Problem Statement:

Consider a telecom service provider has the datasetcontains customer-level information for a span of four consecutive months — June, July, August and September. 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 and hence to mitigate the issue of churn by mapping the same to different customer behaviors during good and actions phases.

Out aim is to build a model to predict whether a high-value customer will churn or not, in near future (i.e. churn phase). By knowing this, the company can take action steps such as providing special plans, discounts on recharge etc. The model will also be used to identify important variables that are strong predictors of churn. These variables may also indicate why customers choose to switch to other networks.

Following steps have been taken to prepare the model:

1. Data Cleaning
2. Filtering the high-value customers
3. Tagging churn and non-churn customers
4. Exploratory Data Analysis, Feature Engineering & Data Visualization
5. Data Preparation
6. Model building (I): Churn prediction
7. Model building (II): Important Feature Identification
8. Actionable recommendations

```
#importing the dependenciesimport numpy as np
import pandas as pdimport matplotlib.pyplot as plt
import seaborn as snsfrom sklearn.decomposition import PCA
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_splitfrom sklearn.linear_model import
LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifierfrom sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import recall_score
from sklearn.metrics import roc_auc_scorefrom sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCVimport imblearn
from imblearn.over_sampling import SMOTEfrom sklearn.feature_selection import RFE
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor#ignore warnings
import warnings
warnings.filterwarnings("ignore")#setting max view display options
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

pd.set_option('display.max_colwidth', -1)*#loading dataset*
df = pd.read_csv('telecom_churn_data.csv')df.head()

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	last_date_of_month_6	last_date_of_month_7	last_date_of_month_8	last_date_o
0	7000842753	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	
1	7001865778	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	
2	7001625959	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	
3	7001204172	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	
4	7000142493	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	

df.shape(99999, 226)

1. Data cleaning

1.1 Check for duplicates

Let's start our data cleaning process by checking for duplicate rows. Since mobile numbers are the unique ids, let's check them and see whether we find any duplicates in them.

#check for duplicate mobile numbers
(df.mobile_number.value_counts()>1).sum()0

From above, we note that there are no any duplicate rows.

1.2 Check for columns with only one unique value:

unique_val_cols = []**for** col **in** df.columns:
  if df[col].value_counts().shape[0]==1:
    unique_val_cols.append(col)print(unique_val_cols)['circle_id', 'loc_og_t2o_mou', 'std_og_t2o_mou', 'loc_ic_t2o_mou', 'last_date_of_month_6', 'last_date_of_month_7', 'last_date_of_month_8', 'last_date_of_month_9', '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']

We have many columns with only one unique values. Let's drop these columns as the same does not help in identifying the churn and hence the model building.

df.drop(unique_val_cols, axis=1, inplace=**True**)

1.3 Missing value check & imputation

#function to return the missing value percentage in each columns
def check_missing(x):
  return
round(x.isnull().sum()/x.shape[0]*100,2).sort_values(ascending=**False**)check_missing(df)night_pck_user_6   74.85
arpu_2g_6   74.85
count_rech_3g_6   74.85
av_rech_amt_data_6   74.85
count_rech_2g_6   74.85
max_rech_data_6   74.85
fb_user_6   74.85
date_of_last_rech_data_6   74.85
total_rech_data_6   74.85

arpu_3g_6	74.85
night_pck_user_7	74.43
arpu_2g_7	74.43
total_rech_data_7	74.43
arpu_3g_7	74.43
max_rech_data_7	74.43
av_rech_amt_data_7	74.43
count_rech_3g_7	74.43
date_of_last_rech_data_7	74.43
count_rech_2g_7	74.43
fb_user_7	74.43
date_of_last_rech_data_9	74.08
arpu_2g_9	74.08
max_rech_data_9	74.08
count_rech_3g_9	74.08
fb_user_9	74.08
av_rech_amt_data_9	74.08
total_rech_data_9	74.08
arpu_3g_9	74.08
count_rech_2g_9	74.08
night_pck_user_9	74.08
av_rech_amt_data_8	73.66
max_rech_data_8	73.66
fb_user_8	73.66
arpu_2g_8	73.66
night_pck_user_8	73.66
total_rech_data_8	73.66
date_of_last_rech_data_8	73.66
count_rech_3g_8	73.66
arpu_3g_8	73.66
count_rech_2g_8	73.66
std_og_t2t_mou_9	7.75
loc_ic_t2f_mou_9	7.75
std_ic_t2f_mou_9	7.75
std_og_t2m_mou_9	7.75
loc_og_t2m_mou_9	7.75
loc_og_t2f_mou_9	7.75
loc_og_mou_9	7.75
std_ic_t2m_mou_9	7.75
spl_ic_mou_9	7.75
loc_ic_t2t_mou_9	7.75
isd_ic_mou_9	7.75
std_ic_t2t_mou_9	7.75
loc_og_t2c_mou_9	7.75
ic_others_9	7.75
loc_ic_mou_9	7.75
loc_ic_t2m_mou_9	7.75
std_ic_mou_9	7.75

og_others_9	7.75
roam_og_mou_9	7.75
isd_og_mou_9	7.75
spl_og_mou_9	7.75
std_og_mou_9	7.75
onnet_mou_9	7.75
roam_ic_mou_9	7.75
std_og_t2f_mou_9	7.75
offnet_mou_9	7.75
loc_og_t2t_mou_9	7.75
ic_others_8	5.38
std_ic_t2t_mou_8	5.38
offnet_mou_8	5.38
onnet_mou_8	5.38
isd_og_mou_8	5.38
std_og_t2t_mou_8	5.38
spl_og_mou_8	5.38
isd_ic_mou_8	5.38
loc_og_mou_8	5.38
loc_ic_mou_8	5.38
spl_ic_mou_8	5.38
loc_og_t2m_mou_8	5.38
std_ic_mou_8	5.38
std_ic_t2m_mou_8	5.38
loc_og_t2c_mou_8	5.38
loc_ic_t2f_mou_8	5.38
std_ic_t2f_mou_8	5.38
og_others_8	5.38
loc_ic_t2m_mou_8	5.38
loc_og_t2f_mou_8	5.38
roam_ic_mou_8	5.38
roam_og_mou_8	5.38
std_og_t2f_mou_8	5.38
std_og_t2m_mou_8	5.38
loc_og_t2t_mou_8	5.38
std_og_mou_8	5.38
loc_ic_t2t_mou_8	5.38
date_of_last_rech_9	4.76
std_ic_t2f_mou_6	3.94
isd_og_mou_6	3.94
std_ic_mou_6	3.94
std_ic_t2m_mou_6	3.94
spl_og_mou_6	3.94
std_ic_t2t_mou_6	3.94
og_others_6	3.94
loc_ic_t2f_mou_6	3.94
loc_ic_t2m_mou_6	3.94
std_og_t2f_mou_6	3.94

loc_ic_t2t_mou_6	3.94
loc_ic_mou_6	3.94
loc_og_t2c_mou_6	3.94
std_og_t2t_mou_6	3.94
ic_others_6	3.94
loc_og_t2m_mou_6	3.94
loc_og_t2t_mou_6	3.94
std_og_mou_6	3.94
roam_og_mou_6	3.94
loc_og_mou_6	3.94
roam_ic_mou_6	3.94
offnet_mou_6	3.94
loc_og_t2f_mou_6	3.94
isd_ic_mou_6	3.94
onnet_mou_6	3.94
spl_ic_mou_6	3.94
std_og_t2m_mou_6	3.94
spl_og_mou_7	3.86
offnet_mou_7	3.86
onnet_mou_7	3.86
loc_og_t2m_mou_7	3.86
og_others_7	3.86
roam_ic_mou_7	3.86
roam_og_mou_7	3.86
isd_og_mou_7	3.86
std_og_t2f_mou_7	3.86
loc_og_t2t_mou_7	3.86
loc_ic_t2t_mou_7	3.86
std_ic_mou_7	3.86
loc_og_t2f_mou_7	3.86
std_og_t2m_mou_7	3.86
std_og_t2t_mou_7	3.86
std_ic_t2f_mou_7	3.86
spl_ic_mou_7	3.86
std_ic_t2m_mou_7	3.86
isd_ic_mou_7	3.86
ic_others_7	3.86
loc_ic_t2m_mou_7	3.86
std_ic_t2t_mou_7	3.86
loc_og_mou_7	3.86
loc_ic_mou_7	3.86
loc_og_t2c_mou_7	3.86
loc_ic_t2f_mou_7	3.86
std_og_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
arpu_9	0.00

arpu_8	0.00
arpu_7	0.00
arpu_6	0.00
sep_vbc_3g	0.00
total_og_mou_6	0.00
vol_2g_mb_8	0.00
vol_3g_mb_6	0.00
vol_3g_mb_7	0.00
vol_3g_mb_8	0.00
vol_3g_mb_9	0.00
monthly_2g_6	0.00
monthly_2g_7	0.00
monthly_2g_8	0.00
monthly_2g_9	0.00
sachet_2g_6	0.00
sachet_2g_7	0.00
sachet_2g_8	0.00
sachet_2g_9	0.00
monthly_3g_6	0.00
monthly_3g_7	0.00
monthly_3g_8	0.00
monthly_3g_9	0.00
sachet_3g_6	0.00
sachet_3g_7	0.00
sachet_3g_8	0.00
sachet_3g_9	0.00
aon	0.00
aug_vbc_3g	0.00
jul_vbc_3g	0.00
vol_2g_mb_9	0.00
vol_2g_mb_7	0.00
total_og_mou_7	0.00
vol_2g_mb_6	0.00
total_og_mou_8	0.00
total_og_mou_9	0.00
jun_vbc_3g	0.00
total_ic_mou_6	0.00
total_ic_mou_7	0.00
total_ic_mou_8	0.00
total_ic_mou_9	0.00
total_rech_num_6	0.00
total_rech_num_7	0.00
total_rech_num_8	0.00
total_rech_num_9	0.00
total_rech_amt_6	0.00
total_rech_amt_7	0.00
total_rech_amt_8	0.00
total_rech_amt_9	0.00

```
max_rech_amt_6           0.00
max_rech_amt_7           0.00
max_rech_amt_8           0.00
max_rech_amt_9           0.00
last_day_rch_amt_6        0.00
last_day_rch_amt_7        0.00
last_day_rch_amt_8        0.00
last_day_rch_amt_9        0.00
mobile_number            0.00
dtype: float64
```

From the above, we note that there are specific patterns in the data as the columns of the same months have same percentage of missing values. Lets explore them one by one.

```
#bunching the June month columns with same percentage of missing values
cols_june = ['night_pck_user_6', 'arpu_2g_6', 'count_rech_3g_6',
     'av_rech_amt_data_6', 'count_rech_2g_6', 'max_rech_data_6', 'fb_user_6',
     'date_of_last_rech_data_6', 'total_rech_data_6', 'arpu_3g_6']
```

Let’s check whether all the columns above have occurances of **NAN** at the same instances.

```
#sanity check
for i in cols_june:
   print(sum(df['night_pck_user_6'].isnull()!=df[i].isnull()))0
0
0
0
0
0
0
0
0
0
```

From above, we notice that nan occurs at the same instances for all the above bunched columns. We further observe that in the absence of data recharge (date_of_last_rech_data_6) done for that particular month, user is not using corresponding internet related services, which is understandable. Hence we should impute these **NAN** values with **0**.

```
#function to convert NAN to 0
def nan_to_zero(x):
   if str(x)=='nan':
      return 0
   else:
      return xfor i in cols_june:
   df[i] = df[i].apply(nan_to_zero)#check again for missing values
check_missing(df)max_rech_data_7           74.43
av_rech_amt_data_7        74.43
date_of_last_rech_data_7   74.43
count_rech_3g_7           74.43
```

fb_user_7	74.43
arpu_2g_7	74.43
total_rech_data_7	74.43
count_rech_2g_7	74.43
arpu_3g_7	74.43
night_pck_user_7	74.43
total_rech_data_9	74.08
count_rech_3g_9	74.08
arpu_2g_9	74.08
arpu_3g_9	74.08
date_of_last_rech_data_9	74.08
max_rech_data_9	74.08
count_rech_2g_9	74.08
fb_user_9	74.08
av_rech_amt_data_9	74.08
night_pck_user_9	74.08
total_rech_data_8	73.66
max_rech_data_8	73.66
arpu_3g_8	73.66
count_rech_2g_8	73.66
arpu_2g_8	73.66
av_rech_amt_data_8	73.66
count_rech_3g_8	73.66
night_pck_user_8	73.66
date_of_last_rech_data_8	73.66
fb_user_8	73.66
std_ic_t2m_mou_9	7.75
og_others_9	7.75
isd_og_mou_9	7.75
loc_ic_t2t_mou_9	7.75
loc_ic_t2m_mou_9	7.75
loc_ic_t2f_mou_9	7.75
loc_ic_mou_9	7.75
std_ic_t2t_mou_9	7.75
std_ic_t2f_mou_9	7.75
loc_og_t2c_mou_9	7.75
std_og_mou_9	7.75
spl_ic_mou_9	7.75
isd_ic_mou_9	7.75
ic_others_9	7.75
std_og_t2f_mou_9	7.75
std_og_t2m_mou_9	7.75
std_og_t2t_mou_9	7.75
loc_og_mou_9	7.75
std_ic_mou_9	7.75
spl_og_mou_9	7.75
loc_og_t2f_mou_9	7.75
loc_og_t2m_mou_9	7.75

offnet_mou_9	7.75
roam_og_mou_9	7.75
loc_og_t2t_mou_9	7.75
onnet_mou_9	7.75
roam_ic_mou_9	7.75
std_og_mou_8	5.38
std_og_t2m_mou_8	5.38
roam_ic_mou_8	5.38
std_og_t2f_mou_8	5.38
ic_others_8	5.38
og_others_8	5.38
isd_ic_mou_8	5.38
offnet_mou_8	5.38
loc_og_t2f_mou_8	5.38
loc_ic_t2m_mou_8	5.38
loc_ic_t2f_mou_8	5.38
isd_og_mou_8	5.38
std_ic_t2f_mou_8	5.38
std_og_t2t_mou_8	5.38
std_ic_t2m_mou_8	5.38
loc_ic_t2t_mou_8	5.38
onnet_mou_8	5.38
std_ic_t2t_mou_8	5.38
loc_ic_mou_8	5.38
std_ic_mou_8	5.38
spl_ic_mou_8	5.38
roam_og_mou_8	5.38
spl_og_mou_8	5.38
loc_og_t2t_mou_8	5.38
loc_og_mou_8	5.38
loc_og_t2c_mou_8	5.38
loc_og_t2m_mou_8	5.38
date_of_last_rech_9	4.76
loc_ic_t2m_mou_6	3.94
loc_og_t2f_mou_6	3.94
loc_ic_t2f_mou_6	3.94
loc_ic_t2t_mou_6	3.94
isd_og_mou_6	3.94
loc_ic_mou_6	3.94
std_ic_t2t_mou_6	3.94
loc_og_t2m_mou_6	3.94
spl_og_mou_6	3.94
loc_og_t2c_mou_6	3.94
std_ic_t2m_mou_6	3.94
og_others_6	3.94
loc_og_t2t_mou_6	3.94
offnet_mou_6	3.94
std_ic_mou_6	3.94

onnet_mou_6	3.94
std_ic_t2f_mou_6	3.94
std_og_t2t_mou_6	3.94
loc_og_mou_6	3.94
std_og_mou_6	3.94
ic_others_6	3.94
roam_og_mou_6	3.94
isd_ic_mou_6	3.94
std_og_t2f_mou_6	3.94
spl_ic_mou_6	3.94
std_og_t2m_mou_6	3.94
roam_ic_mou_6	3.94
spl_og_mou_7	3.86
loc_og_t2f_mou_7	3.86
loc_ic_t2t_mou_7	3.86
offnet_mou_7	3.86
std_og_t2f_mou_7	3.86
std_og_t2m_mou_7	3.86
loc_ic_t2m_mou_7	3.86
loc_og_t2c_mou_7	3.86
og_others_7	3.86
roam_ic_mou_7	3.86
loc_ic_t2f_mou_7	3.86
roam_og_mou_7	3.86
loc_ic_mou_7	3.86
loc_og_t2t_mou_7	3.86
std_og_mou_7	3.86
isd_og_mou_7	3.86
std_ic_mou_7	3.86
spl_ic_mou_7	3.86
loc_og_mou_7	3.86
loc_og_t2m_mou_7	3.86
std_ic_t2f_mou_7	3.86
std_ic_t2m_mou_7	3.86
isd_ic_mou_7	3.86
std_ic_t2t_mou_7	3.86
ic_others_7	3.86
onnet_mou_7	3.86
std_og_t2t_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
arpu_8	0.00
arpu_7	0.00
arpu_9	0.00
arpu_6	0.00
sep_vbc_3g	0.00
total_og_mou_6	0.00

sachet_2g_7	0.00
vol_2g_mb_9	0.00
vol_3g_mb_6	0.00
vol_3g_mb_7	0.00
vol_3g_mb_8	0.00
vol_3g_mb_9	0.00
arpu_3g_6	0.00
arpu_2g_6	0.00
night_pck_user_6	0.00
monthly_2g_6	0.00
monthly_2g_7	0.00
monthly_2g_8	0.00
monthly_2g_9	0.00
sachet_2g_6	0.00
sachet_2g_8	0.00
vol_2g_mb_7	0.00
sachet_2g_9	0.00
monthly_3g_6	0.00
monthly_3g_7	0.00
monthly_3g_8	0.00
monthly_3g_9	0.00
sachet_3g_6	0.00
sachet_3g_7	0.00
sachet_3g_8	0.00
sachet_3g_9	0.00
fb_user_6	0.00
aon	0.00
aug_vbc_3g	0.00
jul_vbc_3g	0.00
vol_2g_mb_8	0.00
vol_2g_mb_6	0.00
total_og_mou_7	0.00
total_rech_amt_8	0.00
total_og_mou_8	0.00
total_og_mou_9	0.00
jun_vbc_3g	0.00
total_ic_mou_6	0.00
total_ic_mou_7	0.00
total_ic_mou_8	0.00
total_ic_mou_9	0.00
total_rech_num_6	0.00
total_rech_num_7	0.00
total_rech_num_8	0.00
total_rech_num_9	0.00
total_rech_amt_6	0.00
total_rech_amt_7	0.00
total_rech_amt_9	0.00
av_rech_amt_data_6	0.00

max_rech_amt_6 0.00
max_rech_amt_7 0.00
max_rech_amt_8 0.00
max_rech_amt_9 0.00
last_day_rch_amt_6 0.00
last_day_rch_amt_7 0.00
last_day_rch_amt_8 0.00
last_day_rch_amt_9 0.00
date_of_last_rech_data_6 0.00
total_rech_data_6 0.00
max_rech_data_6 0.00
count_rech_2g_6 0.00
count_rech_3g_6 0.00
mobile_number 0.00
dtype: float64*#bunch the July month columns with same percentage of missing values*
cols_july = ['max_rech_data_7', 'av_rech_amt_data_7', 'date_of_last_rech_data_7',
    'count_rech_3g_7', 'fb_user_7', 'arpu_2g_7', 'total_rech_data_7',
    'count_rech_2g_7', 'arpu_3g_7', 'night_pck_user_7']

Here as well, let's check whether all the columns above have occurrences of **NAN** at the same instances.

for i **in** cols_july:
  print(sum(df['max_rech_data_7'].isnull()!=df[i].isnull()))0
0
0
0
0
0
0
0
0
0

NAN occurring at the exact same instance for all the above bunched columns. Here also, we notice that in the absence of data recharge (date_of_last_rech_data_7) done for that particular month, user is not using corresponding internet related services, which is understandable. Hence we should impute these **NAN** values with **0**.

for i **in** cols_july:
  df[i] = df[i].apply(nan_to_zero)*#check against for missing values*
check_missing(df)date_of_last_rech_data_9 74.08
total_rech_data_9 74.08
count_rech_3g_9 74.08
arpu_3g_9 74.08
count_rech_2g_9 74.08
arpu_2g_9 74.08
max_rech_data_9 74.08
night_pck_user_9 74.08
av_rech_amt_data_9 74.08

fb_user_9	74.08
max_rech_data_8	73.66
night_pck_user_8	73.66
av_rech_amt_data_8	73.66
count_rech_3g_8	73.66
arpu_3g_8	73.66
count_rech_2g_8	73.66
date_of_last_rech_data_8	73.66
arpu_2g_8	73.66
total_rech_data_8	73.66
fb_user_8	73.66
loc_og_t2c_mou_9	7.75
loc_ic_t2t_mou_9	7.75
loc_ic_t2m_mou_9	7.75
loc_ic_t2f_mou_9	7.75
loc_og_mou_9	7.75
std_ic_t2m_mou_9	7.75
loc_ic_mou_9	7.75
std_ic_t2f_mou_9	7.75
std_ic_t2t_mou_9	7.75
std_og_t2t_mou_9	7.75
loc_og_t2f_mou_9	7.75
std_og_t2f_mou_9	7.75
std_og_mou_9	7.75
isd_og_mou_9	7.75
ic_others_9	7.75
isd_ic_mou_9	7.75
spl_ic_mou_9	7.75
spl_og_mou_9	7.75
og_others_9	7.75
std_ic_mou_9	7.75
std_og_t2m_mou_9	7.75
offnet_mou_9	7.75
loc_og_t2m_mou_9	7.75
roam_og_mou_9	7.75
onnet_mou_9	7.75
loc_og_t2t_mou_9	7.75
roam_ic_mou_9	7.75
isd_ic_mou_8	5.38
std_og_t2f_mou_8	5.38
roam_ic_mou_8	5.38
std_og_mou_8	5.38
isd_og_mou_8	5.38
loc_ic_t2t_mou_8	5.38
spl_og_mou_8	5.38
ic_others_8	5.38
offnet_mou_8	5.38
loc_ic_mou_8	5.38

loc_ic_t2f_mou_8	5.38
og_others_8	5.38
std_og_t2m_mou_8	5.38
loc_ic_t2m_mou_8	5.38
std_ic_mou_8	5.38
onnet_mou_8	5.38
std_ic_t2f_mou_8	5.38
std_ic_t2m_mou_8	5.38
std_ic_t2t_mou_8	5.38
spl_ic_mou_8	5.38
loc_og_t2f_mou_8	5.38
loc_og_mou_8	5.38
loc_og_t2c_mou_8	5.38
roam_og_mou_8	5.38
loc_og_t2m_mou_8	5.38
loc_og_t2t_mou_8	5.38
std_og_t2t_mou_8	5.38
date_of_last_rech_9	4.76
loc_og_t2c_mou_6	3.94
std_ic_t2f_mou_6	3.94
loc_og_t2m_mou_6	3.94
ic_others_6	3.94
loc_og_t2t_mou_6	3.94
loc_ic_mou_6	3.94
loc_og_t2f_mou_6	3.94
isd_ic_mou_6	3.94
std_og_t2t_mou_6	3.94
loc_og_mou_6	3.94
spl_ic_mou_6	3.94
offnet_mou_6	3.94
std_ic_t2t_mou_6	3.94
roam_ic_mou_6	3.94
spl_og_mou_6	3.94
onnet_mou_6	3.94
std_ic_t2m_mou_6	3.94
isd_og_mou_6	3.94
loc_ic_t2f_mou_6	3.94
std_ic_mou_6	3.94
std_og_mou_6	3.94
std_og_t2m_mou_6	3.94
loc_ic_t2m_mou_6	3.94
roam_og_mou_6	3.94
loc_ic_t2t_mou_6	3.94
std_og_t2f_mou_6	3.94
og_others_6	3.94
std_ic_t2m_mou_7	3.86
std_og_t2m_mou_7	3.86
std_ic_t2t_mou_7	3.86

loc_ic_mou_7	3.86
loc_og_t2f_mou_7	3.86
loc_ic_t2f_mou_7	3.86
loc_ic_t2m_mou_7	3.86
loc_og_t2c_mou_7	3.86
loc_ic_t2t_mou_7	3.86
onnet_mou_7	3.86
og_others_7	3.86
std_ic_t2f_mou_7	3.86
loc_og_t2t_mou_7	3.86
std_og_mou_7	3.86
roam_og_mou_7	3.86
roam_ic_mou_7	3.86
isd_og_mou_7	3.86
spl_og_mou_7	3.86
loc_og_t2m_mou_7	3.86
std_og_t2t_mou_7	3.86
ic_others_7	3.86
isd_ic_mou_7	3.86
offnet_mou_7	3.86
spl_ic_mou_7	3.86
std_og_t2f_mou_7	3.86
std_ic_mou_7	3.86
loc_og_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
arpu_6	0.00
arpu_8	0.00
arpu_7	0.00
arpu_9	0.00
total_og_mou_7	0.00
total_og_mou_6	0.00
sep_vbc_3g	0.00
total_og_mou_8	0.00
arpu_2g_6	0.00
monthly_2g_8	0.00
monthly_2g_7	0.00
monthly_2g_6	0.00
night_pck_user_7	0.00
night_pck_user_6	0.00
arpu_2g_7	0.00
arpu_3g_7	0.00
sachet_2g_6	0.00
arpu_3g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
vol_3g_mb_7	0.00

vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
monthly_2g_9	0.00
sachet_2g_7	0.00
vol_2g_mb_7	0.00
sachet_3g_8	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_7	0.00
sachet_2g_8	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
vol_2g_mb_8	0.00
vol_2g_mb_6	0.00
total_og_mou_9	0.00
total_rech_num_8	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_7	0.00
total_rech_amt_6	0.00
total_rech_num_9	0.00
total_rech_num_7	0.00
max_rech_amt_8	0.00
total_rech_num_6	0.00
total_ic_mou_9	0.00
total_ic_mou_8	0.00
total_ic_mou_7	0.00
total_ic_mou_6	0.00
jun_vbc_3g	0.00
max_rech_amt_7	0.00
max_rech_amt_9	0.00
av_rech_amt_data_7	0.00
max_rech_data_6	0.00
av_rech_amt_data_6	0.00
count_rech_3g_7	0.00
count_rech_3g_6	0.00
count_rech_2g_7	0.00
count_rech_2g_6	0.00
max_rech_data_7	0.00

```
total_rech_data_7         0.00
last_day_rch_amt_6        0.00
total_rech_data_6         0.00
date_of_last_rech_data_7   0.00
date_of_last_rech_data_6   0.00
last_day_rch_amt_9        0.00
last_day_rch_amt_8        0.00
last_day_rch_amt_7        0.00
mobile_number            0.00
dtype: float64#bunching the September month columns together with same percentage of missing values
cols_sep = ['date_of_last_rech_data_9', 'total_rech_data_9', 'count_rech_3g_9',
      'arpu_3g_9', 'count_rech_2g_9', 'arpu_2g_9', 'max_rech_data_9',
      'night_pck_user_9', 'av_rech_amt_data_9', 'fb_user_9']
```

Here as well, let's check whether all the columns above have occurrences of **NAN** at the same instances.

