4. **AUC Score of Model is also good as it is 87%
5. **Comparing the f1 scores and Confusion matrices of both logistic and Random Forest Models Random Forest emerges as the clear winner

Building Model without PCA

Model- Random Forest

** Building the model on training data sets without PCA

In [727]:

```
from sklearn.ensemble import RandomForestClassifier
rfcnp = RandomForestClassifier(bootstrap=True,class_weight="balanced",
                             max_depth=10,
                             min_samples_leaf=100,
                             min_samples_split=50,
                             max_features=8,
                             n_estimators=350,
                             random_state=10)
```

In [728]:

```
rfcnp.fit(X_train_np,y_train)
```

Out[728]:

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight
='balanced',
                       criterion='gini', max_depth=10, max_features=
8,
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split
=None,
                       min_samples_leaf=100, min_samples_split=50,
                       min_weight_fraction_leaf=0.0, n_estimators=35
0,
                       n_jobs=None, oob_score=False, random_state=1
0, verbose=0,
                       warm_start=False)
```

In [729]:

```
dtrain_predict_np=rfcnp.predict(X_train_np)
dtrain_predprob_np = rfcnp.predict_proba(X_train_np)[:,1]
print("Training Model parameters-Training Set: ")
print ("Accuracy : %.4g" % metrics.roc_auc_score(y_train, dtrain_predict_np))
print ("Recall/Sensitivity : %.4g" % metrics.recall_score(y_train, dtrain_predic
t_np))
print ("AUC Score (Train): %f" % metrics.roc_auc_score(y_train, dtrain_predprob_
np))
```

```
Training Model parameters-Training Set:
Accuracy : 0.919
Recall/Sensitivity : 0.9114
AUC Score (Train): 0.974261
```

In [730]:

```
dtest_predict_np=rfcnp.predict(X_test_np)
dtest_predprob_np = rfcnp.predict_proba(X_test_np)[:,1]
print("Evluation report on Test Data: ")
print ("Accuracy : %.4g" % metrics.roc_auc_score(y_test, dtest_predict_np))
print ("Recall/Sensitivity : %.4g" % metrics.recall_score(y_test ,dtest_predict_
np))
print ("AUC Score (Train): %f" % metrics.roc_auc_score(y_test, dtest_predprob_np
))
```

```
Evluation report on Test Data:
Accuracy : 0.9135
Recall/Sensitivity : 0.9028
AUC Score (Train): 0.970386
```

Notes

```
1. Model has done very well with Accuracy of 91%
2. Sensitivity of the model is very good approx 90%
```

Deriving feature importance

In [746]:

```
imp=rfcnp.feature_importances_
imp
```

Out[746]:

```
array([4.28406129e-04, 1.46933881e-03, 4.99775909e-02, 1.06645913e-0
3,
       1.19060770e-03, 3.76053500e-03, 7.88559306e-04, 1.11976740e-0
3,
       4.60896835e-03, 1.79070852e-03, 1.93241880e-02, 1.42151004e-0
1,
       2.82342698e-03, 2.36997904e-02, 1.46970850e-01, 1.28715924e-0
3,
       3.34782708e-03, 1.92605665e-02, 3.06355989e-03, 3.88396719e-0
3,
       5.55624398e-03, 1.28872254e-03, 1.14078208e-03, 2.08157597e-0
2,
       6.75915442e-03, 5.17215525e-03, 2.74383157e-03, 4.67885679e-0
3,
       1.70227840e-03, 2.67741121e-02, 9.55609555e-04, 2.14797361e-0
3,
       3.33455616e-02, 8.58912093e-04, 2.04809262e-03, 2.33877004e-0
2,
       9.73027147e-04, 1.27485719e-03, 4.48493437e-03, 1.42073412e-0
3,
       2.96178745e-03, 7.63403344e-02, 5.29574932e-03, 1.08817509e-0
3,
       8.37034371e-03, 1.88695311e-03, 6.34319645e-04, 4.68574534e-0
3,
       1.38418725e-03, 7.84641863e-04, 2.72854647e-03, 1.17336010e-0
3,
       2.89634812e-03, 1.19944299e-02, 3.44923205e-04, 1.28900048e-0
3,
       5.18553960e-02, 1.53882013e-03, 1.98838638e-03, 3.41786505e-0
2,
       1.97939775e-03, 3.06894265e-03, 3.44285821e-02, 1.82570034e-0
3,
       2.64333292e-03, 2.78338842e-02, 1.20040173e-03, 2.18236196e-0
3,
       1.42132265e-02, 1.37492546e-03, 1.45509452e-03, 5.83906024e-0
3,
       1.00036596e-03, 1.26076474e-03, 8.28397975e-03, 8.17013409e-0
4,
       1.14378826e-03, 1.02167552e-02, 1.97575998e-06, 0.00000000e+0
0,
       0.00000000e+00, 1.17886092e-03, 8.54015131e-04, 2.48225053e-0
3,
       9.49852812e-04, 1.27472303e-03, 5.06610689e-03, 5.31594133e-0
4,
       4.95524284e-04, 1.71566556e-03, 3.16088047e-04, 7.38318797e-0
4,
       1.15123772e-04, 2.91408135e-03, 4.82000023e-03, 5.23007174e-0
2,
       2.23309280e-03, 1.89962982e-03, 4.00858912e-04, 4.69535011e-0
4,
       5.93217828e-04, 8.68655739e-04, 2.10360117e-03, 3.38462871e-0
4,
       1.09797081e-03, 5.09820424e-04])
```

mapping column names with importance

In [747]:

```
#for name, importance in zip(df_cols, imp):
for name, importance in zip(df_cols, imp):
    print(name, "=", importance)
```

```
arpu_6 = 0.000428406128694019
arpu_7 = 0.001469338809749534
arpu_8 = 0.0499775909374433
onnet_mou_6 = 0.0010664591255723727
onnet_mou_7 = 0.0011906076989066274
onnet_mou_8 = 0.003760534995909619
offnet_mou_6 = 0.0007885593059849056
offnet_mou_7 = 0.0011197673996465522
offnet_mou_8 = 0.004608968351902497
roam_ic_mou_6 = 0.0017907085242518947
roam_ic_mou_7 = 0.01932418799101418
roam_ic_mou_8 = 0.14215100384340487
roam_og_mou_6 = 0.0028234269767497755
roam_og_mou_7 = 0.023699790380323636
roam_og_mou_8 = 0.14697084992987614
loc_og_mou_6 = 0.0012871592444620395
loc_og_mou_7 = 0.0033478270757533245
loc_og_mou_8 = 0.019260566543982654
std_og_mou_6 = 0.003063559885434841
std_og_mou_7 = 0.003883967186024259
std_og_mou_8 = 0.005556243977794144
isd_og_mou_6 = 0.0012887225382097866
isd_og_mou_7 = 0.0011407820835001943
isd_og_mou_8 = 0.020815759711131705
spl_og_mou_6 = 0.006759154416626769
spl_og_mou_7 = 0.005172155252757629
spl_og_mou_8 = 0.0027438315663630285
og_others_6 = 0.004678856789222028
og_others_7 = 0.0017022784019672169
og_others_8 = 0.02677411207547937
total_og_mou_6 = 0.0009556095554990137
total_og_mou_7 = 0.0021479736060000002
total_og_mou_8 = 0.033345561592081546
loc_ic_mou_6 = 0.0008589120932630188
loc_ic_mou_7 = 0.002048092618519195
loc_ic_mou_8 = 0.02338770044172436
std_ic_mou_6 = 0.0009730271471843873
std_ic_mou_7 = 0.001274857192012496
std_ic_mou_8 = 0.004484934372663194
total_ic_mou_6 = 0.0014207341184947782
total_ic_mou_7 = 0.0029617874536306681
total_ic_mou_8 = 0.07634033436774731
spl_ic_mou_6 = 0.005295749322722625
spl_ic_mou_7 = 0.0010881750914075873
spl_ic_mou_8 = 0.008370343712221888
isd_ic_mou_6 = 0.0018869531076647153
isd_ic_mou_7 = 0.0006343196447684852
isd_ic_mou_8 = 0.004685745344232016
ic_others_6 = 0.0013841872464140405
ic_others_7 = 0.0007846418629660333
ic_others_8 = 0.0027285464664759855
total_rech_num_6 = 0.0011733601019935122
total_rech_num_7 = 0.0028963481179398514
total_rech_num_8 = 0.011994429944571675
total_rech_amt_6 = 0.0003449232048335955
total_rech_amt_7 = 0.001289000480204327
total_rech_amt_8 = 0.05185539597954208
max_rech_amt_6 = 0.0015388201284257629
max_rech_amt_7 = 0.0019883863837016607
max_rech_amt_8 = 0.034178650488380646
total_rech_data_6 = 0.001979397754019947
```