```
for i in cols_sep:
   print(sum(df['date_of_last_rech_data_9'].isnull()!=df[i].isnull()))0
0
0
0
0
0
0
0
0
0
```

NAN occurring at the exact same instances for all the above bunched columns. From above also, we notice that in the absence of data recharge (date_of_last_rech_data_9) done for that particular month, user is not using corresponding internet related services, which is understandable. Hence we should impute these **NAN** values with **0**.

```
for i in cols_sep:
   df[i] = df[i].apply(nan_to_zero)#check against for missing values
check_missing(df)arpu_2g_8               73.66
date_of_last_rech_data_8   73.66
arpu_3g_8               73.66
night_pck_user_8         73.66
fb_user_8               73.66
av_rech_amt_data_8        73.66
count_rech_3g_8          73.66
count_rech_2g_8          73.66
max_rech_data_8          73.66
total_rech_data_8         73.66
loc_og_t2f_mou_9          7.75
loc_og_t2c_mou_9          7.75
loc_og_mou_9             7.75
```

std_og_t2t_mou_9	7.75
std_og_t2m_mou_9	7.75
std_og_t2f_mou_9	7.75
std_ic_mou_9	7.75
loc_og_t2m_mou_9	7.75
isd_og_mou_9	7.75
spl_og_mou_9	7.75
og_others_9	7.75
ic_others_9	7.75
isd_ic_mou_9	7.75
spl_ic_mou_9	7.75
loc_ic_t2t_mou_9	7.75
std_ic_t2f_mou_9	7.75
std_ic_t2m_mou_9	7.75
std_ic_t2t_mou_9	7.75
loc_ic_mou_9	7.75
loc_ic_t2f_mou_9	7.75
std_og_mou_9	7.75
loc_ic_t2m_mou_9	7.75
roam_ic_mou_9	7.75
onnet_mou_9	7.75
roam_og_mou_9	7.75
offnet_mou_9	7.75
loc_og_t2t_mou_9	7.75
roam_ic_mou_8	5.38
loc_ic_t2m_mou_8	5.38
isd_og_mou_8	5.38
spl_og_mou_8	5.38
offnet_mou_8	5.38
og_others_8	5.38
ic_others_8	5.38
loc_og_t2m_mou_8	5.38
std_og_t2f_mou_8	5.38
onnet_mou_8	5.38
spl_ic_mou_8	5.38
loc_ic_t2t_mou_8	5.38
std_ic_mou_8	5.38
std_ic_t2f_mou_8	5.38
std_ic_t2m_mou_8	5.38
std_ic_t2t_mou_8	5.38
loc_ic_mou_8	5.38
loc_ic_t2f_mou_8	5.38
isd_ic_mou_8	5.38
std_og_mou_8	5.38
loc_og_t2t_mou_8	5.38
std_og_t2m_mou_8	5.38
roam_og_mou_8	5.38
std_og_t2t_mou_8	5.38

loc_og_t2f_mou_8	5.38
loc_og_mou_8	5.38
loc_og_t2c_mou_8	5.38
date_of_last_rech_9	4.76
loc_ic_t2m_mou_6	3.94
ic_others_6	3.94
roam_og_mou_6	3.94
isd_ic_mou_6	3.94
loc_og_mou_6	3.94
spl_ic_mou_6	3.94
onnet_mou_6	3.94
std_ic_mou_6	3.94
loc_ic_t2t_mou_6	3.94
loc_og_t2c_mou_6	3.94
std_ic_t2f_mou_6	3.94
loc_og_t2m_mou_6	3.94
std_ic_t2m_mou_6	3.94
std_ic_t2t_mou_6	3.94
loc_ic_mou_6	3.94
loc_ic_t2f_mou_6	3.94
offnet_mou_6	3.94
std_og_t2f_mou_6	3.94
std_og_t2m_mou_6	3.94
loc_og_t2t_mou_6	3.94
isd_og_mou_6	3.94
std_og_t2t_mou_6	3.94
loc_og_t2f_mou_6	3.94
spl_og_mou_6	3.94
og_others_6	3.94
roam_ic_mou_6	3.94
std_og_mou_6	3.94
std_og_t2m_mou_7	3.86
isd_og_mou_7	3.86
std_ic_t2f_mou_7	3.86
roam_ic_mou_7	3.86
std_ic_t2m_mou_7	3.86
offnet_mou_7	3.86
std_og_mou_7	3.86
std_ic_mou_7	3.86
loc_og_t2f_mou_7	3.86
loc_ic_mou_7	3.86
roam_og_mou_7	3.86
loc_og_t2m_mou_7	3.86
loc_ic_t2f_mou_7	3.86
std_og_t2f_mou_7	3.86
std_ic_t2t_mou_7	3.86
loc_og_t2c_mou_7	3.86
isd_ic_mou_7	3.86

loc_og_mou_7	3.86
loc_og_t2t_mou_7	3.86
ic_others_7	3.86
std_og_t2t_mou_7	3.86
spl_og_mou_7	3.86
loc_ic_t2m_mou_7	3.86
og_others_7	3.86
spl_ic_mou_7	3.86
loc_ic_t2t_mou_7	3.86
onnet_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
arpu_8	0.00
arpu_9	0.00
arpu_7	0.00
arpu_6	0.00
total_og_mou_9	0.00
total_og_mou_8	0.00
total_og_mou_7	0.00
total_og_mou_6	0.00
sep_vbc_3g	0.00
jun_vbc_3g	0.00
arpu_2g_6	0.00
monthly_2g_7	0.00
monthly_2g_6	0.00
night_pck_user_9	0.00
night_pck_user_7	0.00
night_pck_user_6	0.00
arpu_2g_9	0.00
arpu_2g_7	0.00
arpu_3g_9	0.00
monthly_2g_9	0.00
arpu_3g_7	0.00
arpu_3g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
vol_3g_mb_7	0.00
vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
monthly_2g_8	0.00
sachet_2g_6	0.00
vol_2g_mb_7	0.00
sachet_3g_8	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_9	0.00

fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_7	0.00
sachet_2g_7	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
vol_2g_mb_8	0.00
vol_2g_mb_6	0.00
total_ic_mou_6	0.00
total_rech_amt_7	0.00
last_day_rch_amt_6	0.00
max_rech_amt_9	0.00
max_rech_amt_8	0.00
max_rech_amt_7	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_6	0.00
last_day_rch_amt_8	0.00
total_rech_num_9	0.00
total_rech_num_8	0.00
total_rech_num_7	0.00
total_rech_num_6	0.00
total_ic_mou_9	0.00
total_ic_mou_8	0.00
total_ic_mou_7	0.00
last_day_rch_amt_7	0.00
last_day_rch_amt_9	0.00
av_rech_amt_data_9	0.00
count_rech_2g_6	0.00
av_rech_amt_data_7	0.00
av_rech_amt_data_6	0.00
count_rech_3g_9	0.00
count_rech_3g_7	0.00
count_rech_3g_6	0.00
count_rech_2g_9	0.00
count_rech_2g_7	0.00
max_rech_data_9	0.00
date_of_last_rech_data_6	0.00
max_rech_data_7	0.00
max_rech_data_6	0.00
total_rech_data_9	0.00

total_rech_data_7   0.00
total_rech_data_6   0.00
date_of_last_rech_data_9   0.00
date_of_last_rech_data_7   0.00
mobile_number   0.00
dtype: float64*#bunching the August month columns together with same percentage of missing values*

```
cols_aug = ['arpu_2g_8', 'date_of_last_rech_data_8', 'arpu_3g_8',
     'night_pck_user_8', 'fb_user_8', 'av_rech_amt_data_8',
     'count_rech_3g_8', 'count_rech_2g_8', 'max_rech_data_8',
     'total_rech_data_8']
```

Here as well, let's check whether all the columns above have occurrences of **NAN** at the same instances.

```
for i in cols_aug:
   print(sum(df['date_of_last_rech_data_8'].isnull()!=df[i].isnull()))0
0
0
0
0
0
0
0
0
0
```

NAN occurring at the exact same instances for all the above bunched columns. From above also, we notice that in the absence of data recharge (date_of_last_rech_data_8) done for that particular month, user is not using corresponding internet related services, which is understandable. Hence we should impute these **NAN** values with **0**.

```
for i in cols_aug:
   df[i] = df[i].apply(nan_to_zero)#check against for missing values
check_missing(df)std_ic_mou_9             7.75
spl_og_mou_9             7.75
roam_og_mou_9            7.75
loc_ic_t2m_mou_9         7.75
loc_og_t2t_mou_9         7.75
loc_ic_t2t_mou_9         7.75
og_others_9              7.75
loc_og_t2m_mou_9         7.75
loc_og_t2f_mou_9         7.75
isd_ic_mou_9             7.75
isd_og_mou_9             7.75
std_og_mou_9             7.75
loc_og_t2c_mou_9         7.75
std_og_t2f_mou_9         7.75
std_og_t2m_mou_9         7.75
loc_og_mou_9             7.75
```

ic_others_9	7.75
std_og_t2t_mou_9	7.75
roam_ic_mou_9	7.75
offnet_mou_9	7.75
std_ic_t2t_mou_9	7.75
std_ic_t2m_mou_9	7.75
std_ic_t2f_mou_9	7.75
loc_ic_mou_9	7.75
loc_ic_t2f_mou_9	7.75
onnet_mou_9	7.75
spl_ic_mou_9	7.75
loc_ic_t2m_mou_8	5.38
loc_ic_t2t_mou_8	5.38
std_og_t2m_mou_8	5.38
std_ic_t2t_mou_8	5.38
isd_ic_mou_8	5.38
std_og_t2f_mou_8	5.38
std_ic_t2m_mou_8	5.38
std_og_mou_8	5.38
std_ic_t2f_mou_8	5.38
std_og_t2t_mou_8	5.38
std_ic_mou_8	5.38
spl_og_mou_8	5.38
ic_others_8	5.38
og_others_8	5.38
spl_ic_mou_8	5.38
loc_ic_mou_8	5.38
loc_ic_t2f_mou_8	5.38
isd_og_mou_8	5.38
loc_og_t2c_mou_8	5.38
roam_og_mou_8	5.38
loc_og_t2m_mou_8	5.38
loc_og_mou_8	5.38
roam_ic_mou_8	5.38
loc_og_t2f_mou_8	5.38
loc_og_t2t_mou_8	5.38
onnet_mou_8	5.38
offnet_mou_8	5.38
date_of_last_rech_9	4.76
spl_ic_mou_6	3.94
offnet_mou_6	3.94
loc_ic_mou_6	3.94
loc_ic_t2m_mou_6	3.94
loc_ic_t2t_mou_6	3.94
roam_ic_mou_6	3.94
loc_og_t2m_mou_6	3.94
std_og_t2m_mou_6	3.94
isd_ic_mou_6	3.94

loc_ic_t2f_mou_6	3.94
loc_og_t2t_mou_6	3.94
ic_others_6	3.94
loc_og_t2f_mou_6	3.94
og_others_6	3.94
isd_og_mou_6	3.94
std_ic_t2m_mou_6	3.94
std_og_t2t_mou_6	3.94
std_og_t2f_mou_6	3.94
std_ic_t2f_mou_6	3.94
loc_og_mou_6	3.94
std_og_mou_6	3.94
onnet_mou_6	3.94
std_ic_t2t_mou_6	3.94
loc_og_t2c_mou_6	3.94
spl_og_mou_6	3.94
std_ic_mou_6	3.94
roam_og_mou_6	3.94
spl_ic_mou_7	3.86
onnet_mou_7	3.86
std_ic_mou_7	3.86
roam_ic_mou_7	3.86
std_ic_t2f_mou_7	3.86
isd_ic_mou_7	3.86
std_ic_t2m_mou_7	3.86
loc_ic_mou_7	3.86
offnet_mou_7	3.86
std_og_t2t_mou_7	3.86
ic_others_7	3.86
roam_og_mou_7	3.86
std_og_t2m_mou_7	3.86
std_og_t2f_mou_7	3.86
loc_og_mou_7	3.86
std_og_mou_7	3.86
loc_og_t2c_mou_7	3.86
isd_og_mou_7	3.86
spl_og_mou_7	3.86
loc_og_t2f_mou_7	3.86
og_others_7	3.86
loc_og_t2m_mou_7	3.86
loc_ic_t2t_mou_7	3.86
loc_ic_t2f_mou_7	3.86
loc_og_t2t_mou_7	3.86
loc_ic_t2m_mou_7	3.86
std_ic_t2t_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61

total_og_mou_9	0.00
total_og_mou_7	0.00
arpu_9	0.00
arpu_8	0.00
total_og_mou_6	0.00
arpu_7	0.00
arpu_6	0.00
total_og_mou_8	0.00
sep_vbc_3g	0.00
jun_vbc_3g	0.00
vol_2g_mb_6	0.00
monthly_2g_6	0.00
night_pck_user_9	0.00
night_pck_user_8	0.00
night_pck_user_7	0.00
night_pck_user_6	0.00
arpu_2g_9	0.00
arpu_2g_8	0.00
arpu_2g_7	0.00
arpu_2g_6	0.00
arpu_3g_9	0.00
arpu_3g_8	0.00
arpu_3g_7	0.00
arpu_3g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
vol_3g_mb_7	0.00
vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_8	0.00
monthly_2g_7	0.00
monthly_2g_8	0.00
monthly_2g_9	0.00
sachet_3g_8	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_9	0.00
fb_user_8	0.00
fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_7	0.00
sachet_2g_6	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00

monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
vol_2g_mb_7	0.00
av_rech_amt_data_9	0.00
total_ic_mou_6	0.00
av_rech_amt_data_8	0.00
last_day_rch_amt_9	0.00
last_day_rch_amt_8	0.00
last_day_rch_amt_7	0.00
last_day_rch_amt_6	0.00
max_rech_amt_9	0.00
max_rech_amt_8	0.00
max_rech_amt_7	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_7	0.00
total_rech_amt_6	0.00
total_rech_num_9	0.00
total_rech_num_8	0.00
total_rech_num_7	0.00
total_rech_num_6	0.00
total_ic_mou_9	0.00
total_ic_mou_8	0.00
total_ic_mou_7	0.00
date_of_last_rech_data_6	0.00
date_of_last_rech_data_7	0.00
date_of_last_rech_data_8	0.00
count_rech_2g_7	0.00
av_rech_amt_data_7	0.00
av_rech_amt_data_6	0.00
count_rech_3g_9	0.00
count_rech_3g_8	0.00
count_rech_3g_7	0.00
count_rech_3g_6	0.00
count_rech_2g_9	0.00
count_rech_2g_8	0.00
count_rech_2g_6	0.00
date_of_last_rech_data_9	0.00
max_rech_data_9	0.00
max_rech_data_8	0.00
max_rech_data_7	0.00
max_rech_data_6	0.00
total_rech_data_9	0.00
total_rech_data_8	0.00
total_rech_data_7	0.00

total_rech_data_6   0.00
mobile_number   0.00
dtype: float64

Here, we notice that for 4.76% of the rows, date_of_last_rech_9 is NAN which means voice service recharge have note been done for September month for those cases. However, there are 7.75% of the cases where NAN values are there for September month, which seems erroneous.

Let's do further analysis.

Lets impute NAN in date_of_last_rech_9 column with 0, as the same depicts absence of voice service recharge.

df['date_of_last_rech_9'] = df['date_of_last_rech_9'].apply(nan_to_zero)

It is understood that if a customer has not recharged (for voice services) for a certain month and hence is not using services for that particular month. So, we need to convert corresponding those NAN values with 0.

Let's gather all the September columns with missing values.

cols_sep_2 = ['std_ic_mou_9',
 'spl_og_mou_9',
 'loc_ic_t2f_mou_9',
 'roam_og_mou_9',
 'loc_ic_t2t_mou_9',
 'loc_og_t2t_mou_9',
 'og_others_9',
 'loc_og_t2m_mou_9',
 'isd_og_mou_9',
 'roam_ic_mou_9',
 'loc_og_t2f_mou_9',
 'std_og_mou_9',
 'loc_og_t2c_mou_9',
 'std_og_t2f_mou_9',
 'std_og_t2m_mou_9',
 'loc_og_mou_9',
 'ic_others_9',
 'loc_ic_t2m_mou_9',
 'std_og_t2t_mou_9',
 'std_ic_t2t_mou_9',
 'offnet_mou_9',
 'spl_ic_mou_9',
 'std_ic_t2m_mou_9',
 'std_ic_t2f_mou_9',
 'onnet_mou_9',
 'isd_ic_mou_9',
 'loc_ic_mou_9']*#convert those NAN values in cols_sep_2 to 0, where the corresponding recharges (date_of_last_rech_9) have not been done.*ref = df['date_of_last_rech_9'].values**for** col **in** cols_sep_2:
    piv = df[col].values

```
    for i,j in enumerate(piv):
        if ref[i]==0 and str(piv[i])=='nan':
            piv[i]=0
    df[col]=piv#check again for the missing values
check_missing(df)std_ic_t2t_mou_8          5.38
spl_og_mou_8             5.38
og_others_8              5.38
loc_og_t2m_mou_8         5.38
loc_ic_t2t_mou_8         5.38
isd_og_mou_8             5.38
loc_og_t2t_mou_8         5.38
loc_ic_t2m_mou_8         5.38
std_og_t2t_mou_8         5.38
loc_ic_t2f_mou_8         5.38
roam_og_mou_8            5.38
loc_og_t2c_mou_8         5.38
ic_others_8              5.38
roam_ic_mou_8            5.38
std_og_mou_8             5.38
isd_ic_mou_8             5.38
offnet_mou_8             5.38
spl_ic_mou_8             5.38
loc_ic_mou_8             5.38
std_og_t2f_mou_8         5.38
onnet_mou_8              5.38
std_ic_mou_8             5.38
loc_og_mou_8             5.38
std_ic_t2f_mou_8         5.38
std_ic_t2m_mou_8         5.38
std_og_t2m_mou_8         5.38
loc_og_t2f_mou_8         5.38
std_og_t2f_mou_9         4.86
std_og_mou_9             4.86
std_og_t2m_mou_9         4.86
isd_og_mou_9             4.86
loc_ic_t2m_mou_9         4.86
spl_og_mou_9             4.86
og_others_9              4.86
loc_ic_t2t_mou_9         4.86
loc_ic_t2f_mou_9         4.86
ic_others_9              4.86
isd_ic_mou_9             4.86
spl_ic_mou_9             4.86
loc_ic_mou_9             4.86
std_ic_t2f_mou_9         4.86
std_ic_t2m_mou_9         4.86
std_ic_t2t_mou_9         4.86
std_og_t2t_mou_9         4.86
```

std_ic_mou_9	4.86
loc_og_t2m_mou_9	4.86
loc_og_t2c_mou_9	4.86
roam_og_mou_9	4.86
loc_og_t2t_mou_9	4.86
offnet_mou_9	4.86
onnet_mou_9	4.86
loc_og_t2f_mou_9	4.86
roam_ic_mou_9	4.86
loc_og_mou_9	4.86
loc_og_mou_6	3.94
offnet_mou_6	3.94
roam_og_mou_6	3.94
std_ic_t2m_mou_6	3.94
roam_ic_mou_6	3.94
loc_ic_t2f_mou_6	3.94
loc_og_t2t_mou_6	3.94
std_og_t2m_mou_6	3.94
loc_ic_t2m_mou_6	3.94
std_og_t2t_mou_6	3.94
loc_og_t2m_mou_6	3.94
isd_ic_mou_6	3.94
loc_ic_t2t_mou_6	3.94
spl_ic_mou_6	3.94
std_og_mou_6	3.94
loc_ic_mou_6	3.94
std_og_t2f_mou_6	3.94
loc_og_t2f_mou_6	3.94
std_ic_t2f_mou_6	3.94
onnet_mou_6	3.94
isd_og_mou_6	3.94
std_ic_mou_6	3.94
loc_og_t2c_mou_6	3.94
spl_og_mou_6	3.94
og_others_6	3.94
std_ic_t2t_mou_6	3.94
ic_others_6	3.94
onnet_mou_7	3.86
std_ic_mou_7	3.86
loc_ic_mou_7	3.86
std_ic_t2m_mou_7	3.86
isd_ic_mou_7	3.86
offnet_mou_7	3.86
spl_ic_mou_7	3.86
roam_ic_mou_7	3.86
std_ic_t2f_mou_7	3.86
std_og_t2t_mou_7	3.86
loc_ic_t2m_mou_7	3.86

ic_others_7	3.86
loc_og_t2m_mou_7	3.86
std_og_t2m_mou_7	3.86
std_og_t2f_mou_7	3.86
loc_og_mou_7	3.86
std_og_mou_7	3.86
loc_og_t2c_mou_7	3.86
std_ic_t2t_mou_7	3.86
spl_og_mou_7	3.86
loc_og_t2f_mou_7	3.86
roam_og_mou_7	3.86
og_others_7	3.86
loc_ic_t2t_mou_7	3.86
loc_og_t2t_mou_7	3.86
loc_ic_t2f_mou_7	3.86
isd_og_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
total_og_mou_6	0.00
total_og_mou_7	0.00
total_og_mou_8	0.00
total_og_mou_9	0.00
arpu_9	0.00
arpu_8	0.00
arpu_7	0.00
arpu_6	0.00
sep_vbc_3g	0.00
jun_vbc_3g	0.00
monthly_2g_7	0.00
night_pck_user_9	0.00
night_pck_user_8	0.00
night_pck_user_7	0.00
night_pck_user_6	0.00
arpu_2g_9	0.00
arpu_2g_8	0.00
arpu_2g_7	0.00
arpu_2g_6	0.00
arpu_3g_9	0.00
arpu_3g_8	0.00
arpu_3g_7	0.00
arpu_3g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
vol_3g_mb_7	0.00
vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_8	0.00

vol_2g_mb_7	0.00
monthly_2g_6	0.00
monthly_2g_8	0.00
total_ic_mou_6	0.00
monthly_2g_9	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_9	0.00
fb_user_8	0.00
fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_8	0.00
sachet_3g_7	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_9	0.00
av_rech_amt_data_8	0.00
av_rech_amt_data_7	0.00
last_day_rch_amt_8	0.00
last_day_rch_amt_7	0.00
last_day_rch_amt_6	0.00
date_of_last_rech_9	0.00
max_rech_amt_9	0.00
max_rech_amt_8	0.00
max_rech_amt_7	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_7	0.00
total_rech_amt_6	0.00
total_rech_num_9	0.00
total_rech_num_8	0.00
total_rech_num_7	0.00
total_rech_num_6	0.00
total_ic_mou_9	0.00
total_ic_mou_8	0.00
total_ic_mou_7	0.00
last_day_rch_amt_9	0.00

```
date_of_last_rech_data_6    0.00
date_of_last_rech_data_7    0.00
count_rech_2g_6             0.00
av_rech_amt_data_6          0.00
count_rech_3g_9             0.00
count_rech_3g_8             0.00
count_rech_3g_7             0.00
count_rech_3g_6             0.00
count_rech_2g_9             0.00
count_rech_2g_8             0.00
count_rech_2g_7             0.00
max_rech_data_9             0.00
date_of_last_rech_data_8    0.00
max_rech_data_8             0.00
max_rech_data_7             0.00
max_rech_data_6             0.00
total_rech_data_9           0.00
total_rech_data_8           0.00
total_rech_data_7           0.00
total_rech_data_6           0.00
date_of_last_rech_data_9    0.00
mobile_number               0.00
dtype: float64
```

We are still left with 4.86% of the data which are 'nan', in the columns of September month. That means customers have recharged but have not used the services during that particular month. The same may be special group of customers with high churn. So let's not drop them and instead impute their NAN values with zero, as of now.

```
for col in cols_sep_2:
    df[col]=df[col].apply(nan_to_zero)#check again for missing values
check_missing(df)std_og_t2m_mou_8          5.38
roam_ic_mou_8             5.38
og_others_8               5.38
loc_og_t2f_mou_8          5.38
loc_og_mou_8              5.38
loc_og_t2m_mou_8          5.38
ic_others_8               5.38
loc_ic_t2f_mou_8          5.38
std_ic_t2t_mou_8          5.38
loc_og_t2t_mou_8          5.38
std_og_t2t_mou_8          5.38
roam_og_mou_8             5.38
loc_ic_t2t_mou_8          5.38
loc_og_t2c_mou_8          5.38
std_ic_mou_8              5.38
isd_ic_mou_8              5.38
spl_ic_mou_8              5.38
spl_og_mou_8              5.38
```

isd_og_mou_8	5.38
std_ic_t2f_mou_8	5.38
std_ic_t2m_mou_8	5.38
std_og_mou_8	5.38
onnet_mou_8	5.38
loc_ic_t2m_mou_8	5.38
loc_ic_mou_8	5.38
offnet_mou_8	5.38
std_og_t2f_mou_8	5.38
std_og_mou_6	3.94
std_og_t2m_mou_6	3.94
std_og_t2f_mou_6	3.94
og_others_6	3.94
std_og_t2t_mou_6	3.94
spl_ic_mou_6	3.94
isd_og_mou_6	3.94
loc_og_mou_6	3.94
ic_others_6	3.94
isd_ic_mou_6	3.94
loc_ic_mou_6	3.94
std_ic_mou_6	3.94
onnet_mou_6	3.94
loc_ic_t2m_mou_6	3.94
std_ic_t2m_mou_6	3.94
roam_ic_mou_6	3.94
loc_og_t2c_mou_6	3.94
roam_og_mou_6	3.94
loc_ic_t2f_mou_6	3.94
loc_og_t2t_mou_6	3.94
loc_ic_t2t_mou_6	3.94
loc_og_t2m_mou_6	3.94
std_ic_t2f_mou_6	3.94
loc_og_t2f_mou_6	3.94
spl_og_mou_6	3.94
std_ic_t2t_mou_6	3.94
offnet_mou_6	3.94
spl_og_mou_7	3.86
loc_ic_mou_7	3.86
loc_ic_t2m_mou_7	3.86
isd_ic_mou_7	3.86
loc_ic_t2t_mou_7	3.86
og_others_7	3.86
ic_others_7	3.86
std_ic_t2m_mou_7	3.86
std_og_t2t_mou_7	3.86
isd_og_mou_7	3.86
loc_og_t2m_mou_7	3.86
std_ic_t2f_mou_7	3.86

onnet_mou_7	3.86
offnet_mou_7	3.86
std_ic_mou_7	3.86
roam_ic_mou_7	3.86
roam_og_mou_7	3.86
loc_og_t2t_mou_7	3.86
std_og_mou_7	3.86
loc_ic_t2f_mou_7	3.86
std_ic_t2t_mou_7	3.86
loc_og_t2f_mou_7	3.86
loc_og_t2c_mou_7	3.86
loc_og_mou_7	3.86
spl_ic_mou_7	3.86
std_og_t2m_mou_7	3.86
std_og_t2f_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
std_ic_t2t_mou_9	0.00
loc_ic_mou_9	0.00
loc_ic_t2f_mou_9	0.00
sep_vbc_3g	0.00
loc_ic_t2m_mou_9	0.00
loc_ic_t2t_mou_9	0.00
arpu_6	0.00
arpu_7	0.00
arpu_8	0.00
arpu_9	0.00
onnet_mou_9	0.00
offnet_mou_9	0.00
roam_ic_mou_9	0.00
roam_og_mou_9	0.00
loc_og_t2t_mou_9	0.00
loc_og_t2m_mou_9	0.00
loc_og_t2f_mou_9	0.00
loc_og_t2c_mou_9	0.00
loc_og_mou_9	0.00
std_og_t2t_mou_9	0.00
std_og_t2m_mou_9	0.00
std_og_t2f_mou_9	0.00
isd_og_mou_9	0.00
spl_og_mou_9	0.00
og_others_9	0.00
total_og_mou_6	0.00
total_og_mou_7	0.00
total_og_mou_8	0.00
total_og_mou_9	0.00
std_og_mou_9	0.00

std_ic_mou_9	0.00
std_ic_t2m_mou_9	0.00
arpu_3g_7	0.00
night_pck_user_8	0.00
night_pck_user_7	0.00
night_pck_user_6	0.00
arpu_2g_9	0.00
arpu_2g_8	0.00
arpu_2g_7	0.00
arpu_2g_6	0.00
arpu_3g_9	0.00
arpu_3g_8	0.00
arpu_3g_6	0.00
monthly_2g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
vol_3g_mb_7	0.00
vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_8	0.00
vol_2g_mb_7	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_9	0.00
night_pck_user_9	0.00
monthly_2g_7	0.00
av_rech_amt_data_7	0.00
sachet_3g_7	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_9	0.00
fb_user_8	0.00
fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_8	0.00
sachet_3g_6	0.00
monthly_2g_8	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00
monthly_2g_9	0.00
av_rech_amt_data_8	0.00

av_rech_amt_data_6	0.00
std_ic_t2f_mou_9	0.00
total_rech_num_8	0.00
max_rech_amt_9	0.00
max_rech_amt_8	0.00
max_rech_amt_7	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_7	0.00
total_rech_amt_6	0.00
total_rech_num_9	0.00
total_rech_num_7	0.00
last_day_rch_amt_6	0.00
total_rech_num_6	0.00
ic_others_9	0.00
isd_ic_mou_9	0.00
spl_ic_mou_9	0.00
total_ic_mou_9	0.00
total_ic_mou_8	0.00
total_ic_mou_7	0.00
total_ic_mou_6	0.00
jun_vbc_3g	0.00
date_of_last_rech_9	0.00
last_day_rch_amt_7	0.00
count_rech_3g_9	0.00
max_rech_data_7	0.00
count_rech_3g_8	0.00
count_rech_3g_7	0.00
count_rech_3g_6	0.00
count_rech_2g_9	0.00
count_rech_2g_8	0.00
count_rech_2g_7	0.00
count_rech_2g_6	0.00
max_rech_data_9	0.00
max_rech_data_8	0.00
max_rech_data_6	0.00
last_day_rch_amt_8	0.00
total_rech_data_9	0.00
total_rech_data_8	0.00
total_rech_data_7	0.00
total_rech_data_6	0.00
date_of_last_rech_data_9	0.00
date_of_last_rech_data_8	0.00
date_of_last_rech_data_7	0.00
date_of_last_rech_data_6	0.00
last_day_rch_amt_9	0.00

mobile_number 0.00
dtype: float64

Let’s do the similar exercise for the month of August as well.

df.date_of_last_rech_8.isnull().sum()3622

From above, we notice that there are certain customers who have not done voice service recharge for the month of August. Let’s replace the corresponding NAN values with 0.

df.date_of_last_rech_8 = df.date_of_last_rech_8.apply(nan_to_zero)

Gathering the columns of August with NAN values.

```
cols_aug_2 = ['std_og_mou_8',
 'roam_ic_mou_8',
 'loc_og_t2f_mou_8',
 'loc_og_t2m_mou_8',
 'og_others_8',
 'isd_og_mou_8',
 'loc_ic_t2t_mou_8',
 'loc_og_t2t_mou_8',
 'loc_ic_t2m_mou_8',
 'std_og_t2t_mou_8',
 'roam_og_mou_8',
 'loc_ic_t2f_mou_8',
 'std_ic_t2m_mou_8',
 'ic_others_8',
 'loc_og_t2c_mou_8',
 'loc_ic_mou_8',
 'isd_ic_mou_8',
 'offnet_mou_8',
 'spl_ic_mou_8',
 'std_og_t2f_mou_8',
 'onnet_mou_8',
 'std_ic_t2t_mou_8',
 'loc_og_mou_8',
 'std_ic_mou_8',
 'std_og_t2m_mou_8',
 'std_ic_t2f_mou_8',
 'spl_og_mou_8']#convert those NAN values in cols_aug_2 to 0, where the corresponding recharges (date_of_last_rech_8) have not been done.ref = df['date_of_last_rech_8'].valuesfor col in cols_aug_2:
    piv = df[col].values
    for i,j in enumerate(piv):
        if ref[i]==0 and str(piv[i])=='nan':
            piv[i]=0
    df[col]=piv#check for missing values
check_missing(df)std_ic_t2f_mou_6          3.94
loc_ic_t2m_mou_6          3.94
```

std_og_t2m_mou_6	3.94
loc_og_t2m_mou_6	3.94
isd_ic_mou_6	3.94
std_og_t2t_mou_6	3.94
loc_ic_t2f_mou_6	3.94
loc_og_t2t_mou_6	3.94
std_og_t2f_mou_6	3.94
spl_ic_mou_6	3.94
loc_og_mou_6	3.94
roam_og_mou_6	3.94
std_ic_t2t_mou_6	3.94
og_others_6	3.94
roam_ic_mou_6	3.94
std_og_mou_6	3.94
std_ic_t2m_mou_6	3.94
ic_others_6	3.94
offnet_mou_6	3.94
loc_og_t2c_mou_6	3.94
isd_og_mou_6	3.94
loc_ic_mou_6	3.94
onnet_mou_6	3.94
std_ic_mou_6	3.94
loc_ic_t2t_mou_6	3.94
spl_og_mou_6	3.94
loc_og_t2f_mou_6	3.94
std_og_t2t_mou_7	3.86
loc_ic_mou_7	3.86
std_og_t2f_mou_7	3.86
loc_ic_t2f_mou_7	3.86
std_og_t2m_mou_7	3.86
loc_ic_t2m_mou_7	3.86
std_og_mou_7	3.86
loc_ic_t2t_mou_7	3.86
isd_og_mou_7	3.86
spl_og_mou_7	3.86
loc_og_mou_7	3.86
og_others_7	3.86
std_ic_t2t_mou_7	3.86
std_ic_t2m_mou_7	3.86
offnet_mou_7	3.86
onnet_mou_7	3.86
roam_ic_mou_7	3.86
ic_others_7	3.86
roam_og_mou_7	3.86
spl_ic_mou_7	3.86
loc_og_t2t_mou_7	3.86
loc_og_t2m_mou_7	3.86
isd_ic_mou_7	3.86

std_ic_t2f_mou_7	3.86
loc_og_t2f_mou_7	3.86
loc_og_t2c_mou_7	3.86
std_ic_mou_7	3.86
std_ic_mou_8	3.40
og_others_8	3.40
std_ic_t2f_mou_8	3.40
ic_others_8	3.40
loc_ic_t2t_mou_8	3.40
std_ic_t2t_mou_8	3.40
loc_ic_t2m_mou_8	3.40
spl_ic_mou_8	3.40
loc_ic_t2f_mou_8	3.40
isd_ic_mou_8	3.40
loc_ic_mou_8	3.40
std_og_mou_8	3.40
loc_og_mou_8	3.40
std_ic_t2m_mou_8	3.40
loc_og_t2c_mou_8	3.40
spl_og_mou_8	3.40
loc_og_t2t_mou_8	3.40
std_og_t2t_mou_8	3.40
roam_og_mou_8	3.40
std_og_t2m_mou_8	3.40
roam_ic_mou_8	3.40
std_og_t2f_mou_8	3.40
loc_og_t2m_mou_8	3.40
loc_og_t2f_mou_8	3.40
offnet_mou_8	3.40
isd_og_mou_8	3.40
onnet_mou_8	3.40
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
std_ic_t2t_mou_9	0.00
roam_ic_mou_9	0.00
onnet_mou_9	0.00
arpu_9	0.00
roam_og_mou_9	0.00
arpu_8	0.00
arpu_7	0.00
loc_ic_mou_9	0.00
arpu_6	0.00
loc_og_t2t_mou_9	0.00
offnet_mou_9	0.00
spl_og_mou_9	0.00
loc_og_t2m_mou_9	0.00
loc_og_t2f_mou_9	0.00
isd_og_mou_9	0.00

og_others_9	0.00
total_og_mou_6	0.00
total_og_mou_7	0.00
total_og_mou_8	0.00
total_og_mou_9	0.00
std_og_mou_9	0.00
loc_ic_t2t_mou_9	0.00
std_og_t2f_mou_9	0.00
std_og_t2m_mou_9	0.00
loc_ic_t2m_mou_9	0.00
std_og_t2t_mou_9	0.00
loc_ic_t2f_mou_9	0.00
loc_og_mou_9	0.00
loc_og_t2c_mou_9	0.00
sep_vbc_3g	0.00
std_ic_mou_9	0.00
std_ic_t2m_mou_9	0.00
std_ic_t2f_mou_9	0.00
night_pck_user_8	0.00
night_pck_user_7	0.00
night_pck_user_6	0.00
arpu_2g_9	0.00
arpu_2g_8	0.00
arpu_2g_7	0.00
arpu_2g_6	0.00
arpu_3g_9	0.00
arpu_3g_8	0.00
arpu_3g_7	0.00
arpu_3g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
vol_3g_mb_7	0.00
vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_8	0.00
vol_2g_mb_7	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_9	0.00
av_rech_amt_data_8	0.00
night_pck_user_9	0.00
monthly_2g_6	0.00
monthly_2g_7	0.00
sachet_3g_7	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_9	0.00
fb_user_8	0.00

fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_8	0.00
sachet_3g_6	0.00
monthly_2g_8	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00
monthly_2g_9	0.00
av_rech_amt_data_7	0.00
av_rech_amt_data_6	0.00
count_rech_3g_9	0.00
total_rech_num_8	0.00
max_rech_amt_9	0.00
max_rech_amt_8	0.00
max_rech_amt_7	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_7	0.00
total_rech_amt_6	0.00
total_rech_num_9	0.00
total_rech_num_7	0.00
date_of_last_rech_9	0.00
total_rech_num_6	0.00
ic_others_9	0.00
isd_ic_mou_9	0.00
spl_ic_mou_9	0.00
total_ic_mou_9	0.00
total_ic_mou_8	0.00
total_ic_mou_7	0.00
total_ic_mou_6	0.00
jun_vbc_3g	0.00
date_of_last_rech_8	0.00
last_day_rch_amt_6	0.00
count_rech_3g_8	0.00
max_rech_data_6	0.00
count_rech_3g_7	0.00
count_rech_3g_6	0.00
count_rech_2g_9	0.00
count_rech_2g_8	0.00
count_rech_2g_7	0.00

count_rech_2g_6   0.00
max_rech_data_9   0.00
max_rech_data_8   0.00
max_rech_data_7   0.00
total_rech_data_9   0.00
last_day_rch_amt_7   0.00
total_rech_data_8   0.00
total_rech_data_7   0.00
total_rech_data_6   0.00
date_of_last_rech_data_9   0.00
date_of_last_rech_data_8   0.00
date_of_last_rech_data_7   0.00
date_of_last_rech_data_6   0.00
last_day_rch_amt_9   0.00
last_day_rch_amt_8   0.00
mobile_number   0.00
dtype: float64

We are still left with 3.40% of the data which are 'nan', in the columns of August month. That means customers have recharged but have not used the services during that particular month. The same may be special group of customers with high churn. So let's not drop them and instead impute their NAN values with zero, as of now.

```
for col in cols_aug_2:
    df[col] = df[col].apply(nan_to_zero)#check for missing values
check_missing(df)std_og_t2t_mou_6          3.94
og_others_6              3.94
loc_ic_t2t_mou_6         3.94
spl_og_mou_6             3.94
loc_og_t2m_mou_6         3.94
loc_ic_t2m_mou_6         3.94
loc_og_t2c_mou_6         3.94
loc_ic_t2f_mou_6         3.94
loc_og_t2t_mou_6         3.94
std_og_t2m_mou_6         3.94
loc_ic_mou_6             3.94
roam_og_mou_6            3.94
isd_og_mou_6             3.94
ic_others_6              3.94
std_ic_t2t_mou_6         3.94
roam_ic_mou_6            3.94
std_og_mou_6             3.94
isd_ic_mou_6             3.94
loc_og_mou_6             3.94
offnet_mou_6             3.94
spl_ic_mou_6             3.94
std_ic_t2m_mou_6         3.94
onnet_mou_6              3.94
std_og_t2f_mou_6         3.94
```

std_ic_t2f_mou_6	3.94
std_ic_mou_6	3.94
loc_og_t2f_mou_6	3.94
isd_og_mou_7	3.86
std_og_t2f_mou_7	3.86
std_og_t2m_mou_7	3.86
spl_og_mou_7	3.86
std_og_mou_7	3.86
og_others_7	3.86
loc_ic_t2t_mou_7	3.86
loc_ic_t2m_mou_7	3.86
loc_ic_mou_7	3.86
ic_others_7	3.86
isd_ic_mou_7	3.86
std_ic_t2t_mou_7	3.86
spl_ic_mou_7	3.86
std_ic_t2m_mou_7	3.86
std_ic_mou_7	3.86
loc_ic_t2f_mou_7	3.86
std_ic_t2f_mou_7	3.86
loc_og_t2m_mou_7	3.86
loc_og_mou_7	3.86
roam_ic_mou_7	3.86
offnet_mou_7	3.86
loc_og_t2c_mou_7	3.86
roam_og_mou_7	3.86
loc_og_t2t_mou_7	3.86
onnet_mou_7	3.86
std_og_t2t_mou_7	3.86
loc_og_t2f_mou_7	3.86
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
roam_og_mou_9	0.00
roam_ic_mou_8	0.00
loc_ic_t2f_mou_8	0.00
loc_ic_t2f_mou_9	0.00
roam_og_mou_8	0.00
loc_ic_t2m_mou_9	0.00
loc_ic_t2m_mou_8	0.00
loc_ic_mou_8	0.00
roam_ic_mou_9	0.00
offnet_mou_9	0.00
loc_ic_mou_9	0.00
loc_og_t2t_mou_9	0.00
offnet_mou_8	0.00
std_ic_t2t_mou_8	0.00
onnet_mou_9	0.00
onnet_mou_8	0.00

std_ic_t2t_mou_9	0.00
arpu_9	0.00
std_ic_t2m_mou_8	0.00
std_ic_t2m_mou_9	0.00
arpu_8	0.00
arpu_7	0.00
arpu_6	0.00
loc_og_t2t_mou_8	0.00
std_og_t2t_mou_8	0.00
loc_ic_t2t_mou_9	0.00
isd_og_mou_9	0.00
loc_og_mou_9	0.00
std_og_t2m_mou_8	0.00
std_og_t2m_mou_9	0.00
loc_og_mou_8	0.00
std_og_t2f_mou_8	0.00
std_og_t2f_mou_9	0.00
loc_og_t2c_mou_9	0.00
std_ic_t2f_mou_8	0.00
std_og_mou_8	0.00
std_og_mou_9	0.00
loc_og_t2c_mou_8	0.00
isd_og_mou_8	0.00
loc_og_t2f_mou_9	0.00
loc_ic_t2t_mou_8	0.00
loc_og_t2f_mou_8	0.00
spl_og_mou_8	0.00
spl_og_mou_9	0.00
loc_og_t2m_mou_9	0.00
og_others_8	0.00
og_others_9	0.00
total_og_mou_6	0.00
total_og_mou_7	0.00
total_og_mou_8	0.00
total_og_mou_9	0.00
loc_og_t2m_mou_8	0.00
std_og_t2t_mou_9	0.00
sep_vbc_3g	0.00
std_ic_mou_9	0.00
std_ic_t2f_mou_9	0.00
night_pck_user_9	0.00
night_pck_user_7	0.00
night_pck_user_6	0.00
arpu_2g_9	0.00
arpu_2g_8	0.00
arpu_2g_7	0.00
arpu_2g_6	0.00
arpu_3g_9	0.00

arpu_3g_8	0.00
arpu_3g_7	0.00
arpu_3g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
vol_3g_mb_7	0.00
vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_8	0.00
vol_2g_mb_7	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_9	0.00
av_rech_amt_data_8	0.00
av_rech_amt_data_7	0.00
night_pck_user_8	0.00
monthly_2g_6	0.00
count_rech_3g_9	0.00
monthly_2g_7	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_9	0.00
fb_user_8	0.00
fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_8	0.00
sachet_3g_7	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00
monthly_2g_9	0.00
monthly_2g_8	0.00
av_rech_amt_data_6	0.00
count_rech_3g_8	0.00
std_ic_mou_8	0.00
max_rech_amt_9	0.00
max_rech_amt_7	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_7	0.00

```
total_rech_amt_6         0.00
total_rech_num_9         0.00
total_rech_num_8         0.00
total_rech_num_7         0.00
total_rech_num_6         0.00
ic_others_9              0.00
ic_others_8              0.00
isd_ic_mou_9             0.00
isd_ic_mou_8             0.00
spl_ic_mou_9             0.00
spl_ic_mou_8             0.00
total_ic_mou_9           0.00
total_ic_mou_8           0.00
total_ic_mou_7           0.00
total_ic_mou_6           0.00
jun_vbc_3g               0.00
max_rech_amt_8           0.00
date_of_last_rech_8      0.00
count_rech_3g_7          0.00
date_of_last_rech_9      0.00
count_rech_3g_6          0.00
count_rech_2g_9          0.00
count_rech_2g_8          0.00
count_rech_2g_7          0.00
count_rech_2g_6          0.00
max_rech_data_9          0.00
max_rech_data_8          0.00
max_rech_data_7          0.00
max_rech_data_6          0.00
total_rech_data_9        0.00
total_rech_data_8        0.00
total_rech_data_7        0.00
total_rech_data_6        0.00
date_of_last_rech_data_9    0.00
date_of_last_rech_data_8    0.00
date_of_last_rech_data_7    0.00
date_of_last_rech_data_6    0.00
last_day_rch_amt_9       0.00
last_day_rch_amt_8       0.00
last_day_rch_amt_7       0.00
last_day_rch_amt_6       0.00
mobile_number            0.00
dtype: float64
```

From above, we notice that there are certain customers who have not done voice service recharge for the month of June. Let’s replace the corresponding NAN values with 0.

```
df['date_of_last_rech_6'] = df['date_of_last_rech_6'].apply(nan_to_zero)
```

Gathering columns of June month with missing values.

```
cols_june_2 = ['std_og_mou_6',
 'loc_og_t2t_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',
 'isd_og_mou_6',
 'spl_og_mou_6',
 'og_others_6',
 'loc_ic_t2t_mou_6',
 'loc_ic_t2m_mou_6',
 'loc_ic_t2f_mou_6',
 'loc_ic_mou_6',
 'ic_others_6',
 'std_ic_t2t_mou_6',
 'isd_ic_mou_6',
 'spl_ic_mou_6',
 'std_ic_t2m_mou_6',
 'std_ic_t2f_mou_6',
 'loc_og_t2m_mou_6',
 'std_ic_mou_6',
 'onnet_mou_6',
 'offnet_mou_6',
 'roam_og_mou_6',
 'roam_ic_mou_6']#convert those NAN values in cols_june_2 to 0, where the corresponding recharges (date_of_last_rech_6) have not been done.
ref = df['date_of_last_rech_6'].valuesfor col in cols_june_2:
   piv = df[col].values
   for i,j in enumerate(piv):
      if ref[i]==0 and str(piv[i])=='nan':
         piv[i]=0
   df[col]=pivcheck_missing(df)loc_ic_t2f_mou_7          3.86
std_og_mou_7              3.86
spl_og_mou_7              3.86
loc_og_t2m_mou_7          3.86
loc_ic_t2t_mou_7          3.86
loc_ic_t2m_mou_7          3.86
loc_og_t2t_mou_7          3.86
isd_og_mou_7              3.86
std_og_t2t_mou_7          3.86
loc_og_t2c_mou_7          3.86
roam_og_mou_7             3.86
loc_ic_mou_7              3.86
ic_others_7               3.86
```

loc_og_t2f_mou_7	3.86
roam_ic_mou_7	3.86
std_ic_t2t_mou_7	3.86
isd_ic_mou_7	3.86
offnet_mou_7	3.86
std_og_t2f_mou_7	3.86
spl_ic_mou_7	3.86
loc_og_mou_7	3.86
onnet_mou_7	3.86
std_ic_t2m_mou_7	3.86
std_og_t2m_mou_7	3.86
std_ic_t2f_mou_7	3.86
std_ic_mou_7	3.86
og_others_7	3.86
isd_og_mou_6	3.16
std_og_t2f_mou_6	3.16
spl_og_mou_6	3.16
std_og_mou_6	3.16
og_others_6	3.16
loc_ic_t2t_mou_6	3.16
loc_ic_t2m_mou_6	3.16
loc_ic_t2f_mou_6	3.16
loc_ic_mou_6	3.16
ic_others_6	3.16
std_ic_t2t_mou_6	3.16
isd_ic_mou_6	3.16
spl_ic_mou_6	3.16
std_ic_t2m_mou_6	3.16
std_ic_t2f_mou_6	3.16
std_og_t2m_mou_6	3.16
std_ic_mou_6	3.16
loc_og_t2m_mou_6	3.16
loc_og_mou_6	3.16
loc_og_t2f_mou_6	3.16
offnet_mou_6	3.16
loc_og_t2c_mou_6	3.16
roam_og_mou_6	3.16
onnet_mou_6	3.16
loc_og_t2t_mou_6	3.16
std_og_t2t_mou_6	3.16
roam_ic_mou_6	3.16
date_of_last_rech_7	1.77
roam_og_mou_9	0.00
loc_ic_t2f_mou_8	0.00
roam_ic_mou_9	0.00
loc_ic_t2f_mou_9	0.00
roam_og_mou_8	0.00
loc_ic_mou_8	0.00

loc_ic_t2m_mou_9	0.00
loc_ic_t2m_mou_8	0.00
loc_ic_mou_9	0.00
offnet_mou_8	0.00
roam_ic_mou_8	0.00
offnet_mou_9	0.00
loc_og_t2t_mou_9	0.00
std_ic_t2t_mou_8	0.00
std_ic_t2t_mou_9	0.00
onnet_mou_9	0.00
onnet_mou_8	0.00
arpu_9	0.00
std_ic_t2m_mou_8	0.00
std_ic_t2m_mou_9	0.00
arpu_8	0.00
arpu_7	0.00
arpu_6	0.00
loc_og_t2t_mou_8	0.00
std_og_t2t_mou_8	0.00
loc_ic_t2t_mou_9	0.00
isd_og_mou_9	0.00
loc_og_mou_9	0.00
std_og_t2m_mou_8	0.00
std_og_t2m_mou_9	0.00
loc_og_mou_8	0.00
std_og_t2f_mou_8	0.00
std_og_t2f_mou_9	0.00
std_ic_t2f_mou_8	0.00
loc_og_t2c_mou_9	0.00
std_og_mou_8	0.00
std_og_mou_9	0.00
loc_og_t2c_mou_8	0.00
isd_og_mou_8	0.00
loc_og_t2f_mou_9	0.00
loc_ic_t2t_mou_8	0.00
loc_og_t2f_mou_8	0.00
spl_og_mou_8	0.00
spl_og_mou_9	0.00
loc_og_t2m_mou_9	0.00
og_others_8	0.00
og_others_9	0.00
total_og_mou_6	0.00
total_og_mou_7	0.00
total_og_mou_8	0.00
total_og_mou_9	0.00
loc_og_t2m_mou_8	0.00
std_og_t2t_mou_9	0.00
sep_vbc_3g	0.00

std_ic_mou_9	0.00
std_ic_t2f_mou_9	0.00
vol_3g_mb_9	0.00
night_pck_user_7	0.00
night_pck_user_6	0.00
arpu_2g_9	0.00
arpu_2g_8	0.00
arpu_2g_7	0.00
arpu_2g_6	0.00
arpu_3g_9	0.00
arpu_3g_8	0.00
arpu_3g_7	0.00
arpu_3g_6	0.00
vol_3g_mb_8	0.00
std_ic_mou_8	0.00
vol_3g_mb_7	0.00
vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_8	0.00
vol_2g_mb_7	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_9	0.00
av_rech_amt_data_8	0.00
av_rech_amt_data_7	0.00
av_rech_amt_data_6	0.00
night_pck_user_8	0.00
night_pck_user_9	0.00
monthly_2g_6	0.00
monthly_2g_7	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_9	0.00
fb_user_8	0.00
fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_8	0.00
sachet_3g_7	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00

monthly_2g_9	0.00
monthly_2g_8	0.00
count_rech_3g_9	0.00
count_rech_3g_8	0.00
count_rech_3g_7	0.00
max_rech_amt_9	0.00
max_rech_amt_7	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_7	0.00
total_rech_amt_6	0.00
total_rech_num_9	0.00
total_rech_num_8	0.00
total_rech_num_7	0.00
total_rech_num_6	0.00
ic_others_9	0.00
ic_others_8	0.00
isd_ic_mou_9	0.00
isd_ic_mou_8	0.00
spl_ic_mou_9	0.00
spl_ic_mou_8	0.00
total_ic_mou_9	0.00
total_ic_mou_8	0.00
total_ic_mou_7	0.00
total_ic_mou_6	0.00
jun_vbc_3g	0.00
max_rech_amt_8	0.00
date_of_last_rech_6	0.00
count_rech_3g_6	0.00
date_of_last_rech_8	0.00
count_rech_2g_9	0.00
count_rech_2g_8	0.00
count_rech_2g_7	0.00
count_rech_2g_6	0.00
max_rech_data_9	0.00
max_rech_data_8	0.00
max_rech_data_7	0.00
max_rech_data_6	0.00
total_rech_data_9	0.00
total_rech_data_8	0.00
total_rech_data_7	0.00
total_rech_data_6	0.00
date_of_last_rech_data_9	0.00
date_of_last_rech_data_8	0.00
date_of_last_rech_data_7	0.00
date_of_last_rech_data_6	0.00
last_day_rch_amt_9	0.00

last_day_rch_amt_8   0.00
last_day_rch_amt_7   0.00
last_day_rch_amt_6   0.00
date_of_last_rech_9   0.00
mobile_number   0.00
dtype: float64

We are still left with 3.16% of the data which are 'nan', in the columns of June month. That means customers have recharged but have not used the services during that particular month. The same may be special group of customers with high churn. So let's not drop them and instead impute their NAN values with zero, as of now.

for col **in** cols_june_2:
    df[col] = df[col].apply(nan_to_zero)*#check for missing values*
check_missing(df)roam_og_mou_7   3.86
og_others_7   3.86
loc_og_t2c_mou_7   3.86
loc_ic_t2m_mou_7   3.86
std_og_t2t_mou_7   3.86
loc_og_t2f_mou_7   3.86
loc_ic_t2f_mou_7   3.86
loc_og_t2m_mou_7   3.86
std_og_t2m_mou_7   3.86
loc_ic_mou_7   3.86
loc_og_t2t_mou_7   3.86
ic_others_7   3.86
loc_og_mou_7   3.86
std_og_t2f_mou_7   3.86
std_ic_t2t_mou_7   3.86
loc_ic_t2t_mou_7   3.86
roam_ic_mou_7   3.86
spl_ic_mou_7   3.86
isd_og_mou_7   3.86
spl_og_mou_7   3.86
std_ic_t2f_mou_7   3.86
isd_ic_mou_7   3.86
std_og_mou_7   3.86
onnet_mou_7   3.86
std_ic_t2m_mou_7   3.86
offnet_mou_7   3.86
std_ic_mou_7   3.86
date_of_last_rech_7   1.77
total_og_mou_6   0.00
og_others_9   0.00
og_others_8   0.00
total_og_mou_7   0.00
spl_og_mou_9   0.00
total_og_mou_8   0.00
spl_og_mou_8   0.00

total_og_mou_9	0.00
og_others_6	0.00
loc_ic_t2t_mou_6	0.00
sep_vbc_3g	0.00
loc_ic_t2f_mou_6	0.00
loc_ic_t2t_mou_8	0.00
std_ic_t2t_mou_6	0.00
std_ic_t2f_mou_9	0.00
std_ic_t2f_mou_8	0.00
std_ic_t2f_mou_6	0.00
std_ic_t2m_mou_9	0.00
std_ic_t2m_mou_8	0.00
std_ic_t2m_mou_6	0.00
std_ic_t2t_mou_9	0.00
std_ic_t2t_mou_8	0.00
loc_ic_mou_9	0.00
loc_ic_t2t_mou_9	0.00
loc_ic_mou_8	0.00
loc_ic_mou_6	0.00
loc_ic_t2f_mou_9	0.00
loc_ic_t2f_mou_8	0.00
isd_og_mou_9	0.00
loc_ic_t2m_mou_9	0.00
loc_ic_t2m_mou_8	0.00
loc_ic_t2m_mou_6	0.00
spl_og_mou_6	0.00
std_og_t2f_mou_9	0.00
isd_og_mou_8	0.00
loc_og_t2m_mou_8	0.00
loc_og_t2t_mou_9	0.00
loc_og_t2t_mou_8	0.00
loc_og_t2t_mou_6	0.00
roam_og_mou_9	0.00
roam_og_mou_8	0.00
roam_og_mou_6	0.00
roam_ic_mou_9	0.00
roam_ic_mou_8	0.00
roam_ic_mou_6	0.00
offnet_mou_9	0.00
offnet_mou_8	0.00
offnet_mou_6	0.00
onnet_mou_9	0.00
onnet_mou_8	0.00
onnet_mou_6	0.00
arpu_9	0.00
arpu_8	0.00
arpu_7	0.00
arpu_6	0.00

loc_og_t2m_mou_6	0.00
loc_og_t2m_mou_9	0.00
isd_og_mou_6	0.00
loc_og_t2f_mou_6	0.00
std_og_mou_9	0.00
std_og_mou_8	0.00
std_og_mou_6	0.00
std_og_t2f_mou_8	0.00
std_og_t2f_mou_6	0.00
std_og_t2m_mou_9	0.00
std_og_t2m_mou_8	0.00
std_og_t2m_mou_6	0.00
std_og_t2t_mou_9	0.00
std_og_t2t_mou_8	0.00
std_og_t2t_mou_6	0.00
loc_og_mou_9	0.00
loc_og_mou_8	0.00
loc_og_mou_6	0.00
loc_og_t2c_mou_9	0.00
loc_og_t2c_mou_8	0.00
loc_og_t2c_mou_6	0.00
loc_og_t2f_mou_9	0.00
loc_og_t2f_mou_8	0.00
std_ic_mou_6	0.00
std_ic_mou_9	0.00
std_ic_mou_8	0.00
vol_3g_mb_8	0.00
night_pck_user_6	0.00
arpu_2g_9	0.00
arpu_2g_8	0.00
arpu_2g_7	0.00
arpu_2g_6	0.00
arpu_3g_9	0.00
arpu_3g_8	0.00
arpu_3g_7	0.00
arpu_3g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_7	0.00
night_pck_user_8	0.00
vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_8	0.00
vol_2g_mb_7	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_9	0.00
av_rech_amt_data_8	0.00
av_rech_amt_data_7	0.00
av_rech_amt_data_6	0.00

count_rech_3g_9	0.00
night_pck_user_7	0.00
night_pck_user_9	0.00
jun_vbc_3g	0.00
sachet_3g_6	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_9	0.00
fb_user_8	0.00
fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_8	0.00
sachet_3g_7	0.00
monthly_3g_9	0.00
monthly_2g_6	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00
monthly_2g_9	0.00
monthly_2g_8	0.00
monthly_2g_7	0.00
count_rech_3g_8	0.00
count_rech_3g_7	0.00
count_rech_3g_6	0.00
ic_others_8	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_7	0.00
total_rech_amt_6	0.00
total_rech_num_9	0.00
total_rech_num_8	0.00
total_rech_num_7	0.00
total_rech_num_6	0.00
ic_others_9	0.00
ic_others_6	0.00
count_rech_2g_9	0.00
isd_ic_mou_9	0.00
isd_ic_mou_8	0.00
isd_ic_mou_6	0.00
spl_ic_mou_9	0.00
spl_ic_mou_8	0.00

```
spl_ic_mou_6             0.00
total_ic_mou_9           0.00
total_ic_mou_8           0.00
total_ic_mou_7           0.00
total_ic_mou_6           0.00
max_rech_amt_7           0.00
max_rech_amt_8           0.00
max_rech_amt_9           0.00
date_of_last_rech_6      0.00
count_rech_2g_8          0.00
count_rech_2g_7          0.00
count_rech_2g_6          0.00
max_rech_data_9          0.00
max_rech_data_8          0.00
max_rech_data_7          0.00
max_rech_data_6          0.00
total_rech_data_9        0.00
total_rech_data_8        0.00
total_rech_data_7        0.00
total_rech_data_6        0.00
date_of_last_rech_data_9    0.00
date_of_last_rech_data_8    0.00
date_of_last_rech_data_7    0.00
date_of_last_rech_data_6    0.00
last_day_rch_amt_9       0.00
last_day_rch_amt_8       0.00
last_day_rch_amt_7       0.00
last_day_rch_amt_6       0.00
date_of_last_rech_9      0.00
date_of_last_rech_8      0.00
mobile_number            0.00
dtype: float64
```

From above, we notice that there are certain customers who have not done voice service recharge for the month of July. Let’s replace the corresponding NAN values with 0.

```
df['date_of_last_rech_7'] = df['date_of_last_rech_7'].apply(nan_to_zero)
```

Gathering columns of July month with missing values.

```
cols_july_2 = ['roam_og_mou_7',
 'og_others_7',
 'loc_og_t2c_mou_7',
 'loc_ic_t2m_mou_7',
 'std_og_t2t_mou_7',
 'loc_og_t2f_mou_7',
 'loc_ic_t2f_mou_7',
 'loc_og_t2m_mou_7',
 'std_og_t2m_mou_7',
 'loc_ic_mou_7',
```

```
 'loc_og_t2t_mou_7',
 'ic_others_7',
 'loc_og_mou_7',
 'std_og_t2f_mou_7',
 'std_ic_t2t_mou_7',
 'loc_ic_t2t_mou_7',
 'roam_ic_mou_7',
 'spl_ic_mou_7',
 'isd_og_mou_7',
 'spl_og_mou_7',
 'std_ic_t2f_mou_7',
 'isd_ic_mou_7',
 'std_og_mou_7',
 'onnet_mou_7',
 'std_ic_t2m_mou_7',
 'offnet_mou_7',
 'std_ic_mou_7']#convert those NAN values in cols_july_2 to 0, where the corresponding recharges (date_of_last_rech_7) have not been done.
ref = df['date_of_last_rech_7'].valuesfor col in cols_july_2:
   piv = df[col].values
   for i,j in enumerate(piv):
      if ref[i]==0 and str(piv[i])=='nan':
         piv[i]=0
   df[col]=pivcheck_missing(df)isd_og_mou_7              2.91
std_og_t2f_mou_7          2.91
loc_og_t2c_mou_7          2.91
loc_ic_t2m_mou_7          2.91
std_og_t2t_mou_7          2.91
loc_og_t2f_mou_7          2.91
loc_ic_t2f_mou_7          2.91
loc_og_t2m_mou_7          2.91
std_og_t2m_mou_7          2.91
loc_ic_mou_7              2.91
loc_og_t2t_mou_7          2.91
og_others_7               2.91
loc_og_mou_7              2.91
ic_others_7               2.91
std_ic_t2t_mou_7          2.91
roam_og_mou_7             2.91
roam_ic_mou_7             2.91
std_ic_t2m_mou_7          2.91
spl_og_mou_7              2.91
std_ic_t2f_mou_7          2.91
std_og_mou_7              2.91
spl_ic_mou_7              2.91
onnet_mou_7               2.91
offnet_mou_7              2.91
std_ic_mou_7              2.91
```

isd_ic_mou_7	2.91
loc_ic_t2t_mou_7	2.91
og_others_9	0.00
spl_og_mou_9	0.00
og_others_8	0.00
total_og_mou_6	0.00
og_others_6	0.00
total_og_mou_7	0.00
total_og_mou_8	0.00
spl_og_mou_8	0.00
total_og_mou_9	0.00
spl_og_mou_6	0.00
loc_ic_t2t_mou_6	0.00
sep_vbc_3g	0.00
loc_ic_t2t_mou_8	0.00
std_ic_t2t_mou_6	0.00
std_ic_t2f_mou_9	0.00
std_ic_t2f_mou_8	0.00
std_ic_t2f_mou_6	0.00
std_ic_t2m_mou_9	0.00
std_ic_t2m_mou_8	0.00
std_ic_t2m_mou_6	0.00
std_ic_t2t_mou_9	0.00
std_ic_t2t_mou_8	0.00
loc_ic_mou_9	0.00
loc_ic_t2t_mou_9	0.00
loc_ic_mou_8	0.00
loc_ic_mou_6	0.00
loc_ic_t2f_mou_9	0.00
loc_ic_t2f_mou_8	0.00
isd_og_mou_9	0.00
loc_ic_t2m_mou_9	0.00
loc_ic_t2m_mou_8	0.00
loc_ic_t2m_mou_6	0.00
loc_ic_t2f_mou_6	0.00
std_og_t2f_mou_9	0.00
isd_og_mou_8	0.00
loc_og_t2m_mou_8	0.00
loc_og_t2t_mou_9	0.00
loc_og_t2t_mou_8	0.00
loc_og_t2t_mou_6	0.00
roam_og_mou_9	0.00
roam_og_mou_8	0.00
roam_og_mou_6	0.00
roam_ic_mou_9	0.00
roam_ic_mou_8	0.00
roam_ic_mou_6	0.00
offnet_mou_9	0.00

offnet_mou_8	0.00
offnet_mou_6	0.00
onnet_mou_9	0.00
onnet_mou_8	0.00
onnet_mou_6	0.00
arpu_9	0.00
arpu_8	0.00
arpu_7	0.00
arpu_6	0.00
loc_og_t2m_mou_6	0.00
loc_og_t2m_mou_9	0.00
isd_og_mou_6	0.00
loc_og_t2f_mou_6	0.00
std_og_mou_9	0.00
std_og_mou_8	0.00
std_og_mou_6	0.00
std_og_t2f_mou_8	0.00
std_og_t2f_mou_6	0.00
std_og_t2m_mou_9	0.00
std_og_t2m_mou_8	0.00
std_og_t2m_mou_6	0.00
std_og_t2t_mou_9	0.00
std_og_t2t_mou_8	0.00
std_og_t2t_mou_6	0.00
loc_og_mou_9	0.00
loc_og_mou_8	0.00
loc_og_mou_6	0.00
loc_og_t2c_mou_9	0.00
loc_og_t2c_mou_8	0.00
loc_og_t2c_mou_6	0.00
loc_og_t2f_mou_9	0.00
loc_og_t2f_mou_8	0.00
std_ic_mou_6	0.00
std_ic_mou_9	0.00
std_ic_mou_8	0.00
vol_3g_mb_8	0.00
night_pck_user_6	0.00
arpu_2g_9	0.00
arpu_2g_8	0.00
arpu_2g_7	0.00
arpu_2g_6	0.00
arpu_3g_9	0.00
arpu_3g_8	0.00
arpu_3g_7	0.00
arpu_3g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_7	0.00
night_pck_user_8	0.00

vol_3g_mb_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_8	0.00
vol_2g_mb_7	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_9	0.00
av_rech_amt_data_8	0.00
av_rech_amt_data_7	0.00
av_rech_amt_data_6	0.00
count_rech_3g_9	0.00
night_pck_user_7	0.00
night_pck_user_9	0.00
count_rech_3g_7	0.00
sachet_3g_6	0.00
jul_vbc_3g	0.00
aug_vbc_3g	0.00
aon	0.00
fb_user_9	0.00
fb_user_8	0.00
fb_user_7	0.00
fb_user_6	0.00
sachet_3g_9	0.00
sachet_3g_8	0.00
sachet_3g_7	0.00
monthly_3g_9	0.00
monthly_2g_6	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00
monthly_2g_9	0.00
monthly_2g_8	0.00
monthly_2g_7	0.00
count_rech_3g_8	0.00
count_rech_3g_6	0.00
jun_vbc_3g	0.00
ic_others_8	0.00
max_rech_amt_6	0.00
total_rech_amt_9	0.00
total_rech_amt_8	0.00
total_rech_amt_7	0.00
total_rech_amt_6	0.00
total_rech_num_9	0.00
total_rech_num_8	0.00
total_rech_num_7	0.00

```
total_rech_num_6          0.00
ic_others_9               0.00
ic_others_6               0.00
max_rech_amt_8            0.00
isd_ic_mou_9              0.00
isd_ic_mou_8              0.00
isd_ic_mou_6              0.00
spl_ic_mou_9              0.00
spl_ic_mou_8              0.00
spl_ic_mou_6              0.00
total_ic_mou_9            0.00
total_ic_mou_8            0.00
total_ic_mou_7            0.00
total_ic_mou_6            0.00
max_rech_amt_7            0.00
max_rech_amt_9            0.00
count_rech_2g_9           0.00
total_rech_data_6         0.00
count_rech_2g_8           0.00
count_rech_2g_7           0.00
count_rech_2g_6           0.00
max_rech_data_9           0.00
max_rech_data_8           0.00
max_rech_data_7           0.00
max_rech_data_6           0.00
total_rech_data_9         0.00
total_rech_data_8         0.00
total_rech_data_7         0.00
date_of_last_rech_data_9  0.00
date_of_last_rech_6       0.00
date_of_last_rech_data_8  0.00
date_of_last_rech_data_7  0.00
date_of_last_rech_data_6  0.00
last_day_rch_amt_9        0.00
last_day_rch_amt_8        0.00
last_day_rch_amt_7        0.00
last_day_rch_amt_6        0.00
date_of_last_rech_9       0.00
date_of_last_rech_8       0.00
date_of_last_rech_7       0.00
mobile_number             0.00
dtype: float64
```

We are still left with 2.91% of the data which are 'nan', in the columns of July month. That means customers have recharged but have not used the services during that particular month. The same may be special group of customers with high churn. So let's not drop them and instead impute their NAN values with zero, as of now.

```
for col in cols_july_2:
    df[col] = df[col].apply(nan_to_zero)#check for missing values
check_missing(df)sep_vbc_3g             0.0
std_og_t2f_mou_9        0.0
loc_ic_t2t_mou_9        0.0
loc_ic_t2t_mou_8        0.0
loc_ic_t2t_mou_7        0.0
loc_ic_t2t_mou_6        0.0
total_og_mou_9          0.0
total_og_mou_8          0.0
total_og_mou_7          0.0
total_og_mou_6          0.0
og_others_9             0.0
og_others_8             0.0
og_others_7             0.0
og_others_6             0.0
spl_og_mou_9            0.0
spl_og_mou_8            0.0
spl_og_mou_7            0.0
spl_og_mou_6            0.0
isd_og_mou_9            0.0
isd_og_mou_8            0.0
isd_og_mou_7            0.0
isd_og_mou_6            0.0
std_og_mou_9            0.0
std_og_mou_8            0.0
std_og_mou_7            0.0
loc_ic_t2m_mou_6        0.0
loc_ic_t2m_mou_7        0.0
loc_ic_t2m_mou_8        0.0
std_ic_t2t_mou_9        0.0
std_ic_mou_7            0.0
std_ic_mou_6            0.0
std_ic_t2f_mou_9        0.0
std_ic_t2f_mou_8        0.0
std_ic_t2f_mou_7        0.0
std_ic_t2f_mou_6        0.0
std_ic_t2m_mou_9        0.0
std_ic_t2m_mou_8        0.0
std_ic_t2m_mou_7        0.0
std_ic_t2m_mou_6        0.0
std_ic_t2t_mou_8        0.0
loc_ic_t2m_mou_9        0.0
std_ic_t2t_mou_7        0.0
std_ic_t2t_mou_6        0.0
loc_ic_mou_9            0.0
loc_ic_mou_8            0.0
loc_ic_mou_7            0.0
```

loc_ic_mou_6	0.0
loc_ic_t2f_mou_9	0.0
loc_ic_t2f_mou_8	0.0
loc_ic_t2f_mou_7	0.0
loc_ic_t2f_mou_6	0.0
std_og_mou_6	0.0
std_og_t2f_mou_8	0.0
jun_vbc_3g	0.0
std_og_t2f_mou_7	0.0
loc_og_t2t_mou_8	0.0
loc_og_t2t_mou_7	0.0
loc_og_t2t_mou_6	0.0
roam_og_mou_9	0.0
roam_og_mou_8	0.0
roam_og_mou_7	0.0
roam_og_mou_6	0.0
roam_ic_mou_9	0.0
roam_ic_mou_8	0.0
roam_ic_mou_7	0.0
roam_ic_mou_6	0.0
offnet_mou_9	0.0
offnet_mou_8	0.0
offnet_mou_7	0.0
offnet_mou_6	0.0
onnet_mou_9	0.0
onnet_mou_8	0.0
onnet_mou_7	0.0
onnet_mou_6	0.0
arpu_9	0.0
arpu_8	0.0
arpu_7	0.0
arpu_6	0.0
loc_og_t2t_mou_9	0.0
loc_og_t2m_mou_6	0.0
loc_og_t2m_mou_7	0.0
loc_og_mou_8	0.0
std_og_t2f_mou_6	0.0
std_og_t2m_mou_9	0.0
std_og_t2m_mou_8	0.0
std_og_t2m_mou_7	0.0
std_og_t2m_mou_6	0.0
std_og_t2t_mou_9	0.0
std_og_t2t_mou_8	0.0
std_og_t2t_mou_7	0.0
std_og_t2t_mou_6	0.0
loc_og_mou_9	0.0
loc_og_mou_7	0.0
loc_og_t2m_mou_8	0.0

loc_og_mou_6	0.0
loc_og_t2c_mou_9	0.0
loc_og_t2c_mou_8	0.0
loc_og_t2c_mou_7	0.0
loc_og_t2c_mou_6	0.0
loc_og_t2f_mou_9	0.0
loc_og_t2f_mou_8	0.0
loc_og_t2f_mou_7	0.0
loc_og_t2f_mou_6	0.0
loc_og_t2m_mou_9	0.0
std_ic_mou_8	0.0
std_ic_mou_9	0.0
total_ic_mou_6	0.0
total_ic_mou_7	0.0
night_pck_user_6	0.0
arpu_2g_9	0.0
arpu_2g_8	0.0
arpu_2g_7	0.0
arpu_2g_6	0.0
arpu_3g_9	0.0
arpu_3g_8	0.0
arpu_3g_7	0.0
arpu_3g_6	0.0
vol_3g_mb_9	0.0
vol_3g_mb_8	0.0
vol_3g_mb_7	0.0
vol_3g_mb_6	0.0
vol_2g_mb_9	0.0
vol_2g_mb_8	0.0
vol_2g_mb_7	0.0
vol_2g_mb_6	0.0
av_rech_amt_data_9	0.0
av_rech_amt_data_8	0.0
av_rech_amt_data_7	0.0
av_rech_amt_data_6	0.0
count_rech_3g_9	0.0
count_rech_3g_8	0.0
night_pck_user_7	0.0
night_pck_user_8	0.0
night_pck_user_9	0.0
sachet_3g_6	0.0
jul_vbc_3g	0.0
aug_vbc_3g	0.0
aon	0.0
fb_user_9	0.0
fb_user_8	0.0
fb_user_7	0.0
fb_user_6	0.0

sachet_3g_9	0.0
sachet_3g_8	0.0
sachet_3g_7	0.0
monthly_3g_9	0.0
monthly_2g_6	0.0
monthly_3g_8	0.0
monthly_3g_7	0.0
monthly_3g_6	0.0
sachet_2g_9	0.0
sachet_2g_8	0.0
sachet_2g_7	0.0
sachet_2g_6	0.0
monthly_2g_9	0.0
monthly_2g_8	0.0
monthly_2g_7	0.0
count_rech_3g_7	0.0
count_rech_3g_6	0.0
count_rech_2g_9	0.0
ic_others_7	0.0
total_rech_amt_9	0.0
total_rech_amt_8	0.0
total_rech_amt_7	0.0
total_rech_amt_6	0.0
total_rech_num_9	0.0
total_rech_num_8	0.0
total_rech_num_7	0.0
total_rech_num_6	0.0
ic_others_9	0.0
ic_others_8	0.0
ic_others_6	0.0
max_rech_amt_7	0.0
isd_ic_mou_9	0.0
isd_ic_mou_8	0.0
isd_ic_mou_7	0.0
isd_ic_mou_6	0.0
spl_ic_mou_9	0.0
spl_ic_mou_8	0.0
spl_ic_mou_7	0.0
spl_ic_mou_6	0.0
total_ic_mou_9	0.0
total_ic_mou_8	0.0
max_rech_amt_6	0.0
max_rech_amt_8	0.0
count_rech_2g_8	0.0
date_of_last_rech_data_9	0.0
count_rech_2g_7	0.0
count_rech_2g_6	0.0
max_rech_data_9	0.0

```
max_rech_data_8          0.0
max_rech_data_7          0.0
max_rech_data_6          0.0
total_rech_data_9        0.0
total_rech_data_8        0.0
total_rech_data_7        0.0
total_rech_data_6        0.0
date_of_last_rech_data_8    0.0
max_rech_amt_9           0.0
date_of_last_rech_data_7    0.0
date_of_last_rech_data_6    0.0
last_day_rch_amt_9       0.0
last_day_rch_amt_8       0.0
last_day_rch_amt_7       0.0
last_day_rch_amt_6       0.0
date_of_last_rech_9      0.0
date_of_last_rech_8      0.0
date_of_last_rech_7      0.0
date_of_last_rech_6      0.0
mobile_number            0.0
dtype: float64
```

Hence we have treated all the missing values in the dataset. From our above exercise, we noticed that,

- there are certain customers who have not recharged (voice and/or data) and hence not used the corresponding services for that particular months.
- there are some customers who have recharged (voice and/or data), but stopped using services. Those may be the cohort of customers who may have relatively high churn rates. We would explore this further in EDA.

2. Filtering the high-value customers

Now that we have cleaned out dataset, its time to filter-in the high value customers, which is the cohort of focus for this case study. As per the given definition of *high-value customers*, we have to filter-in those customers 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).

We have average recharge amount for data (av_rech_amt_data_6) and the total no. of recharges for data (total_rech_data_6) for all the customers. Thus we can multiply both to get the **data recharge** done by each customers for that particular months.

```
df.data_recharge_6 = df.total_rech_data_6 * df.av_rech_amt_data_6
df.data_recharge_7 = df.total_rech_data_7 * df.av_rech_amt_data_7
df.data_recharge_8 = df.total_rech_data_8 * df.av_rech_amt_data_8
```

Now let’s get the total average recharge (voice + data) done by customers for the June and July months.

```
df['total_avg_rech_amt_good_phase'] = (df.total_rech_amt_6 + df.total_rech_amt_7 +
                                       df.data_recharge_6 + df.data_recharge_7)/2#filtering in the high value
```

```
customers by 0.7 percentile and hence getting filtered dataset
df_hvc = df[df.total_avg_rech_amt_good_phase >=
df.total_avg_rech_amt_good_phase.quantile(0.7)]#check the shape of data now
df_hvc.shape(30001, 211)
```

Since we have already make use of total_avg_rech_amt_good_phase, we can drop it.

```
df_hvc.drop(['total_avg_rech_amt_good_phase'], axis=1, inplace=True)
```

3. Tagging churn and non-churn customers

As per the given definition, those who have not made any calls (either incoming or outgoing) AND have not used mobile internet even once in the churn phase i.e during September month, are churners. For the same, we have to look
after total_ic_mou_9, total_og_mou_9, vol_2g_mb_9 & vol_3g_mb_9 columns.

```
#function to tag churn/non-churn
def is_churn(x):
   if x==0:
      return 1  #1 for churn
   else:
      return 0   #0 for non-churn df_hvc['churn'] = df_hvc.total_ic_mou_9 + df_hvc.total_og_mou_9 +
df_hvc.vol_2g_mb_9 + df_hvc.vol_3g_mb_9df_hvc.churn = df_hvc.churn.apply(is_churn)#checking
the distribution of churn and non-churn
print(df_hvc.churn.value_counts(normalize=True)*100)
df_hvc.churn.value_counts().plot.pie(shadow=True, explode=(0, 0.3), startangle=0,
autopct='%1.1f%%', fontsize=13)
plt.show()0    91.863605
1    8.136395
Name: churn, dtype: float64
```

From the above, we note that among the high value customers, there are approximately 92% non-churners while 8% churners.

Since we have already tagged churners, we have to remove all the attributes corresponding to the churn phase i.e. September month as the same would not be available to us while predicting the churn with our model.

```
#identifying the columns related to September month
sep_cols = []for i in df_hvc.columns:
   if i[-2:]=='_9':
      sep_cols.append(i)for i in sep_cols:
   print(i)arpu_9
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_mou_9
```

loc_og_mou_9
std_og_t2t_mou_9
std_og_t2m_mou_9
std_og_t2f_mou_9
std_og_mou_9
isd_og_mou_9
spl_og_mou_9
og_others_9
total_og_mou_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_mou_9
total_ic_mou_9
spl_ic_mou_9
isd_ic_mou_9
ic_others_9
total_rech_num_9
total_rech_amt_9
max_rech_amt_9
date_of_last_rech_9
last_day_rch_amt_9
date_of_last_rech_data_9
total_rech_data_9
max_rech_data_9
count_rech_2g_9
count_rech_3g_9
av_rech_amt_data_9
vol_2g_mb_9
vol_3g_mb_9
arpu_3g_9
arpu_2g_9
night_pck_user_9
monthly_2g_9
sachet_2g_9
monthly_3g_9
sachet_3g_9
fb_user_9*#appending left out Sep month column*
sep_cols.append('sep_vbc_3g')*#dropping the Sep month columns*
df_hvc.drop(sep_cols, axis=1, inplace=**True**)*#check shape of dataframe*
df_hvc.shape(30001, 159)

4. Exploratory Data Analysis, Feature Engineering & Data Visualization

#check the datatype of all the columns of df_hvc

```
df_hvc.info(verbose=True)<class 'pandas.core.frame.DataFrame'>
Int64Index: 30001 entries, 0 to 99997
Data columns (total 159 columns):
 #   Column              Dtype
---  ------              -----
 0   mobile_number       int64
 1   arpu_6              float64
 2   arpu_7              float64
 3   arpu_8              float64
 4   onnet_mou_6         float64
 5   onnet_mou_7         float64
 6   onnet_mou_8         float64
 7   offnet_mou_6        float64
 8   offnet_mou_7        float64
 9   offnet_mou_8        float64
 10  roam_ic_mou_6       float64
 11  roam_ic_mou_7       float64
 12  roam_ic_mou_8       float64
 13  roam_og_mou_6       float64
 14  roam_og_mou_7       float64
 15  roam_og_mou_8       float64
 16  loc_og_t2t_mou_6    float64
 17  loc_og_t2t_mou_7    float64
 18  loc_og_t2t_mou_8    float64
 19  loc_og_t2m_mou_6    float64
 20  loc_og_t2m_mou_7    float64
 21  loc_og_t2m_mou_8    float64
 22  loc_og_t2f_mou_6    float64
 23  loc_og_t2f_mou_7    float64
 24  loc_og_t2f_mou_8    float64
 25  loc_og_t2c_mou_6    float64
 26  loc_og_t2c_mou_7    float64
 27  loc_og_t2c_mou_8    float64
 28  loc_og_mou_6        float64
 29  loc_og_mou_7        float64
 30  loc_og_mou_8        float64
 31  std_og_t2t_mou_6    float64
 32  std_og_t2t_mou_7    float64
 33  std_og_t2t_mou_8    float64
 34  std_og_t2m_mou_6    float64
 35  std_og_t2m_mou_7    float64
 36  std_og_t2m_mou_8    float64
 37  std_og_t2f_mou_6    float64
 38  std_og_t2f_mou_7    float64
 39  std_og_t2f_mou_8    float64
 40  std_og_mou_6        float64
 41  std_og_mou_7        float64
```

42	std_og_mou_8	float64
43	isd_og_mou_6	float64
44	isd_og_mou_7	float64
45	isd_og_mou_8	float64
46	spl_og_mou_6	float64
47	spl_og_mou_7	float64
48	spl_og_mou_8	float64
49	og_others_6	float64
50	og_others_7	float64
51	og_others_8	float64
52	total_og_mou_6	float64
53	total_og_mou_7	float64
54	total_og_mou_8	float64
55	loc_ic_t2t_mou_6	float64
56	loc_ic_t2t_mou_7	float64
57	loc_ic_t2t_mou_8	float64
58	loc_ic_t2m_mou_6	float64
59	loc_ic_t2m_mou_7	float64
60	loc_ic_t2m_mou_8	float64
61	loc_ic_t2f_mou_6	float64
62	loc_ic_t2f_mou_7	float64
63	loc_ic_t2f_mou_8	float64
64	loc_ic_mou_6	float64
65	loc_ic_mou_7	float64
66	loc_ic_mou_8	float64
67	std_ic_t2t_mou_6	float64
68	std_ic_t2t_mou_7	float64
69	std_ic_t2t_mou_8	float64
70	std_ic_t2m_mou_6	float64
71	std_ic_t2m_mou_7	float64
72	std_ic_t2m_mou_8	float64
73	std_ic_t2f_mou_6	float64
74	std_ic_t2f_mou_7	float64
75	std_ic_t2f_mou_8	float64
76	std_ic_mou_6	float64
77	std_ic_mou_7	float64
78	std_ic_mou_8	float64
79	total_ic_mou_6	float64
80	total_ic_mou_7	float64
81	total_ic_mou_8	float64
82	spl_ic_mou_6	float64
83	spl_ic_mou_7	float64
84	spl_ic_mou_8	float64
85	isd_ic_mou_6	float64
86	isd_ic_mou_7	float64
87	isd_ic_mou_8	float64
88	ic_others_6	float64
89	ic_others_7	float64

90	ic_others_8	float64
91	total_rech_num_6	int64
92	total_rech_num_7	int64
93	total_rech_num_8	int64
94	total_rech_amt_6	int64
95	total_rech_amt_7	int64
96	total_rech_amt_8	int64
97	max_rech_amt_6	int64
98	max_rech_amt_7	int64
99	max_rech_amt_8	int64
100	date_of_last_rech_6	object
101	date_of_last_rech_7	object
102	date_of_last_rech_8	object
103	last_day_rch_amt_6	int64
104	last_day_rch_amt_7	int64
105	last_day_rch_amt_8	int64
106	date_of_last_rech_data_6	object
107	date_of_last_rech_data_7	object
108	date_of_last_rech_data_8	object
109	total_rech_data_6	float64
110	total_rech_data_7	float64
111	total_rech_data_8	float64
112	max_rech_data_6	float64
113	max_rech_data_7	float64
114	max_rech_data_8	float64
115	count_rech_2g_6	float64
116	count_rech_2g_7	float64
117	count_rech_2g_8	float64
118	count_rech_3g_6	float64
119	count_rech_3g_7	float64
120	count_rech_3g_8	float64
121	av_rech_amt_data_6	float64
122	av_rech_amt_data_7	float64
123	av_rech_amt_data_8	float64
124	vol_2g_mb_6	float64
125	vol_2g_mb_7	float64
126	vol_2g_mb_8	float64
127	vol_3g_mb_6	float64
128	vol_3g_mb_7	float64
129	vol_3g_mb_8	float64
130	arpu_3g_6	float64
131	arpu_3g_7	float64
132	arpu_3g_8	float64
133	arpu_2g_6	float64
134	arpu_2g_7	float64
135	arpu_2g_8	float64
136	night_pck_user_6	float64
137	night_pck_user_7	float64

```
 138 night_pck_user_8         float64
 139 monthly_2g_6            int64
 140 monthly_2g_7            int64
 141 monthly_2g_8            int64
 142 sachet_2g_6             int64
 143 sachet_2g_7             int64
 144 sachet_2g_8             int64
 145 monthly_3g_6            int64
 146 monthly_3g_7            int64
 147 monthly_3g_8            int64
 148 sachet_3g_6             int64
 149 sachet_3g_7             int64
 150 sachet_3g_8             int64
 151 fb_user_6               float64
 152 fb_user_7               float64
 153 fb_user_8               float64
 154 aon                     int64
 155 aug_vbc_3g              float64
 156 jul_vbc_3g              float64
 157 jun_vbc_3g              float64
 158 churn                   int64
dtypes: float64(126), int64(27), object(6)
memory usage: 36.6+ MB
```

From the above, we notice that there are float, int and object type columns in our dataset. Let's bunch them by continuous and categorical types, for our further analysis.

We noticed that
columns fb_user_6, fb_user_7, fb_user_8, night_pck_user_6, night_pck_user_7, night_pck_user_8 have been marked as float64 but are of categorical type. So let's deal with them accordingly.

```
#continuous variables
cont_col = df_hvc.select_dtypes(['int64','float64']).columns
cont_col = list( set(cont_col) - set(['fb_user_6', 'fb_user_7', 'fb_user_8',
                             'night_pck_user_6', 'night_pck_user_7', 'night_pck_user_8']) )#categorical variables
cat_col = set(df_hvc.select_dtypes(['object']).columns)
cat_col.add('fb_user_6')
cat_col.add('fb_user_7')
cat_col.add('fb_user_8')
cat_col.add('night_pck_user_6')
cat_col.add('night_pck_user_7')
cat_col.add('night_pck_user_8')
cat_col = list(cat_col)print('cont_col:', cont_col)cont_col: ['loc_og_t2t_mou_6', 'isd_ic_mou_7',
'std_ic_t2f_mou_8', 'arpu_6', 'sachet_2g_6', 'jun_vbc_3g', 'arpu_8', 'std_ic_t2f_mou_7',
'total_rech_data_8', 'total_og_mou_7', 'std_ic_mou_7', 'spl_ic_mou_7', 'total_rech_amt_7',
'onnet_mou_8', 'loc_og_t2m_mou_7', 'loc_ic_t2f_mou_6', 'loc_og_t2m_mou_8',
'total_rech_num_7', 'arpu_7', 'loc_ic_t2m_mou_6', 'offnet_mou_8', 'arpu_3g_6', 'og_others_7',
'sachet_2g_7', 'std_ic_t2m_mou_6', 'roam_og_mou_8', 'total_rech_num_8', 'last_day_rch_amt_6',
```

'spl_og_mou_6', 'max_rech_data_6', 'total_rech_num_6', 'last_day_rch_amt_8', 'count_rech_2g_8', 'std_og_t2t_mou_7', 'loc_ic_mou_6', 'std_og_mou_8', 'mobile_number', 'std_ic_t2t_mou_8', 'vol_2g_mb_8', 'max_rech_amt_8', 'std_ic_t2t_mou_7', 'count_rech_3g_6', 'vol_2g_mb_7', 'monthly_2g_6', 'vol_3g_mb_8', 'isd_ic_mou_6', 'total_rech_amt_8', 'roam_ic_mou_6', 'loc_og_t2c_mou_6', 'monthly_3g_7', 'aon', 'vol_3g_mb_7', 'loc_og_t2c_mou_7', 'roam_og_mou_7', 'std_og_t2m_mou_7', 'total_rech_data_7', 'offnet_mou_7', 'og_others_6', 'spl_og_mou_7', 'monthly_3g_6', 'arpu_2g_6', 'spl_ic_mou_6', 'std_og_t2m_mou_8', 'av_rech_amt_data_6', 'loc_ic_mou_8', 'last_day_rch_amt_7', 'loc_ic_mou_7', 'total_rech_data_6', 'loc_ic_t2t_mou_6', 'loc_og_t2m_mou_6', 'count_rech_2g_7', 'og_others_8', 'total_ic_mou_7', 'isd_og_mou_7', 'loc_ic_t2f_mou_8', 'std_og_t2f_mou_6', 'std_og_t2t_mou_8', 'spl_og_mou_8', 'isd_og_mou_6', 'monthly_2g_8', 'total_ic_mou_8', 'max_rech_data_7', 'count_rech_3g_7', 'sachet_2g_8', 'vol_2g_mb_6', 'aug_vbc_3g', 'max_rech_amt_6', 'churn', 'loc_og_t2f_mou_8', 'loc_og_mou_7', 'onnet_mou_7', 'roam_ic_mou_7', 'monthly_2g_7', 'std_og_t2f_mou_8', 'arpu_2g_8', 'sachet_3g_8', 'monthly_3g_8', 'isd_ic_mou_8', 'total_rech_amt_6', 'std_ic_t2f_mou_6', 'std_og_t2m_mou_6', 'loc_og_t2f_mou_6', 'total_ic_mou_6', 'loc_og_t2f_mou_7', 'onnet_mou_6', 'jul_vbc_3g', 'ic_others_7', 'roam_ic_mou_8', 'arpu_3g_8', 'spl_ic_mou_8', 'std_og_mou_7', 'std_og_t2t_mou_6', 'std_ic_mou_6', 'vol_3g_mb_6', 'loc_og_mou_8', 'loc_ic_t2f_mou_7', 'loc_og_t2t_mou_8', 'loc_og_t2t_mou_7', 'loc_og_mou_6', 'loc_ic_t2m_mou_7', 'total_og_mou_8', 'loc_ic_t2m_mou_8', 'arpu_3g_7', 'loc_ic_t2t_mou_7', 'sachet_3g_6', 'std_ic_t2m_mou_7', 'std_ic_mou_8', 'std_ic_t2m_mou_8', 'ic_others_6', 'av_rech_amt_data_7', 'av_rech_amt_data_8', 'ic_others_8', 'offnet_mou_6', 'count_rech_2g_6', 'loc_og_t2c_mou_8', 'total_og_mou_6', 'max_rech_data_8', 'max_rech_amt_7', 'count_rech_3g_8', 'arpu_2g_7', 'sachet_3g_7', 'loc_ic_t2t_mou_8', 'std_og_mou_6', 'std_ic_t2t_mou_6', 'std_og_t2f_mou_7', 'roam_og_mou_6', 'isd_og_mou_8']print('cat_col:', cat_col)cat_col: ['fb_user_7', 'night_pck_user_8', 'date_of_last_rech_data_6', 'night_pck_user_7', 'date_of_last_rech_6', 'fb_user_6', 'date_of_last_rech_8', 'date_of_last_rech_data_7', 'night_pck_user_6', 'fb_user_8', 'date_of_last_rech_data_8', 'date_of_last_rech_7']

4.1 Categorical data

Let's check the categorical columns.

df_hvc[cat_col].head()

	fb_user_7	night_pck_user_8	date_of_last_rech_data_6	night_pck_user_7	date_of_last_rech_6	fb_user_6	date_of_last_rech_8	date_of_last_rech_data_7	nig
0	1.0	0.0	6/21/2014	0.0	6/21/2014	1.0	8/8/2014	7/16/2014	
7	0.0	0.0	0	0.0	6/27/2014	0.0	8/26/2014	0	
8	1.0	0.0	0	0.0	6/25/2014	0.0	8/30/2014	7/31/2014	
21	0.0	0.0	0	0.0	6/30/2014	0.0	8/31/2014	0	
23	1.0	0.0	0	0.0	6/18/2014	0.0	8/24/2014	7/7/2014	

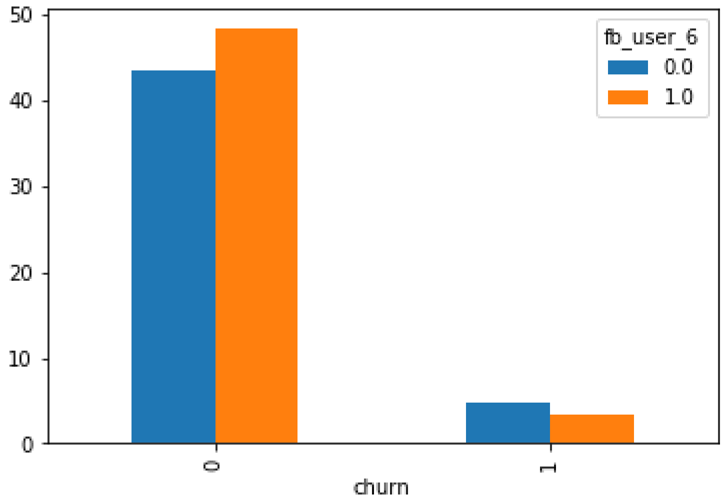
```
#fuction to impute the date columns, as mentioned above.
def date_impute(x):
  if x==0:
    return 0
  else:
    return 1

date_type = ['date_of_last_rech_6', 'date_of_last_rech_7', 'date_of_last_rech_8',
       'date_of_last_rech_data_6', 'date_of_last_rech_data_7','date_of_last_rech_data_8']for col in
```

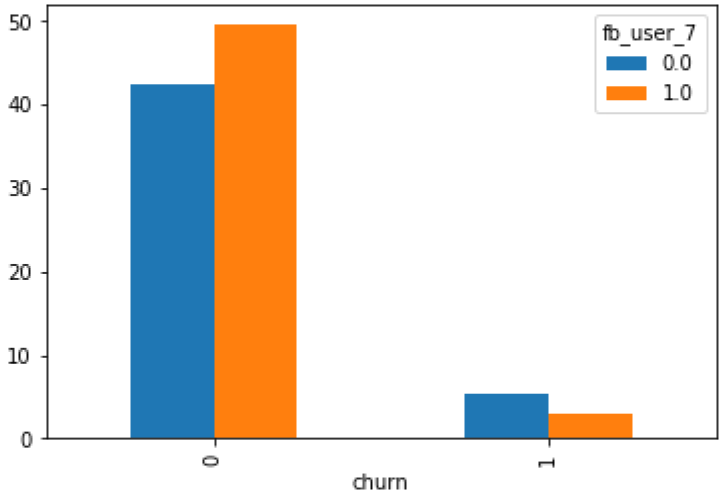
date_type:
    df_hvc[col] = df_hvc[col].apply(date_impute)

We have categorical column viz. date_of_last_rech_6 date_of_last_rech_7 date_of_last_rech_8 date_of_last_rech_data_6 date_of_last_rech_data_7 date_of_last_rech_data_8 fb_user_6 fb_user_7 fb_user_8, night_pck_user_6, night_pck_user_7, night_pck_user_8. Let's visualize the relation of categorical variables with the churn.

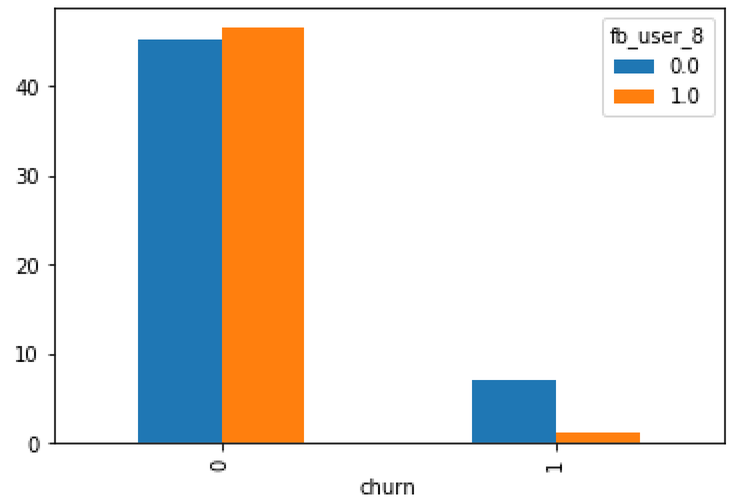
```
plt.figure(figsize=(5,5))
(pd.crosstab(df_hvc['churn'], df_hvc['fb_user_6'], normalize='all')*100).plot.bar()
plt.show()
```




```
plt.figure(figsize=(5,5))
(pd.crosstab(df_hvc['churn'], df_hvc['fb_user_7'], normalize='all')*100).plot.bar()
plt.show()
```




```
plt.figure(figsize=(5,5))
(pd.crosstab(df_hvc['churn'], df_hvc['fb_user_8'], normalize='all')*100).plot.bar()
plt.show()
```



From the above, we notice that customers who have tendency for churn tend to also use less social media websites such as **Facebook**. While on the other end, non-churn customers tend to use these services more often.

pd.crosstab(df_hvc['churn'],df_hvc['night_pck_user_6'], normalize='index')*100

night_pck_user_6	0.0	1.0
churn		
0	98.661103	1.338897
1	98.443261	1.556739

pd.crosstab(df_hvc['churn'],df_hvc['night_pck_user_7'], normalize='index')*100

night_pck_user_7	0.0	1.0
churn		
0	98.722787	1.277213
1	99.057763	0.942237

pd.crosstab(df_hvc['churn'],df_hvc['night_pck_user_8'], normalize='index')*100

night_pck_user_8	0.0	1.0
churn		
0	98.795356	1.204644
1	99.631299	0.368701

From above, we notice that among churners, the nigh pack usage is low but not that significantly low relative to non-churners, for all the phases.

pd.crosstab(df_hvc['churn'],df_hvc['date_of_last_rech_data_6'], normalize='index')*100

date_of_last_rech_data_6	0	1
churn		
0	43.312772	56.687228
1	53.584596	46.415404

pd.crosstab(df_hvc['churn'],df_hvc['date_of_last_rech_data_7'], normalize='index')*100

pd.crosstab(df_hvc['churn'],df_hvc['date_of_last_rech_data_8'], normalize='index')*100

date_of_last_rech_data_8	0	1
churn		
0	43.780842	56.219158
1	81.196231	18.803769

From the above two crosstables, we notice that for all the months in good and actions phases, churners tend not to recharge (date plan) while non-churner tend to recharge relatively more often.

(pd.crosstab(df_hvc['churn'],df_hvc['date_of_last_rech_6'], normalize='index')*100)

date_of_last_rech_6	0	1
churn		
0	0.203193	99.796807
1	0.696436	99.303564

pd.crosstab(df_hvc['churn'],df_hvc['date_of_last_rech_7'], normalize='index')*100

date_of_last_rech_7	0	1
churn		
0	0.163280	99.836720
1	2.171241	97.828759

pd.crosstab(df_hvc['churn'],df_hvc['date_of_last_rech_8'], normalize='index')*100

date_of_last_rech_8	0	1
churn		
0	0.928882	99.071118
1	13.396149	86.603851

From the above, we notice that there is hike in percentage of customers who does not recharge (voice services) in action phase, amongst churners.

Let's get derived matrices such that for date columns, if a user has recharged during good phase and not during the action phase, we mark them as 1 and 0 otherwise. Likewise for fb_user column, if user has used such services during good phase and not during action phase, we mark them as 1 and 0 otherwise. We would not derive such matric for night pack data as the different does not seem significant.

*#logic to obtain the columns as mentioned above*df_hvc['date_of_last_rech_'] = (df_hvc['date_of_last_rech_6'] |
df_hvc['date_of_last_rech_7']) & (~ df_hvc['date_of_last_rech_8'])df_hvc['date_of_last_rech_data_'] = (df_hvc['date_of_last_rech_data_6'] |
df_hvc['date_of_last_rech_data_7']) & (~ df_hvc['date_of_last_rech_data_6'])df_hvc['fb_user_'] = (df_hvc['fb_user_6'].astype('int64') |
df_hvc['fb_user_7'].astype('int64')) & (~ df_hvc['fb_user_8'].astype('int64'))

Let's visualize the relation of all the above three derived categorical features with the churn.

pd.crosstab(df_hvc.churn, df_hvc.date_of_last_rech_, normalize='index')*100

date_of_last_rech_	0	1
churn		
0	99.071118	0.928882
1	86.603851	13.396149

pd.crosstab(df_hvc.churn, df_hvc.date_of_last_rech_data_, normalize='index')*100

date_of_last_rech_data_	0	1
churn		
0	90.791001	9.208999
1	91.560836	8.439164

From above, we note that among churners, more percentage of customers (13.39%) tend to stop recharging for voice services in action phase as compared with non-churners (0.92%). The similar trend is not detected in data service.

pd.crosstab(df_hvc.churn, df_hvc.fb_user_, normalize='index')*100

fb_user_	0	1
churn		
0	87.198839	12.801161
1	63.334699	36.665301

We note that more customers (36.66%) who churned, deliberately stopped using social media services during action phase, as compared with those (12.80%) who did not churn.

Let’s utilize the three derived features as well, for our model.

4.2 Continuous data

Let’s check the continuous columns.

```
df_hvc[cont_col].head()
```

	loc_og_t2t_mou_6	isd_ic_mou_7	std_ic_t2f_mou_8	arpu_6	sachet_2g_6	jun_vbc_3g	arpu_8	std_ic_t2f_mou_7	total_rech_data_8	total_og_mou_7	st
0	0.00	0.00	0.00	197.385	0	101.20	213.803	0.00	1.0	0.00	
7	51.39	14.53	22.21	1069.180	0	18.74	3171.480	34.24	0.0	609.24	
8	297.13	0.00	0.00	378.721	0	122.16	137.362	0.00	3.0	431.66	
21	4.48	0.00	0.00	514.453	0	0.00	637.760	0.00	0.0	1028.79	
23	48.96	28.23	0.00	74.350	0	0.00	366.966	0.00	2.0	140.04	

We can drop mobile_number, as the same seems to be serving the purpose of identity only.

```
df_hvc.drop(['mobile_number'], axis=1, inplace=True)#removing mobile_number from cont_col
cont_col = set(cont_col)cont_col.remove('mobile_number')cont_col= list(cont_col)
```

As per the problem statement, we have months 6 (June) and 7 (July) as *The ‘good’ phase* while month 8 (August) as *The ‘action’ phase*. Let’s check whether there is any significant difference amongst the average statistics for the month of June & July as compared with the month of August.

For the purpose of statistical analysis, let’s get the average values of different predictors for the month of **good phase** (i.e. June and July) and compare the same with the **actions phase** (i.e. August).

```
#bunching the different continuous columns based on their monthscols_6_mon = []
cols_7_mon = []
cols_8_mon = []for col in set(df_hvc.columns) - set(cat_col):
    if col[-1]=='6':
        cols_6_mon.append(col)

for col in set(df_hvc.columns) - set(cat_col):
    if col[-1]=='7':
        cols_7_mon.append(col)

for col in set(df_hvc.columns) - set(cat_col):
    if col[-1]=='8':
        cols_8_mon.append(col)

#sorting the columns
cols_6_mon = sorted(cols_6_mon)
cols_7_mon = sorted(cols_7_mon)
cols_8_mon = sorted(cols_8_mon)desc = []
mean_6_7 = []#getting the average values for the months of June and July and appending their means
for col6,col7 in zip(cols_6_mon,cols_7_mon):
    desc.append(col6[:-1])
    mean_6_7.append(((df_hvc[col6] + df_hvc[col7])/2).mean())
    #appending the means of different columns of august
col8_val = []
```

```
for col8 in cols_8_mon:
    col8_val.append(df_hvc[col8].mean())#preparing the dataframe to display the statistics for good phase and actions phasemonthly_stats_df = 
pd.DataFrame(data={'desc':desc,'mean_6_7':mean_6_7,'col8_val':col8_val})
monthly_stats_df['val_diff']= monthly_stats_df['col8_val'] - monthly_stats_df['mean_6_7']
monthly_stats_df['percentage_diff']=(monthly_stats_df['col8_val']-monthly_stats_df['mean_6_7']
                                    )/monthly_stats_df['mean_6_7']*100
avg_vbc_3g = ((df_hvc.jun_vbc_3g+df_hvc.jul_vbc_3g)/2).mean()
mean_aug_vbc_3g = df_hvc.aug_vbc_3g.mean()monthly_stats_df = 
monthly_stats_df.append({'desc':'vbc_3g',
                         'mean_6_7':avg_vbc_3g,
                         'col8_val':mean_aug_vbc_3g,
                         'val_diff':(mean_aug_vbc_3g-avg_vbc_3g),
                         'percentage_diff':(mean_aug_vbc_3g-avg_vbc_3g)/avg_vbc_3g*100},
                         ignore_index=True)#display the statistics dataframe
monthly_stats_df.sort_values('percentage_diff', ascending=True)
```

	desc	mean_6_7	col8_val	val_diff	percentage_diff
24	og_others_	0.351998	0.057607	-0.294391	-83.634280
30	spl_ic_mou_	0.040400	0.026567	-0.013833	-34.239794
45	vol_2g_mb_	125.809755	105.913072	-19.896683	-15.814897
44	total_rech_num_	11.784924	9.972868	-1.812056	-15.376054
27	roam_og_mou_	23.361816	19.865615	-3.496201	-14.965451
38	std_og_t2m_mou_	183.677078	157.350068	-26.327010	-14.333313
21	monthly_2g_	0.178877	0.153628	-0.025249	-14.115345
36	std_og_mou_	355.555232	307.379315	-48.175917	-13.549489
26	roam_ic_mou_	14.376429	12.500551	-1.875878	-13.048288
39	std_og_t2t_mou_	170.059634	148.441175	-21.618459	-12.712281
37	std_og_t2f_mou_	1.814799	1.584734	-0.230066	-12.677205
42	total_rech_amt_	660.615179	584.365454	-76.249725	-11.542230
25	onnet_mou_	264.306159	234.112539	-30.193620	-11.423729
41	total_og_mou_	619.116149	551.678812	-67.437337	-10.892518
23	offnet_mou_	375.898565	335.077044	-40.821520	-10.859717
3	av_rech_amt_data_	135.218053	122.132258	-13.085795	-9.677550
2	arpu_	559.636514	508.597957	-51.038557	-9.119948
8	isd_og_mou_	2.138634	1.948970	-0.189665	-8.868488
0	arpu_2g_	64.070401	58.395301	-5.675100	-8.857600
4	count_rech_2g_	1.318923	1.208493	-0.110430	-8.372716
18	loc_og_t2t_mou_	85.079520	78.077112	-7.002408	-8.230427

From the above, we notice that majority of services has consumption reduced in action phase as compared to good phase.

#columns with reduction in usage
reduction_cols = monthly_stats_df[monthly_stats_df.percentage_diff < 0].desc.values

These difference columns may be pivotal for our model building as the same might indicate churn. So, let's get the derived matrix out of these columns by getting the difference and use them as predictor for our model building.

*#deriving the difference columns between good and actions phase for reduction_cols***for** col **in** reduction_cols:

name='diff_'+col
col_june = col+'6'
col_july = col+'7'
col_aug = col+'8'
df_hvc[name] = df_hvc[col_aug] - ((df_hvc[col_june]+df_hvc[col_july])/2)*#check the shape of df_hvc now*
df_hvc.shape(30001, 207)*#check the head of df_hvc*
df_hvc.head()

	arpu_6	arpu_7	arpu_8	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	roa
0	197.385	214.816	213.803	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
7	1069.180	1349.850	3171.480	57.84	54.68	52.29	453.43	567.16	325.91	16.23	33.49	
8	378.721	492.223	137.362	413.69	351.03	35.08	94.66	80.63	136.48	0.00	0.00	
21	514.453	597.753	637.760	102.41	132.11	85.14	757.93	896.68	983.39	0.00	0.00	
23	74.350	193.897	366.966	48.96	50.66	33.58	85.41	89.36	205.89	0.00	0.00	

Now let's checkout the correlation of all the continuous predictors with the target variable i.e. Churn and hence find the top negatively correlated predictors.

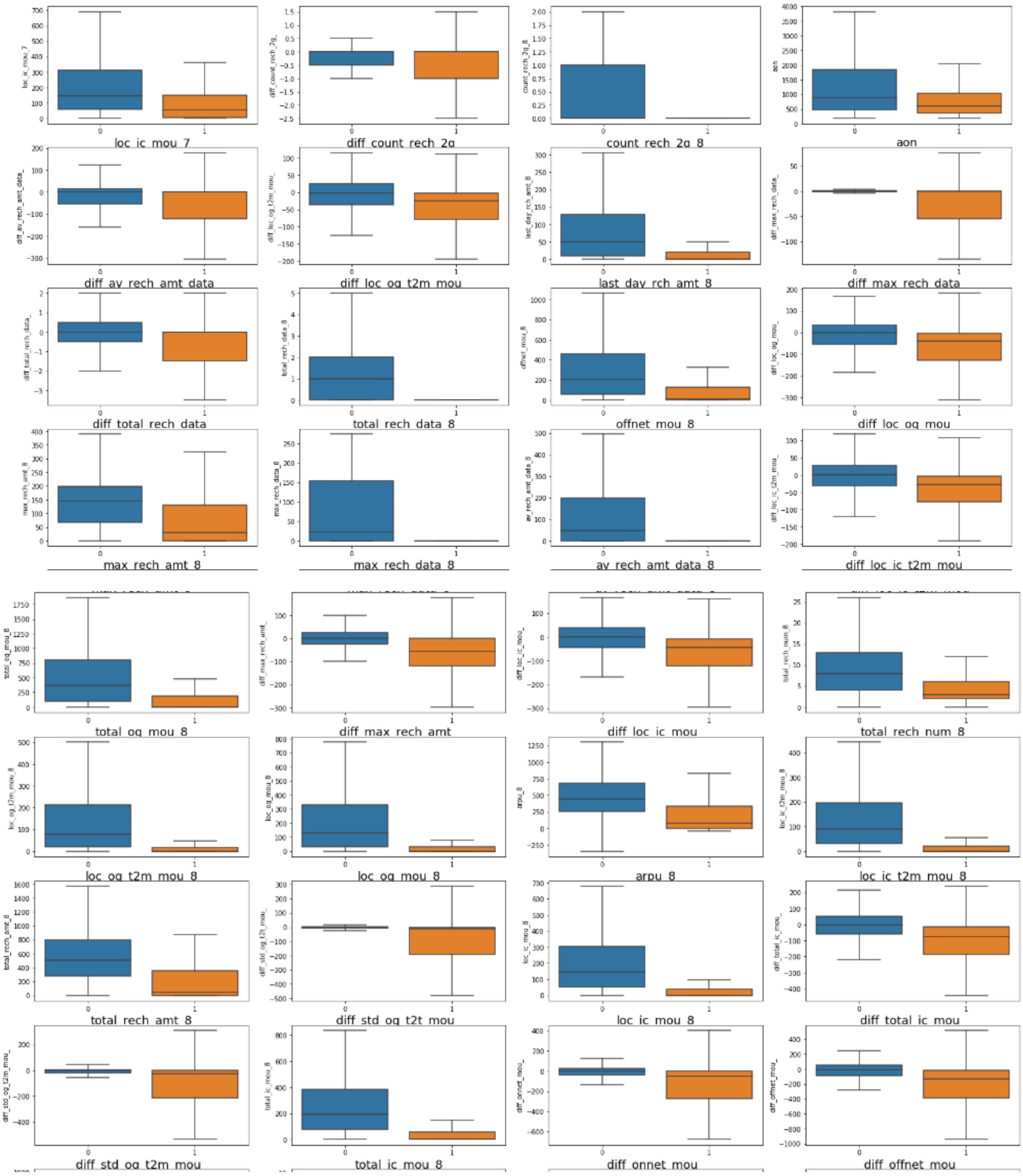
corr_df = round(df_hvc[list(set(df_hvc.columns) - set(cat_col))].corr().churn.sort_values(ascending=**False**)*100, 3)corr_df[corr_df.values<-10]loc_ic_mou_7 -10.009
diff_count_rech_2g_ -10.019
count_rech_2g_8 -10.739
aon -10.828
diff_av_rech_amt_data_ -11.026
diff_loc_og_t2m_mou_ -11.488
last_day_rch_amt_8 -11.626
diff_max_rech_data_ -11.682
diff_total_rech_data_ -11.895
total_rech_data_8 -11.989
offnet_mou_8 -12.152
diff_loc_og_mou_ -12.238
max_rech_amt_8 -12.848
max_rech_data_8 -13.552
av_rech_amt_data_8 -13.746
diff_loc_ic_t2m_mou_ -13.785
total_og_mou_8 -14.544
diff_max_rech_amt_ -15.152
diff_loc_ic_mou_ -15.174
total_rech_num_8 -15.190
loc_og_t2m_mou_8 -15.247
loc_og_mou_8 -15.259
arpu_8 -16.091
loc_ic_t2m_mou_8 -16.113
total_rech_amt_8 -16.127
diff_std_og_t2t_mou_ -17.114
loc_ic_mou_8 -17.239
diff_total_ic_mou_ -17.476

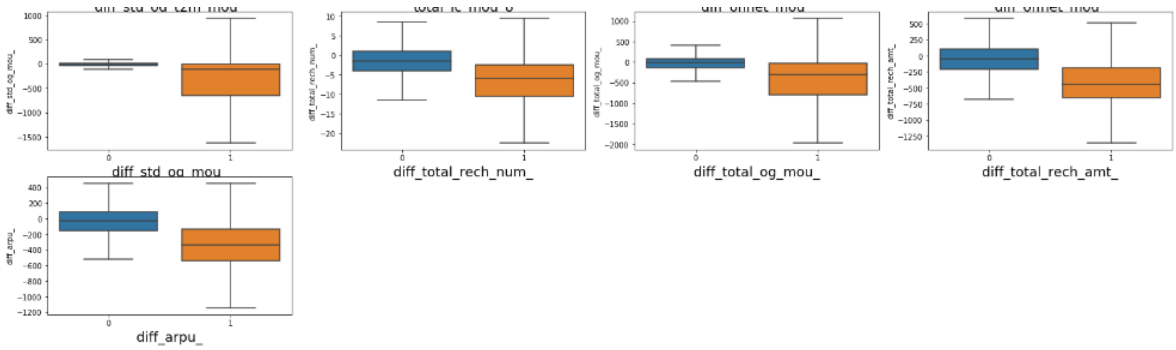
diff_std_og_t2m_mou_   -17.663
total_ic_mou_8   -17.838
diff_onnet_mou_   -18.057
diff_offnet_mou_   -21.063
diff_std_og_mou_   -23.498
diff_total_rech_num_   -24.648
diff_total_og_mou_   -25.626
diff_total_rech_amt_   -26.818
diff_arpu_   -27.855
Name: churn, dtype: float64

Let’s plot them with respect to churn, so as to visualize them better.

```
#bunching the top negatively correlated (with churn) columns
neg_corr_pre = list(corr_df[corr_df.values<-10].index)
neg_corr_pre['loc_ic_mou_7',
 'diff_count_rech_2g_',
 'count_rech_2g_8',
 'aon',
 'diff_av_rech_amt_data_',
 'diff_loc_og_t2m_mou_',
 'last_day_rch_amt_8',
 'diff_max_rech_data_',
 'diff_total_rech_data_',
 'total_rech_data_8',
 'offnet_mou_8',
 'diff_loc_og_mou_',
 'max_rech_amt_8',
 'max_rech_data_8',
 'av_rech_amt_data_8',
 'diff_loc_ic_t2m_mou_',
 'total_og_mou_8',
 'diff_max_rech_amt_',
 'diff_loc_ic_mou_',
 'total_rech_num_8',
 'loc_og_t2m_mou_8',
 'loc_og_mou_8',
 'arpu_8',
 'loc_ic_t2m_mou_8',
 'total_rech_amt_8',
 'diff_std_og_t2t_mou_',
 'loc_ic_mou_8',
 'diff_total_ic_mou_',
 'diff_std_og_t2m_mou_',
 'total_ic_mou_8',
 'diff_onnet_mou_',
 'diff_offnet_mou_',
 'diff_std_og_mou_',
 'diff_total_rech_num_',
```

```
 'diff_total_og_mou_',
 'diff_total_rech_amt_',
 'diff_arpu_']#plotting the continuous negatively correlated columnsplt.figure(figsize=(27,60))
for m,n in enumerate(neg_corr_pre):
    plt.subplot(15,4,(m+1))
    sns.boxplot(df_hvc['churn'], df_hvc[n], showfliers=False)   #put showfliers=False to remove outliers from plot
    plt.xlabel(n,fontsize=18)
plt.show()
```





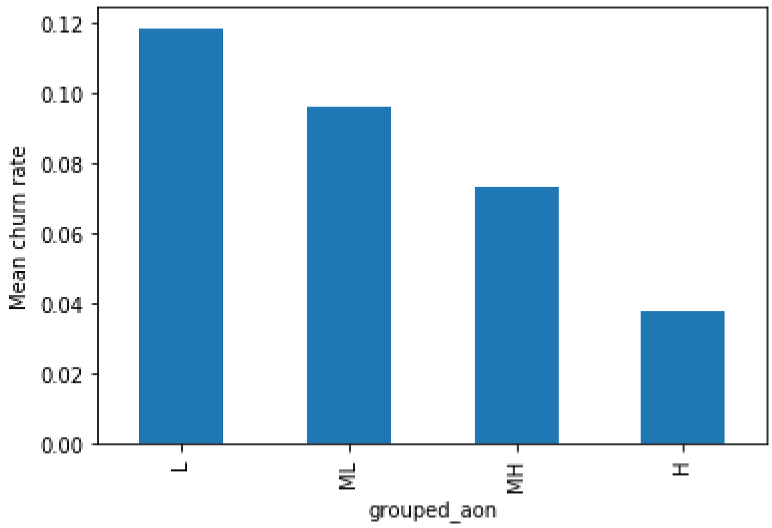
From the above, we note that in case of high negatively correlated variables, the median values in case of churn is lower as compared to non-churn cases. The same is intuitive as we note the significant reduction in the usage of different service during the action month (i.e. August) as compared to good months.

Let’s check the churn rate for different AON i.e. Age on network - number of days the customer is using the operator T network.

df_hvc.aon.describe()count   30001.000000
mean   1209.368754
std   957.677989
min   180.000000
25%   460.000000
50%   846.000000
75%   1756.000000
max   4321.000000
Name: aon, dtype: float64

Let’s group this column into different categories, for ease of analysis.

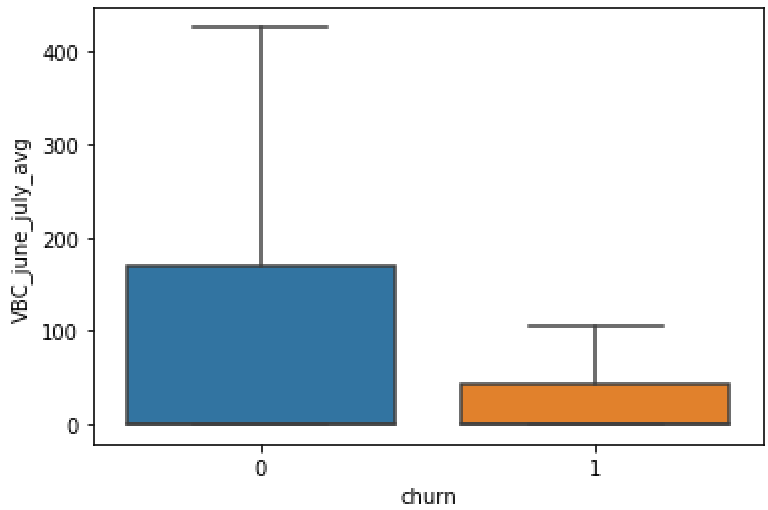
df_hvc['grouped_aon'] = pd.cut(df_hvc['aon'],[180,460,846,1756,4321], labels=['L','ML','MH','H'])
df_hvc['grouped_aon'].value_counts()MH   7500
H   7499
L   7499
ML   7488
Name: grouped_aon, dtype: int64df_hvc.groupby('grouped_aon').churn.mean().plot.bar()
plt.ylabel('Mean churn rate')
plt.show()df_hvc.drop('grouped_aon', axis=1, inplace=**True**)



From the above, we note that amongst high value customers, as their age as a user in network T increases, the mean churn rate decreases.

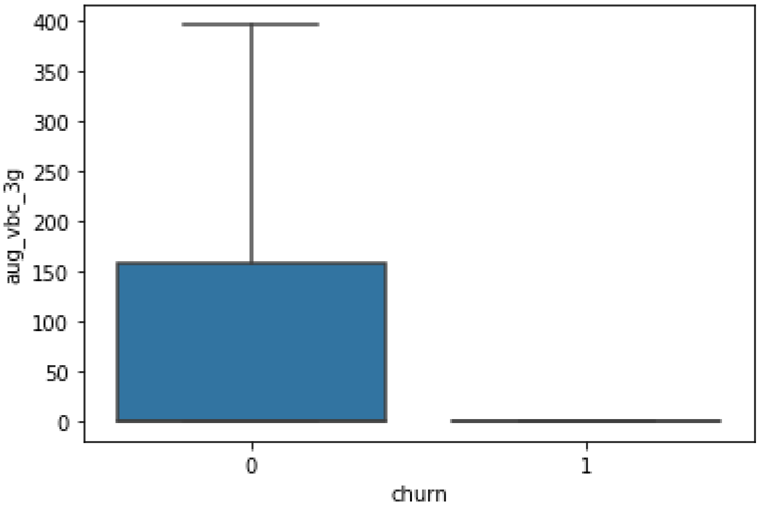
Let’s check out the volume based cost (**VBC**) for different phases (**good** and **action**) for both churners and non-churners.

df_hvc['VBC_june_july_avg'] = (df_hvc.jun_vbc_3g + df_hvc.jul_vbc_3g)/2print(df_hvc['VBC_june_july_avg'].describe())sns.boxplot(x=df_hvc.churn, y=df_hvc.VBC_june_july_avg, showfliers=**False**)
plt.show()



count 30001.000000
mean 168.698363
std 392.776395
min 0.000000
25% 0.000000
50% 0.000000
75% 158.000000

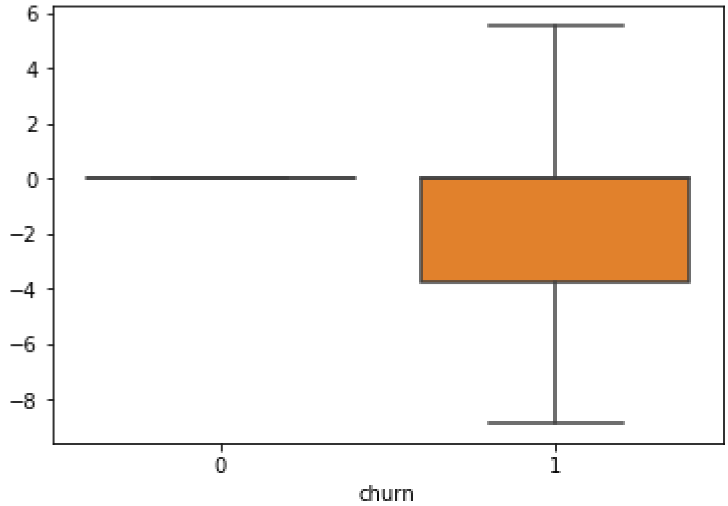
max   8190.585000
Name: VBC_june_july_avg, dtype:
float64print(df_hvc['aug_vbc_3g'].describe())sns.boxplot(x=df_hvc.churn, y=df_hvc.aug_vbc_3g, showfliers=**False**)
plt.show()count   30001.000000
mean   169.138860
std   420.974354
min   0.000000
25%   0.000000
50%   0.000000
75%   128.800000
max   12916.220000
Name: aug_vbc_3g, dtype: float64



From the above, we notice that VBC i.e. volume based cost are less for churners for both good as well as action phase. Especially in action phase, the VBC has reduced down to almost zero for churners. Let's keep VBC_june_july_avg as the same seems an important indicator of churn.

Let's get the difference between the VBC_june_july_avg and aug_vbc_3g and plot the same against churn.

df_hvc.diff_vbc = df_hvc.aug_vbc_3g - df_hvc.VBC_june_july_avgsns.boxplot(x=df_hvc.churn, y=df_hvc.diff_vbc, showfliers=**False**)



From the above, we note that there is reduction in volume based cost in action phase as compared with the good phase.

4.3 Summary insights after EDA:

1. There are total two kinds of missing values:

- One where customers have not used voice/data as they have not recharged for voice/data for the corresponding months.
- Second where customers have deliberately not used voice/data even after recharging for voice/data for the corresponding months.

2. Churn rate is relatively high amongst customers who have deliberately not used services even after recharging for the same, which shows their dissatisfaction towards network.

3. As the customers starts to reduce their service usage from Good phase to Action phase, the likelihood of churn increases. The same is visible from the box plot of various continuous negatively correlated derived variables above.

4. Tendency of data/ voice recharge also decreases from Good phase to Action phase, amongst churners.

5. Churners tend to use relatively less social media websites (such as Facebook, etc.) from Good phase to Action phase

6. Old customers tend to churn less as compared with new customers.

7. There is significant reduction in usage of volume based cost (VBC) services amongst churners, while the same trend is not noticed amongst non-churners.

5. Data Preparation

5.1 Seperating X and y

y = df_hvc.churn
X = df_hvc.drop('churn', axis=1)print(X.shape, y.shape)(30001, 207) (30001,)

5.2 Handling the class imbalance

Let’s check the percentage of churn left in our final cleaned dataset.

y.value_counts(normalize=**True**)*1000   91.863605
1   8.136395
Name: churn, dtype: float64

From the above, we notice that in our final prepared data, we have only **8.13%** of churn while **91.86%** non-churn. Hence our dataset is highly imbalanced. We need to take care of this imbalance since otherwise dimensionality reduction like PCA might eliminate those dimensions, which may be the indicators of minority class i.e. churn here.

Let’s use **SMOTE** i.e. Synthetic Minority Oversampling Technique to handle such situation. SMOTE works by selecting examples that are close in the feature space, drawing a line between the examples in the feature space and drawing a new sample at a point along that line.

courtesy: https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/

*#using SMOTE to oversample the dataset properly*smote = SMOTE(random_state=1)X_sm, y_sm = smote.fit_sample(X=X, y=y)*#check the shape of X_sm*
X_sm.shape(55120, 207)*#check the shape of y_sm*
y_sm.shape(55120,)*#check the percantage value counts of churn*
y_sm.value_counts(normalize=**True**)*1001   50.0
0   50.0
Name: churn, dtype: float64

From above, we notice that both the classed have become perfectly balanced now. So now we can fearlessly apply dimensionality reduction technique i.e. PCA to our dataset.

5.3 Train-Test split

X_train, X_test, y_train, y_test = train_test_split(X_sm, y_sm, test_size=0.3)

5.4 Scalling the X

#use MinMaxScaler is scale the predictors (X)
scaler = MinMaxScaler()X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)*#converting array into dataframe*
X_train_scaled = pd.DataFrame(X_train_scaled, columns=X.columns)
X_test_scaled = pd.DataFrame(X_test_scaled, columns=X.columns)X_train_scaled.head()

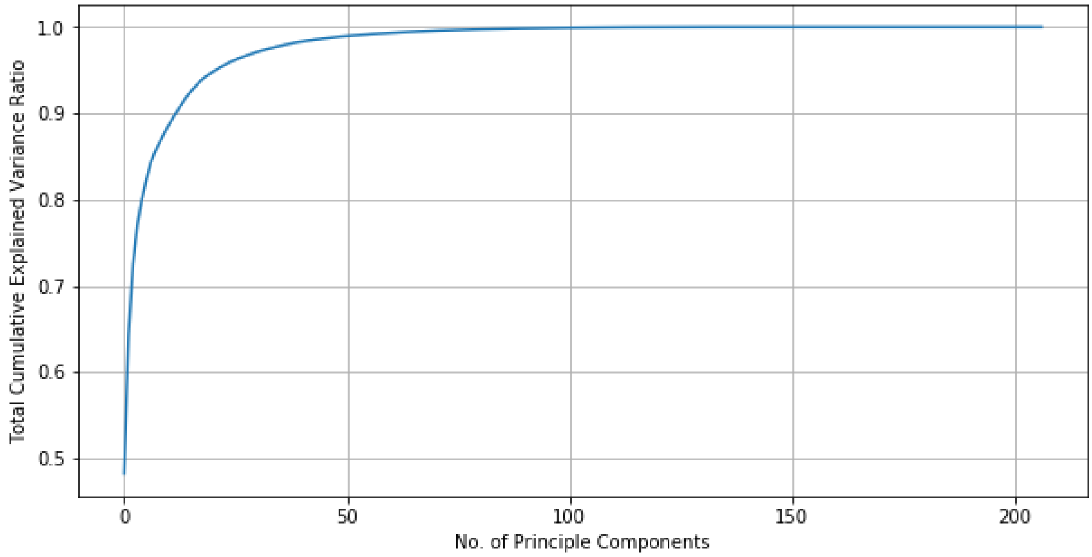
	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roar
0	0.087136	0.069110	0.027494	0.069166	0.070038	0.000166	0.033507	0.041449	0.000085	0.000000	0.00000	
1	0.128012	0.091907	0.070580	0.016269	0.013341	0.011033	0.161006	0.100706	0.067001	0.000000	0.00000	
2	0.076556	0.071791	0.031872	0.000000	0.007642	0.003403	0.003115	0.023559	0.022658	0.000000	0.00000	
3	0.108634	0.062944	0.027436	0.003845	0.000292	0.000000	0.293241	0.065964	0.000000	0.000000	0.00000	
4	0.086687	0.073517	0.031127	0.003214	0.004165	0.000184	0.023739	0.035205	0.002973	0.019508	0.02801	

X_test_scaled.head()

	arpu_6	arpu_7	arpu_8	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	roar
0	0.094511	0.076075	0.035451	0.007124	0.007184	0.001431	0.054791	0.047592	0.008216	0.023557	0.013026	
1	0.086061	0.063741	0.040388	0.010972	0.001194	0.000525	0.011496	0.004004	0.002100	0.000000	0.000501	
2	0.105326	0.069415	0.027423	0.000000	0.000396	0.000000	0.000000	0.000227	0.000000	0.000000	0.000000	
3	0.089664	0.073456	0.052668	0.081239	0.060063	0.035738	0.063982	0.083925	0.049791	0.000000	0.000000	
4	0.085474	0.070730	0.034014	0.083094	0.101927	0.021425	0.041366	0.036923	0.006054	0.000377	0.000000	

5.5 Dimentionality reduction using PCA

*#use principal component analysis (PCA) for dimensionality reduction*pca = PCA(random_state=100)
pca.fit(X_train_scaled)
var_cumu = np.cumsum(pca.explained_variance_ratio_)
*#plotting different variance for chosen no. of principle components*plt.figure(figsize=(10,5))
plt.plot(var_cumu)
plt.xlabel('No. of Principle Components')
plt.ylabel('Total Cumulative Explained Variance Ratio')
plt.grid()
plt.show()



#check cumulative variance explained by top 25 principle components
var_cumu[25-1]0.9598669231171647

From the above, we note that after **25**, the total explained variance ratio seems to flatten. Hence we should go ahead with those PCs only.

#using top PCs for data preparation for our model
pc2 = PCA(25, random_state=100)new_train_data = pc2.fit_transform(X_train_scaled)
new_test_data = pc2.transform(X_test_scaled)pc_cols = []
for i **in** range(25):
    pc_cols.append('PC'+str(i))X_train_pca = pd.DataFrame(new_train_data, columns=pc_cols)
X_test_pca = pd.DataFrame(new_test_data, columns=pc_cols)

In [126]:

X_train_pca.head()

	PC0	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	I
0	-0.163098	0.192554	0.083113	-0.104479	-0.546051	0.503059	-0.621904	0.252761	0.239593	0.205801	0.094554	-0.180637	-0.084319	0.022739	0.21
1	-1.004537	-0.209525	-0.012546	-0.136882	0.052720	0.265707	-0.008186	0.097363	-0.047292	-0.094237	0.005329	0.324855	-0.226831	0.314418	-0.07
2	0.868464	0.372020	0.165164	-0.186161	-0.615253	0.065556	0.185418	-0.128717	-0.195286	0.330292	0.156287	0.345517	0.440653	0.074323	-0.00
3	-1.069193	0.139745	-0.188342	1.055810	-0.032124	0.086976	0.188895	0.089392	-0.044980	-0.302367	0.560260	0.268083	-0.175927	-0.120229	0.06
4	-0.998481	-0.166396	-0.001647	-0.114699	-0.093836	-0.082635	0.006897	-0.208422	0.072827	-0.078771	-0.013395	0.043928	0.023288	-0.011794	0.00

X_train_pca.shape(38584, 25)y_train.shape(38584,)X_test_pca.head()

	PC0	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	I
0	-0.949071	-0.165067	0.050845	-0.104232	-0.140247	-0.064837	-0.025207	-0.152772	0.082632	-0.087728	-0.009392	0.016102	0.032504	-0.025165	-0.03
1	1.491424	-0.316825	-0.149708	0.014399	-0.128368	-0.090505	0.051211	-0.072207	0.225900	0.162856	0.065641	-0.094476	-0.152918	-0.012427	-0.00
2	0.755886	1.380023	0.322837	0.560452	-0.122834	0.056347	0.152185	0.077491	-0.031464	-0.073563	-0.335475	0.104895	0.263577	-0.066392	0.01
3	-1.015889	-0.190998	-0.005759	-0.140340	-0.061883	-0.041184	0.036302	0.030031	-0.020116	-0.013087	0.017838	-0.000771	0.002132	-0.006356	-0.01
4	-1.016702	-0.178211	-0.004260	-0.129529	-0.106274	-0.134357	0.040111	-0.015286	-0.013800	-0.032338	0.006328	-0.025088	0.033593	-0.043449	-0.00

6. Model building (I): Churn prediction

Here, our 1st aim is churn classification. Target is to classify all the churners more accurately. We know that Recall/ Sensitivity is given by,

Recall=Sensitivity=TP/(TP+FN)Recall=Sensitivity=TP/(TP+FN).

So False Negatives (FN) should be as low as possible. For the same, our Recall score (Sensitivity) should be as high as possible. Hence Recall score should be our metric of focus for comparison of different ML models.

Let's use the following ML techniques with PCA for our classification task:

1. Logistic Regression
2. Random Forrest
3. XGBoost

We would initially run the above models on all the default parameters and check the Recall score and subsequently tune the corresponding hyperparameters and then check the Recall score again on the best obtained set of hyperparameters.

6.1 Logistics Regression with PCA:

6.1.1 Model with default hyperparameters

lrm = LogisticRegression()lrm.fit(X_train_pca, y_train)*#print the classification report*
print(classification_report(y_test, lrm.predict(X_test_pca)))
print("ROC score:", roc_auc_score(y_test, lrm.predict(X_test_pca)))precision recall f1-score support 0 0.84 0.84 0.84 8353
1 0.84 0.84 0.84 8183 accuracy 0.84 16536
macro avg 0.84 0.84 0.84 16536
weighted avg 0.84 0.84 0.84 16536ROC score: 0.8394984073685334

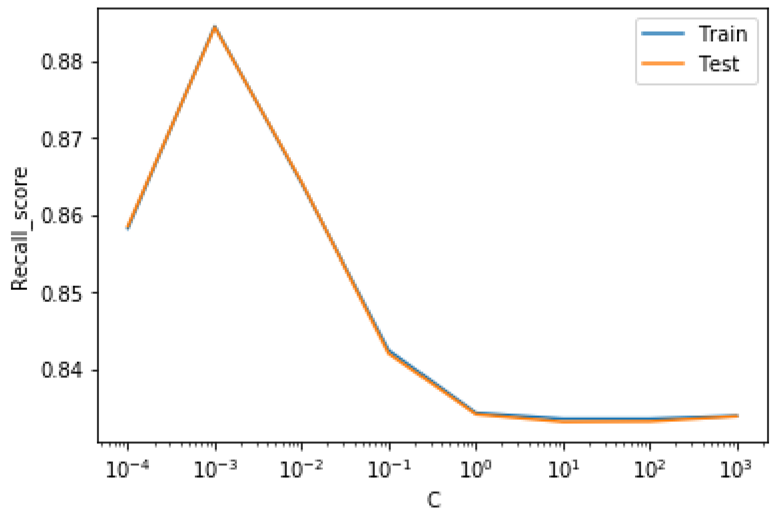
6.1.2 Tuning the hyperparameters

Let's use l2 regularizations along with tuning of C hyperpameter using RandomizedSearchCV and find the best set of hyprparameters for the given problem.

Let's tune the hyperparameters in the following fashion:

- 'penalty': Used to specify the norm used in the penalization i.e. l1 or l2 regularization. Let's keep it [l2]
- 'C': Inverse of regularization strength. Let's keep it [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]

```
# Create the parameter grid based on the results of random search
param_grid = {
   'penalty': ['l2'],
   'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
}
# Create a based model
lr_model = LogisticRegression()# Instantiate the grid search model
lr_model_random_search = RandomizedSearchCV(estimator = lr_model, param_distributions =
param_grid, scoring= 'recall',
                    cv = 5, n_jobs = -1,verbose = 1,return_train_score=True,
n_iter=15)lr_model_random_search.fit(X_train_pca, y_train)Fitting 5 folds for each of 8 candidates,
totalling 40 fitsRandomizedSearchCV(cv=5, estimator=LogisticRegression(), n_iter=15, n_jobs=-1,
               param_distributions={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10,
                                          100, 1000],
                                     'penalty': ['l2']},
               return_train_score=True, scoring='recall',
verbose=1)lr_model_random_search.best_estimator_LogisticRegression(C=0.001)#saving the CV
results into an object
cv_results= pd.DataFrame(lr_model_random_search.cv_results_)#plotting R2 score vs alpha value
plt.plot(cv_results['param_C'], cv_results['mean_train_score'], label='Train')
plt.plot(cv_results['param_C'], cv_results['mean_test_score'], label='Test')
plt.xlabel('C')
plt.ylabel('Recall_score')
plt.xscale('log')
plt.legend()
plt.show()
```



Let’s check C=0.001 and C=0.01 along with l2 regularization. Let’s use them and build our final model for logistic regression.

```
lrm_final = LogisticRegression(penalty='l2', C=0.01)lrm_final.fit(X_train_pca, y_train)#print the
classification report
print(classification_report(y_test, lrm_final.predict(X_test_pca)))
print("ROC score:", roc_auc_score(y_test, lrm_final.predict(X_test_pca)))precision    recall  f1-score
```

support 0 0.85 0.76 0.81 8353
1 0.78 0.86 0.82 8183 accuracy 0.81 16536
macro avg 0.82 0.81 0.81 16536
weighted avg 0.82 0.81 0.81 16536ROC score: 0.8140751824228365lrm_final = LogisticRegression(penalty='l2', C=0.001)lrm_final.fit(X_train_pca, y_train)*#print the classification report*
print(classification_report(y_test, lrm_final.predict(X_test_pca)))
print("ROC score:", roc_auc_score(y_test, lrm_final.predict(X_test_pca)))precision recall f1-score support 0 0.85 0.61 0.71 8353
1 0.69 0.89 0.78 8183 accuracy 0.75 16536
macro avg 0.77 0.75 0.74 16536
weighted avg 0.77 0.75 0.74 16536ROC score: 0.7501178557965295

We notice that C=0.001 is increasing recall but reducing ROC score. So from above, we have got C=0.01 as the best value of hyperparameter for logistic regression with l2 regularization.

6.2 Random Forest with PCA

6.2.1 Model with default hyperparameters

rfcm = RandomForestClassifier()rfcm.fit(X_train_pca, y_train)print(classification_report(y_test, rfcm.predict(X_test_pca)))
print("ROC score:", roc_auc_score(y_test, rfcm.predict(X_test_pca)))precision recall f1-score support 0 0.94 0.94 0.94 8353
1 0.94 0.94 0.94 8183 accuracy 0.94 16536
macro avg 0.94 0.94 0.94 16536
weighted avg 0.94 0.94 0.94 16536ROC score: 0.9433403329696359

6.2.2 Tuning the hyperparameters

Let’s tune the hyperparameters in the following fashion:

- ‘max_depth’: The maximum depth of the tree. Let’s keep it [12,18]
- ‘n_estimators’: The number of trees in the forest. Let’s keep it [100],
- ‘max_features’: The number of features to consider when looking for the best split. Let’s keept it as total no. of predictors i.e. [X_train_pca.shape[1]],
- ‘min_samples_leaf’: The minimum number of samples required to be at a leaf node.Let’s keep it as [10,20],
- ‘min_samples_split’: The minimum number of samples required to split an internal node. Let’s keep it as [10,20,30]

 # Create the parameter grid based on the results of random search
#param_grid = {
 # 'max_depth': [12,18],
 # 'n_estimators': [100],
 # 'max_features': [X_train_pca.shape[1]],
 # 'min_samples_leaf': [10,20],
 # 'min_samples_split': [10,20,30]
#}

 # Create a based model
#rf_model = RandomForestClassifier()# Instantiate the grid search model
#rf_random_search = RandomizedSearchCV(estimator = rf_model, param_distributions = param_grid, scoring= 'recall',
*#   cv = 5, n_jobs = -1,verbose = 1,return_train_score=True, n_iter=10)#rf_random_search.fit(X_train_pca, y_train)#rf_random_search.best_estimator_*

The above code has been hashed out as it is time consuming. The same was ran on Google colab and the results obtained has been reproduced below.

Upon running the above code, the best values of hyperparameters obtained as as under:

- max_depth= 18
- n_estimators= 100
- max_features= 25
- min_samples_leaf= 10
- min_samples_split= 10

#running the model on best obtained set of hyperparameters
rfcm = RandomForestClassifier(max_depth= 18, n_estimators= 100, max_features= 25,
min_samples_leaf= 10, min_samples_split= 10)rfcm.fit(X_train_pca, y_train)print(classification_report(y_test, rfcm.predict(X_test_pca)))
print("ROC score:", roc_auc_score(y_test, rfcm.predict(X_test_pca)))precision recall f1-score support 0 0.91 0.93 0.92 8353
1 0.93 0.91 0.92 8183 accuracy 0.92 16536
macro avg 0.92 0.92 0.92 16536
weighted avg 0.92 0.92 0.92 16536ROC score: 0.9194227201221712

6.3 XGBoost

6.3.1 Model with default hyperparameters

xgbm = XGBClassifier()
xgbm.fit(X_train_pca, y_train)print(classification_report(y_test, xgbm.predict(X_test_pca)))
print("ROC score:", roc_auc_score(y_test, xgbm.predict(X_test_pca)))[19:21:56] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
precision recall f1-score support 0 0.92 0.93 0.92 8353
1 0.92 0.92 0.92 8183 accuracy 0.92 16536
macro avg 0.92 0.92 0.92 16536
weighted avg 0.92 0.92 0.92 16536ROC score: 0.9223842315052277

6.3.2 Tuning the hyperparameters

Let’s tune the hyperparameters in the following fashion:

- ‘learning_rate’: It is the rate at which model learns. Let’s keep it [0.1,0.2,0.3]
- ‘subsample’: Subsample ratio of the training instances. Let’s keep it [0.3,0.4,0.5],

 # hyperparameter tuning with XGBoost# creating a KFold object
#folds = 5# specify range of hyperparameters
#param_grid = {'learning_rate': [0.1,0.2,0.3],
 # 'subsample': [0.3,0.4,0.5]}
 # specify model
#xgb_model = XGBClassifier(max_depth=2, n_estimators=200)# set up GridSearchCV()
#model_cv = RandomizedSearchCV(estimator = xgb_model,
 # param_distributions = param_grid,
 # scoring= 'recall',
 # cv = folds,
 # n_jobs = -1,
 # verbose = 1,
*# return_train_score=True, n_iter=10) #model_cv.fit(X_train_pca, y_train)#model_cv.best_estimator_*

The above code has been hashed out as it is time consuming. The same was ran on Google colab and the results obtained has been reproduced below.

Upon running the above code, the best values of hyperparameters obtained as as under:

- learning_rate=0.3
- subsample=0.5

#running the model on the best obtained set of hyperparameters
xgbm = XGBClassifier(learning_rate=0.3, subsample=0.5)
xgbm.fit(X_train_pca, y_train)print(classification_report(y_test, xgbm.predict(X_test_pca)))
print("ROC score:", roc_auc_score(y_test, xgbm.predict(X_test_pca)))[19:22:10] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
precision recall f1-score support 0 0.92 0.92 0.92 8353
1 0.92 0.91 0.92 8183 accuracy 0.92 16536
macro avg 0.92 0.92 0.92 16536
weighted avg 0.92 0.92 0.92 16536ROC score: 0.9181344296798429

6.4 Conclusion:

- Upon running the above models and tuning the corresponding hyperparameters, we note that hyperparameter tuning does not result in any significant imporvement in the performance of the model when we consider Recall and ROR as the metric of measurement.
- The summary of different models and the corresponding obtained performance metrics values are as under:

Model name	Hyperparameter tuning	Recall	ROC score
Logistic Regression	Before	0.83	0.83
Logistic Regression	After	0.86	0.80
Random Forest	Before	0.94	0.94
Random Forest	After	0.91	0.91
XGBoost	Before	0.92	0.92
XGBoost	After	0.92	0.92

- From the above, we note that Logistic Regression is giving inferior results as compared with the other two ML techniques.
- The best model out of the above three would be **XGBoost classifier** with Recall of 92% and ROC score of 92%. Though Random Forest gives the same level of performance for the given dataset, but it is relatively slow and computationally expensive. Hyperparameter tuning should be used as the same reduces the hyperparameter space and hence fast track the modeling.

Best Model of choice: **XGBoost** [with learning_rate=0.3 and subsample=0.5]

7. Model building (II): Important Feature Identification

Now our second objective is to identify the important features for the recommendations purpose. Let's use the logistic regression for the same to identify them. Firstly, let's identify the presence of multi-collinearity in our cleaned dataset.

We would use new scalar to scale train and test predictors since we do not want to use augmented data created by SMOTE.

7.1 Data preparation for model without PCA & Data Augmentation (SMOTE)

#splitting into train and test sets
#stratify=y to get balance in train and test splits
X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.3, random_state=1, stratify=y)
#use MinMaxScaler is scale the predictors (X)
scaler2 = MinMaxScaler()X_train_scaled2 = scaler2.fit_transform(X_train2)
X_test_scaled2 = scaler2.transform(X_test2)*#converting array into dataframe*
X_train_scaled2 = pd.DataFrame(X_train_scaled2, columns=X_train2.columns)
X_test_scaled2 = pd.DataFrame(X_test_scaled2, columns=X_test2.columns)

Let's first check the shape of the dataset.

print(X_train_scaled2.shape, X_test_scaled2.shape, y_train2.shape, y_test2.shape)(21000, 207) (9001, 207) (21000,) (9001,)

7.2 Recursive Feature Elimination (RFE)

Let's first use RFE (recursive feature elimination) to eliminate features with high multi-collinearity. We would use RFE to reduce our no. of features down to top 15.

```
lr = LogisticRegression(random_state=1)
rfe = RFE(lr, 15)
rfe = rfe.fit(X_train_scaled2, y_train2)#check for the different support and ranking
list(zip(X_train_scaled2.columns,rfe.support_,rfe.ranking_))[('arpu_6', False, 22),
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('diff_vol_2g_mb_', False, 13),
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('VBC_june_july_avg', False, 169)]*#seperate RFE support and non-support columns*
col = X_train_scaled2.columns[rfe.support_]
print('Columns whom RFE supports are: ', X_train_scaled2.columns[rfe.support_])
print('Columns whom RFE doesnt support are: ', X_train_scaled2.columns[~rfe.support_])Columns whom RFE supports are: Index(['loc_og_t2m_mou_8', 'total_og_mou_8', 'loc_ic_t2m_mou_8',
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    'monthly_2g_8', 'diff_arpu_', 'diff_total_ic_mou_',
    'diff_total_og_mou_', 'diff_total_rech_amt_', 'diff_total_rech_num_'],
   dtype='object')
Columns whom RFE doesnt support are: Index(['arpu_6', 'arpu_7', 'arpu_8', 'onnet_mou_6', 'onnet_mou_7',
    'onnet_mou_8', 'offnet_mou_6', 'offnet_mou_7', 'offnet_mou_8',
    'roam_ic_mou_6',
    ...
    'diff_std_ic_t2m_mou_', 'diff_std_ic_t2t_mou_', 'diff_std_og_mou_',
    'diff_std_og_t2f_mou_', 'diff_std_og_t2m_mou_', 'diff_std_og_t2t_mou_',
    'diff_total_rech_data_', 'diff_vol_2g_mb_', 'diff_vol_3g_mb_',
    'VBC_june_july_avg'],
   dtype='object', length=192)

We are left with above 15 columns whom RFE supports. Let's build model using statsmodel, for the detailed statistical analysis and manual feature elimination.

7.3 Manual feature elimination

```
# function to find VIF of different features
def find_vif(X):
  vif = pd.DataFrame()
  vif['Features'] = X.columns
  vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
  vif['VIF'] = round(vif['VIF'], 2)
```

```
    vif = vif.sort_values(by = "VIF", ascending = False)
    return vif# Creating X_train dataframe with RFE selected 15 variablesX_train_rfe =
X_train_scaled2[col]
X_train_rfe = sm.add_constant(X_train_rfe)lm_1 = sm.GLM(y_train2.tolist(), X_train_rfe, family =
sm.families.Binomial())
res = lm_1.fit()
print(res.summary())Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                  y   No. Observations:             21000
Model:                        GLM   Df Residuals:                 20984
Model Family:            Binomial   Df Model:                        15
Link Function:              logit   Scale:                       1.0000
Method:                      IRLS   Log-Likelihood:             -3999.1
Date:            Mon, 22 Feb 2021   Deviance:                    7998.3
Time:                    19:24:23   Pearson chi2:              1.56e+06
No. Iterations:                 8
Covariance Type:        nonrobust
==============================================================================
======
                    coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const                15.3647      1.022     15.030      0.000      13.361      17.368
loc_og_t2m_mou_8      -5.4831      2.199     -2.494      0.013      -9.793      -1.173
total_og_mou_8        -7.3093      1.318     -5.548      0.000      -9.892      -4.727
loc_ic_t2m_mou_8       1.6784      6.836      0.246      0.806     -11.720      15.077
loc_ic_mou_8         -25.1278      5.469     -4.595      0.000     -35.846     -14.409
total_ic_mou_8        -9.0700      2.871     -3.159      0.002     -14.698      -3.442
total_rech_num_8      -4.7754      0.861     -5.549      0.000      -6.462      -3.089
last_day_rch_amt_8   -11.5340      1.951     -5.911      0.000     -15.359      -7.709
count_rech_2g_8       -7.8073      1.049     -7.441      0.000      -9.864      -5.751
av_rech_amt_data_8   -14.2472      1.519     -9.379      0.000     -17.225     -11.270
monthly_2g_8          -4.8621      0.879     -5.534      0.000      -6.584      -3.140
diff_arpu_           -14.3062      3.810     -3.755      0.000     -21.774      -6.838
diff_total_ic_mou_   -12.8968      1.410     -9.144      0.000     -15.661     -10.133
diff_total_og_mou_    -3.1023      1.351     -2.296      0.022      -5.750      -0.454
diff_total_rech_amt_  -3.2924      3.498     -0.941      0.347     -10.149       3.564
diff_total_rech_num_  -2.2745      0.964     -2.361      0.018      -4.163      -0.386
==============================================================================
======
```

Looking at the p-values, there are certain predictors with p-values more that 5%. Let's checkout the VIF as well.

```
#find VIF of different features of X_train_rfe
find_vif(X_train_rfe)
```

	Features	VIF
0	const	1228.41
4	loc_ic_mou_8	7.51
5	total_ic_mou_8	5.31
3	loc_ic_t2m_mou_8	3.99
11	diff_arpu_	3.99
14	diff_total_rech_amt_	3.83
13	diff_total_og_mou_	2.04
2	total_og_mou_8	1.87
6	total_rech_num_8	1.77
15	diff_total_rech_num_	1.76
1	loc_og_t2m_mou_8	1.59
8	count_rech_2g_8	1.33
12	diff_total_ic_mou_	1.27
7	last_day_rch_amt_8	1.26
9	av_rech_amt_data_8	1.26
10	monthly_2g_8	1.09

From above, let's drop loc_ic_t2m_mou_8 column, being high in p-value.

```
X_train_rfe.drop('loc_ic_t2m_mou_8', axis=1, inplace=True)#fit GLM again on the remaining dataset
lm_2 = sm.GLM(y_train2.tolist(), X_train_rfe, family = sm.families.Binomial())
res = lm_2.fit()
print(res.summary())Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                21000
Model:                            GLM   Df Residuals:                    20985
Model Family:                Binomial   Df Model:                           14
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -3999.2
Date:                Mon, 22 Feb 2021   Deviance:                       7998.3
Time:                        19:24:24   Pearson chi2:                 1.63e+06
No. Iterations:                     8
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------
const               15.3607      1.022     15.025      0.000      13.357      17.364
loc_og_t2m_mou_8    -5.3801      2.155     -2.497      0.013      -9.604      -1.157
total_og_mou_8      -7.3276      1.316     -5.569      0.000      -9.906      -4.749
loc_ic_mou_8       -24.0639      3.308     -7.274      0.000     -30.548     -17.580
total_ic_mou_8      -9.0666      2.870     -3.159      0.002     -14.692      -3.442
```

```
total_rech_num_8       -4.7669      0.860     -5.545      0.000      -6.452      -3.082
last_day_rch_amt_8    -11.5479      1.951     -5.920      0.000     -15.371      -7.725
count_rech_2g_8        -7.8048      1.049     -7.438      0.000      -9.861      -5.748
av_rech_amt_data_8    -14.2489      1.519     -9.380      0.000     -17.226     -11.272
monthly_2g_8           -4.8629      0.879     -5.535      0.000      -6.585      -3.141
diff_arpu_            -14.3222      3.810     -3.760      0.000     -21.789      -6.856
diff_total_ic_mou_    -12.8851      1.410     -9.138      0.000     -15.649     -10.121
diff_total_og_mou_     -3.1022      1.351     -2.296      0.022      -5.750      -0.454
diff_total_rech_amt_   -3.2871      3.498     -0.940      0.347     -10.143       3.568
diff_total_rech_num_   -2.2747      0.963     -2.361      0.018      -4.163      -0.386
================================================================================
======
```

Looking at the p-values, there are certain predictor with p-valus more that 5%. Let's checkout the VIF as well.

```
#find VIF of different features of X_train_rfe
find_vif(X_train_rfe)
```

	Features	VIF
0	const	1226.71
4	total_ic_mou_8	5.31
3	loc_ic_mou_8	5.28
10	diff_arpu_	3.99
13	diff_total_rech_amt_	3.83
12	diff_total_og_mou_	2.04
2	total_og_mou_8	1.86
5	total_rech_num_8	1.77
14	diff_total_rech_num_	1.76
1	loc_og_t2m_mou_8	1.48
7	count_rech_2g_8	1.33
6	last_day_rch_amt_8	1.26
8	av_rech_amt_data_8	1.26
11	diff_total_ic_mou_	1.26
9	monthly_2g_8	1.09

From above, let's drop diff_total_rech_amt_ column, being high in p-value.

```
X_train_rfe.drop('diff_total_rech_amt_', axis=1, inplace=True)#fit GLM again on the remaining
dataset
lm_3 = sm.GLM(y_train2.tolist(), X_train_rfe, family = sm.families.Binomial())
res = lm_3.fit()
print(res.summary())Generalized Linear Model Regression Results
==============================================================================
```

```
Dep. Variable:                  y   No. Observations:            21000
Model:                        GLM   Df Residuals:                20986
Model Family:            Binomial   Df Model:                       13
Link Function:              logit   Scale:                      1.0000
Method:                      IRLS   Log-Likelihood:            -3999.6
Date:            Mon, 22 Feb 2021   Deviance:                   7999.2
Time:                    19:24:24   Pearson chi2:             1.59e+06
No. Iterations:                 8
Covariance Type:        nonrobust
==============================================================================
======
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const              15.1964      1.007     15.096      0.000      13.223      17.169
loc_og_t2m_mou_8    -5.2374      2.146     -2.441      0.015      -9.443      -1.032
total_og_mou_8      -7.2738      1.315     -5.532      0.000      -9.851      -4.697
loc_ic_mou_8       -24.1517      3.305     -7.307      0.000     -30.630     -17.674
total_ic_mou_8      -9.0068      2.865     -3.144      0.002     -14.622      -3.391
total_rech_num_8    -4.9018      0.850     -5.764      0.000      -6.569      -3.235
last_day_rch_amt_8  -11.8570      1.921     -6.172      0.000     -15.622      -8.092
count_rech_2g_8     -7.8208      1.050     -7.449      0.000      -9.879      -5.763
av_rech_amt_data_8  -14.3407      1.516     -9.457      0.000     -17.313     -11.369
monthly_2g_8        -4.8750      0.879     -5.548      0.000      -6.597      -3.153
diff_arpu_         -16.9228      2.659     -6.365      0.000     -22.134     -11.712
diff_total_ic_mou_  -12.8820      1.412     -9.123      0.000     -15.650     -10.114
diff_total_og_mou_   -3.3041      1.333     -2.479      0.013      -5.917      -0.692
diff_total_rech_num_  -2.3005     0.963     -2.388      0.017      -4.188      -0.413
==============================================================================
======
```

Looking at the p-values, all of them are less than 5%. Let's checkout the VIF as well.

```
#find VIF of different features of X_train_rfe
find_vif(X_train_rfe)
```

	Features	VIF
0	const	1217.74
4	total_ic_mou_8	5.31
3	loc_ic_mou_8	5.28
12	diff_total_og_mou_	2.02
10	diff_arpu_	1.96
2	total_og_mou_8	1.86
13	diff_total_rech_num_	1.74
5	total_rech_num_8	1.73
1	loc_og_t2m_mou_8	1.48
7	count_rech_2g_8	1.32
11	diff_total_ic_mou_	1.26
8	av_rech_amt_data_8	1.25
6	last_day_rch_amt_8	1.17
9	monthly_2g_8	1.08

From above, let's drop total_ic_mou_8 column, being high in VIF.

```
X_train_rfe.drop('total_ic_mou_8', axis=1, inplace=True)#fit GLM again on the remaining dataset
lm_4 = sm.GLM(y_train2.tolist(), X_train_rfe, family = sm.families.Binomial())
res = lm_4.fit()
print(res.summary())Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                  y   No. Observations:           21000
Model:                        GLM   Df Residuals:             20987
Model Family:            Binomial   Df Model:                    12
Link Function:              logit   Scale:                   1.0000
Method:                      IRLS   Log-Likelihood:          -4006.5
Date:            Mon, 22 Feb 2021   Deviance:                 8012.9
Time:                    19:24:25   Pearson chi2:           1.71e+06
No. Iterations:                 8
Covariance Type:        nonrobust
==================================================================================
======
                     coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------------
const             15.0307      0.984     15.275      0.000      13.102      16.959
loc_og_t2m_mou_8      -4.7329      2.142     -2.209      0.027      -8.932      -0.534
total_og_mou_8      -7.7919      1.318     -5.911      0.000     -10.375      -5.208
loc_ic_mou_8       -32.2304      2.169    -14.861      0.000     -36.481     -27.980
total_rech_num_8      -5.1165      0.850     -6.022      0.000      -6.782      -3.451
last_day_rch_amt_8     -12.3515      1.917     -6.444      0.000     -16.109      -8.595
count_rech_2g_8      -7.7519      1.050     -7.381      0.000      -9.810      -5.693
```

```
av_rech_amt_data_8    -14.3527     1.515     -9.476     0.000     -17.321     -11.384
monthly_2g_8         -4.8626     0.878     -5.539     0.000     -6.583     -3.142
diff_arpu_          -16.7558     2.640     -6.347     0.000     -21.930     -11.582
diff_total_ic_mou_    -12.5877     1.356     -9.286     0.000     -15.245     -9.931
diff_total_og_mou_     -3.4915     1.329     -2.627     0.009     -6.097     -0.886
diff_total_rech_num_   -2.3288     0.963     -2.418     0.016     -4.217     -0.441
================================================================================
======
```

Looking at the p-values, all of them are less than 5%. Let's checkout the VIF as well.

```
#find VIF of different features of X_train_rfe
find_vif(X_train_rfe)
```

	Features	VIF
0	const	1185.73
11	diff_total_og_mou_	2.02
9	diff_arpu_	1.96
2	total_og_mou_8	1.84
12	diff_total_rech_num_	1.74
4	total_rech_num_8	1.73
1	loc_og_t2m_mou_8	1.48
3	loc_ic_mou_8	1.39
6	count_rech_2g_8	1.32
7	av_rech_amt_data_8	1.25
10	diff_total_ic_mou_	1.19
5	last_day_rch_amt_8	1.17
8	monthly_2g_8	1.08

Now we have all the p-values less than 5% and all the VIF values less than 5. Hence we can say that we have handled the multi-collinearity and insignificance of the different variables. Now let's fit LogisticsRegression on the remaining columns to get the corresponding importance.

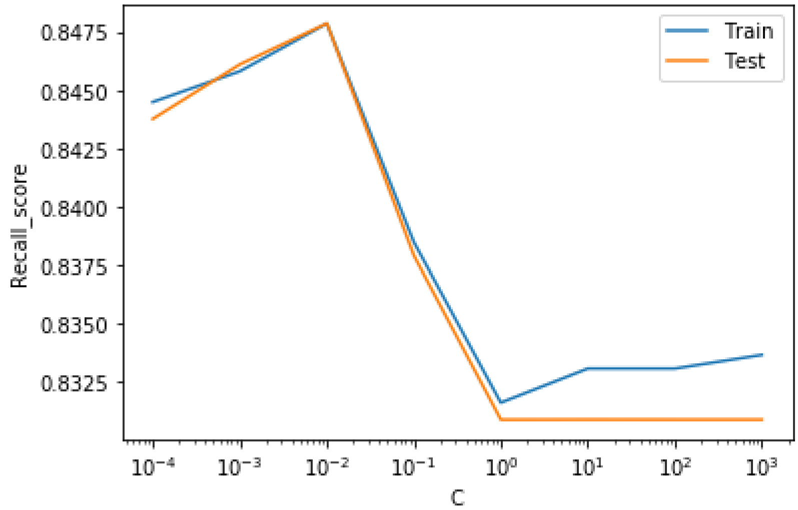
7.4 Model building and Feature importance check

```
#drop the constant column from X_train_rfe
X_train_rfe.drop('const', axis=1, inplace=True)
```

Now that we have out features chosen, let's tune the hyperparameters to get the best possible model.

```
# Create the parameter grid based on the results of random search
param_grid = {
   'penalty': ['l2'],
   'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
}
```

 # Create a based model
lr_model2 = LogisticRegression(class_weight='balanced')*# Instantiate the grid search model*
lr_model_random_search2 = RandomizedSearchCV(estimator = lr_model2, param_distributions = param_grid, scoring= 'recall',
                   cv = 5, n_jobs = -1,verbose = 1, return_train_score=**True**,
n_iter=15)lr_model_random_search2.fit(X_train_rfe, y_train2)Fitting 5 folds for each of 8 candidates, totalling 40 fitsRandomizedSearchCV(cv=5, estimator=LogisticRegression(class_weight='balanced'),
              n_iter=15, n_jobs=-1,
              param_distributions={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10,
                                   100, 1000],
                          'penalty': ['l2']},
              return_train_score=True, scoring='recall',
verbose=1)lr_model_random_search2.best_estimator_LogisticRegression(C=0.01, class_weight='balanced')*#saving the CV results into an object*
cv_results2= pd.DataFrame(lr_model_random_search2.cv_results_)*#plotting R2 score vs alpha value*
plt.plot(cv_results2['param_C'], cv_results2['mean_train_score'], label='Train')
plt.plot(cv_results2['param_C'], cv_results2['mean_test_score'], label='Test')
plt.xlabel('C')
plt.ylabel('Recall_score')
plt.xscale('log')
plt.legend()
plt.show()



Hence l2 regularization along with C=0.01 should be our hyperparameters of choice.

#use class_weight=balanced to give equal weightage
logregmodel = LogisticRegression(C=0.01, penalty='l2', class_weight='balanced')
logregmodel.fit(X_train_rfe, y_train2)LogisticRegression(C=0.01, class_weight='balanced')*#flatten the logregmodel.coef_ array*
coef_list = []
for i **in** list(logregmodel.coef_):
  for j **in** i:
    coef_list.append(j)*#build dataframe for features and corresponding coefficients*
coef_df = pd.DataFrame({'Variable':list(X_train_rfe.columns),

'Coefficient':coef_list})*#displaying the different coefficients, sort by their coefficient values*
coef_df.set_index('Variable', inplace=**True**)
coef_df.sort_values('Coefficient', ascending=**True**)

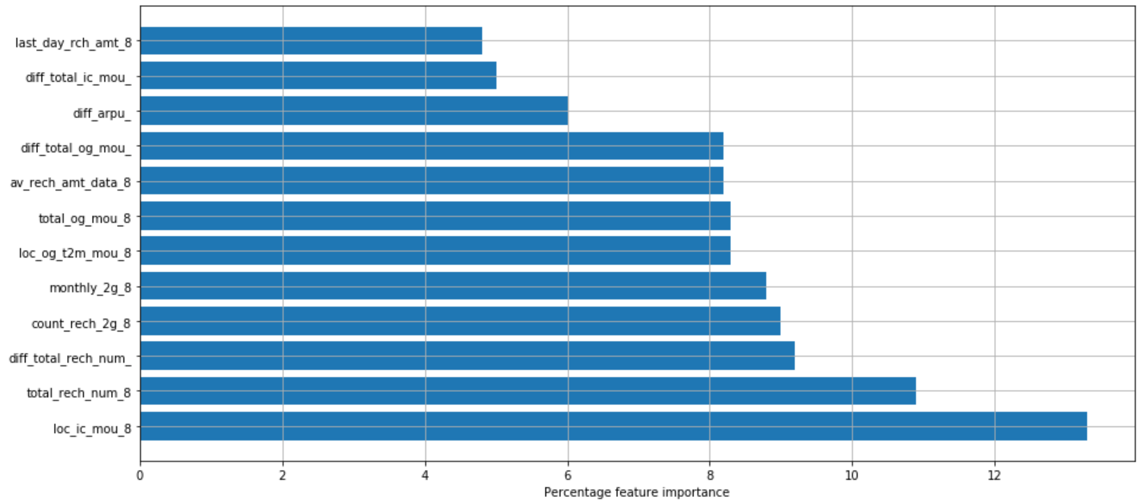
	Coefficient
Variable	
loc_ic_mou_8	-1.673297
total_rech_num_8	-1.376947
diff_total_rech_num_	-1.152667
count_rech_2g_8	-1.135242
monthly_2g_8	-1.101831
total_og_mou_8	-1.047856
loc_og_t2m_mou_8	-1.039752
diff_total_og_mou_	-1.037370
av_rech_amt_data_8	-1.032038
diff_arpu_	-0.750202
diff_total_ic_mou_	-0.627211
last_day_rch_amt_8	-0.606293

We decide the importance of different predictors based on the obtained magnitudes of different coefficients after the application of logistic regression on our dataset.

#get the percentage feature importance based on magnitude of coefficients
coef_df['feature_importance'] = round((coef_df.Coefficient.apply(np.abs) / coef_df.Coefficient.apply(np.abs).sum())*100,1)
coef_df = coef_df.sort_values('feature_importance', ascending=**False**)
coef_df

Variable	Coefficient	feature_importance
loc_ic_mou_8	-1.673297	13.3
total_rech_num_8	-1.376947	10.9
diff_total_rech_num_	-1.152667	9.2
count_rech_2g_8	-1.135242	9.0
monthly_2g_8	-1.101831	8.8
loc_og_t2m_mou_8	-1.039752	8.3
total_og_mou_8	-1.047856	8.3
av_rech_amt_data_8	-1.032038	8.2
diff_total_og_mou_	-1.037370	8.2
diff_arpu_	-0.750202	6.0
diff_total_ic_mou_	-0.627211	5.0
last_day_rch_amt_8	-0.606293	4.8

```
plt.figure(figsize=(15,7))
plt.barh(y=coef_df.index, width=coef_df.feature_importance)
plt.xlabel('Percentage feature importance')
plt.grid()
plt.show()
```



From the above, we note that the following top features which are influencing the churn most:

1. loc_ic_mou_8: Local incoming minutes of usage during action phase i.e. August month.
2. total_rech_num_8: Total no. of recharge done during action phase i.e. August month.
3. diff_total_rech_num_: Difference in total recharge number between action phase and good phase.
4. count_rech_2g_8: Count of 2G data recharge during action phase i.e. August month.

5. monthly_2g_8: Monthly 2G services usage during action phase i.e. August month.
6. loc_og_t2m_mou_8: Local outgoing t2m minutes of usage during action phase i.e. August month.
7. total_og_mou_8: Total outgoing minutes of usage during action phase i.e. August month.
8. av_rech_amt_data_8: Average amount on data recharges done during action phase i.e. August month.
9. diff_total_og_mou_: Difference in total outgoing minutes of usage between action phase and good phase.
10. diff_arpu_: Difference in average revenue per user between action phase and good phase.

8. Actionable recommendations:

Following strategies are recommended to manage customer churn:

- Free local incoming and outgoing minutes should be offered during the action phase to the customers whom our ML model-I identify as churners. It incentives the use of voice services of network by those customers and hence reduce churn rate.
- Those customers with low ARPU during the action phase as compared with the good phase may be given additional benefits.
- Those with low monthly 2G data usage during action phase may be given free data with enhanced speed (if it is permissible), to not make them switch to other network.
- Those customers who have not recharged during the month of action phase can be given additional validity of network with free talktimes.
- Those with large difference in MOU between action phase and good phase may be given freebies, as they have high churn rates.