```
total_rech_data_7 = 0.0030689426456023744
total_rech_data_8 = 0.0344285820592214
max_rech_data_6 = 0.0018257003421222379
max_rech_data_7 = 0.002643332915545892
max_rech_data_8 = 0.027833884208403985
count_rech_2g_6 = 0.0012004017327724877
count_rech_2g_7 = 0.002182361963848955
count_rech_2g_8 = 0.014213226532918495
count_rech_3g_6 = 0.001374925455146684
count_rech_3g_7 = 0.0014550945183788705
count_rech_3g_8 = 0.005839060243450501
vol_2g_mb_6 = 0.0010003659601310897
vol_2g_mb_7 = 0.001260764738850463
vol_2g_mb_8 = 0.008283979750134231
vol_3g_mb_6 = 0.0008170134090197137
vol_3g_mb_7 = 0.001143788264345923
vol_3g_mb_8 = 0.010216755162265577
night_pck_user_6 = 1.9757599814280796e-06
night_pck_user_7 = 0.0
night_pck_user_8 = 0.0
monthly_2g_6 = 0.001178860918650319
monthly_2g_7 = 0.0008540151307726339
monthly_2g_8 = 0.002482250530946055
sachet_2g_6 = 0.000949852811930499
sachet_2g_7 = 0.001274723032631917
sachet_2g_8 = 0.005066106890423425
monthly_3g_6 = 0.0005315941327581485
monthly_3g_7 = 0.0004955242844644428
monthly_3g_8 = 0.001715665563693029
sachet_3g_6 = 0.000316088047187600
sachet_3g_7 = 0.000738318797478707
sachet_3g_8 = 0.0001151237720879154
fb_user_6 = 0.002914081353352586
fb_user_7 = 0.004820000227692812
fb_user_8 = 0.052300717373213075
aon = 0.0022330927999574227
aug_vbc_3g = 0.001899629817741992
jul_vbc_3g = 0.000400858911795797
jun_vbc_3g = 0.0004695350105681734
sep_vbc_3g = 0.000593217828461129
rech_data_6_total = 0.0008686557394525258
rech_data_7_total = 0.0021036011673263508
Total rech_6 = 0.00033846287119815527
Total rech_7 = 0.0010979708103992583
avg_amt_6_7 = 0.0005098204242302779
```

In [748]:

```
featmap=list(zip(df_cols, imp))
```

In [749]:

```
featmap
```

Out[749]:

```
[('arpu_6', 0.000428406128694019),
 ('arpu_7', 0.001469338809749534),
 ('arpu_8', 0.04997759093744338),
 ('onnet_mou_6', 0.0010664591255723727),
 ('onnet_mou_7', 0.0011906076989066274),
 ('onnet_mou_8', 0.003760534995909619),
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 ('offnet_mou_7', 0.0011197673996465522),
 ('offnet_mou_8', 0.004608968351902497),
 ('roam_ic_mou_6', 0.0017907085242518947),
 ('roam_ic_mou_7', 0.01932418799101418),
 ('roam_ic_mou_8', 0.14215100384340487),
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 ('roam_og_mou_7', 0.023699790380323636),
 ('roam_og_mou_8', 0.14697084992987614),
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 ('loc_ic_mou_6', 0.0008589120932630188),
 ('loc_ic_mou_7', 0.002048092618519195),
 ('loc_ic_mou_8', 0.02338770044172436),
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 ('total_ic_mou_8', 0.07634033436774731),
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 ('spl_ic_mou_8', 0.008370343712221888),
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 ('isd_ic_mou_8', 0.004685745344232016),
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 ('max_rech_amt_8', 0.034178650488380646),
 ('total_rech_data_6', 0.001979397754019947),
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 ('total_rech_data_8', 0.0344285820592214),
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 ('max_rech_data_8', 0.027833884208403985),
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 ('count_rech_2g_7', 0.002182361963848955),
 ('count_rech_2g_8', 0.014213226532918495),
 ('count_rech_3g_6', 0.001374925455146684),
 ('count_rech_3g_7', 0.0014550945183788705),
 ('count_rech_3g_8', 0.005839060243450501),
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 ('vol_2g_mb_7', 0.0012607647388504463),
 ('vol_2g_mb_8', 0.008283979750134231),
 ('vol_3g_mb_6', 0.0008170134090197137),
 ('vol_3g_mb_7', 0.0011437882643459234),
 ('vol_3g_mb_8', 0.010216755162265577),
 ('night_pck_user_6', 1.9757599814280796e-06),
 ('night_pck_user_7', 0.0),
 ('night_pck_user_8', 0.0),
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 ('monthly_2g_7', 0.0008540151307726339),
 ('monthly_2g_8', 0.002482250530946055),
 ('sachet_2g_6', 0.0009498528119304991),
 ('sachet_2g_7', 0.0012747230326319173),
 ('sachet_2g_8', 0.005066106890423425),
 ('monthly_3g_6', 0.0005315941327581485),
 ('monthly_3g_7', 0.0004955242844644428),
 ('monthly_3g_8', 0.001715665563693029),
 ('sachet_3g_6', 0.00031608804718760095),
 ('sachet_3g_7', 0.0007383187974787073),
 ('sachet_3g_8', 0.00011512377208791548),
 ('fb_user_6', 0.002914081353352586),
 ('fb_user_7', 0.004820000227692812),
 ('fb_user_8', 0.05230071737321307 5),
 ('aon', 0.002233092799957 4227),
 ('aug_vbc_3g', 0.0018996298177419927),
 ('jul_vbc_3g', 0.0004008589117957976),
 ('jun_vbc_3g', 0.00046953501056817343),
 ('sep_vbc_3g', 0.0005932178284611293),
 ('rech_data_6_total', 0.0008686557394525258),
 ('rech_data_7_total', 0.0021036011673263508),
 ('Total rech_6', 0.00033846287119815527),
 ('Total rech_7', 0.0010979708103992583),
 ('avg_amt_6_7', 0.0005098204242302779)]
```

In [750]:

```python
def Sort_Tuple(tup):
    return(sorted(tup, key = lambda x: x[1],reverse=True))
```

Sorting Feature Names based on importance in descending order

In [751]:

```
Sort_Tuple(featmap)
```

Out[751]:

```
[('roam_og_mou_8', 0.14697084992987614),
 ('roam_ic_mou_8', 0.14215100384340487),
 ('total_ic_mou_8', 0.07634033436774731),
 ('fb_user_8', 0.05230071737321307),
 ('total_rech_amt_8', 0.0518553959795420 8),
 ('arpu_8', 0.04997759093744338),
 ('total_rech_data_8', 0.0344285820592214),
 ('max_rech_amt_8', 0.03417865048838064 6),
 ('total_og_mou_8', 0.03334556159208154 6),
 ('max_rech_data_8', 0.027833884208403985),
 ('og_others_8', 0.02677411207547937),
 ('roam_og_mou_7', 0.023699790380323636),
 ('loc_ic_mou_8', 0.0233877004417243 6),
 ('isd_og_mou_8', 0.020815759711131705),
 ('roam_ic_mou_7', 0.01932418799101418),
 ('loc_og_mou_8', 0.019260566543982654),
 ('count_rech_2g_8', 0.014213226532918495),
 ('total_rech_num_8', 0.011994429944571675),
 ('vol_3g_mb_8', 0.010216755162265577),
 ('spl_ic_mou_8', 0.008370343712221888),
 ('vol_2g_mb_8', 0.008283979750134231),
 ('spl_og_mou_6', 0.006759154416626769),
 ('count_rech_3g_8', 0.005839060243450501),
 ('std_og_mou_8', 0.005556243977794144),
 ('spl_ic_mou_6', 0.005295749322722625),
 ('spl_og_mou_7', 0.005172155252757629),
 ('sachet_2g_8', 0.005066106890423425),
 ('fb_user_7', 0.004820000227692812),
 ('isd_ic_mou_8', 0.004685745344232016),
 ('og_others_6', 0.004678856789222028),
 ('offnet_mou_8', 0.004608968351902497),
 ('std_ic_mou_8', 0.004484934372663194),
 ('std_og_mou_7', 0.003883967186024259),
 ('onnet_mou_8', 0.003760534995909619),
 ('loc_og_mou_7', 0.003347827075753324 5),
 ('total_rech_data_7', 0.0030689426456023744),
 ('std_og_mou_6', 0.003063559885434841),
 ('total_ic_mou_7', 0.002961787453630681),
 ('fb_user_6', 0.002914081353352586),
 ('total_rech_num_7', 0.0028963481179398514),
 ('roam_og_mou_6', 0.002823426976749755),
 ('spl_og_mou_8', 0.002743831566363028 5),
 ('ic_others_8', 0.002728546466475985 5),
 ('max_rech_data_7', 0.002643332915545892),
 ('monthly_2g_8', 0.002482250530946055),
 ('aon', 0.002233092799957422 7),
 ('count_rech_2g_7', 0.002182361963848955),
 ('total_og_mou_7', 0.00214797360600002),
 ('rech_data_7_total', 0.0021036011673263508),
 ('loc_ic_mou_7', 0.00204809261851919 5),
 ('max_rech_amt_7', 0.001988386383701660 7),
 ('total_rech_data_6', 0.001979397754019947),
 ('aug_vbc_3g', 0.0018996298177419927),
 ('isd_ic_mou_6', 0.0018869531076647153),
 ('max_rech_data_6', 0.0018257003421222379),
 ('roam_ic_mou_6', 0.0017907085242518947),
 ('monthly_3g_8', 0.001715665563693029),
 ('og_others_7', 0.0017022784019672169),
 ('max_rech_amt_6', 0.0015388201284257629),
 ('arpu_7', 0.001469338809749534),
 ('count_rech_3g_7', 0.0014550945183788705),
 ('total_ic_mou_6', 0.001420734118494782),
 ('ic_others_6', 0.0013841872464140405),
 ('count_rech_3g_6', 0.001374925455146684),
 ('total_rech_amt_7', 0.0012890004802043270),
 ('isd_og_mou_6', 0.0012887225382097866),
 ('loc_og_mou_6', 0.0012871592444620395),
 ('std_ic_mou_7', 0.0012748571920124896),
 ('sachet_2g_7', 0.0012747230326319173),
 ('vol_2g_mb_7', 0.0012607647388504463),
 ('count_rech_2g_6', 0.0012004017327724877),
 ('onnet_mou_7', 0.0011906076989066274),
 ('monthly_2g_6', 0.0011788609186503190),
 ('total_rech_num_6', 0.0011733601019935122),
 ('vol_3g_mb_7', 0.0011437882643459234),
 ('isd_og_mou_7', 0.0011407820835001943),
 ('offnet_mou_7', 0.0011197673996465522),
 ('Total rech_7', 0.0010979708103992583),
 ('spl_ic_mou_7', 0.0010881750914075873),
 ('onnet_mou_6', 0.0010664591255723727),
 ('vol_2g_mb_6', 0.0010003659601310897),
 ('std_ic_mou_6', 0.0009730271471843873),
 ('total_og_mou_6', 0.0009556095554990137),
 ('sachet_2g_6', 0.0009498528119304991),
 ('rech_data_6_total', 0.0008686557394525258),
 ('loc_ic_mou_6', 0.0008589120932630188),
 ('monthly_2g_7', 0.0008540151307726339),
 ('vol_3g_mb_6', 0.0008170134090197137),
 ('offnet_mou_6', 0.0007885593059849056),
 ('ic_others_7', 0.0007846418629660333),
 ('sachet_3g_7', 0.0007383187974787073),
 ('isd_ic_mou_7', 0.0006343196447684852),
 ('sep_vbc_3g', 0.0005932178284611293),
 ('monthly_3g_6', 0.0005315941327581485),
 ('avg_amt_6_7', 0.0005098204242302779),
 ('monthly_3g_7', 0.0004955242844644428),
 ('jun_vbc_3g', 0.0004695350105681734),
 ('arpu_6', 0.00042840612869401 9),
 ('jul_vbc_3g', 0.0004008589117957976),
 ('total_rech_amt_6', 0.0003449232048335955),
 ('Total rech_6', 0.00033846287119815527),
 ('sachet_3g_6', 0.00031608804718760095),
 ('sachet_3g_8', 0.00011512377208791548),
 ('night_pck_user_6', 1.9757599814280796e-06),
 ('night_pck_user_7', 0.0),
 ('night_pck_user_8', 0.0)]
```

In [754]:

```
#Storing data frame with Features & importances
df_feat=pd.DataFrame(imp,index=df_cols)
```

In [755]:

```
df_feat.head()
```

Out[755]:

	0
arpu_6	0.000428
arpu_7	0.001469
arpu_8	0.049978
onnet_mou_6	0.001066
onnet_mou_7	0.001191

In [756]:

```
#sorting the dataframe based on feature importance
final_df = df_feat.sort_values(by=[0], ascending=False)
```

In [757]:

```
final_df.head()
```

Out[757]:

	0
roam_og_mou_8	0.146971
roam_ic_mou_8	0.142151
total_ic_mou_8	0.076340
fb_user_8	0.052301
total_rech_amt_8	0.051855

In [766]:

```
# Deriving top 21 variables

final=final_df[:21]
```

In [767]:

```
final.head(21)
```

Out[767]:

	0
roam_og_mou_8	0.146971
roam_ic_mou_8	0.142151
total_ic_mou_8	0.076340
fb_user_8	0.052301
total_rech_amt_8	0.051855
arpu_8	0.049978
total_rech_data_8	0.034429
max_rech_amt_8	0.034179
total_og_mou_8	0.033346
max_rech_data_8	0.027834
og_others_8	0.026774
roam_og_mou_7	0.023700
loc_ic_mou_8	0.023388
isd_og_mou_8	0.020816
roam_ic_mou_7	0.019324
loc_og_mou_8	0.019261
count_rech_2g_8	0.014213
total_rech_num_8	0.011994
vol_3g_mb_8	0.010217
spl_ic_mou_8	0.008370
vol_2g_mb_8	0.008284

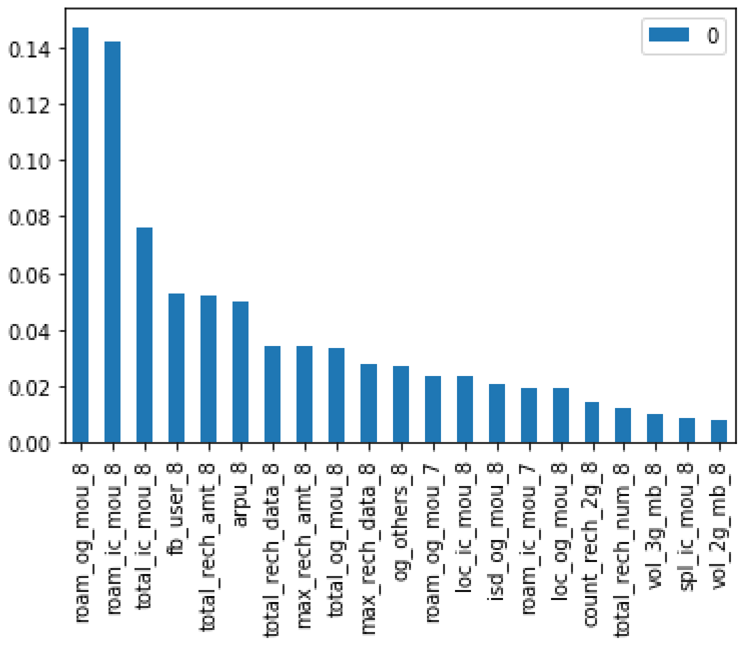
Plotting Bar Graph- Visual Analysis of Important Feature

In [768]:

```
final.plot.bar()
```

Out[768]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1414f57f0>
```



Important Feature Analysis

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. **roam_og_mou_8** -- ***outgoing roaming calls minutes of usage in month 8***
2. **roam_ic_mou_8** -- ***incoming roaming calls minutes of usage in month 8***
3. **total_ic_mou_8** -- ***Total incoming minutes of usage in month 8***
4. **fb_user_8** -- ***services of Facebook and similar social networking sites for month 8***
5. **total_rech_amt_8** -- ***total recharge amount in month 8***
6. **arpu_8** -- ***average revenue per user in month 8***
7. **total_rech_data_8** -- ***total data recharge (MB) in month 8***
8. **max_rech_amt_8** -- ***maximum recharge amount in month 8***
9. **total_og_mou_8** -- ***total outgoing calls minutes of usage in month 8***
10. **max_rech_amt_8** -- ***maximum recharge amount in month 8***
11. **og_others_8**
12. **roam_og_mou_7** -- ***outgoing roaming calls minutes of usage in month 7***
13. **loc_ic_mou_8** -- ***local incoming minutes of usage in month 8***
14. **isd_og_mou_8** -- ***outgoing ISD minutes of usage in month 8***
15. **roam_ic_mou_7** -- ***incoming roaming calls minutes of usage in month 8***
16. **loc_og_mou_8** -- ***local outgoing calls minutes of usage in month 8***
17. **count_rech_2g_8** -- ***Number of 2g data recharge in month 8***
18. **total_rech_num_8** -- ***total number of recharges done in the month 8***
19. **vol_3g_mb_8** -- ***volume of 3G data (MB) consumed for month 8***
20. **spl_ic_mou_8** -- ***Special incoming call for the month of 7***
21. **vol_2g_mb_8** -- ***volume of 2G data (MB) consumed for month 8***

Notes

1. **Local& Roaming calls Mou's be it incoming or outgoing have a very important role for churn predictions.**
2. **Reduction in these KPI's forms a clear indicator of churn.**
3. **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.**
4. **Data Usage and Social Networking sites packages also are a vital factor in retaining customers**

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

Strategies to Manage customer churn

1. **Monitoring Drop in usage**

   --***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. -- *offer them attractive data recharge coupons or other incentives to continue to use the services, while the company fixes the issues reported.

1. **Improving Outgoing services**
2. --*The Network operators must futher investigate their outgoing tariffs, plans and campaigns.
3. --*There could be a possibility that the outgoing tariffs offered to it's customer are less competitive to the outgoing tariffs of their competitor.
4. --***Attractive offers like Discounted outgoing rates during particular hours of the day for these customers or For every X mou, grant customer with some % of X free mou.***
5. --***Free monthly outgoing mou's depending on the users past roaming mou usage.***

1. **Improving Roaming services**
2. --***Churners show higher roaming usage than non-churners.***
3. --***The Network operators must futher investigate their roaming tariffs, and quality of service.***
4. --*Might be that the roaming tariffs offered are less competitive than their competitor.
5. --***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.***
6. --***New campaigns which targets the roaming customers can be rolled out. Like Discounted roaming rates during particular hours of the day or Free monthly roaming mou's depending on the users past roaming mou usage.***

1. **Offer Attractive packages and monthly recharge plans for

```
    --*2G & 3G Data Recharge packs*
    --*Facebook an other scoial Networking Sites*
```

In [ ]: