Telecom Churn Case Study

Analysis Approach :

- Telecommunications industry experiences an average of 15 - 25% annual churn rate. Given the fact that it costs 5-10 times more to acquire a new customer than to retain an existing one, customer retention has become even more important than customer acquisition.
- Here we are given with 4 months of data related to customer usage. In this case study, we analyse customer-level data of a leading telecom firm, build predictive models to identify customers at high risk of churn and identify the main indicators of churn.
- Churn is predicted using two approaches. Usage based churn and Revenue based churn. Usage based churn:
- Customers who have zero usage, either incoming or outgoing - in terms of calls, internet etc. over a period of time.
- This case study only considers usage based churn.
- In the Indian and the southeast Asian market, approximately 80% of revenue comes from the top 20% customers (called high-value customers). Thus, if we can reduce churn of the high-value customers, we will be able to reduce significant revenue leakage. Hence, this case study focuses on high value customers only.
- The dataset contains customer-level information for a span of four consecutive months - June, July, August and September. The months are encoded as 6, 7, 8 and 9, respectively.
- 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.
- This is a classification problem, where we need to predict whether the customers is about to churn or not. We have carried out Baseline Logistic Regression, then Logistic Regression with PCA, PCA + Random Forest, PCA + XGBoost.

Analysis Steps

Data Cleaning and EDA

1. We have started with importing Necessary packages and libraries.
2. We have loaded the dataset into a dataframe.
3. We have checked the number of columns, their data types, Null count and unique value_value_count to get some understanding about data and to check if the columns are under correct data-type.
4. Checking for duplicate records (rows) in the data. There were no duplicates.
5. Since 'mobile_number' is the unique identifier available, we have made it our index to retain the identity.
6. Have found some columns that donot follow the naming standard, we have renamed those columns to make sure all the variables follow the same naming convention.
7. Follwing with column renaming, we have dealt with converting the columns into their respective data types. Here, we have evaluated all the columns which are having less than or equal to 29 unique values as catrgorical columns and rest as contineous columns.
8. The date columns were having 'object' as their data type, we have converted to the proper datetime format.
9. Since, our analysis is focused on the HVC(High value customers), we have filtered for high value customers to carryout the further analysis. The metric of this filtering of HVC is such that all the customers whose 'Average_rech_amt' of months 6 and 7 greater than or equal to 70th percentile of the 'Average_rech_amt' are considered as High Value Customers.
10. Checked for missing values.
11. Dropped all the columns with missing values greater than 50%.
12. We have been given 4 months data. Since each months revenue and usage data is not related to other, we did month-wise drill down on missing values.

13. Some columns had similar range of missing values. So, we have looked at their related columns and checked if these might be imputed with zero.
14. We have found that 'last_date_of_the_month' had some misisng values, so this is very meaningful and we have imputed the last date based on the month.
15. We have found some columns with only one unique value, so it is of no use for the analysis, hence we have dropped those columns.
16. Once after checking all the data preparation tasks, tagged the Churn variable(which is our target variable).
17. After imputing, we have dropped churn phase columns (Columns belonging to month - 9).
18. After all the above processing, we have retained 30,011 rows and 126 columns.
19. Exploratory Data Analysis

- The telecom company has many users with negative average revenues in both phases. These users are likely to churn.
- Most customers prefer the plans of '0' category.
- The customers with lesser 'aon' are more likely to Churn when compared to the Customers with higer 'aon'.
- Revenue generated by the Customers who are about to churn is very unstable.
- The Customers whose arpu decreases in 7th month are more likely to churn when compared to ones with increase in arpu.
- The Customers with high total_og_mou in 6th month and lower total_og_mou in 7th month are more likely to churn compared to the rest.
- The Customers with decrease in rate of total_ic_mou in 7th month are more likely to churn, compared to the rest.
- Customers with stable usage of 2g volume throughout 6 and 7 months are less likely to churn.
- Customers with fall in usage of 2g volume in 7th month are more likely to Churn.
- Customers with stable usage of 3g volume throughout 6 and 7 months are less likely to churn.
- Customers with fall in consumption of 3g volume in 7th month are more likely to Churn.
- The customers with lower total_og_mou in 6th and 8th months are more likely to Churn compared to the ones with higher total_og_mou.
- The customers with lesser total_og_mou_8 and aon are more likely to churn compared to the one with higher total_og_mou_8 and aon.
- The customers with less total_ic_mou_8 are more likely to churn irrespective of aon.
- The customers with total_ic_mou_8 > 2000 are very less likely to churn.

1. Correlation analysis has been performed.
2. We have created the derived variables and then removed the variables that were used to derive new ones.
3. Outlier treatment has been performed. We have looked at the quantiles to understand the spread of Data.
4. We have capped the upper outliers to 99th percentile.
5. We have checked categorical variables and contribution of classes in those variables. The classes with less ccontribution are grouped into 'Others'.
6. Dummy Variables were created.

Pre-processing Steps

1. Train-Test Split has been performed.
2. The data has high class-imbalance with the ratio of 0.095 (class 1 : class 0).
3. SMOTE technique has been used to overcome class-imbalance.
4. Predictor columns have been standardized to mean - 0 and standard_deviation- 1.

Modelling

Model 1 : Logistic Regression with RFE & Manual Elimination (Interpretable Model)
Most important predictors of Churn , in order of importance and their coefficients are as follows :

- loc_ic_t2f_mou_8 -1.2736
- total_rech_num_8 -1.2033
- total_rech_num_6 0.6053
- monthly_3g_8_0 0.3994
- monthly_2g_8_0 0.3666
- std_ic_t2f_mou_8 -0.3363
- std_og_t2f_mou_8 -0.2474
- const -0.2336
- monthly_3g_7_0 -0.2099
- std_ic_t2f_mou_7 0.1532
- sachet_2g_6_0 -0.1108
- sachet_2g_7_0 -0.0987
- sachet_2g_8_0 0.0488
- sachet_3g_6_0 -0.0399

PCA: PCA : 95% of variance in the train set can be explained by first 16 principal components and 100% of variance is explained by the first 45 principal components.

Model 2 : PCA + Logistic Regression

```
Train Performance :

Accuracy : 0.627
Sensitivity / True Positive Rate / Recall : 0.918
Specificity / True Negative Rate :  0.599
Precision / Positive Predictive Value : 0.179
F1-score : 0.3

Test Performance :

Accuracy : 0.086
Sensitivity / True Positive Rate / Recall : 1.0
Specificity / True Negative Rate :  0.0
Precision / Positive Predictive Value : 0.086
F1-score : 0.158
```

Model 3 : PCA + Random Forest Classifier

```
Train Performance :

Accuracy : 0.882
Sensitivity / True Positive Rate / Recall : 0.816
Specificity / True Negative Rate :  0.888
Precision / Positive Predictive Value : 0.408
F1-score : 0.544

Test Performance :

Accuracy : 0.86
Sensitivity / True Positive Rate / Recall : 0.80
Specificity / True Negative Rate :  0.78
Precision / Positive Predictive Value :0.37
F1-score :0.51
```

Model 4 : PCA + XGBoost

```
Train Performance :

Accuracy : 0.873
Sensitivity / True Positive Rate / Recall : 0.887
Specificity / True Negative Rate :  0.872
Precision / Positive Predictive Value : 0.396
F1-score : 0.548

Test Performance :

Accuracy : 0.086
Sensitivity / True Positive Rate / Recall : 1.0
Specificity / True Negative Rate :  0.0
Precision / Positive Predictive Value : 0.086
F1-score : 0.158
```

Recommendations :

Following are the strongest indicators of churn

Customers who churn show lower average monthly local incoming calls from fixed line in the action period by 1.27 standard deviations , compared to users who don't churn , when all other factors are held constant. This is the strongest indicator of churn. Customers who churn show lower number of recharges done in action period by 1.20 standard deviations, when all other factors are held constant. This is the second strongest indicator of churn. Further customers who churn have done 0.6 standard deviations higher recharge than non-churn customers. This factor when coupled with above factors is a good indicator of churn. Customers who churn are more likely to be users of 'monthly 2g package-0 / monthly 3g package-0' in action period (approximately 0.3 std deviations higher than other packages), when all other factors are held constant.

Based on the above indicators the recommendations to the telecom company are :

Concentrate on users with 1.27 std devations lower than average incoming calls from fixed line. They are most likely to churn. Concentrate on users who recharge less number of times (less than 1.2 std deviations compared to avg) in the 8th month. They are second most likely to churn. Models with high sensitivity are the best for predicting churn. Use the PCA + Logistic Regression model to predict churn. It has an ROC score of 0.87, test sensitivity of 100%.

Analysis

Data Understanding

In [6]:
```
# Importing Necessary Libraries.
import numpy as np, pandas as pd, matplotlib.pyplot as plt, seaborn as sns
import warnings
warnings.filterwarnings('ignore')

# Setting max display columns and rows.
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
```

In [7]:
```
# Reading Dataset into a DataFrame.
data=pd.read_csv('telecom_churn_data.csv')
data.head()
```

Out[7]:

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

In [8]:
```
# Checking information about data.
print(data.info())
def metadata_matrix(data) :
    return pd.DataFrame({
                'Datatype' : data.dtypes.astype(str),
                'Non_Null_Count': data.count(axis = 0).astype(int),
                'Null_Count': data.isnull().sum().astype(int),
                'Null_Percentage': round(data.isnull().sum()/len(data) * 10
0 , 2),
                'Unique_Values_Count': data.nunique().astype(int)
                 }).sort_values(by='Null_Percentage', ascending=False)

metadata_matrix(data)
```

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

Out[8]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Val
arpu_3g_6	float64	25153	74846	74.85	
night_pck_user_6	float64	25153	74846	74.85	
total_rech_data_6	float64	25153	74846	74.85	
arpu_2g_6	float64	25153	74846	74.85	
max_rech_data_6	float64	25153	74846	74.85	
fb_user_6	float64	25153	74846	74.85	
av_rech_amt_data_6	float64	25153	74846	74.85	
date_of_last_rech_data_6	object	25153	74846	74.85	
count_rech_2g_6	float64	25153	74846	74.85	
count_rech_3g_6	float64	25153	74846	74.85	
date_of_last_rech_data_7	object	25571	74428	74.43	
total_rech_data_7	float64	25571	74428	74.43	
fb_user_7	float64	25571	74428	74.43	
max_rech_data_7	float64	25571	74428	74.43	
night_pck_user_7	float64	25571	74428	74.43	
count_rech_2g_7	float64	25571	74428	74.43	
av_rech_amt_data_7	float64	25571	74428	74.43	
arpu_2g_7	float64	25571	74428	74.43	
count_rech_3g_7	float64	25571	74428	74.43	
arpu_3g_7	float64	25571	74428	74.43	
total_rech_data_9	float64	25922	74077	74.08	
count_rech_3g_9	float64	25922	74077	74.08	
fb_user_9	float64	25922	74077	74.08	
max_rech_data_9	float64	25922	74077	74.08	
arpu_3g_9	float64	25922	74077	74.08	
date_of_last_rech_data_9	object	25922	74077	74.08	
night_pck_user_9	float64	25922	74077	74.08	
arpu_2g_9	float64	25922	74077	74.08	
count_rech_2g_9	float64	25922	74077	74.08	
av_rech_amt_data_9	float64	25922	74077	74.08	
total_rech_data_8	float64	26339	73660	73.66	
arpu_3g_8	float64	26339	73660	73.66	
fb_user_8	float64	26339	73660	73.66	
night_pck_user_8	float64	26339	73660	73.66	
av_rech_amt_data_8	float64	26339	73660	73.66	
max_rech_data_8	float64	26339	73660	73.66	
count_rech_3g_8	float64	26339	73660	73.66	
arpu_2g_8	float64	26339	73660	73.66	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Val
count_rech_2g_8	float64	26339	73660	73.66	
date_of_last_rech_data_8	object	26339	73660	73.66	
ic_others_9	float64	92254	7745	7.75	
std_og_mou_9	float64	92254	7745	7.75	
std_og_t2c_mou_9	float64	92254	7745	7.75	
isd_ic_mou_9	float64	92254	7745	7.75	
std_ic_mou_9	float64	92254	7745	7.75	
isd_og_mou_9	float64	92254	7745	7.75	
spl_og_mou_9	float64	92254	7745	7.75	
spl_ic_mou_9	float64	92254	7745	7.75	
og_others_9	float64	92254	7745	7.75	
loc_ic_t2t_mou_9	float64	92254	7745	7.75	
std_ic_t2o_mou_9	float64	92254	7745	7.75	
loc_ic_t2m_mou_9	float64	92254	7745	7.75	
std_ic_t2f_mou_9	float64	92254	7745	7.75	
loc_ic_t2f_mou_9	float64	92254	7745	7.75	
loc_ic_mou_9	float64	92254	7745	7.75	
std_ic_t2m_mou_9	float64	92254	7745	7.75	
std_og_t2f_mou_9	float64	92254	7745	7.75	
std_og_t2t_mou_9	float64	92254	7745	7.75	
std_ic_t2t_mou_9	float64	92254	7745	7.75	
loc_og_mou_9	float64	92254	7745	7.75	
roam_og_mou_9	float64	92254	7745	7.75	
loc_og_t2m_mou_9	float64	92254	7745	7.75	
loc_og_t2f_mou_9	float64	92254	7745	7.75	
roam_ic_mou_9	float64	92254	7745	7.75	
offnet_mou_9	float64	92254	7745	7.75	
loc_og_t2c_mou_9	float64	92254	7745	7.75	
loc_og_t2t_mou_9	float64	92254	7745	7.75	
std_og_t2m_mou_9	float64	92254	7745	7.75	
onnet_mou_9	float64	92254	7745	7.75	
onnet_mou_8	float64	94621	5378	5.38	
std_ic_t2t_mou_8	float64	94621	5378	5.38	
std_ic_mou_8	float64	94621	5378	5.38	
loc_ic_t2t_mou_8	float64	94621	5378	5.38	
roam_og_mou_8	float64	94621	5378	5.38	
std_ic_t2m_mou_8	float64	94621	5378	5.38	
loc_ic_mou_8	float64	94621	5378	5.38	
std_ic_t2f_mou_8	float64	94621	5378	5.38	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Val
roam_ic_mou_8	float64	94621	5378	5.38	
std_ic_t2o_mou_8	float64	94621	5378	5.38	
loc_og_t2t_mou_8	float64	94621	5378	5.38	
loc_ic_t2f_mou_8	float64	94621	5378	5.38	
offnet_mou_8	float64	94621	5378	5.38	
loc_ic_t2m_mou_8	float64	94621	5378	5.38	
loc_og_t2m_mou_8	float64	94621	5378	5.38	
isd_og_mou_8	float64	94621	5378	5.38	
ic_others_8	float64	94621	5378	5.38	
og_others_8	float64	94621	5378	5.38	
spl_ic_mou_8	float64	94621	5378	5.38	
loc_og_t2f_mou_8	float64	94621	5378	5.38	
std_og_t2m_mou_8	float64	94621	5378	5.38	
spl_og_mou_8	float64	94621	5378	5.38	
std_og_t2c_mou_8	float64	94621	5378	5.38	
isd_ic_mou_8	float64	94621	5378	5.38	
loc_og_t2c_mou_8	float64	94621	5378	5.38	
std_og_t2f_mou_8	float64	94621	5378	5.38	
std_og_t2t_mou_8	float64	94621	5378	5.38	
loc_og_mou_8	float64	94621	5378	5.38	
std_og_mou_8	float64	94621	5378	5.38	
date_of_last_rech_9	object	95239	4760	4.76	
std_ic_t2f_mou_6	float64	96062	3937	3.94	
ic_others_6	float64	96062	3937	3.94	
isd_ic_mou_6	float64	96062	3937	3.94	
std_ic_t2m_mou_6	float64	96062	3937	3.94	
std_ic_mou_6	float64	96062	3937	3.94	
spl_ic_mou_6	float64	96062	3937	3.94	
std_ic_t2o_mou_6	float64	96062	3937	3.94	
loc_ic_t2f_mou_6	float64	96062	3937	3.94	
loc_ic_t2t_mou_6	float64	96062	3937	3.94	
std_og_t2c_mou_6	float64	96062	3937	3.94	
std_og_t2f_mou_6	float64	96062	3937	3.94	
std_og_mou_6	float64	96062	3937	3.94	
std_og_t2m_mou_6	float64	96062	3937	3.94	
isd_og_mou_6	float64	96062	3937	3.94	
std_og_t2t_mou_6	float64	96062	3937	3.94	
spl_og_mou_6	float64	96062	3937	3.94	
loc_og_mou_6	float64	96062	3937	3.94	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Val
og_others_6	float64	96062	3937	3.94	
loc_og_t2c_mou_6	float64	96062	3937	3.94	
loc_og_t2m_mou_6	float64	96062	3937	3.94	
loc_og_t2f_mou_6	float64	96062	3937	3.94	
loc_og_t2t_mou_6	float64	96062	3937	3.94	
roam_og_mou_6	float64	96062	3937	3.94	
std_ic_t2t_mou_6	float64	96062	3937	3.94	
onnet_mou_6	float64	96062	3937	3.94	
loc_ic_mou_6	float64	96062	3937	3.94	
offnet_mou_6	float64	96062	3937	3.94	
roam_ic_mou_6	float64	96062	3937	3.94	
loc_ic_t2m_mou_6	float64	96062	3937	3.94	
loc_og_t2c_mou_7	float64	96140	3859	3.86	
roam_ic_mou_7	float64	96140	3859	3.86	
loc_og_mou_7	float64	96140	3859	3.86	
loc_og_t2t_mou_7	float64	96140	3859	3.86	
offnet_mou_7	float64	96140	3859	3.86	
loc_og_t2f_mou_7	float64	96140	3859	3.86	
std_og_t2t_mou_7	float64	96140	3859	3.86	
std_ic_t2t_mou_7	float64	96140	3859	3.86	
onnet_mou_7	float64	96140	3859	3.86	
std_og_t2m_mou_7	float64	96140	3859	3.86	
loc_og_t2m_mou_7	float64	96140	3859	3.86	
std_og_t2f_mou_7	float64	96140	3859	3.86	
roam_og_mou_7	float64	96140	3859	3.86	
std_og_t2c_mou_7	float64	96140	3859	3.86	
std_ic_t2m_mou_7	float64	96140	3859	3.86	
isd_og_mou_7	float64	96140	3859	3.86	
ic_others_7	float64	96140	3859	3.86	
loc_ic_t2f_mou_7	float64	96140	3859	3.86	
loc_ic_t2m_mou_7	float64	96140	3859	3.86	
std_ic_mou_7	float64	96140	3859	3.86	
loc_ic_t2t_mou_7	float64	96140	3859	3.86	
std_ic_t2f_mou_7	float64	96140	3859	3.86	
loc_ic_mou_7	float64	96140	3859	3.86	
spl_ic_mou_7	float64	96140	3859	3.86	
og_others_7	float64	96140	3859	3.86	
spl_og_mou_7	float64	96140	3859	3.86	
isd_ic_mou_7	float64	96140	3859	3.86	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Val
std_ic_t2o_mou_7	float64	96140	3859	3.86	
std_og_mou_7	float64	96140	3859	3.86	
date_of_last_rech_8	object	96377	3622	3.62	
date_of_last_rech_7	object	98232	1767	1.77	
last_date_of_month_9	object	98340	1659	1.66	
date_of_last_rech_6	object	98392	1607	1.61	
last_date_of_month_8	object	98899	1100	1.10	
loc_ic_t2o_mou	float64	98981	1018	1.02	
std_og_t2o_mou	float64	98981	1018	1.02	
loc_og_t2o_mou	float64	98981	1018	1.02	
last_date_of_month_7	object	99398	601	0.60	
sachet_3g_8	int64	99999	0	0.00	
jul_vbc_3g	float64	99999	0	0.00	
aug_vbc_3g	float64	99999	0	0.00	
aon	int64	99999	0	0.00	
jun_vbc_3g	float64	99999	0	0.00	
monthly_2g_9	int64	99999	0	0.00	
sachet_3g_6	int64	99999	0	0.00	
vol_3g_mb_9	float64	99999	0	0.00	
sachet_3g_7	int64	99999	0	0.00	
monthly_2g_8	int64	99999	0	0.00	
monthly_3g_9	int64	99999	0	0.00	
monthly_3g_8	int64	99999	0	0.00	
sachet_3g_9	int64	99999	0	0.00	
monthly_3g_7	int64	99999	0	0.00	
monthly_3g_6	int64	99999	0	0.00	
sachet_2g_9	int64	99999	0	0.00	
sachet_2g_8	int64	99999	0	0.00	
sachet_2g_7	int64	99999	0	0.00	
sachet_2g_6	int64	99999	0	0.00	
monthly_2g_7	int64	99999	0	0.00	
monthly_2g_6	int64	99999	0	0.00	
mobile_number	int64	99999	0	0.00	
vol_3g_mb_8	float64	99999	0	0.00	
total_og_mou_9	float64	99999	0	0.00	
total_rech_num_7	int64	99999	0	0.00	
total_rech_num_6	int64	99999	0	0.00	
total_ic_mou_9	float64	99999	0	0.00	
total_ic_mou_8	float64	99999	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Val
total_ic_mou_7	float64	99999	0	0.00	
total_ic_mou_6	float64	99999	0	0.00	
circle_id	int64	99999	0	0.00	
total_og_mou_8	float64	99999	0	0.00	
vol_3g_mb_7	float64	99999	0	0.00	
total_og_mou_7	float64	99999	0	0.00	
total_og_mou_6	float64	99999	0	0.00	
arpu_9	float64	99999	0	0.00	
arpu_8	float64	99999	0	0.00	
arpu_7	float64	99999	0	0.00	
arpu_6	float64	99999	0	0.00	
last_date_of_month_6	object	99999	0	0.00	
total_rech_num_8	int64	99999	0	0.00	
total_rech_num_9	int64	99999	0	0.00	
total_rech_amt_6	int64	99999	0	0.00	
total_rech_amt_7	int64	99999	0	0.00	
vol_3g_mb_6	float64	99999	0	0.00	
vol_2g_mb_9	float64	99999	0	0.00	
vol_2g_mb_8	float64	99999	0	0.00	
vol_2g_mb_7	float64	99999	0	0.00	
vol_2g_mb_6	float64	99999	0	0.00	
last_day_rch_amt_9	int64	99999	0	0.00	
last_day_rch_amt_8	int64	99999	0	0.00	
last_day_rch_amt_7	int64	99999	0	0.00	
last_day_rch_amt_6	int64	99999	0	0.00	
max_rech_amt_9	int64	99999	0	0.00	
max_rech_amt_8	int64	99999	0	0.00	
max_rech_amt_7	int64	99999	0	0.00	
max_rech_amt_6	int64	99999	0	0.00	
total_rech_amt_9	int64	99999	0	0.00	
total_rech_amt_8	int64	99999	0	0.00	
sep_vbc_3g	float64	99999	0	0.00	

Data Cleaning

In [9]:
```
# Checking if there are any duplicate records.
data['mobile_number'].value_counts().sum()
```

Out[9]:
```
99999
```

- Since number of rows is same as distinct mobile numbers, there is no duplicate data

In [10]:
```
# mobile_number is a unique identifier
# Setting mobile_number as the index
data = data.set_index('mobile_number')
```

In [11]:
```
# Renaming columns
data = data.rename({'jun_vbc_3g' : 'vbc_3g_6', 'jul_vbc_3g' : 'vbc_3g_7',
'aug_vbc_3g' : 'vbc_3g_8', 'sep_vbc_3g' : 'vbc_3g_9'}, axis=1)
```

In [12]:
```
#Converting columns into appropriate data types and extracting singe value
columns.
# Columns with unique values < 29 are considered as categorical variables.
# The number 30 is arrived at, by looking at the above metadata_matrix outp
ut.

columns=data.columns
change_to_cat=[]
single_value_col=[]
for column in columns:
    unique_value_count=data[column].nunique()
    if unique_value_count==1:
        single_value_col.append(column)
    if unique_value_count<=29 and unique_value_count!=0 and data[column].dt
ype in ['int','float']:
        change_to_cat.append(column)
print( ' Columns to change to categorical data type : \n' ,pd.DataFrame(cha
nge_to_cat), '\n')
```

```
 Columns to change to categorical data type : 
                    0
0          circle_id
1      loc_og_t2o_mou
2      std_og_t2o_mou
3      loc_ic_t2o_mou
4    std_og_t2c_mou_6
5    std_og_t2c_mou_7
6    std_og_t2c_mou_8
7    std_og_t2c_mou_9
8    std_ic_t2o_mou_6
9    std_ic_t2o_mou_7
10   std_ic_t2o_mou_8
11   std_ic_t2o_mou_9
12    count_rech_3g_6
13    count_rech_3g_7
14    count_rech_3g_8
15    count_rech_3g_9
16   night_pck_user_6
17   night_pck_user_7
18   night_pck_user_8
19   night_pck_user_9
20       monthly_2g_6
21       monthly_2g_7
22       monthly_2g_8
23       monthly_2g_9
24       monthly_3g_6
25       monthly_3g_7
26       monthly_3g_8
27       monthly_3g_9
28        sachet_3g_6
29        sachet_3g_7
30        sachet_3g_8
31        sachet_3g_9
32          fb_user_6
33          fb_user_7
34          fb_user_8
35          fb_user_9
```

In [13]:
```
# Converting all the above columns having <=29 unique values into categoric
al data type.
data[change_to_cat]=data[change_to_cat].astype('category')
```

In [14]:
```
# Converting *sachet* variables to categorical data type
sachet_columns = data.filter(regex='.*sachet.*', axis=1).columns.values
data[sachet_columns] = data[sachet_columns].astype('category')
```

In [15]:
```
#Changing datatype of date variables to datetime.
columns=data.columns
col_with_date=[]
import re
for column in columns:
    x = re.findall("^date", column)
    if x:
        col_with_date.append(column)
data[col_with_date].dtypes
```

Out[15]:
```
date_of_last_rech_6         object
date_of_last_rech_7         object
date_of_last_rech_8         object
date_of_last_rech_9         object
date_of_last_rech_data_6    object
date_of_last_rech_data_7    object
date_of_last_rech_data_8    object
date_of_last_rech_data_9    object
dtype: object
```

In [16]:
```
# Checking the date format
data[col_with_date].head()
```

Out[16]:

	date_of_last_rech_6	date_of_last_rech_7	date_of_last_rech_8	date_of_last_rec
mobile_number				
7000842753	6/21/2014	7/16/2014	8/8/2014	9/28/2
7001865778	6/29/2014	7/31/2014	8/28/2014	9/30/2
7001625959	6/17/2014	7/24/2014	8/14/2014	9/29/2
7001204172	6/28/2014	7/31/2014	8/31/2014	9/30/2
7000142493	6/26/2014	7/28/2014	8/9/2014	9/28/2

- Lets convert the above columns to datetime data type.

In [17]:
```
for col in col_with_date:
    data[col]=pd.to_datetime(data[col], format="%m/%d/%Y")
data[col_with_date].head()
```

Out[17]:

	date_of_last_rech_6	date_of_last_rech_7	date_of_last_rech_8	date_of_last_rec
mobile_number				
7000842753	2014-06-21	2014-07-16	2014-08-08	2014-0
7001865778	2014-06-29	2014-07-31	2014-08-28	2014-0
7001625959	2014-06-17	2014-07-24	2014-08-14	2014-0
7001204172	2014-06-28	2014-07-31	2014-08-31	2014-0
7000142493	2014-06-26	2014-07-28	2014-08-09	2014-0

Filtering High Value Customers

- Customers are High Values if their Average recharge amount of june and july is more than or equal to 70th percentile of Average recharge amount.

In [18]:
```
#Deriving Average recharge amount of June and July.
data['Average_rech_amt_6n7']=(data['total_rech_amt_6']+data['total_rech_amt
_7'])/2
```

In [19]:
```
#Filtering based HIGH VALUED CUSTOMERS based on (Average_rech_amt_6n7 >= 70
th percentile of Average_rech_amt_6n7)
data=data[(data['Average_rech_amt_6n7']>= data['Average_rech_amt_6n7'].quan
tile(0.7))]
```

Missing Values

In [20]:
```
#Checking for missing values.
missing_values = metadata_matrix(data)[['Datatype', 'Null_Percentage']].sor
t_values(by='Null_Percentage', ascending=False)
missing_values
```

Out[20]:

	Datatype	Null_Percentage
av_rech_amt_data_6	float64	62.02
count_rech_2g_6	float64	62.02
arpu_2g_6	float64	62.02
max_rech_data_6	float64	62.02
night_pck_user_6	category	62.02
date_of_last_rech_data_6	datetime64[ns]	62.02
total_rech_data_6	float64	62.02
arpu_3g_6	float64	62.02
fb_user_6	category	62.02
count_rech_3g_6	category	62.02
av_rech_amt_data_9	float64	61.81
count_rech_2g_9	float64	61.81
night_pck_user_9	category	61.81
arpu_3g_9	float64	61.81
arpu_2g_9	float64	61.81
fb_user_9	category	61.81
date_of_last_rech_data_9	datetime64[ns]	61.81
total_rech_data_9	float64	61.81
count_rech_3g_9	category	61.81
max_rech_data_9	float64	61.81
count_rech_2g_7	float64	61.14
count_rech_3g_7	category	61.14
arpu_2g_7	float64	61.14
arpu_3g_7	float64	61.14
av_rech_amt_data_7	float64	61.14
max_rech_data_7	float64	61.14
fb_user_7	category	61.14
total_rech_data_7	float64	61.14
date_of_last_rech_data_7	datetime64[ns]	61.14
night_pck_user_7	category	61.14
av_rech_amt_data_8	float64	60.83
count_rech_3g_8	category	60.83
total_rech_data_8	float64	60.83
arpu_3g_8	float64	60.83
max_rech_data_8	float64	60.83
date_of_last_rech_data_8	datetime64[ns]	60.83
arpu_2g_8	float64	60.83
fb_user_8	category	60.83

	Datatype	Null_Percentage
night_pck_user_8	category	60.83
count_rech_2g_8	float64	60.83
loc_og_t2t_mou_9	float64	5.68
ic_others_9	float64	5.68
isd_ic_mou_9	float64	5.68
og_others_9	float64	5.68
loc_og_t2f_mou_9	float64	5.68
roam_ic_mou_9	float64	5.68
loc_og_mou_9	float64	5.68
std_og_t2f_mou_9	float64	5.68
loc_og_t2m_mou_9	float64	5.68
std_og_t2m_mou_9	float64	5.68
loc_og_t2c_mou_9	float64	5.68
std_og_t2t_mou_9	float64	5.68
std_ic_t2o_mou_9	category	5.68
std_ic_mou_9	float64	5.68
spl_ic_mou_9	float64	5.68
std_ic_t2f_mou_9	float64	5.68
roam_og_mou_9	float64	5.68
std_ic_t2m_mou_9	float64	5.68
offnet_mou_9	float64	5.68
std_og_mou_9	float64	5.68
spl_og_mou_9	float64	5.68
loc_ic_t2t_mou_9	float64	5.68
onnet_mou_9	float64	5.68
loc_ic_t2m_mou_9	float64	5.68
loc_ic_t2f_mou_9	float64	5.68
std_og_t2c_mou_9	category	5.68
loc_ic_mou_9	float64	5.68
std_ic_t2t_mou_9	float64	5.68
isd_og_mou_9	float64	5.68
std_og_t2t_mou_8	float64	3.13
std_og_t2c_mou_8	category	3.13
std_og_t2f_mou_8	float64	3.13
std_og_mou_8	float64	3.13
roam_og_mou_8	float64	3.13
isd_og_mou_8	float64	3.13
loc_og_t2t_mou_8	float64	3.13
spl_ic_mou_8	float64	3.13

	Datatype	Null_Percentage
std_og_t2m_mou_8	float64	3.13
ic_others_8	float64	3.13
offnet_mou_8	float64	3.13
og_others_8	float64	3.13
isd_ic_mou_8	float64	3.13
roam_ic_mou_8	float64	3.13
spl_og_mou_8	float64	3.13
loc_og_t2f_mou_8	float64	3.13
std_ic_t2m_mou_8	float64	3.13
std_ic_t2f_mou_8	float64	3.13
std_ic_t2t_mou_8	float64	3.13
loc_og_t2c_mou_8	float64	3.13
loc_ic_mou_8	float64	3.13
onnet_mou_8	float64	3.13
loc_og_t2m_mou_8	float64	3.13
loc_ic_t2f_mou_8	float64	3.13
std_ic_t2o_mou_8	category	3.13
loc_og_mou_8	float64	3.13
loc_ic_t2m_mou_8	float64	3.13
std_ic_mou_8	float64	3.13
loc_ic_t2t_mou_8	float64	3.13
date_of_last_rech_9	datetime64[ns]	2.89
date_of_last_rech_8	datetime64[ns]	1.98
last_date_of_month_9	object	1.20
loc_og_mou_6	float64	1.05
std_ic_t2m_mou_6	float64	1.05
roam_og_mou_6	float64	1.05
std_ic_t2t_mou_6	float64	1.05
loc_ic_mou_6	float64	1.05
roam_ic_mou_6	float64	1.05
loc_ic_t2f_mou_6	float64	1.05
loc_ic_t2m_mou_6	float64	1.05
std_og_t2t_mou_6	float64	1.05
onnet_mou_6	float64	1.05
loc_ic_t2t_mou_6	float64	1.05
offnet_mou_6	float64	1.05
og_others_6	float64	1.05
loc_og_t2t_mou_6	float64	1.05
isd_og_mou_6	float64	1.05

	Datatype	Null_Percentage
std_og_t2m_mou_6	float64	1.05
loc_og_t2f_mou_6	float64	1.05
spl_ic_mou_6	float64	1.05
std_ic_mou_6	float64	1.05
isd_ic_mou_6	float64	1.05
loc_og_t2m_mou_6	float64	1.05
std_ic_t2o_mou_6	category	1.05
spl_og_mou_6	float64	1.05
ic_others_6	float64	1.05
std_ic_t2f_mou_6	float64	1.05
loc_og_t2c_mou_6	float64	1.05
std_og_mou_6	float64	1.05
std_og_t2f_mou_6	float64	1.05
std_og_t2c_mou_6	category	1.05
roam_ic_mou_7	float64	1.01
loc_og_t2c_mou_7	float64	1.01
loc_og_t2f_mou_7	float64	1.01
loc_og_t2m_mou_7	float64	1.01
loc_og_t2t_mou_7	float64	1.01
roam_og_mou_7	float64	1.01
std_ic_t2t_mou_7	float64	1.01
offnet_mou_7	float64	1.01
onnet_mou_7	float64	1.01
std_ic_t2f_mou_7	float64	1.01
std_ic_mou_7	float64	1.01
loc_ic_t2f_mou_7	float64	1.01
std_ic_t2m_mou_7	float64	1.01
loc_og_mou_7	float64	1.01
loc_ic_t2t_mou_7	float64	1.01
std_og_t2t_mou_7	float64	1.01
std_og_t2c_mou_7	category	1.01
std_og_mou_7	float64	1.01
isd_og_mou_7	float64	1.01
spl_og_mou_7	float64	1.01
og_others_7	float64	1.01
spl_ic_mou_7	float64	1.01
loc_ic_t2m_mou_7	float64	1.01
loc_ic_mou_7	float64	1.01
ic_others_7	float64	1.01

	Datatype	Null_Percentage
std_og_t2m_mou_7	float64	1.01
isd_ic_mou_7	float64	1.01
std_ic_t2o_mou_7	category	1.01
std_og_t2f_mou_7	float64	1.01
last_date_of_month_8	object	0.52
loc_og_t2o_mou	category	0.38
loc_ic_t2o_mou	category	0.38
date_of_last_rech_7	datetime64[ns]	0.38
std_og_t2o_mou	category	0.38
date_of_last_rech_6	datetime64[ns]	0.21
last_date_of_month_7	object	0.10
vol_3g_mb_6	float64	0.00
arpu_6	float64	0.00
total_rech_amt_8	int64	0.00
total_rech_amt_7	int64	0.00
total_rech_amt_6	int64	0.00
total_rech_num_9	int64	0.00
last_date_of_month_6	object	0.00
vol_3g_mb_8	float64	0.00
arpu_7	float64	0.00
arpu_8	float64	0.00
arpu_9	float64	0.00
total_og_mou_6	float64	0.00
total_og_mou_7	float64	0.00
vol_3g_mb_7	float64	0.00
max_rech_amt_9	int64	0.00
vol_2g_mb_9	float64	0.00
vol_2g_mb_8	float64	0.00
vol_2g_mb_7	float64	0.00
vol_2g_mb_6	float64	0.00
last_day_rch_amt_9	int64	0.00
last_day_rch_amt_8	int64	0.00
last_day_rch_amt_7	int64	0.00
last_day_rch_amt_6	int64	0.00
max_rech_amt_8	int64	0.00
max_rech_amt_7	int64	0.00
max_rech_amt_6	int64	0.00
total_rech_amt_9	int64	0.00
total_ic_mou_6	float64	0.00

	Datatype	Null_Percentage
total_og_mou_8	float64	0.00
vbc_3g_8	float64	0.00
total_ic_mou_7	float64	0.00
total_ic_mou_8	float64	0.00
sachet_3g_9	category	0.00
sachet_3g_7	category	0.00
vbc_3g_9	float64	0.00
vbc_3g_6	float64	0.00
vbc_3g_7	float64	0.00
aon	int64	0.00
sachet_3g_6	category	0.00
monthly_3g_8	category	0.00
monthly_3g_9	category	0.00
sachet_3g_8	category	0.00
monthly_3g_7	category	0.00
sachet_2g_9	category	0.00
sachet_2g_8	category	0.00
sachet_2g_7	category	0.00
sachet_2g_6	category	0.00
monthly_2g_9	category	0.00
monthly_2g_8	category	0.00
monthly_2g_7	category	0.00
monthly_2g_6	category	0.00
monthly_3g_6	category	0.00
circle_id	category	0.00
vol_3g_mb_9	float64	0.00
total_og_mou_9	float64	0.00
total_rech_num_8	int64	0.00
total_rech_num_7	int64	0.00
total_rech_num_6	int64	0.00
total_ic_mou_9	float64	0.00
Average_rech_amt_6n7	float64	0.00

In [21]:
```
# Columns with high missing values , > 50%
metadata = metadata_matrix(data)
condition = metadata['Null_Percentage'] > 50
high_missing_values = metadata[condition]
high_missing_values
```

Out[21]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique
av_rech_amt_data_6	float64	11397	18614	62.02	
count_rech_3g_6	category	11397	18614	62.02	
count_rech_2g_6	float64	11397	18614	62.02	
arpu_2g_6	float64	11397	18614	62.02	
max_rech_data_6	float64	11397	18614	62.02	
night_pck_user_6	category	11397	18614	62.02	
date_of_last_rech_data_6	datetime64[ns]	11397	18614	62.02	
total_rech_data_6	float64	11397	18614	62.02	
arpu_3g_6	float64	11397	18614	62.02	
fb_user_6	category	11397	18614	62.02	
max_rech_data_9	float64	11461	18550	61.81	
count_rech_3g_9	category	11461	18550	61.81	
fb_user_9	category	11461	18550	61.81	
total_rech_data_9	float64	11461	18550	61.81	
date_of_last_rech_data_9	datetime64[ns]	11461	18550	61.81	
av_rech_amt_data_9	float64	11461	18550	61.81	
arpu_2g_9	float64	11461	18550	61.81	
arpu_3g_9	float64	11461	18550	61.81	
night_pck_user_9	category	11461	18550	61.81	
count_rech_2g_9	float64	11461	18550	61.81	
fb_user_7	category	11662	18349	61.14	
date_of_last_rech_data_7	datetime64[ns]	11662	18349	61.14	
total_rech_data_7	float64	11662	18349	61.14	
night_pck_user_7	category	11662	18349	61.14	
max_rech_data_7	float64	11662	18349	61.14	
count_rech_2g_7	float64	11662	18349	61.14	
arpu_3g_7	float64	11662	18349	61.14	
av_rech_amt_data_7	float64	11662	18349	61.14	
arpu_2g_7	float64	11662	18349	61.14	
count_rech_3g_7	category	11662	18349	61.14	
night_pck_user_8	category	11754	18257	60.83	
fb_user_8	category	11754	18257	60.83	
arpu_2g_8	float64	11754	18257	60.83	
count_rech_2g_8	float64	11754	18257	60.83	
date_of_last_rech_data_8	datetime64[ns]	11754	18257	60.83	
av_rech_amt_data_8	float64	11754	18257	60.83	
arpu_3g_8	float64	11754	18257	60.83	
total_rech_data_8	float64	11754	18257	60.83	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique
count_rech_3g_8	category	11754	18257	60.83	
max_rech_data_8	float64	11754	18257	60.83	

In [22]:
```
# Dropping above columns with high missing values
high_missing_value_columns = high_missing_values.index
data.drop(columns=high_missing_value_columns, inplace=True)
```

```
In [23]: # Looking at remaining columns with missing values
         metadata_matrix(data)
```

Out[23]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
std_ic_t2o_mou_9	category	28307	1704	5.68	
spl_og_mou_9	float64	28307	1704	5.68	
isd_og_mou_9	float64	28307	1704	5.68	
roam_ic_mou_9	float64	28307	1704	5.68	
std_og_mou_9	float64	28307	1704	5.68	
roam_og_mou_9	float64	28307	1704	5.68	
std_ic_t2f_mou_9	float64	28307	1704	5.68	
std_og_t2c_mou_9	category	28307	1704	5.68	
loc_og_t2t_mou_9	float64	28307	1704	5.68	
std_og_t2f_mou_9	float64	28307	1704	5.68	
std_ic_mou_9	float64	28307	1704	5.68	
loc_og_t2m_mou_9	float64	28307	1704	5.68	
std_og_t2m_mou_9	float64	28307	1704	5.68	
loc_og_t2f_mou_9	float64	28307	1704	5.68	
std_og_t2t_mou_9	float64	28307	1704	5.68	
loc_ic_mou_9	float64	28307	1704	5.68	
loc_og_t2c_mou_9	float64	28307	1704	5.68	
offnet_mou_9	float64	28307	1704	5.68	
loc_og_mou_9	float64	28307	1704	5.68	
spl_ic_mou_9	float64	28307	1704	5.68	
std_ic_t2m_mou_9	float64	28307	1704	5.68	
loc_ic_t2f_mou_9	float64	28307	1704	5.68	
ic_others_9	float64	28307	1704	5.68	
loc_ic_t2m_mou_9	float64	28307	1704	5.68	
loc_ic_t2t_mou_9	float64	28307	1704	5.68	
std_ic_t2t_mou_9	float64	28307	1704	5.68	
isd_ic_mou_9	float64	28307	1704	5.68	
og_others_9	float64	28307	1704	5.68	
onnet_mou_9	float64	28307	1704	5.68	
std_og_mou_8	float64	29073	938	3.13	
std_og_t2m_mou_8	float64	29073	938	3.13	
og_others_8	float64	29073	938	3.13	
loc_ic_t2f_mou_8	float64	29073	938	3.13	
std_og_t2t_mou_8	float64	29073	938	3.13	
loc_og_mou_8	float64	29073	938	3.13	
std_ic_t2o_mou_8	category	29073	938	3.13	
loc_ic_t2m_mou_8	float64	29073	938	3.13	
std_ic_t2m_mou_8	float64	29073	938	3.13	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
std_ic_t2t_mou_8	float64	29073	938	3.13	
std_og_t2f_mou_8	float64	29073	938	3.13	
std_ic_t2f_mou_8	float64	29073	938	3.13	
spl_og_mou_8	float64	29073	938	3.13	
loc_ic_t2t_mou_8	float64	29073	938	3.13	
std_og_t2c_mou_8	category	29073	938	3.13	
isd_og_mou_8	float64	29073	938	3.13	
loc_ic_mou_8	float64	29073	938	3.13	
roam_ic_mou_8	float64	29073	938	3.13	
isd_ic_mou_8	float64	29073	938	3.13	
onnet_mou_8	float64	29073	938	3.13	
loc_og_t2c_mou_8	float64	29073	938	3.13	
spl_ic_mou_8	float64	29073	938	3.13	
loc_og_t2f_mou_8	float64	29073	938	3.13	
std_ic_mou_8	float64	29073	938	3.13	
roam_og_mou_8	float64	29073	938	3.13	
ic_others_8	float64	29073	938	3.13	
loc_og_t2m_mou_8	float64	29073	938	3.13	
loc_og_t2t_mou_8	float64	29073	938	3.13	
offnet_mou_8	float64	29073	938	3.13	
date_of_last_rech_9	datetime64[ns]	29145	866	2.89	
date_of_last_rech_8	datetime64[ns]	29417	594	1.98	
last_date_of_month_9	object	29651	360	1.20	
std_ic_mou_6	float64	29695	316	1.05	
offnet_mou_6	float64	29695	316	1.05	
std_ic_t2f_mou_6	float64	29695	316	1.05	
isd_ic_mou_6	float64	29695	316	1.05	
ic_others_6	float64	29695	316	1.05	
onnet_mou_6	float64	29695	316	1.05	
std_ic_t2m_mou_6	float64	29695	316	1.05	
loc_ic_t2t_mou_6	float64	29695	316	1.05	
loc_ic_t2m_mou_6	float64	29695	316	1.05	
loc_ic_t2f_mou_6	float64	29695	316	1.05	
loc_ic_mou_6	float64	29695	316	1.05	
std_ic_t2t_mou_6	float64	29695	316	1.05	
og_others_6	float64	29695	316	1.05	
spl_og_mou_6	float64	29695	316	1.05	
roam_ic_mou_6	float64	29695	316	1.05	
spl_ic_mou_6	float64	29695	316	1.05	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
std_og_t2t_mou_6	float64	29695	316	1.05	
loc_og_t2c_mou_6	float64	29695	316	1.05	
std_og_t2m_mou_6	float64	29695	316	1.05	
loc_og_t2f_mou_6	float64	29695	316	1.05	
std_og_t2f_mou_6	float64	29695	316	1.05	
loc_og_t2m_mou_6	float64	29695	316	1.05	
std_ic_t2o_mou_6	category	29695	316	1.05	
std_og_t2c_mou_6	category	29695	316	1.05	
std_og_mou_6	float64	29695	316	1.05	
loc_og_t2t_mou_6	float64	29695	316	1.05	
isd_og_mou_6	float64	29695	316	1.05	
roam_og_mou_6	float64	29695	316	1.05	
loc_og_mou_6	float64	29695	316	1.05	
isd_ic_mou_7	float64	29708	303	1.01	
std_ic_t2f_mou_7	float64	29708	303	1.01	
std_ic_t2m_mou_7	float64	29708	303	1.01	
std_ic_t2o_mou_7	category	29708	303	1.01	
ic_others_7	float64	29708	303	1.01	
spl_ic_mou_7	float64	29708	303	1.01	
std_ic_t2t_mou_7	float64	29708	303	1.01	
std_ic_mou_7	float64	29708	303	1.01	
loc_ic_t2f_mou_7	float64	29708	303	1.01	
og_others_7	float64	29708	303	1.01	
loc_ic_mou_7	float64	29708	303	1.01	
std_og_t2f_mou_7	float64	29708	303	1.01	
onnet_mou_7	float64	29708	303	1.01	
roam_ic_mou_7	float64	29708	303	1.01	
roam_og_mou_7	float64	29708	303	1.01	
loc_og_t2t_mou_7	float64	29708	303	1.01	
loc_og_t2m_mou_7	float64	29708	303	1.01	
loc_og_t2f_mou_7	float64	29708	303	1.01	
loc_og_t2c_mou_7	float64	29708	303	1.01	
loc_og_mou_7	float64	29708	303	1.01	
std_og_t2t_mou_7	float64	29708	303	1.01	
std_og_t2m_mou_7	float64	29708	303	1.01	
offnet_mou_7	float64	29708	303	1.01	
std_og_t2c_mou_7	category	29708	303	1.01	
loc_ic_t2t_mou_7	float64	29708	303	1.01	
isd_og_mou_7	float64	29708	303	1.01	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
spl_og_mou_7	float64	29708	303	1.01	
std_og_mou_7	float64	29708	303	1.01	
loc_ic_t2m_mou_7	float64	29708	303	1.01	
last_date_of_month_8	object	29854	157	0.52	
std_og_t2o_mou	category	29897	114	0.38	
loc_ic_t2o_mou	category	29897	114	0.38	
date_of_last_rech_7	datetime64[ns]	29897	114	0.38	
loc_og_t2o_mou	category	29897	114	0.38	
date_of_last_rech_6	datetime64[ns]	29949	62	0.21	
last_date_of_month_7	object	29980	31	0.10	
sachet_3g_6	category	30011	0	0.00	
monthly_2g_8	category	30011	0	0.00	
vol_2g_mb_8	float64	30011	0	0.00	
vol_2g_mb_9	float64	30011	0	0.00	
vol_2g_mb_6	float64	30011	0	0.00	
sachet_3g_9	category	30011	0	0.00	
sachet_3g_8	category	30011	0	0.00	
monthly_3g_9	category	30011	0	0.00	
vol_3g_mb_6	float64	30011	0	0.00	
vol_3g_mb_7	float64	30011	0	0.00	
vol_3g_mb_8	float64	30011	0	0.00	
vol_3g_mb_9	float64	30011	0	0.00	
monthly_2g_6	category	30011	0	0.00	
monthly_2g_7	category	30011	0	0.00	
monthly_2g_9	category	30011	0	0.00	
sachet_3g_7	category	30011	0	0.00	
sachet_2g_6	category	30011	0	0.00	
sachet_2g_7	category	30011	0	0.00	
sachet_2g_8	category	30011	0	0.00	
sachet_2g_9	category	30011	0	0.00	
vbc_3g_9	float64	30011	0	0.00	
monthly_3g_8	category	30011	0	0.00	
monthly_3g_7	category	30011	0	0.00	
vbc_3g_6	float64	30011	0	0.00	
vbc_3g_7	float64	30011	0	0.00	
vbc_3g_8	float64	30011	0	0.00	
aon	int64	30011	0	0.00	
monthly_3g_6	category	30011	0	0.00	
vol_2g_mb_7	float64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
circle_id	category	30011	0	0.00	
last_day_rch_amt_9	int64	30011	0	0.00	
last_day_rch_amt_8	int64	30011	0	0.00	
last_date_of_month_6	object	30011	0	0.00	
arpu_6	float64	30011	0	0.00	
arpu_7	float64	30011	0	0.00	
arpu_8	float64	30011	0	0.00	
arpu_9	float64	30011	0	0.00	
total_og_mou_6	float64	30011	0	0.00	
total_og_mou_7	float64	30011	0	0.00	
total_og_mou_8	float64	30011	0	0.00	
total_og_mou_9	float64	30011	0	0.00	
total_ic_mou_6	float64	30011	0	0.00	
total_ic_mou_7	float64	30011	0	0.00	
total_ic_mou_8	float64	30011	0	0.00	
total_ic_mou_9	float64	30011	0	0.00	
total_rech_num_6	int64	30011	0	0.00	
total_rech_num_7	int64	30011	0	0.00	
total_rech_num_8	int64	30011	0	0.00	
total_rech_num_9	int64	30011	0	0.00	
total_rech_amt_6	int64	30011	0	0.00	
total_rech_amt_7	int64	30011	0	0.00	
total_rech_amt_8	int64	30011	0	0.00	
total_rech_amt_9	int64	30011	0	0.00	
max_rech_amt_6	int64	30011	0	0.00	
max_rech_amt_7	int64	30011	0	0.00	
max_rech_amt_8	int64	30011	0	0.00	
max_rech_amt_9	int64	30011	0	0.00	
last_day_rch_amt_6	int64	30011	0	0.00	
last_day_rch_amt_7	int64	30011	0	0.00	
Average_rech_amt_6n7	float64	30011	0	0.00	

- data contains information of 04 months - 6,7,8,9.
- For the purpose of missing value treatment, each month's revenue and usage data is not related to the other months.
- hence, missing value treatment could be performed month wise.

In [24]:
```
# Month 6
```

In [25]:
```
sixth_month_columns = []
for column in data.columns:
    x = re.search("6$", column)
    if x:
        sixth_month_columns.append(column)
# missing_values.loc[sixth_month_columns].sort_values(by='Null_Percentage',
ascending=False)
metadata = metadata_matrix(data)
condition = metadata.index.isin(sixth_month_columns)
sixth_month_metadata = metadata[condition]
sixth_month_metadata
```

Out[25]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
std_ic_mou_6	float64	29695	316	1.05	
offnet_mou_6	float64	29695	316	1.05	
std_ic_t2f_mou_6	float64	29695	316	1.05	
isd_ic_mou_6	float64	29695	316	1.05	
ic_others_6	float64	29695	316	1.05	
onnet_mou_6	float64	29695	316	1.05	
std_ic_t2m_mou_6	float64	29695	316	1.05	
loc_ic_t2t_mou_6	float64	29695	316	1.05	
loc_ic_t2m_mou_6	float64	29695	316	1.05	
loc_ic_t2f_mou_6	float64	29695	316	1.05	
loc_ic_mou_6	float64	29695	316	1.05	
std_ic_t2t_mou_6	float64	29695	316	1.05	
og_others_6	float64	29695	316	1.05	
spl_og_mou_6	float64	29695	316	1.05	
roam_ic_mou_6	float64	29695	316	1.05	
spl_ic_mou_6	float64	29695	316	1.05	
std_og_t2t_mou_6	float64	29695	316	1.05	
loc_og_t2c_mou_6	float64	29695	316	1.05	
std_og_t2m_mou_6	float64	29695	316	1.05	
loc_og_t2f_mou_6	float64	29695	316	1.05	
std_og_t2f_mou_6	float64	29695	316	1.05	
loc_og_t2m_mou_6	float64	29695	316	1.05	
std_ic_t2o_mou_6	category	29695	316	1.05	
std_og_t2c_mou_6	category	29695	316	1.05	
std_og_mou_6	float64	29695	316	1.05	
loc_og_t2t_mou_6	float64	29695	316	1.05	
isd_og_mou_6	float64	29695	316	1.05	
roam_og_mou_6	float64	29695	316	1.05	
loc_og_mou_6	float64	29695	316	1.05	
date_of_last_rech_6	datetime64[ns]	29949	62	0.21	
sachet_3g_6	category	30011	0	0.00	
vol_2g_mb_6	float64	30011	0	0.00	
vol_3g_mb_6	float64	30011	0	0.00	
monthly_2g_6	category	30011	0	0.00	
sachet_2g_6	category	30011	0	0.00	
vbc_3g_6	float64	30011	0	0.00	
monthly_3g_6	category	30011	0	0.00	
last_date_of_month_6	object	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
arpu_6	float64	30011	0	0.00	
total_og_mou_6	float64	30011	0	0.00	
total_ic_mou_6	float64	30011	0	0.00	
total_rech_num_6	int64	30011	0	0.00	
total_rech_amt_6	int64	30011	0	0.00	
max_rech_amt_6	int64	30011	0	0.00	
last_day_rch_amt_6	int64	30011	0	0.00	

- Note that all the columns with *_mou have exactly 3.94% rows with missing values.
- This is an indicator of a meaningful missing values.
- Further note that *_mou columns indicate minutes of usage, which are applicable only to customers using calling plans. It is probable that, the 3.94% customers not using calling plans.
- This could confirmed by looking at 'total_og_mou_6' and 'total_ic_mou_6' related columns where _*mou columns have missing values. If these columns are zero for a customer , then all* _mou columns should be zero too.

In [26]:
```
#  columns with meaningful missing in 6th month
sixth_month_meaningful_missing_condition = sixth_month_metadata['Null_Perce
ntage'] == 1.05
sixth_month_meaningful_missing_cols = sixth_month_metadata[sixth_month_mean
ingful_missing_condition].index.values
sixth_month_meaningful_missing_cols
```

Out[26]:
```
array(['std_ic_mou_6', 'offnet_mou_6', 'std_ic_t2f_mou_6', 'isd_ic_mou_6',
       'ic_others_6', 'onnet_mou_6', 'std_ic_t2m_mou_6',
       'loc_ic_t2t_mou_6', 'loc_ic_t2m_mou_6', 'loc_ic_t2f_mou_6',
       'loc_ic_mou_6', 'std_ic_t2t_mou_6', 'og_others_6', 'spl_og_mou_6',
       'roam_ic_mou_6', 'spl_ic_mou_6', 'std_og_t2t_mou_6',
       'loc_og_t2c_mou_6', 'std_og_t2m_mou_6', 'loc_og_t2f_mou_6',
       'std_og_t2f_mou_6', 'loc_og_t2m_mou_6', 'std_ic_t2o_mou_6',
       'std_og_t2c_mou_6', 'std_og_mou_6', 'loc_og_t2t_mou_6',
       'isd_og_mou_6', 'roam_og_mou_6', 'loc_og_mou_6'], dtype=object)
```

In [27]:
```
# Looking at all sixth month columns where rows of *_mou are null
condition = data[sixth_month_meaningful_missing_cols].isnull()
# data.loc[condition, sixth_month_columns]


# Rows is null for all the above columns
missing_rows = pd.Series([True]*data.shape[0], index = data.index)
for column in sixth_month_meaningful_missing_cols :
    missing_rows = missing_rows & data[column].isnull()

print('Total outgoing mou for each customer with missing *_mou data is ', d
ata.loc[missing_rows,'total_og_mou_6'].unique()[0])
print('Total incoming mou for each customer with missing *_mou data is ', d
ata.loc[missing_rows,'total_ic_mou_6'].unique()[0])
```

```
Total outgoing mou for each customer with missing *_mou data is  0.0
Total incoming mou for each customer with missing *_mou data is  0.0
```

- Hence, these could be imputed with 0

In [28]:
```
# Imputation
data[sixth_month_meaningful_missing_cols] = data[sixth_month_meaningful_mis
sing_cols].fillna(0)

metadata = metadata_matrix(data)

# Remaining Missing Values
metadata.iloc[metadata.index.isin(sixth_month_columns)]
```

Out[28]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
date_of_last_rech_6	datetime64[ns]	29949	62	0.21	
monthly_2g_6	category	30011	0	0.00	
vbc_3g_6	float64	30011	0	0.00	
max_rech_amt_6	int64	30011	0	0.00	
sachet_3g_6	category	30011	0	0.00	
sachet_2g_6	category	30011	0	0.00	
vol_2g_mb_6	float64	30011	0	0.00	
monthly_3g_6	category	30011	0	0.00	
vol_3g_mb_6	float64	30011	0	0.00	
last_day_rch_amt_6	int64	30011	0	0.00	
total_rech_amt_6	int64	30011	0	0.00	
loc_og_t2m_mou_6	float64	30011	0	0.00	
isd_og_mou_6	float64	30011	0	0.00	
std_og_mou_6	float64	30011	0	0.00	
std_og_t2c_mou_6	category	30011	0	0.00	
std_og_t2f_mou_6	float64	30011	0	0.00	
std_og_t2m_mou_6	float64	30011	0	0.00	
std_og_t2t_mou_6	float64	30011	0	0.00	
loc_og_mou_6	float64	30011	0	0.00	
loc_og_t2c_mou_6	float64	30011	0	0.00	
loc_og_t2f_mou_6	float64	30011	0	0.00	
loc_og_t2t_mou_6	float64	30011	0	0.00	
roam_og_mou_6	float64	30011	0	0.00	
roam_ic_mou_6	float64	30011	0	0.00	
offnet_mou_6	float64	30011	0	0.00	
onnet_mou_6	float64	30011	0	0.00	
arpu_6	float64	30011	0	0.00	
last_date_of_month_6	object	30011	0	0.00	
spl_og_mou_6	float64	30011	0	0.00	
og_others_6	float64	30011	0	0.00	
total_og_mou_6	float64	30011	0	0.00	
total_rech_num_6	int64	30011	0	0.00	
ic_others_6	float64	30011	0	0.00	
isd_ic_mou_6	float64	30011	0	0.00	
spl_ic_mou_6	float64	30011	0	0.00	
total_ic_mou_6	float64	30011	0	0.00	
std_ic_mou_6	float64	30011	0	0.00	
std_ic_t2o_mou_6	category	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
std_ic_t2f_mou_6	float64	30011	0	0.00	
std_ic_t2m_mou_6	float64	30011	0	0.00	
std_ic_t2t_mou_6	float64	30011	0	0.00	
loc_ic_mou_6	float64	30011	0	0.00	
loc_ic_t2f_mou_6	float64	30011	0	0.00	
loc_ic_t2m_mou_6	float64	30011	0	0.00	
loc_ic_t2t_mou_6	float64	30011	0	0.00	

- Looks like there '1.61%' customers with missing date of last recharge. Let's look at 'recharge' related columns for such customers

In [29]:
```
# Looking at 'recharge' related 6th month columns for customers with missin
g 'date_of_last_rech_6'
condition = data['date_of_last_rech_6'].isnull()
data[condition].filter(regex='.*rech.*6$', axis=1).head()
```

Out[29]:

	total_rech_num_6	total_rech_amt_6	max_rech_amt_6	date_of_last_rech_6
mobile_number				
7001588448	0	0	0	NaT
7001223277	0	0	0	NaT
7000721536	0	0	0	NaT
7001490351	0	0	0	NaT
7000665415	0	0	0	NaT

In [30]:
```
data[condition].filter(regex='.*rech.*6$', axis=1).nunique()
```

Out[30]:
```
total_rech_num_6       1
total_rech_amt_6       1
max_rech_amt_6         1
date_of_last_rech_6    0
dtype: int64
```

- Notice, that the recharge related columns for customers with missing 'date_of_last_rech_6' has just one unique value. From the first few rows of the output, we see that this is 0.
- Hence, 'date_of_last_rech_6' is missing since there were no recharges made in this month.
- These are meaning missing values

In [31]:
```
# Check for missing values in 6th month variables
metadata = metadata_matrix(data)
metadata[metadata.index.isin(sixth_month_columns)]
```

Out[31]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
date_of_last_rech_6	datetime64[ns]	29949	62	0.21	
monthly_2g_6	category	30011	0	0.00	
vbc_3g_6	float64	30011	0	0.00	
max_rech_amt_6	int64	30011	0	0.00	
sachet_3g_6	category	30011	0	0.00	
sachet_2g_6	category	30011	0	0.00	
vol_2g_mb_6	float64	30011	0	0.00	
monthly_3g_6	category	30011	0	0.00	
vol_3g_mb_6	float64	30011	0	0.00	
last_day_rch_amt_6	int64	30011	0	0.00	
total_rech_amt_6	int64	30011	0	0.00	
loc_og_t2m_mou_6	float64	30011	0	0.00	
isd_og_mou_6	float64	30011	0	0.00	
std_og_mou_6	float64	30011	0	0.00	
std_og_t2c_mou_6	category	30011	0	0.00	
std_og_t2f_mou_6	float64	30011	0	0.00	
std_og_t2m_mou_6	float64	30011	0	0.00	
std_og_t2t_mou_6	float64	30011	0	0.00	
loc_og_mou_6	float64	30011	0	0.00	
loc_og_t2c_mou_6	float64	30011	0	0.00	
loc_og_t2f_mou_6	float64	30011	0	0.00	
loc_og_t2t_mou_6	float64	30011	0	0.00	
roam_og_mou_6	float64	30011	0	0.00	
roam_ic_mou_6	float64	30011	0	0.00	
offnet_mou_6	float64	30011	0	0.00	
onnet_mou_6	float64	30011	0	0.00	
arpu_6	float64	30011	0	0.00	
last_date_of_month_6	object	30011	0	0.00	
spl_og_mou_6	float64	30011	0	0.00	
og_others_6	float64	30011	0	0.00	
total_og_mou_6	float64	30011	0	0.00	
total_rech_num_6	int64	30011	0	0.00	
ic_others_6	float64	30011	0	0.00	
isd_ic_mou_6	float64	30011	0	0.00	
spl_ic_mou_6	float64	30011	0	0.00	
total_ic_mou_6	float64	30011	0	0.00	
std_ic_mou_6	float64	30011	0	0.00	
std_ic_t2o_mou_6	category	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
std_ic_t2f_mou_6	float64	30011	0	0.00	
std_ic_t2m_mou_6	float64	30011	0	0.00	
std_ic_t2t_mou_6	float64	30011	0	0.00	
loc_ic_mou_6	float64	30011	0	0.00	
loc_ic_t2f_mou_6	float64	30011	0	0.00	
loc_ic_t2m_mou_6	float64	30011	0	0.00	
loc_ic_t2t_mou_6	float64	30011	0	0.00	

- No more Missing Values in 6th month columns

In [32]:
```
# Month : 7
seventh_month_columns = data.filter(regex='7$', axis=1).columns
seventh_month_columns
```

Out[32]:
```
Index(['last_date_of_month_7', 'arpu_7', 'onnet_mou_7', 'offnet_mou_7',
       'roam_ic_mou_7', 'roam_og_mou_7', 'loc_og_t2t_mou_7',
       'loc_og_t2m_mou_7', 'loc_og_t2f_mou_7', 'loc_og_t2c_mou_7',
       'loc_og_mou_7', 'std_og_t2t_mou_7', 'std_og_t2m_mou_7',
       'std_og_t2f_mou_7', 'std_og_t2c_mou_7', 'std_og_mou_7', 'isd_og_mou
_7',
       'spl_og_mou_7', 'og_others_7', 'total_og_mou_7', 'loc_ic_t2t_mou_
7',
       'loc_ic_t2m_mou_7', 'loc_ic_t2f_mou_7', 'loc_ic_mou_7',
       'std_ic_t2t_mou_7', 'std_ic_t2m_mou_7', 'std_ic_t2f_mou_7',
       'std_ic_t2o_mou_7', 'std_ic_mou_7', 'total_ic_mou_7', 'spl_ic_mou_
7',
       'isd_ic_mou_7', 'ic_others_7', 'total_rech_num_7', 'total_rech_amt_
7',
       'max_rech_amt_7', 'date_of_last_rech_7', 'last_day_rch_amt_7',
      'vol_2g_mb_7', 'vol_3g_mb_7', 'monthly_2g_7', 'sachet_2g_7',
      'monthly_3g_7', 'sachet_3g_7', 'vbc_3g_7', 'Average_rech_amt_6n7'],
      dtype='object')
```

In [33]:
```
seventh_month_metadata = metadata[metadata.index.isin(seventh_month_column
s)]
seventh_month_metadata
```

Out[33]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
loc_ic_t2t_mou_7	float64	29708	303	1.01	
og_others_7	float64	29708	303	1.01	
loc_ic_t2f_mou_7	float64	29708	303	1.01	
loc_ic_t2m_mou_7	float64	29708	303	1.01	
loc_ic_mou_7	float64	29708	303	1.01	
std_ic_t2t_mou_7	float64	29708	303	1.01	
std_ic_t2f_mou_7	float64	29708	303	1.01	
std_ic_t2o_mou_7	category	29708	303	1.01	
std_ic_mou_7	float64	29708	303	1.01	
spl_ic_mou_7	float64	29708	303	1.01	
isd_ic_mou_7	float64	29708	303	1.01	
ic_others_7	float64	29708	303	1.01	
std_ic_t2m_mou_7	float64	29708	303	1.01	
isd_og_mou_7	float64	29708	303	1.01	
spl_og_mou_7	float64	29708	303	1.01	
std_og_t2f_mou_7	float64	29708	303	1.01	
onnet_mou_7	float64	29708	303	1.01	
offnet_mou_7	float64	29708	303	1.01	
roam_ic_mou_7	float64	29708	303	1.01	
roam_og_mou_7	float64	29708	303	1.01	
loc_og_t2t_mou_7	float64	29708	303	1.01	
loc_og_t2f_mou_7	float64	29708	303	1.01	
loc_og_t2c_mou_7	float64	29708	303	1.01	
loc_og_mou_7	float64	29708	303	1.01	
std_og_t2t_mou_7	float64	29708	303	1.01	
std_og_t2m_mou_7	float64	29708	303	1.01	
loc_og_t2m_mou_7	float64	29708	303	1.01	
std_og_t2c_mou_7	category	29708	303	1.01	
std_og_mou_7	float64	29708	303	1.01	
date_of_last_rech_7	datetime64[ns]	29897	114	0.38	
last_date_of_month_7	object	29980	31	0.10	
vol_2g_mb_7	float64	30011	0	0.00	
max_rech_amt_7	int64	30011	0	0.00	
vbc_3g_7	float64	30011	0	0.00	
sachet_3g_7	category	30011	0	0.00	
total_rech_amt_7	int64	30011	0	0.00	
monthly_2g_7	category	30011	0	0.00	
sachet_2g_7	category	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
last_day_rch_amt_7	int64	30011	0	0.00	
monthly_3g_7	category	30011	0	0.00	
vol_3g_mb_7	float64	30011	0	0.00	
total_rech_num_7	int64	30011	0	0.00	
arpu_7	float64	30011	0	0.00	
total_og_mou_7	float64	30011	0	0.00	
total_ic_mou_7	float64	30011	0	0.00	
Average_rech_amt_6n7	float64	30011	0	0.00	

- Note that all the columns with *_mou have exactly 3.86% rows with missing values.
- This is an indicator of a meaningful missing values.
- Further note that *_mou columns indicate minutes of usage, which are applicable only to customers using calling plans. It is probable that, the 3.86% customers not using calling plans.
- This could confirmed by looking at 'total_og_mou_7' and 'total_ic_mou_7' related columns where _*mou columns have missing values. If these columns are zero for a customer , then all* _mou columns should be zero too.

In [34]:
```
#  columns with meaningful missing in 7th month
seventh_month_meaningful_missing_condition = seventh_month_metadata['Null_P
ercentage'] == 1.01
seventh_month_meaningful_missing_cols = seventh_month_metadata[seventh_mont
h_meaningful_missing_condition].index.values
seventh_month_meaningful_missing_cols
```

Out[34]:
```
array(['loc_ic_t2t_mou_7', 'og_others_7', 'loc_ic_t2f_mou_7',
       'loc_ic_t2m_mou_7', 'loc_ic_mou_7', 'std_ic_t2t_mou_7',
       'std_ic_t2f_mou_7', 'std_ic_t2o_mou_7', 'std_ic_mou_7',
       'spl_ic_mou_7', 'isd_ic_mou_7', 'ic_others_7', 'std_ic_t2m_mou_7',
       'isd_og_mou_7', 'spl_og_mou_7', 'std_og_t2f_mou_7', 'onnet_mou_7',
       'offnet_mou_7', 'roam_ic_mou_7', 'roam_og_mou_7',
       'loc_og_t2t_mou_7', 'loc_og_t2f_mou_7', 'loc_og_t2c_mou_7',
       'loc_og_mou_7', 'std_og_t2t_mou_7', 'std_og_t2m_mou_7',
       'loc_og_t2m_mou_7', 'std_og_t2c_mou_7', 'std_og_mou_7'],
      dtype=object)
```

In [35]:
```
# Looking at all 7th month columns where rows of *_mou are null
condition = data[seventh_month_meaningful_missing_cols].isnull()

# Rows is null for all the above columns
missing_rows = pd.Series([True]*data.shape[0], index = data.index)
for column in seventh_month_meaningful_missing_cols :
    missing_rows = missing_rows & data[column].isnull()

print('Total outgoing mou for each customer with missing *_mou data is ', d
ata.loc[missing_rows,'total_og_mou_7'].unique()[0])
print('Total incoming mou for each customer with missing *_mou data is ', d
ata.loc[missing_rows,'total_ic_mou_7'].unique()[0])
```

```
Total outgoing mou for each customer with missing *_mou data is  0.0
Total incoming mou for each customer with missing *_mou data is  0.0
```

- Hence, these could be imputed with 0

In [36]:
```
# Imputation
data[seventh_month_meaningful_missing_cols] = data[seventh_month_meaningful
_missing_cols].fillna(0)

metadata = metadata_matrix(data)

# Remaining Missing Values
metadata.iloc[metadata.index.isin(seventh_month_columns)]
```

Out[36]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
date_of_last_rech_7	datetime64[ns]	29897	114	0.38	
last_date_of_month_7	object	29980	31	0.10	
total_rech_num_7	int64	30011	0	0.00	
ic_others_7	float64	30011	0	0.00	
isd_ic_mou_7	float64	30011	0	0.00	
spl_ic_mou_7	float64	30011	0	0.00	
total_rech_amt_7	int64	30011	0	0.00	
sachet_2g_7	category	30011	0	0.00	
monthly_3g_7	category	30011	0	0.00	
sachet_3g_7	category	30011	0	0.00	
vbc_3g_7	float64	30011	0	0.00	
max_rech_amt_7	int64	30011	0	0.00	
last_day_rch_amt_7	int64	30011	0	0.00	
vol_2g_mb_7	float64	30011	0	0.00	
monthly_2g_7	category	30011	0	0.00	
vol_3g_mb_7	float64	30011	0	0.00	
loc_ic_t2f_mou_7	float64	30011	0	0.00	
total_ic_mou_7	float64	30011	0	0.00	
loc_og_t2t_mou_7	float64	30011	0	0.00	
std_og_t2m_mou_7	float64	30011	0	0.00	
std_og_t2t_mou_7	float64	30011	0	0.00	
loc_og_mou_7	float64	30011	0	0.00	
loc_og_t2c_mou_7	float64	30011	0	0.00	
loc_og_t2f_mou_7	float64	30011	0	0.00	
loc_og_t2m_mou_7	float64	30011	0	0.00	
roam_og_mou_7	float64	30011	0	0.00	
roam_ic_mou_7	float64	30011	0	0.00	
offnet_mou_7	float64	30011	0	0.00	
onnet_mou_7	float64	30011	0	0.00	
arpu_7	float64	30011	0	0.00	
std_og_t2f_mou_7	float64	30011	0	0.00	
std_og_t2c_mou_7	category	30011	0	0.00	
loc_ic_t2m_mou_7	float64	30011	0	0.00	
std_ic_mou_7	float64	30011	0	0.00	
std_ic_t2o_mou_7	category	30011	0	0.00	
std_ic_t2f_mou_7	float64	30011	0	0.00	
std_ic_t2m_mou_7	float64	30011	0	0.00	
std_ic_t2t_mou_7	float64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
loc_ic_mou_7	float64	30011	0	0.00	
loc_ic_t2t_mou_7	float64	30011	0	0.00	
total_og_mou_7	float64	30011	0	0.00	
og_others_7	float64	30011	0	0.00	
spl_og_mou_7	float64	30011	0	0.00	
isd_og_mou_7	float64	30011	0	0.00	
std_og_mou_7	float64	30011	0	0.00	
Average_rech_amt_6n7	float64	30011	0	0.00	

- Looks like there '1.77%' customers with missing date of last recharge. Let's look at 'recharge' related columns for such customers

In [37]:
```
# Looking at 'recharge' related 7th month columns for customers with missin
g 'date_of_last_rech_7'
condition = data['date_of_last_rech_7'].isnull()
data[condition].filter(regex='.*rech.*7$', axis=1).head()
```

Out[37]:

	total_rech_num_7	total_rech_amt_7	max_rech_amt_7	date_of_last_rech_7	Av
mobile_number					
7000369789	0	0	0	NaT	
7001967148	0	0	0	NaT	
7000066601	0	0	0	NaT	
7001189556	0	0	0	NaT	
7002024450	0	0	0	NaT	

In [38]:
```
data[condition].filter(regex='.*rech.*7$', axis=1).nunique()
```

Out[38]:
```
total_rech_num_7         1
total_rech_amt_7         1
max_rech_amt_7           1
date_of_last_rech_7      0
Average_rech_amt_6n7    90
dtype: int64
```

- Notice, that the recharge related columns for customers with missing 'date_of_last_rech_7' has just one unique value. From the first few rows of the output, we see that this is 0.
- Hence, 'date_of_last_rech_7' is missing since there were no recharges made in this month.
- These are meaning missing values

In [39]:
```
# Month : 8
```

In [40]:
```
eighth_month_columns = data.filter(regex="8$", axis=1).columns
metadata = metadata_matrix(data)
condition = metadata.index.isin(eighth_month_columns)
eighth_month_metadata = metadata[condition]
eighth_month_metadata
```

Out[40]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
std_og_t2c_mou_8	category	29073	938	3.13	
std_og_mou_8	float64	29073	938	3.13	
isd_og_mou_8	float64	29073	938	3.13	
loc_ic_mou_8	float64	29073	938	3.13	
std_og_t2m_mou_8	float64	29073	938	3.13	
loc_ic_t2m_mou_8	float64	29073	938	3.13	
loc_og_mou_8	float64	29073	938	3.13	
std_og_t2t_mou_8	float64	29073	938	3.13	
std_og_t2f_mou_8	float64	29073	938	3.13	
loc_ic_t2f_mou_8	float64	29073	938	3.13	
loc_og_t2c_mou_8	float64	29073	938	3.13	
ic_others_8	float64	29073	938	3.13	
loc_og_t2m_mou_8	float64	29073	938	3.13	
spl_og_mou_8	float64	29073	938	3.13	
roam_ic_mou_8	float64	29073	938	3.13	
std_ic_mou_8	float64	29073	938	3.13	
spl_ic_mou_8	float64	29073	938	3.13	
std_ic_t2o_mou_8	category	29073	938	3.13	
onnet_mou_8	float64	29073	938	3.13	
loc_og_t2f_mou_8	float64	29073	938	3.13	
offnet_mou_8	float64	29073	938	3.13	
std_ic_t2f_mou_8	float64	29073	938	3.13	
og_others_8	float64	29073	938	3.13	
loc_ic_t2t_mou_8	float64	29073	938	3.13	
std_ic_t2m_mou_8	float64	29073	938	3.13	
std_ic_t2t_mou_8	float64	29073	938	3.13	
roam_og_mou_8	float64	29073	938	3.13	
isd_ic_mou_8	float64	29073	938	3.13	
loc_og_t2t_mou_8	float64	29073	938	3.13	
date_of_last_rech_8	datetime64[ns]	29417	594	1.98	
last_date_of_month_8	object	29854	157	0.52	
total_rech_num_8	int64	30011	0	0.00	
total_rech_amt_8	int64	30011	0	0.00	
last_day_rch_amt_8	int64	30011	0	0.00	
sachet_2g_8	category	30011	0	0.00	
monthly_3g_8	category	30011	0	0.00	
sachet_3g_8	category	30011	0	0.00	
vbc_3g_8	float64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
monthly_2g_8	category	30011	0	0.00	
max_rech_amt_8	int64	30011	0	0.00	
total_ic_mou_8	float64	30011	0	0.00	
vol_2g_mb_8	float64	30011	0	0.00	
vol_3g_mb_8	float64	30011	0	0.00	
arpu_8	float64	30011	0	0.00	
total_og_mou_8	float64	30011	0	0.00	

In [41]:
```
#  columns with meaningful missing in 8th month
eighth_month_meaningful_missing_condition = eighth_month_metadata['Null_Per
centage'] == 3.13
eighth_month_meaningful_missing_cols = eighth_month_metadata[eighth_month_m
eaningful_missing_condition].index.values
eighth_month_meaningful_missing_cols
```

Out[41]:
```
array(['std_og_t2c_mou_8', 'std_og_mou_8', 'isd_og_mou_8', 'loc_ic_mou_8',
       'std_og_t2m_mou_8', 'loc_ic_t2m_mou_8', 'loc_og_mou_8',
       'std_og_t2t_mou_8', 'std_og_t2f_mou_8', 'loc_ic_t2f_mou_8',
       'loc_og_t2c_mou_8', 'ic_others_8', 'loc_og_t2m_mou_8',
       'spl_og_mou_8', 'roam_ic_mou_8', 'std_ic_mou_8', 'spl_ic_mou_8',
       'std_ic_t2o_mou_8', 'onnet_mou_8', 'loc_og_t2f_mou_8',
       'offnet_mou_8', 'std_ic_t2f_mou_8', 'og_others_8',
       'loc_ic_t2t_mou_8', 'std_ic_t2m_mou_8', 'std_ic_t2t_mou_8',
       'roam_og_mou_8', 'isd_ic_mou_8', 'loc_og_t2t_mou_8'], dtype=object)
```

In [42]:
```
# Looking at all 8th month columns where rows of *_mou are null
condition = data[eighth_month_meaningful_missing_cols].isnull()

# Rows is null for all the above columns
missing_rows = pd.Series([True]*data.shape[0], index = data.index)
for column in eighth_month_meaningful_missing_cols :
    missing_rows = missing_rows & data[column].isnull()

print('Total outgoing mou for each customer with missing *_mou data is ', d
ata.loc[missing_rows,'total_og_mou_8'].unique()[0])
print('Total incoming mou for each customer with missing *_mou data is ', d
ata.loc[missing_rows,'total_ic_mou_8'].unique()[0])
```

```
Total outgoing mou for each customer with missing *_mou data is  0.0
Total incoming mou for each customer with missing *_mou data is  0.0
```

In [43]:
```
# Imputation
data[eighth_month_meaningful_missing_cols] = data[eighth_month_meaningful_m
issing_cols].fillna(0)

metadata = metadata_matrix(data)

# Remaining Missing Values
metadata.iloc[metadata.index.isin(eighth_month_columns)]
```

Out[43]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
date_of_last_rech_8	datetime64[ns]	29417	594	1.98	
last_date_of_month_8	object	29854	157	0.52	
spl_ic_mou_8	float64	30011	0	0.00	
total_rech_num_8	int64	30011	0	0.00	
std_ic_t2f_mou_8	float64	30011	0	0.00	
ic_others_8	float64	30011	0	0.00	
std_ic_t2o_mou_8	category	30011	0	0.00	
std_ic_mou_8	float64	30011	0	0.00	
total_ic_mou_8	float64	30011	0	0.00	
isd_ic_mou_8	float64	30011	0	0.00	
sachet_2g_8	category	30011	0	0.00	
monthly_3g_8	category	30011	0	0.00	
sachet_3g_8	category	30011	0	0.00	
vbc_3g_8	float64	30011	0	0.00	
monthly_2g_8	category	30011	0	0.00	
total_rech_amt_8	int64	30011	0	0.00	
max_rech_amt_8	int64	30011	0	0.00	
last_day_rch_amt_8	int64	30011	0	0.00	
vol_2g_mb_8	float64	30011	0	0.00	
vol_3g_mb_8	float64	30011	0	0.00	
std_ic_t2m_mou_8	float64	30011	0	0.00	
loc_og_t2m_mou_8	float64	30011	0	0.00	
loc_og_t2f_mou_8	float64	30011	0	0.00	
loc_og_t2c_mou_8	float64	30011	0	0.00	
loc_og_mou_8	float64	30011	0	0.00	
std_og_t2t_mou_8	float64	30011	0	0.00	
loc_og_t2t_mou_8	float64	30011	0	0.00	
onnet_mou_8	float64	30011	0	0.00	
arpu_8	float64	30011	0	0.00	
roam_og_mou_8	float64	30011	0	0.00	
offnet_mou_8	float64	30011	0	0.00	
roam_ic_mou_8	float64	30011	0	0.00	
std_og_t2m_mou_8	float64	30011	0	0.00	
loc_ic_t2t_mou_8	float64	30011	0	0.00	
loc_ic_t2m_mou_8	float64	30011	0	0.00	
loc_ic_t2f_mou_8	float64	30011	0	0.00	
loc_ic_mou_8	float64	30011	0	0.00	
std_ic_t2t_mou_8	float64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
total_og_mou_8	float64	30011	0	0.00	
og_others_8	float64	30011	0	0.00	
std_og_t2f_mou_8	float64	30011	0	0.00	
std_og_t2c_mou_8	category	30011	0	0.00	
std_og_mou_8	float64	30011	0	0.00	
isd_og_mou_8	float64	30011	0	0.00	
spl_og_mou_8	float64	30011	0	0.00	

In [44]:
```
# Looking at 'recharge' related 8th month columns for customers with missin
g 'date_of_last_rech_8'
condition = data['date_of_last_rech_8'].isnull()
data[condition].filter(regex='.*rech.*8$', axis=1).head()
```

Out[44]:

	total_rech_num_8	total_rech_amt_8	max_rech_amt_8	date_of_last_rech_8
mobile_number				
7000340381	0	0	0	NaT
7000608224	0	0	0	NaT
7000369789	0	0	0	NaT
7000248548	0	0	0	NaT
7001967063	0	0	0	NaT

In [45]:
```
data[condition].filter(regex='.*rech.*8$', axis=1).nunique()
```

Out[45]:
```
total_rech_num_8       1
total_rech_amt_8       1
max_rech_amt_8         1
date_of_last_rech_8    0
dtype: int64
```

In [46]:
```
# Month : 9
```

In [47]:
```
ninth_month_columns = data.filter(regex="9$", axis=1).columns
metadata = metadata_matrix(data)
condition = metadata.index.isin(ninth_month_columns)
ninth_month_metadata = metadata[condition]
ninth_month_metadata
```

Out[47]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
std_og_t2c_mou_9	category	28307	1704	5.68	
spl_ic_mou_9	float64	28307	1704	5.68	
loc_og_t2m_mou_9	float64	28307	1704	5.68	
og_others_9	float64	28307	1704	5.68	
loc_og_t2c_mou_9	float64	28307	1704	5.68	
isd_ic_mou_9	float64	28307	1704	5.68	
loc_og_t2t_mou_9	float64	28307	1704	5.68	
spl_og_mou_9	float64	28307	1704	5.68	
loc_ic_t2t_mou_9	float64	28307	1704	5.68	
loc_og_mou_9	float64	28307	1704	5.68	
roam_og_mou_9	float64	28307	1704	5.68	
std_ic_mou_9	float64	28307	1704	5.68	
loc_ic_t2m_mou_9	float64	28307	1704	5.68	
roam_ic_mou_9	float64	28307	1704	5.68	
std_og_t2t_mou_9	float64	28307	1704	5.68	
offnet_mou_9	float64	28307	1704	5.68	
loc_ic_t2f_mou_9	float64	28307	1704	5.68	
std_ic_t2f_mou_9	float64	28307	1704	5.68	
isd_og_mou_9	float64	28307	1704	5.68	
std_og_mou_9	float64	28307	1704	5.68	
std_og_t2f_mou_9	float64	28307	1704	5.68	
ic_others_9	float64	28307	1704	5.68	
std_ic_t2t_mou_9	float64	28307	1704	5.68	
std_ic_t2o_mou_9	category	28307	1704	5.68	
loc_og_t2f_mou_9	float64	28307	1704	5.68	
std_og_t2m_mou_9	float64	28307	1704	5.68	
loc_ic_mou_9	float64	28307	1704	5.68	
std_ic_t2m_mou_9	float64	28307	1704	5.68	
onnet_mou_9	float64	28307	1704	5.68	
date_of_last_rech_9	datetime64[ns]	29145	866	2.89	
last_date_of_month_9	object	29651	360	1.20	
total_rech_num_9	int64	30011	0	0.00	
total_ic_mou_9	float64	30011	0	0.00	
monthly_3g_9	category	30011	0	0.00	
monthly_2g_9	category	30011	0	0.00	
sachet_2g_9	category	30011	0	0.00	
sachet_3g_9	category	30011	0	0.00	
vbc_3g_9	float64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
vol_3g_mb_9	float64	30011	0	0.00	
total_rech_amt_9	int64	30011	0	0.00	
max_rech_amt_9	int64	30011	0	0.00	
last_day_rch_amt_9	int64	30011	0	0.00	
vol_2g_mb_9	float64	30011	0	0.00	
arpu_9	float64	30011	0	0.00	
total_og_mou_9	float64	30011	0	0.00	

In [48]:
```
#  columns with meaningful missing in 9th month
ninth_month_meaningful_missing_condition = ninth_month_metadata['Null_Perce
ntage'] == 5.68
ninth_month_meaningful_missing_cols = ninth_month_metadata[ninth_month_mean
ingful_missing_condition].index.values
ninth_month_meaningful_missing_cols
```

Out[48]:
```
array(['std_og_t2c_mou_9', 'spl_ic_mou_9', 'loc_og_t2m_mou_9',
       'og_others_9', 'loc_og_t2c_mou_9', 'isd_ic_mou_9',
       'loc_og_t2t_mou_9', 'spl_og_mou_9', 'loc_ic_t2t_mou_9',
       'loc_og_mou_9', 'roam_og_mou_9', 'std_ic_mou_9',
       'loc_ic_t2m_mou_9', 'roam_ic_mou_9', 'std_og_t2t_mou_9',
       'offnet_mou_9', 'loc_ic_t2f_mou_9', 'std_ic_t2f_mou_9',
       'isd_og_mou_9', 'std_og_mou_9', 'std_og_t2f_mou_9', 'ic_others_9',
       'std_ic_t2t_mou_9', 'std_ic_t2o_mou_9', 'loc_og_t2f_mou_9',
       'std_og_t2m_mou_9', 'loc_ic_mou_9', 'std_ic_t2m_mou_9',
       'onnet_mou_9'], dtype=object)
```

In [49]:
```
# Looking at all 9th month columns where rows of *_mou are null
condition = data[ninth_month_meaningful_missing_cols].isnull()

# Rows is null for all the above columns
missing_rows = pd.Series([True]*data.shape[0], index = data.index)
for column in ninth_month_meaningful_missing_cols :
    missing_rows = missing_rows & data[column].isnull()

print('Total outgoing mou for each customer with missing *_mou data is ', d
ata.loc[missing_rows,'total_og_mou_9'].unique()[0])
print('Total incoming mou for each customer with missing *_mou data is ', d
ata.loc[missing_rows,'total_ic_mou_9'].unique()[0])
```

```
Total outgoing mou for each customer with missing *_mou data is  0.0
Total incoming mou for each customer with missing *_mou data is  0.0
```

In [50]:
```
# Imputation
data[ninth_month_meaningful_missing_cols] = data[ninth_month_meaningful_mis
sing_cols].fillna(0)

metadata = metadata_matrix(data)

# Remaining Missing Values
metadata.iloc[metadata.index.isin(ninth_month_columns)]
```

Out[50]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
date_of_last_rech_9	datetime64[ns]	29145	866	2.89	
last_date_of_month_9	object	29651	360	1.20	
spl_ic_mou_9	float64	30011	0	0.00	
total_ic_mou_9	float64	30011	0	0.00	
std_ic_mou_9	float64	30011	0	0.00	
isd_ic_mou_9	float64	30011	0	0.00	
ic_others_9	float64	30011	0	0.00	
loc_ic_mou_9	float64	30011	0	0.00	
std_ic_t2t_mou_9	float64	30011	0	0.00	
std_ic_t2m_mou_9	float64	30011	0	0.00	
std_ic_t2f_mou_9	float64	30011	0	0.00	
std_ic_t2o_mou_9	category	30011	0	0.00	
total_rech_amt_9	int64	30011	0	0.00	
total_rech_num_9	int64	30011	0	0.00	
monthly_3g_9	category	30011	0	0.00	
monthly_2g_9	category	30011	0	0.00	
sachet_2g_9	category	30011	0	0.00	
sachet_3g_9	category	30011	0	0.00	
vbc_3g_9	float64	30011	0	0.00	
max_rech_amt_9	int64	30011	0	0.00	
vol_3g_mb_9	float64	30011	0	0.00	
last_day_rch_amt_9	int64	30011	0	0.00	
vol_2g_mb_9	float64	30011	0	0.00	
loc_ic_t2f_mou_9	float64	30011	0	0.00	
loc_og_t2t_mou_9	float64	30011	0	0.00	
loc_og_t2m_mou_9	float64	30011	0	0.00	
loc_og_t2f_mou_9	float64	30011	0	0.00	
loc_og_t2c_mou_9	float64	30011	0	0.00	
loc_og_mou_9	float64	30011	0	0.00	
roam_og_mou_9	float64	30011	0	0.00	
onnet_mou_9	float64	30011	0	0.00	
arpu_9	float64	30011	0	0.00	
offnet_mou_9	float64	30011	0	0.00	
roam_ic_mou_9	float64	30011	0	0.00	
std_og_t2t_mou_9	float64	30011	0	0.00	
spl_og_mou_9	float64	30011	0	0.00	
og_others_9	float64	30011	0	0.00	
total_og_mou_9	float64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Va
loc_ic_t2t_mou_9	float64	30011	0	0.00	
loc_ic_t2m_mou_9	float64	30011	0	0.00	
isd_og_mou_9	float64	30011	0	0.00	
std_og_t2m_mou_9	float64	30011	0	0.00	
std_og_t2f_mou_9	float64	30011	0	0.00	
std_og_t2c_mou_9	category	30011	0	0.00	
std_og_mou_9	float64	30011	0	0.00	

In [51]:
```
# Looking at 'recharge' related 9th month columns for customers with missin
g 'date_of_last_rech_9'
condition = data['date_of_last_rech_9'].isnull()
data[condition].filter(regex='.*rech.*9$', axis=1).head()
```

Out[51]:

	total_rech_num_9	total_rech_amt_9	max_rech_amt_9	date_of_last_rech_9
mobile_number				
7000340381	0	0	0	NaT
7000854899	0	0	0	NaT
7000369789	0	0	0	NaT
7001967063	0	0	0	NaT
7000066601	0	0	0	NaT

In [52]:
```
data[condition].filter(regex='.*rech.*9$', axis=1).nunique()
```

Out[52]:
```
total_rech_num_9       1
total_rech_amt_9       1
max_rech_amt_9         1
date_of_last_rech_9    0
dtype: int64
```

In [53]:
```
# Imputing "last_date_of_month_*"
```

In [54]:
```
print('Missing Value Percentage in last_date_of_month columns : \n', 100*data.filter(regex='last_date_of_month_.*', axis=1).isnull().sum() / data.shape[0], '\n')
print('The unique values in last_date_of_month_6 : ' , data['last_date_of_month_6'].unique())
print('The unique values in last_date_of_month_7 : ' , data['last_date_of_month_7'].unique())
print('The unique values in last_date_of_month_8 : ' , data['last_date_of_month_8'].unique())
print('The unique values in last_date_of_month_9 : ' , data['last_date_of_month_9'].unique())
```

```
Missing Value Percentage in last_date_of_month columns : 
 last_date_of_month_6    0.000000
last_date_of_month_7    0.103295
last_date_of_month_8    0.523142
last_date_of_month_9    1.199560
dtype: float64 

The unique values in last_date_of_month_6 :  ['6/30/2014']
The unique values in last_date_of_month_7 :  ['7/31/2014' nan]
The unique values in last_date_of_month_8 :  ['8/31/2014' nan]
The unique values in last_date_of_month_9 :  ['9/30/2014' nan]
```

- Last date of month is the last calender date of a particular month, it is independent of the churn data.
- Lets impute these missing values using mode.

In [55]:
```
# Imputing last_date_of_month_* values
data['last_date_of_month_7'] = data['last_date_of_month_7'].fillna(data['last_date_of_month_7'].mode()[0])
data['last_date_of_month_8'] = data['last_date_of_month_8'].fillna(data['last_date_of_month_8'].mode()[0])
data['last_date_of_month_9'] = data['last_date_of_month_9'].fillna(data['last_date_of_month_9'].mode()[0])
```

In [56]:
```
data['last_date_of_month_7'].unique()
```

Out[56]:
```
array(['7/31/2014'], dtype=object)
```

```
In [57]: metadata = metadata_matrix(data)
         metadata
```

Out[57]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
date_of_last_rech_9	datetime64[ns]	29145	866	2.89	
date_of_last_rech_8	datetime64[ns]	29417	594	1.98	
loc_og_t2o_mou	category	29897	114	0.38	
date_of_last_rech_7	datetime64[ns]	29897	114	0.38	
std_og_t2o_mou	category	29897	114	0.38	
loc_ic_t2o_mou	category	29897	114	0.38	
date_of_last_rech_6	datetime64[ns]	29949	62	0.21	
isd_ic_mou_6	float64	30011	0	0.00	
total_ic_mou_6	float64	30011	0	0.00	
total_ic_mou_7	float64	30011	0	0.00	
total_ic_mou_8	float64	30011	0	0.00	
total_ic_mou_9	float64	30011	0	0.00	
spl_ic_mou_6	float64	30011	0	0.00	
spl_ic_mou_7	float64	30011	0	0.00	
spl_ic_mou_8	float64	30011	0	0.00	
spl_ic_mou_9	float64	30011	0	0.00	
total_rech_num_6	int64	30011	0	0.00	
ic_others_9	float64	30011	0	0.00	
std_ic_mou_8	float64	30011	0	0.00	
isd_ic_mou_7	float64	30011	0	0.00	
isd_ic_mou_8	float64	30011	0	0.00	
isd_ic_mou_9	float64	30011	0	0.00	
ic_others_6	float64	30011	0	0.00	
ic_others_7	float64	30011	0	0.00	
ic_others_8	float64	30011	0	0.00	
std_ic_mou_9	float64	30011	0	0.00	
std_ic_mou_7	float64	30011	0	0.00	
total_rech_num_8	int64	30011	0	0.00	
std_ic_t2m_mou_7	float64	30011	0	0.00	
loc_ic_mou_6	float64	30011	0	0.00	
loc_ic_mou_7	float64	30011	0	0.00	
loc_ic_mou_8	float64	30011	0	0.00	
loc_ic_mou_9	float64	30011	0	0.00	
std_ic_t2t_mou_6	float64	30011	0	0.00	
std_ic_t2t_mou_7	float64	30011	0	0.00	
std_ic_t2t_mou_8	float64	30011	0	0.00	
std_ic_t2t_mou_9	float64	30011	0	0.00	
std_ic_t2m_mou_6	float64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
std_ic_t2m_mou_8	float64	30011	0	0.00	
std_ic_mou_6	float64	30011	0	0.00	
std_ic_t2m_mou_9	float64	30011	0	0.00	
std_ic_t2f_mou_6	float64	30011	0	0.00	
std_ic_t2f_mou_7	float64	30011	0	0.00	
std_ic_t2f_mou_8	float64	30011	0	0.00	
std_ic_t2f_mou_9	float64	30011	0	0.00	
std_ic_t2o_mou_6	category	30011	0	0.00	
std_ic_t2o_mou_7	category	30011	0	0.00	
std_ic_t2o_mou_8	category	30011	0	0.00	
std_ic_t2o_mou_9	category	30011	0	0.00	
total_rech_num_7	int64	30011	0	0.00	
circle_id	category	30011	0	0.00	
total_rech_num_9	int64	30011	0	0.00	
monthly_3g_9	category	30011	0	0.00	
monthly_2g_9	category	30011	0	0.00	
sachet_2g_6	category	30011	0	0.00	
sachet_2g_7	category	30011	0	0.00	
sachet_2g_8	category	30011	0	0.00	
sachet_2g_9	category	30011	0	0.00	
monthly_3g_6	category	30011	0	0.00	
monthly_3g_7	category	30011	0	0.00	
monthly_3g_8	category	30011	0	0.00	
sachet_3g_6	category	30011	0	0.00	
monthly_2g_7	category	30011	0	0.00	
sachet_3g_7	category	30011	0	0.00	
sachet_3g_8	category	30011	0	0.00	
sachet_3g_9	category	30011	0	0.00	
aon	int64	30011	0	0.00	
vbc_3g_8	float64	30011	0	0.00	
vbc_3g_7	float64	30011	0	0.00	
vbc_3g_6	float64	30011	0	0.00	
vbc_3g_9	float64	30011	0	0.00	
monthly_2g_8	category	30011	0	0.00	
monthly_2g_6	category	30011	0	0.00	
total_rech_amt_6	int64	30011	0	0.00	
last_day_rch_amt_7	int64	30011	0	0.00	
loc_ic_t2f_mou_9	float64	30011	0	0.00	
total_rech_amt_8	int64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
total_rech_amt_9	int64	30011	0	0.00	
max_rech_amt_6	int64	30011	0	0.00	
max_rech_amt_7	int64	30011	0	0.00	
max_rech_amt_8	int64	30011	0	0.00	
max_rech_amt_9	int64	30011	0	0.00	
last_day_rch_amt_6	int64	30011	0	0.00	
last_day_rch_amt_8	int64	30011	0	0.00	
vol_3g_mb_9	float64	30011	0	0.00	
last_day_rch_amt_9	int64	30011	0	0.00	
vol_2g_mb_6	float64	30011	0	0.00	
vol_2g_mb_7	float64	30011	0	0.00	
vol_2g_mb_8	float64	30011	0	0.00	
vol_2g_mb_9	float64	30011	0	0.00	
vol_3g_mb_6	float64	30011	0	0.00	
vol_3g_mb_7	float64	30011	0	0.00	
vol_3g_mb_8	float64	30011	0	0.00	
total_rech_amt_7	int64	30011	0	0.00	
loc_ic_t2f_mou_7	float64	30011	0	0.00	
loc_ic_t2f_mou_8	float64	30011	0	0.00	
roam_og_mou_7	float64	30011	0	0.00	
roam_og_mou_9	float64	30011	0	0.00	
loc_og_t2t_mou_6	float64	30011	0	0.00	
loc_og_t2t_mou_7	float64	30011	0	0.00	
loc_og_t2t_mou_8	float64	30011	0	0.00	
loc_og_t2t_mou_9	float64	30011	0	0.00	
loc_og_t2m_mou_6	float64	30011	0	0.00	
loc_og_t2m_mou_7	float64	30011	0	0.00	
loc_og_t2m_mou_8	float64	30011	0	0.00	
loc_og_t2m_mou_9	float64	30011	0	0.00	
loc_og_t2f_mou_6	float64	30011	0	0.00	
loc_og_t2f_mou_7	float64	30011	0	0.00	
loc_og_t2f_mou_8	float64	30011	0	0.00	
loc_og_t2f_mou_9	float64	30011	0	0.00	
loc_og_t2c_mou_6	float64	30011	0	0.00	
loc_og_t2c_mou_7	float64	30011	0	0.00	
loc_og_t2c_mou_8	float64	30011	0	0.00	
loc_og_t2c_mou_9	float64	30011	0	0.00	
loc_og_mou_6	float64	30011	0	0.00	
loc_og_mou_7	float64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
roam_og_mou_8	float64	30011	0	0.00	
roam_og_mou_6	float64	30011	0	0.00	
loc_og_mou_9	float64	30011	0	0.00	
roam_ic_mou_9	float64	30011	0	0.00	
last_date_of_month_6	object	30011	0	0.00	
last_date_of_month_7	object	30011	0	0.00	
last_date_of_month_8	object	30011	0	0.00	
last_date_of_month_9	object	30011	0	0.00	
arpu_6	float64	30011	0	0.00	
arpu_7	float64	30011	0	0.00	
arpu_8	float64	30011	0	0.00	
arpu_9	float64	30011	0	0.00	
onnet_mou_6	float64	30011	0	0.00	
onnet_mou_7	float64	30011	0	0.00	
onnet_mou_8	float64	30011	0	0.00	
onnet_mou_9	float64	30011	0	0.00	
offnet_mou_6	float64	30011	0	0.00	
offnet_mou_7	float64	30011	0	0.00	
offnet_mou_8	float64	30011	0	0.00	
offnet_mou_9	float64	30011	0	0.00	
roam_ic_mou_6	float64	30011	0	0.00	
roam_ic_mou_7	float64	30011	0	0.00	
roam_ic_mou_8	float64	30011	0	0.00	
loc_og_mou_8	float64	30011	0	0.00	
std_og_t2t_mou_6	float64	30011	0	0.00	
loc_ic_t2f_mou_6	float64	30011	0	0.00	
isd_og_mou_9	float64	30011	0	0.00	
spl_og_mou_7	float64	30011	0	0.00	
spl_og_mou_8	float64	30011	0	0.00	
spl_og_mou_9	float64	30011	0	0.00	
og_others_6	float64	30011	0	0.00	
og_others_7	float64	30011	0	0.00	
og_others_8	float64	30011	0	0.00	
og_others_9	float64	30011	0	0.00	
total_og_mou_6	float64	30011	0	0.00	
total_og_mou_7	float64	30011	0	0.00	
total_og_mou_8	float64	30011	0	0.00	
total_og_mou_9	float64	30011	0	0.00	
loc_ic_t2t_mou_6	float64	30011	0	0.00	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_
loc_ic_t2t_mou_7	float64	30011	0	0.00	
loc_ic_t2t_mou_8	float64	30011	0	0.00	
loc_ic_t2t_mou_9	float64	30011	0	0.00	
loc_ic_t2m_mou_6	float64	30011	0	0.00	
loc_ic_t2m_mou_7	float64	30011	0	0.00	
loc_ic_t2m_mou_8	float64	30011	0	0.00	
loc_ic_t2m_mou_9	float64	30011	0	0.00	
spl_og_mou_6	float64	30011	0	0.00	
isd_og_mou_8	float64	30011	0	0.00	
std_og_t2t_mou_7	float64	30011	0	0.00	
isd_og_mou_7	float64	30011	0	0.00	
std_og_t2t_mou_8	float64	30011	0	0.00	
std_og_t2t_mou_9	float64	30011	0	0.00	
std_og_t2m_mou_6	float64	30011	0	0.00	
std_og_t2m_mou_7	float64	30011	0	0.00	
std_og_t2m_mou_8	float64	30011	0	0.00	
std_og_t2m_mou_9	float64	30011	0	0.00	
std_og_t2f_mou_6	float64	30011	0	0.00	
std_og_t2f_mou_7	float64	30011	0	0.00	
std_og_t2f_mou_8	float64	30011	0	0.00	
std_og_t2f_mou_9	float64	30011	0	0.00	
std_og_t2c_mou_6	category	30011	0	0.00	
std_og_t2c_mou_7	category	30011	0	0.00	
std_og_t2c_mou_8	category	30011	0	0.00	
std_og_t2c_mou_9	category	30011	0	0.00	
std_og_mou_6	float64	30011	0	0.00	
std_og_mou_7	float64	30011	0	0.00	
std_og_mou_8	float64	30011	0	0.00	
std_og_mou_9	float64	30011	0	0.00	
isd_og_mou_6	float64	30011	0	0.00	
Average_rech_amt_6n7	float64	30011	0	0.00	

In [58]:
```
print(data[data['date_of_last_rech_6'].isnull()][['date_of_last_rech_6','to
tal_rech_amt_6','total_rech_num_6']].nunique())
print(data[data['date_of_last_rech_7'].isnull()][['date_of_last_rech_7','to
tal_rech_amt_7','total_rech_num_7']].nunique())
print(data[data['date_of_last_rech_8'].isnull()][['date_of_last_rech_8','to
tal_rech_amt_8','total_rech_num_8']].nunique())
print(data[data['date_of_last_rech_9'].isnull()][['date_of_last_rech_9','to
tal_rech_amt_9','total_rech_num_9']].nunique())
```

```
date_of_last_rech_6    0
total_rech_amt_6       1
total_rech_num_6       1
dtype: int64
date_of_last_rech_7    0
total_rech_amt_7       1
total_rech_num_7       1
dtype: int64
date_of_last_rech_8    0
total_rech_amt_8       1
total_rech_num_8       1
dtype: int64
date_of_last_rech_9    0
total_rech_amt_9       1
total_rech_num_9       1
dtype: int64
```

In [59]:
```
print("\n",data[data['date_of_last_rech_6'].isnull()][['total_rech_amt_
6','total_rech_num_6']].head())
print("\n",data[data['date_of_last_rech_7'].isnull()][['total_rech_amt_
7','total_rech_num_7']].head())
print("\n",data[data['date_of_last_rech_8'].isnull()][['total_rech_amt_
8','total_rech_num_8']].head())
print("\n",data[data['date_of_last_rech_9'].isnull()][['total_rech_amt_
9','total_rech_num_9']].head())
```

```
                total_rech_amt_6  total_rech_num_6
mobile_number
7001588448                     0                 0
7001223277                     0                 0
7000721536                     0                 0
7001490351                     0                 0
7000665415                     0                 0

                total_rech_amt_7  total_rech_num_7
mobile_number
7000369789                     0                 0
7001967148                     0                 0
7000066601                     0                 0
7001189556                     0                 0
7002024450                     0                 0

                total_rech_amt_8  total_rech_num_8
mobile_number
7000340381                     0                 0
7000608224                     0                 0
7000369789                     0                 0
7000248548                     0                 0
7001967063                     0                 0

                total_rech_amt_9  total_rech_num_9
mobile_number
7000340381                     0                 0
7000854899                     0                 0
7000369789                     0                 0
7001967063                     0                 0
7000066601                     0                 0
```

- The columns 'date_of_last_rech' for june,july and August does not have any value becuase there are no recharges done by the user during those months.

Dropping columns with one unique value.

In [60]:
```
metadata=metadata_matrix(data)
singular_value_cols=metadata[metadata['Unique_Values_Count']==1].index.valu
es
#data.loc[metadata_matrix(data)['Unique_Values_Count']==1].index
```

In [61]:
```
#Dropping singular value columns.
data.drop(columns=singular_value_cols,inplace=True)
```

In [62]:
```
# Dropping date columns
# since they are not usage related columns and can't be used for modelling
date_columns = data.filter(regex='^date.*').columns
data.drop(columns=date_columns, inplace=True)
metadata_matrix(data)
```

Out[62]:

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Value
arpu_6	float64	30011	0	0.0	
total_ic_mou_6	float64	30011	0	0.0	
total_ic_mou_8	float64	30011	0	0.0	
total_ic_mou_9	float64	30011	0	0.0	
spl_ic_mou_6	float64	30011	0	0.0	
spl_ic_mou_7	float64	30011	0	0.0	
spl_ic_mou_8	float64	30011	0	0.0	
spl_ic_mou_9	float64	30011	0	0.0	
isd_ic_mou_6	float64	30011	0	0.0	
isd_ic_mou_7	float64	30011	0	0.0	
isd_ic_mou_8	float64	30011	0	0.0	
isd_ic_mou_9	float64	30011	0	0.0	
ic_others_6	float64	30011	0	0.0	
ic_others_7	float64	30011	0	0.0	
ic_others_8	float64	30011	0	0.0	
ic_others_9	float64	30011	0	0.0	
total_rech_num_6	int64	30011	0	0.0	
total_rech_num_7	int64	30011	0	0.0	
total_rech_num_8	int64	30011	0	0.0	
total_ic_mou_7	float64	30011	0	0.0	
std_ic_mou_9	float64	30011	0	0.0	
total_rech_amt_6	int64	30011	0	0.0	
std_ic_mou_8	float64	30011	0	0.0	
loc_ic_mou_7	float64	30011	0	0.0	
loc_ic_mou_8	float64	30011	0	0.0	
loc_ic_mou_9	float64	30011	0	0.0	
std_ic_t2t_mou_6	float64	30011	0	0.0	
std_ic_t2t_mou_7	float64	30011	0	0.0	
std_ic_t2t_mou_8	float64	30011	0	0.0	
std_ic_t2t_mou_9	float64	30011	0	0.0	
std_ic_t2m_mou_6	float64	30011	0	0.0	
std_ic_t2m_mou_7	float64	30011	0	0.0	
std_ic_t2m_mou_8	float64	30011	0	0.0	
std_ic_t2m_mou_9	float64	30011	0	0.0	
std_ic_t2f_mou_6	float64	30011	0	0.0	
std_ic_t2f_mou_7	float64	30011	0	0.0	
std_ic_t2f_mou_8	float64	30011	0	0.0	
std_ic_t2f_mou_9	float64	30011	0	0.0	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Value
std_ic_mou_6	float64	30011	0	0.0	
std_ic_mou_7	float64	30011	0	0.0	
total_rech_num_9	int64	30011	0	0.0	
total_rech_amt_7	int64	30011	0	0.0	
arpu_7	float64	30011	0	0.0	
monthly_2g_8	category	30011	0	0.0	
sachet_2g_6	category	30011	0	0.0	
sachet_2g_7	category	30011	0	0.0	
sachet_2g_8	category	30011	0	0.0	
sachet_2g_9	category	30011	0	0.0	
monthly_3g_6	category	30011	0	0.0	
monthly_3g_7	category	30011	0	0.0	
monthly_3g_8	category	30011	0	0.0	
monthly_3g_9	category	30011	0	0.0	
sachet_3g_6	category	30011	0	0.0	
sachet_3g_7	category	30011	0	0.0	
sachet_3g_8	category	30011	0	0.0	
sachet_3g_9	category	30011	0	0.0	
aon	int64	30011	0	0.0	
vbc_3g_8	float64	30011	0	0.0	
vbc_3g_7	float64	30011	0	0.0	
vbc_3g_6	float64	30011	0	0.0	
vbc_3g_9	float64	30011	0	0.0	
monthly_2g_9	category	30011	0	0.0	
monthly_2g_7	category	30011	0	0.0	
total_rech_amt_8	int64	30011	0	0.0	
monthly_2g_6	category	30011	0	0.0	
total_rech_amt_9	int64	30011	0	0.0	
max_rech_amt_6	int64	30011	0	0.0	
max_rech_amt_7	int64	30011	0	0.0	
max_rech_amt_8	int64	30011	0	0.0	
max_rech_amt_9	int64	30011	0	0.0	
last_day_rch_amt_6	int64	30011	0	0.0	
last_day_rch_amt_7	int64	30011	0	0.0	
last_day_rch_amt_8	int64	30011	0	0.0	
last_day_rch_amt_9	int64	30011	0	0.0	
vol_2g_mb_6	float64	30011	0	0.0	
vol_2g_mb_7	float64	30011	0	0.0	
vol_2g_mb_8	float64	30011	0	0.0	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Value
vol_2g_mb_9	float64	30011	0	0.0	
vol_3g_mb_6	float64	30011	0	0.0	
vol_3g_mb_7	float64	30011	0	0.0	
vol_3g_mb_8	float64	30011	0	0.0	
vol_3g_mb_9	float64	30011	0	0.0	
loc_ic_mou_6	float64	30011	0	0.0	
loc_ic_t2f_mou_9	float64	30011	0	0.0	
loc_ic_t2f_mou_8	float64	30011	0	0.0	
loc_og_t2t_mou_7	float64	30011	0	0.0	
loc_og_t2t_mou_9	float64	30011	0	0.0	
loc_og_t2m_mou_6	float64	30011	0	0.0	
loc_og_t2m_mou_7	float64	30011	0	0.0	
loc_og_t2m_mou_8	float64	30011	0	0.0	
loc_og_t2m_mou_9	float64	30011	0	0.0	
loc_og_t2f_mou_6	float64	30011	0	0.0	
loc_og_t2f_mou_7	float64	30011	0	0.0	
loc_og_t2f_mou_8	float64	30011	0	0.0	
loc_og_t2f_mou_9	float64	30011	0	0.0	
loc_og_t2c_mou_6	float64	30011	0	0.0	
loc_og_t2c_mou_7	float64	30011	0	0.0	
loc_og_t2c_mou_8	float64	30011	0	0.0	
loc_og_t2c_mou_9	float64	30011	0	0.0	
loc_og_mou_6	float64	30011	0	0.0	
loc_og_mou_7	float64	30011	0	0.0	
loc_og_mou_8	float64	30011	0	0.0	
loc_og_mou_9	float64	30011	0	0.0	
loc_og_t2t_mou_8	float64	30011	0	0.0	
loc_og_t2t_mou_6	float64	30011	0	0.0	
loc_ic_t2f_mou_7	float64	30011	0	0.0	
roam_og_mou_9	float64	30011	0	0.0	
arpu_8	float64	30011	0	0.0	
arpu_9	float64	30011	0	0.0	
onnet_mou_6	float64	30011	0	0.0	
onnet_mou_7	float64	30011	0	0.0	
onnet_mou_8	float64	30011	0	0.0	
onnet_mou_9	float64	30011	0	0.0	
offnet_mou_6	float64	30011	0	0.0	
offnet_mou_7	float64	30011	0	0.0	
offnet_mou_8	float64	30011	0	0.0	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Value
offnet_mou_9	float64	30011	0	0.0	
roam_ic_mou_6	float64	30011	0	0.0	
roam_ic_mou_7	float64	30011	0	0.0	
roam_ic_mou_8	float64	30011	0	0.0	
roam_ic_mou_9	float64	30011	0	0.0	
roam_og_mou_6	float64	30011	0	0.0	
roam_og_mou_7	float64	30011	0	0.0	
roam_og_mou_8	float64	30011	0	0.0	
std_og_t2t_mou_6	float64	30011	0	0.0	
std_og_t2t_mou_7	float64	30011	0	0.0	
std_og_t2t_mou_8	float64	30011	0	0.0	
std_og_t2t_mou_9	float64	30011	0	0.0	
og_others_6	float64	30011	0	0.0	
og_others_7	float64	30011	0	0.0	
og_others_8	float64	30011	0	0.0	
og_others_9	float64	30011	0	0.0	
total_og_mou_6	float64	30011	0	0.0	
total_og_mou_7	float64	30011	0	0.0	
total_og_mou_8	float64	30011	0	0.0	
total_og_mou_9	float64	30011	0	0.0	
loc_ic_t2t_mou_6	float64	30011	0	0.0	
loc_ic_t2t_mou_7	float64	30011	0	0.0	
loc_ic_t2t_mou_8	float64	30011	0	0.0	
loc_ic_t2t_mou_9	float64	30011	0	0.0	
loc_ic_t2m_mou_6	float64	30011	0	0.0	
loc_ic_t2m_mou_7	float64	30011	0	0.0	
loc_ic_t2m_mou_8	float64	30011	0	0.0	
loc_ic_t2m_mou_9	float64	30011	0	0.0	
loc_ic_t2f_mou_6	float64	30011	0	0.0	
spl_og_mou_9	float64	30011	0	0.0	
spl_og_mou_8	float64	30011	0	0.0	
spl_og_mou_7	float64	30011	0	0.0	
std_og_t2f_mou_9	float64	30011	0	0.0	
std_og_t2m_mou_6	float64	30011	0	0.0	
std_og_t2m_mou_7	float64	30011	0	0.0	
std_og_t2m_mou_8	float64	30011	0	0.0	
std_og_t2m_mou_9	float64	30011	0	0.0	
std_og_t2f_mou_6	float64	30011	0	0.0	
std_og_t2f_mou_7	float64	30011	0	0.0	

	Datatype	Non_Null_Count	Null_Count	Null_Percentage	Unique_Value
std_og_t2f_mou_8	float64	30011	0	0.0	
std_og_mou_6	float64	30011	0	0.0	
spl_og_mou_6	float64	30011	0	0.0	
std_og_mou_7	float64	30011	0	0.0	
std_og_mou_8	float64	30011	0	0.0	
std_og_mou_9	float64	30011	0	0.0	
isd_og_mou_6	float64	30011	0	0.0	
isd_og_mou_7	float64	30011	0	0.0	
isd_og_mou_8	float64	30011	0	0.0	
isd_og_mou_9	float64	30011	0	0.0	
Average_rech_amt_6n7	float64	30011	0	0.0	

Tagging Churn (TARGET variable)

In [63]:
```
data['Churn'] = 0
churned_customers = data.query('total_og_mou_9 == 0 & total_ic_mou_9 == 0 &
vol_2g_mb_9 == 0 &  vol_3g_mb_9 == 0').index
data.loc[churned_customers,'Churn']=1
data['Churn'] = data['Churn'].astype('category')
```

In [64]:
```
# Churn proportions
data['Churn'].value_counts(normalize=True).to_frame()
```

Out[64]:

	Churn
0	0.913598
1	0.086402

Dropping Churn Phase Columns

In [65]:
```
churn_phase_columns = data.filter(regex='9$').columns
data.drop(columns=churn_phase_columns, inplace=True)
print('Retained Columns')
data.columns.to_frame(index=False)
```

```
Retained Columns
```

Out[65]:

	0
0	arpu_6
1	arpu_7
2	arpu_8
3	onnet_mou_6
4	onnet_mou_7
5	onnet_mou_8
6	offnet_mou_6
7	offnet_mou_7
8	offnet_mou_8
9	roam_ic_mou_6
10	roam_ic_mou_7
11	roam_ic_mou_8
12	roam_og_mou_6
13	roam_og_mou_7
14	roam_og_mou_8
15	loc_og_t2t_mou_6
16	loc_og_t2t_mou_7
17	loc_og_t2t_mou_8
18	loc_og_t2m_mou_6
19	loc_og_t2m_mou_7
20	loc_og_t2m_mou_8
21	loc_og_t2f_mou_6
22	loc_og_t2f_mou_7
23	loc_og_t2f_mou_8
24	loc_og_t2c_mou_6
25	loc_og_t2c_mou_7
26	loc_og_t2c_mou_8
27	loc_og_mou_6
28	loc_og_mou_7
29	loc_og_mou_8
30	std_og_t2t_mou_6
31	std_og_t2t_mou_7
32	std_og_t2t_mou_8
33	std_og_t2m_mou_6
34	std_og_t2m_mou_7
35	std_og_t2m_mou_8
36	std_og_t2f_mou_6
37	std_og_t2f_mou_7

	0
38	std_og_t2f_mou_8
39	std_og_mou_6
40	std_og_mou_7
41	std_og_mou_8
42	isd_og_mou_6
43	isd_og_mou_7
44	isd_og_mou_8
45	spl_og_mou_6
46	spl_og_mou_7
47	spl_og_mou_8
48	og_others_6
49	og_others_7
50	og_others_8
51	total_og_mou_6
52	total_og_mou_7
53	total_og_mou_8
54	loc_ic_t2t_mou_6
55	loc_ic_t2t_mou_7
56	loc_ic_t2t_mou_8
57	loc_ic_t2m_mou_6
58	loc_ic_t2m_mou_7
59	loc_ic_t2m_mou_8
60	loc_ic_t2f_mou_6
61	loc_ic_t2f_mou_7
62	loc_ic_t2f_mou_8
63	loc_ic_mou_6
64	loc_ic_mou_7
65	loc_ic_mou_8
66	std_ic_t2t_mou_6
67	std_ic_t2t_mou_7
68	std_ic_t2t_mou_8
69	std_ic_t2m_mou_6
70	std_ic_t2m_mou_7
71	std_ic_t2m_mou_8
72	std_ic_t2f_mou_6
73	std_ic_t2f_mou_7
74	std_ic_t2f_mou_8
75	std_ic_mou_6
76	std_ic_mou_7

	0
77	std_ic_mou_8
78	total_ic_mou_6
79	total_ic_mou_7
80	total_ic_mou_8
81	spl_ic_mou_6
82	spl_ic_mou_7
83	spl_ic_mou_8
84	isd_ic_mou_6
85	isd_ic_mou_7
86	isd_ic_mou_8
87	ic_others_6
88	ic_others_7
89	ic_others_8
90	total_rech_num_6
91	total_rech_num_7
92	total_rech_num_8
93	total_rech_amt_6
94	total_rech_amt_7
95	total_rech_amt_8
96	max_rech_amt_6
97	max_rech_amt_7
98	max_rech_amt_8
99	last_day_rch_amt_6
100	last_day_rch_amt_7
101	last_day_rch_amt_8
102	vol_2g_mb_6
103	vol_2g_mb_7
104	vol_2g_mb_8
105	vol_3g_mb_6
106	vol_3g_mb_7
107	vol_3g_mb_8
108	monthly_2g_6
109	monthly_2g_7
110	monthly_2g_8
111	sachet_2g_6
112	sachet_2g_7
113	sachet_2g_8
114	monthly_3g_6
115	monthly_3g_7

	0
116	monthly_3g_8
117	sachet_3g_6
118	sachet_3g_7
119	sachet_3g_8
120	aon
121	vbc_3g_8
122	vbc_3g_7
123	vbc_3g_6
124	Average_rech_amt_6n7
125	Churn

In [66]:
```
print('retained no of rows', data.shape[0])
print('retain no of columns', data.shape[1])
```

```
retained no of rows 30011
retain no of columns 126
```

Exploratory Data Analysis

Summary Statistics

In [67]:
```
data.describe()
```

Out[67]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8
count	30011.000000	30011.000000	30011.000000	30011.000000	30011.000000	30011.000000
mean	587.284404	589.135427	534.857433	296.034461	304.343206	267.600412
std	442.722413	462.897814	492.259586	460.775592	481.780488	466.560947
min	-2258.709000	-2014.045000	-945.808000	0.000000	0.000000	0.000000
25%	364.161000	365.004500	289.609500	41.110000	40.950000	27.010000
50%	495.682000	493.561000	452.091000	125.830000	125.460000	99.440000
75%	703.922000	700.788000	671.150000	353.310000	359.925000	297.735000
max	27731.088000	35145.834000	33543.624000	7376.710000	8157.780000	10752.560000

- The telecom company has many users with negative average revenues in both phases. These users are likely to churn

In [68]:
```
categorical_columns = data.dtypes[data.dtypes == 'category'].index.values
print('Mode : ')
data[categorical_columns].mode().T
```

```
Mode :
```

Out[68]:

	0
monthly_2g_6	0
monthly_2g_7	0
monthly_2g_8	0
sachet_2g_6	0
sachet_2g_7	0
sachet_2g_8	0
monthly_3g_6	0
monthly_3g_7	0
monthly_3g_8	0
sachet_3g_6	0
sachet_3g_7	0
sachet_3g_8	0
Churn	0

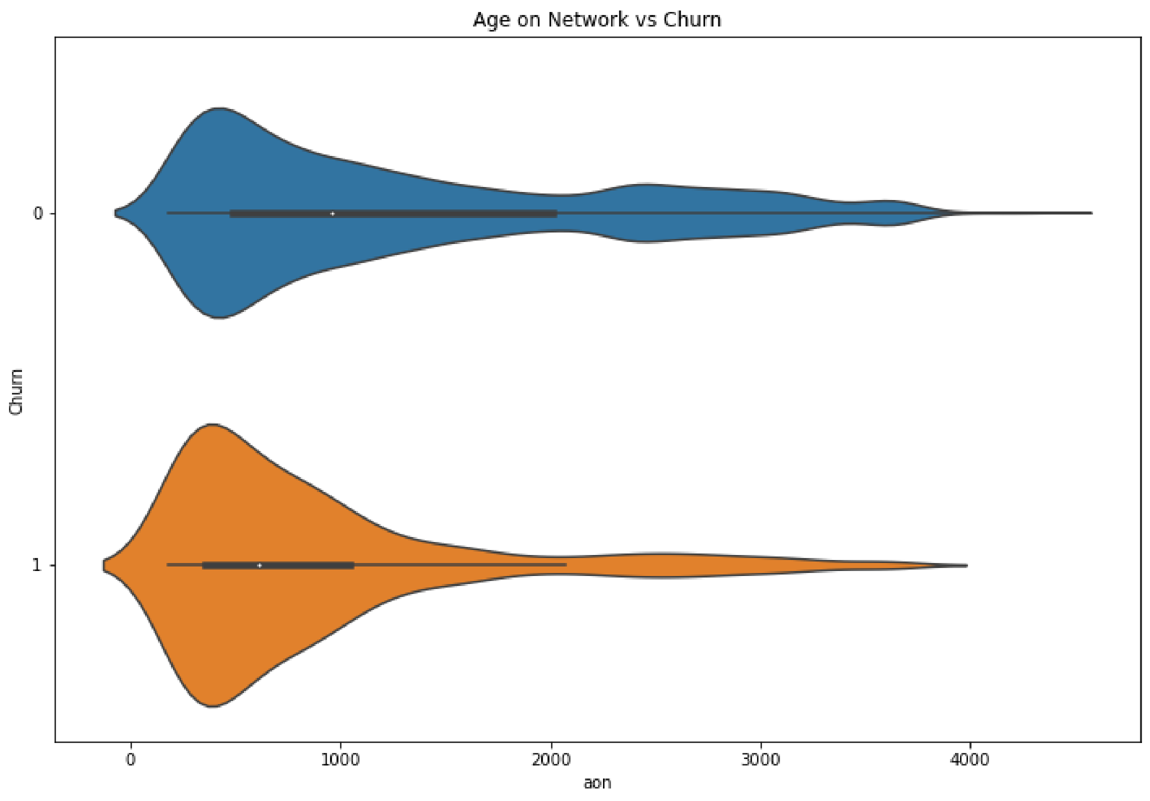
- Most customers prefer the plans of '0' category

Univariate Analysis

In [69]:
```
churned_customers = data[data['Churn'] == 1]
non_churned_customers = data[data['Churn'] == 0]
```

Age on Network

In [70]:
```
plt.figure(figsize=(12,8))
sns.violinplot(x='aon', y='Churn', data=data)
plt.title('Age on Network vs Churn')
plt.show()
```



- The customers with lesser 'aon' are more likely to Churn when compared to the Customers with higer 'aon'

In [71]:
```
# function for numerical variable univariate analysis
from tabulate import tabulate
def num_univariate_analysis(column_names,scale='linear') :
    # boxplot for column vs target

    fig = plt.figure(figsize=(16,8))
    ax1 = fig.add_subplot(1,3,1)
    sns.violinplot(x='Churn', y = column_names[0], data = data, ax=ax1)
    title = ''.join(column_names[0]) +' vs Churn'
    ax1.set(title=title)
    if scale == 'log' :
        plt.yscale('log')
        ax1.set(ylabel= column_names[0] + '(Log Scale)')

    ax2 = fig.add_subplot(1,3,2)
    sns.violinplot(x='Churn', y = column_names[1], data = data, ax=ax2)
    title = ''.join(column_names[1]) +' vs Churn'
    ax2.set(title=title)
    if scale == 'log' :
        plt.yscale('log')
        ax2.set(ylabel= column_names[1] + '(Log Scale)')

    ax3 = fig.add_subplot(1,3,3)
    sns.violinplot(x='Churn', y = column_names[2], data = data, ax=ax3)
    title = ''.join(column_names[2]) +' vs Churn'
    ax3.set(title=title)
    if scale == 'log' :
        plt.yscale('log')
        ax3.set(ylabel= column_names[2] + '(Log Scale)')

    # summary statistic

    print('Customers who churned (Churn : 1)')
    print(churned_customers[column_names].describe())

    print('\nCustomers who did not churn (Churn : 0)')
    print(non_churned_customers[column_names].describe(),'\n')
```

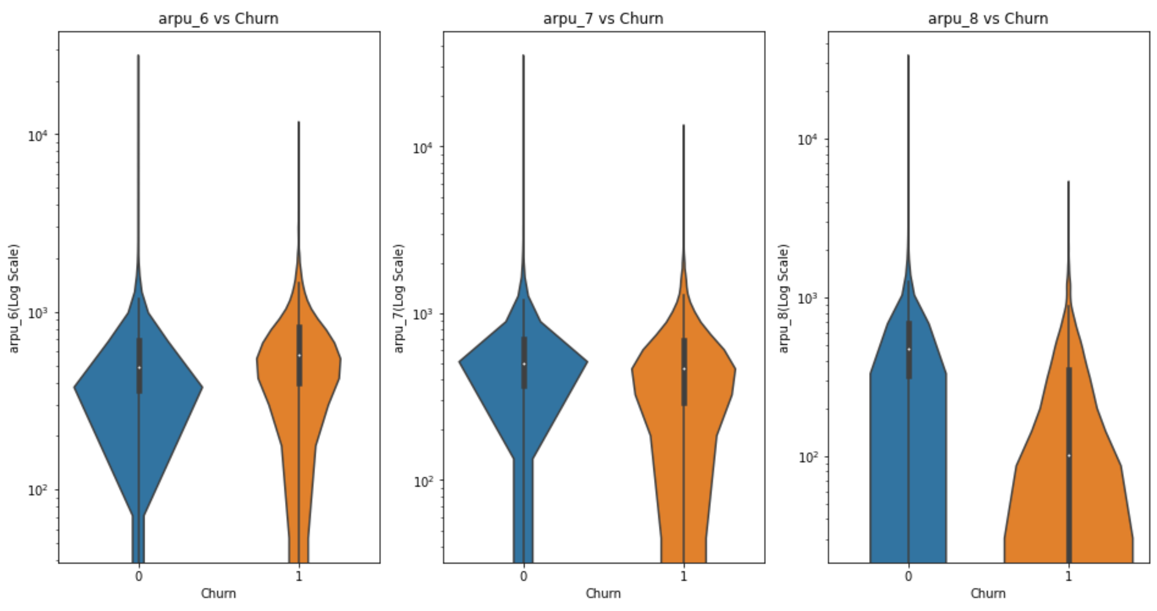
In [72]:
```
# function for categorical variable univariate analysis
!pip install sidetable
import sidetable
def cat_univariate_analysis(column_names,figsize=(16,4)) :

    # column vs target count plot
    fig = plt.figure(figsize=figsize)

    ax1 = fig.add_subplot(1,3,1)
    sns.countplot(x=column_names[0],hue='Churn',data=data, ax=ax1)
    title = column_names[0] + ' vs No of Churned Customers'
    ax1.set(title= title)
    ax1.legend(loc='upper right')


    ax2 = fig.add_subplot(1,3,2)
    sns.countplot(x=column_names[1],hue='Churn',data=data, ax=ax2)
    title = column_names[1] + ' vs No of Churned Customers'
    ax2.set(title= title)
    ax2.legend(loc='upper right')


    ax3 = fig.add_subplot(1,3,3)
    sns.countplot(x=column_names[2],hue='Churn',data=data, ax=ax3)
    title = column_names[2] + ' vs No of Churned Customers'
    ax3.set(title= title)
    ax3.legend(loc='upper right')


    # Percentages
    print('Customers who churned (Churn : 1)')
    print(tabulate(pd.DataFrame(churned_customers.stb.freq([column_names
[0]])), headers='keys', tablefmt='psql'),'\n')
    print(tabulate(pd.DataFrame(churned_customers.stb.freq([column_names
[1]])), headers='keys', tablefmt='psql'),'\n')
    print(tabulate(pd.DataFrame(churned_customers.stb.freq([column_names
[2]])), headers='keys', tablefmt='psql'),'\n')

    print('\nCustomers who did not churn (Churn : 0)')
    print(tabulate(pd.DataFrame(non_churned_customers.stb.freq([column_name
s[0]])), headers='keys', tablefmt='psql'),'\n')
    print(tabulate(pd.DataFrame(non_churned_customers.stb.freq([column_name
s[1]])), headers='keys', tablefmt='psql'),'\n')
    print(tabulate(pd.DataFrame(non_churned_customers.stb.freq([column_name
s[2]])), headers='keys', tablefmt='psql'),'\n')
```

```
Requirement already satisfied: sidetable in /Users/UMAER/Documents/DataSci
ence/anaconda3/lib/python3.8/site-packages (0.7.0)
Requirement already satisfied: pandas>=1.0 in /Users/UMAER/Documents/DataS
cience/anaconda3/lib/python3.8/site-packages (from sidetable) (1.0.5)
Requirement already satisfied: pytz>=2017.2 in /Users/UMAER/Documents/Data
Science/anaconda3/lib/python3.8/site-packages (from pandas>=1.0->sidetabl
e) (2020.1)
Requirement already satisfied: numpy>=1.13.3 in /Users/UMAER/Documents/Dat
aScience/anaconda3/lib/python3.8/site-packages (from pandas>=1.0->sidetabl
e) (1.18.5)
Requirement already satisfied: python-dateutil>=2.6.1 in /Users/UMAER/Docu
ments/DataScience/anaconda3/lib/python3.8/site-packages (from pandas>=1.0-
>sidetable) (2.8.1)
Requirement already satisfied: six>=1.5 in /Users/UMAER/Documents/DataScie
nce/anaconda3/lib/python3.8/site-packages (from python-dateutil>=2.6.1->pa
ndas>=1.0->sidetable) (1.15.0)
```

arpu_6, arpu_7 , arpu_8

In [73]:
```
columns = ['arpu_6','arpu_7','arpu_8']
num_univariate_analysis(columns,'log')
```

```
Customers who churned (Churn : 1)
             arpu_6        arpu_7       arpu_8
count   2593.000000   2593.000000  2593.000000
mean     678.716970    550.511946   243.063343
std      551.792864    517.241221   378.843531
min     -209.465000   -158.963000   -37.887000
25%      396.507000    289.641000     0.000000
50%      573.396000    464.674000   101.894000
75%      819.460000    691.588000   351.028000
max    11505.508000  13224.119000  5228.826000

Customers who did not churn (Churn : 0)
             arpu_6        arpu_7        arpu_8
count  27418.000000  27418.000000  27418.000000
mean     578.637360    592.788162    562.453248
std      429.988265    457.265996    492.802655
min    -2258.709000  -2014.045000   -945.808000
25%      362.218000    369.610500    319.118500
50%      489.324000    496.182500    471.024000
75%      690.891750    701.418000    690.921000
max    27731.088000  35145.834000  33543.624000
```

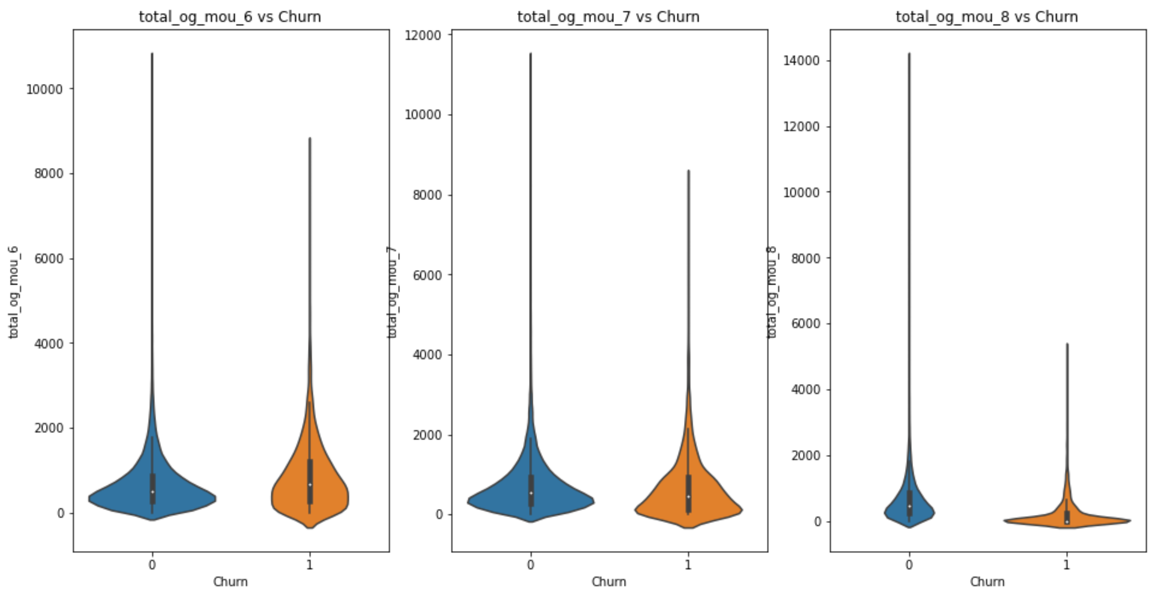


- We can understand from the above plots that revenue generated by the Customers who are about to churn is very unstable.
- The Customers whose arpu decreases in 7th month are more likely to churn when compared to ones with increase in arpu.

total_og_mou_6, total_og_mou_7, total_og_mou_8

```
In [74]: columns = ['total_og_mou_6', 'total_og_mou_7', 'total_og_mou_8']
         num_univariate_analysis(columns)
```

```
Customers who churned (Churn : 1)
       total_og_mou_6  total_og_mou_7  total_og_mou_8
count     2593.000000     2593.000000     2593.000000
mean       867.961342      677.868909      225.083741
std        852.697688      786.961399      471.672718
min          0.000000        0.000000        0.000000
25%        277.880000      110.090000        0.000000
50%        658.360000      466.910000        0.000000
75%       1209.040000      926.760000      255.810000
max       8488.360000     8285.640000     5206.210000

Customers who did not churn (Churn : 0)
       total_og_mou_6  total_og_mou_7  total_og_mou_8
count    27418.000000    27418.000000    27418.000000
mean       669.554896      712.080684      661.480046
std        636.531612      674.580516      691.079113
min          0.000000        0.000000        0.000000
25%        265.682500      284.500000      227.970000
50%        500.410000      529.935000      470.475000
75%        872.070000      931.197500      866.045000
max      10674.030000    11365.310000    14043.060000
```

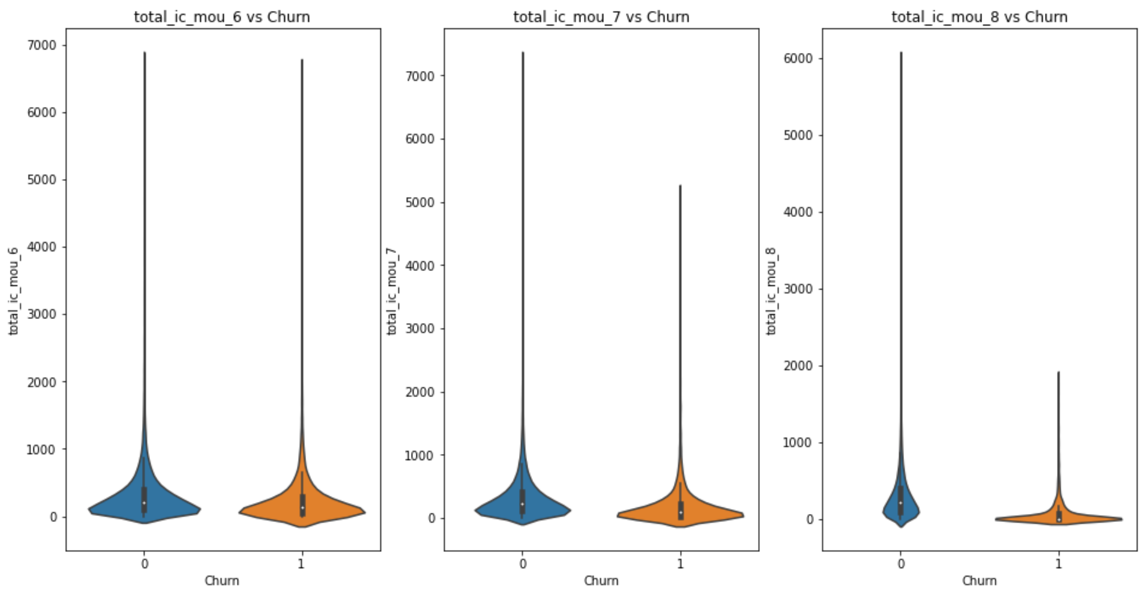


- The Customers with high total_og_mou in 6th month and lower total_og_mou in 7th month are more likely to churn compared to the rest.

'total_ic_mou_6', 'total_ic_mou_7', 'total_ic_mou_8'

```
In [75]: columns = ['total_ic_mou_6', 'total_ic_mou_7', 'total_ic_mou_8']
         num_univariate_analysis(columns)
```

```
Customers who churned (Churn : 1)
       total_ic_mou_6  total_ic_mou_7  total_ic_mou_8
count     2593.000000     2593.000000     2593.000000
mean       241.954404      193.341076       68.807042
std        360.836586      318.183813      154.450340
min          0.000000        0.000000        0.000000
25%         49.460000       27.890000        0.000000
50%        137.330000       99.980000        0.000000
75%        289.510000      235.740000       70.290000
max       6633.180000     5137.560000     1859.280000

Customers who did not churn (Churn : 0)
       total_ic_mou_6  total_ic_mou_7  total_ic_mou_8
count    27418.000000    27418.000000    27418.000000
mean       313.712052      326.369333      316.858595
std        360.580253      372.112086      366.818717
min          0.000000        0.000000        0.000000
25%         94.460000      107.802500       98.265000
50%        212.160000      222.290000      212.360000
75%        401.602500      410.182500      402.270000
max       6798.640000     7279.080000     5990.710000
```

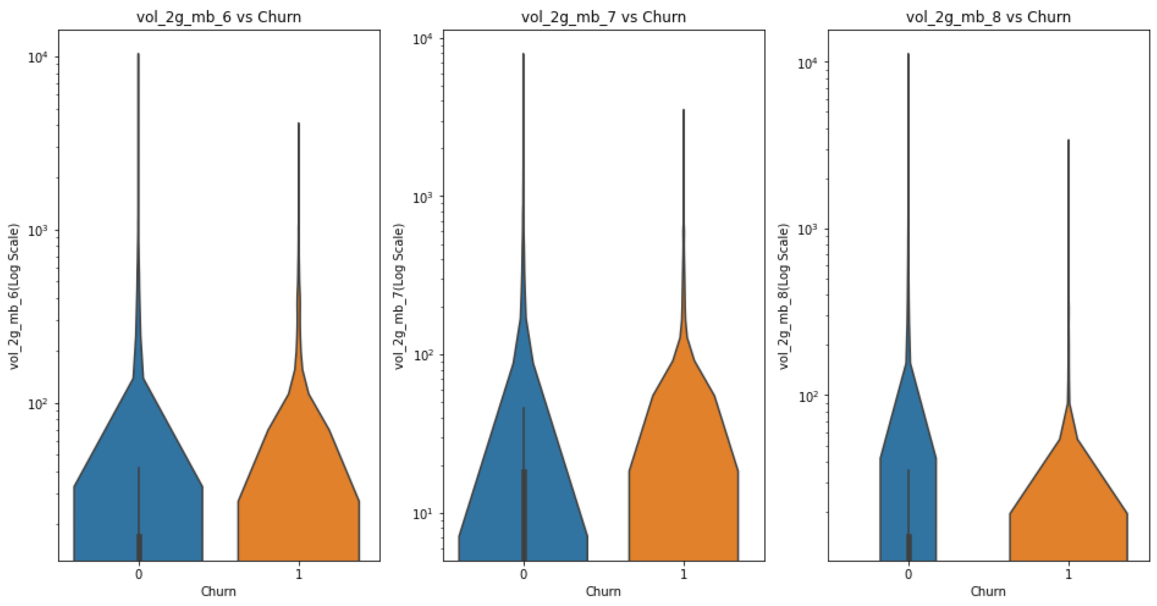


- The Customers with decrease in rate of total_ic_mou in 7th month are more likely to churn, compared to the rest.

vol_2g_mb_6, vol_2g_mb_7, vol_2g_mb_8

```
In [76]: columns = ['vol_2g_mb_6', 'vol_2g_mb_7', 'vol_2g_mb_8']
         num_univariate_analysis(columns, 'log')
```

```
Customers who churned (Churn : 1)
       vol_2g_mb_6  vol_2g_mb_7  vol_2g_mb_8
count  2593.000000  2593.000000  2593.000000
mean     60.775588    49.054393    15.283185
std     243.084276   219.485813   120.975111
min       0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000
max    4017.160000  3430.730000  3349.190000

Customers who did not churn (Churn : 0)
        vol_2g_mb_6   vol_2g_mb_7   vol_2g_mb_8
count  27418.000000  27418.000000  27418.000000
mean      80.569210     80.925060     74.309036
std      280.420463    285.265125    277.889339
min        0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000
75%       16.937500     18.267500     14.245000
max    10285.900000   7873.550000  11117.610000
```

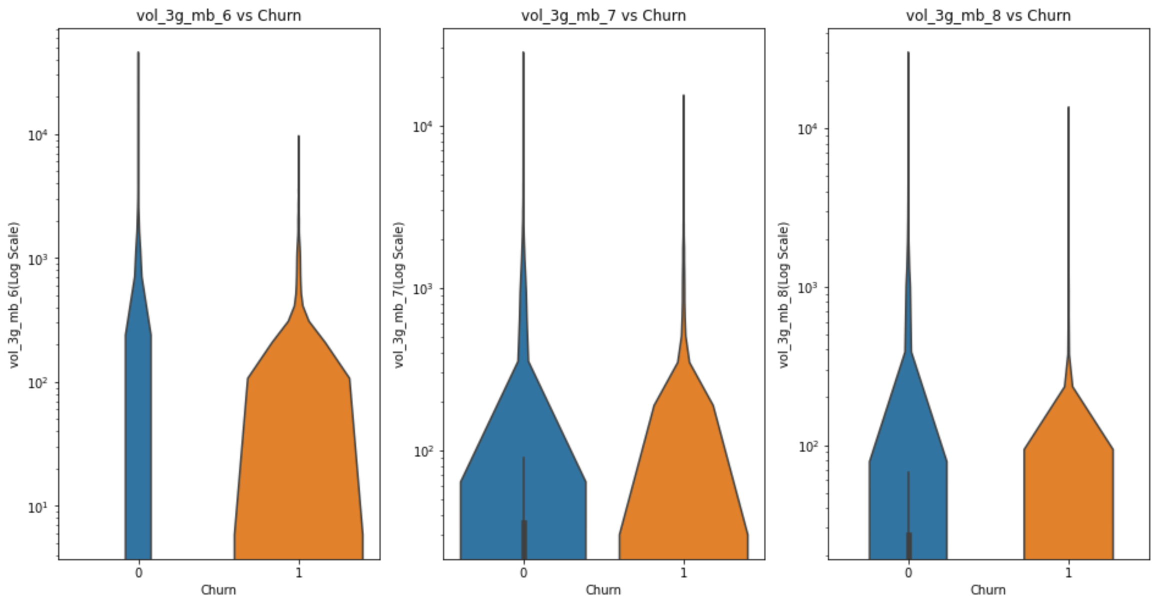


- Customers with stable usage of 2g volumes throughout 6 and 7 months are less likely to churn.
- Customers with fall in consumption of 2g volumes in 7th month are more likely to Churn.

vol_3g_mb_6, vol_3g_mb_7, vol_3g_mb_8, monthly_3g_6

```
In [77]: columns = ['vol_3g_mb_6', 'vol_3g_mb_7', 'vol_3g_mb_8', 'monthly_3g_6']
         num_univariate_analysis(columns, 'log')
```

```
Customers who churned (Churn : 1)
       vol_3g_mb_6   vol_3g_mb_7   vol_3g_mb_8
count  2593.000000   2593.000000   2593.000000
mean    188.395461    157.714254     56.776880
std     715.327843    690.773561    446.532769
min       0.000000      0.000000      0.000000
25%       0.000000      0.000000      0.000000
50%       0.000000      0.000000      0.000000
75%       0.000000      0.000000      0.000000
max    9400.120000  15115.510000  13440.720000

Customers who did not churn (Churn : 0)
        vol_3g_mb_6   vol_3g_mb_7   vol_3g_mb_8
count  27418.000000  27418.000000  27418.000000
mean     265.012522    289.478375    290.016390
std      878.846885    868.808831    885.821105
min        0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000
75%        0.000000     35.855000     27.120000
max    45735.400000  28144.120000  30036.060000
```

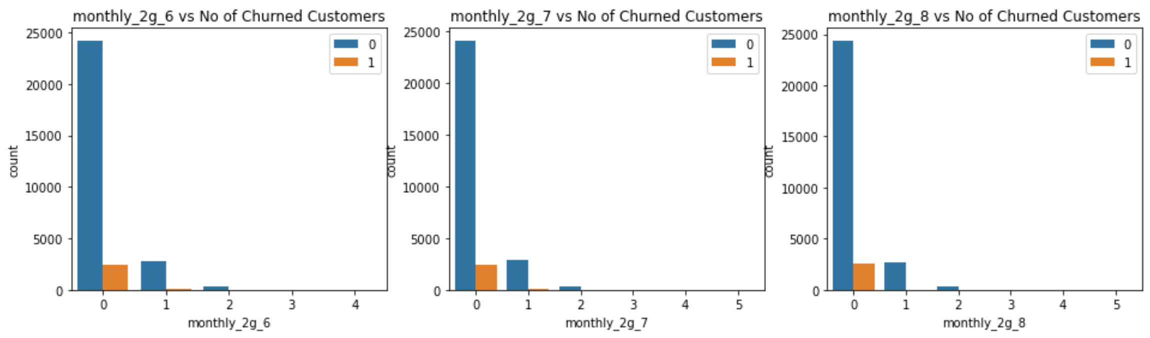


- Customers with stable usage of 3g volumes throughout 6 and 7 months are less likely to churn.
- Customers with fall in consumption of 3g volumes in 7th month are more likely to Churn.

monthly_2g_6, monthly_2g_7, monthly_2g_8

In [78]:
```
columns = ['monthly_2g_6', 'monthly_2g_7', 'monthly_2g_8']
cat_univariate_analysis(columns)
```

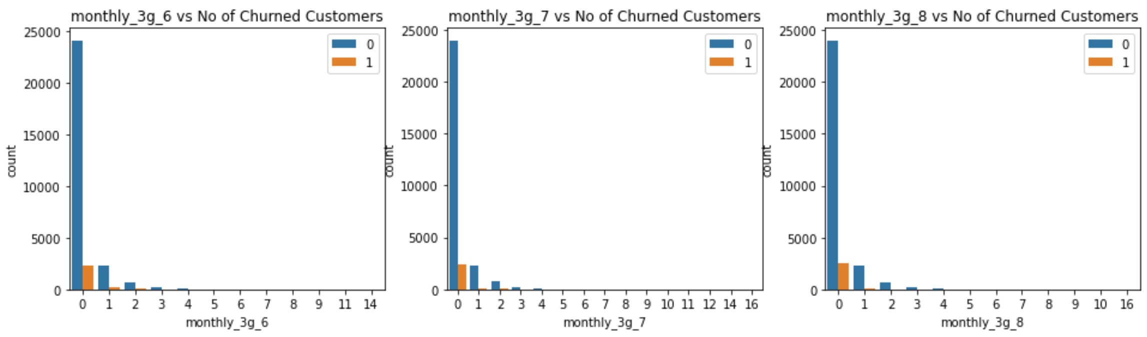
```
Customers who churned (Churn : 1)
+----+----------------+---------+------------+-------------------+-------
-----------------------+
|    |   monthly_2g_6 |   count |    percent |   cumulative_count |   cumu
lative_percent |
|----+----------------+---------+------------+-------------------+-------
-----------------------|
|  0 |              0 |    2454 | 94.6394    |              2454 |
94.6394 |
|  1 |              1 |     126 |  4.85924   |              2580 |
99.4987 |
|  2 |              2 |      11 |  0.424219  |              2591 |
99.9229 |
|  3 |              4 |       2 |  0.0771307 |              2593 |
100      |
+----+----------------+---------+------------+-------------------+-------
-----------------------+

+----+----------------+---------+-----------+-------------------+--------
---------------------+
|    |   monthly_2g_7 |   count |   percent |   cumulative_count |   cumul
ative_percent |
|----+----------------+---------+-----------+-------------------+--------
---------------------|
|  0 |              0 |    2477 | 95.5264   |              2477 |
95.5264 |
|  1 |              1 |     104 |  4.0108   |              2581 |
99.5372 |
|  2 |              2 |      12 |  0.462784 |              2593 |
100      |
+----+----------------+---------+-----------+-------------------+--------
---------------------+

+----+----------------+---------+------------+-------------------+-------
-----------------------+
|    |   monthly_2g_8 |   count |    percent |   cumulative_count |   cumu
lative_percent |
|----+----------------+---------+------------+-------------------+-------
-----------------------|
|  0 |              0 |    2555 | 98.5345    |              2555 |
98.5345 |
|  1 |              1 |      37 |  1.42692   |              2592 |
99.9614 |
|  2 |              2 |       1 |  0.0385654 |              2593 |
100      |
+----+----------------+---------+------------+-------------------+-------
-----------------------+


Customers who did not churn (Churn : 0)
+----+----------------+---------+------------+-------------------+-------
-----------------------+
|    |   monthly_2g_6 |   count |    percent |   cumulative_count |   cumu
lative_percent |
|----+----------------+---------+------------+-------------------+-------
-----------------------|
|  0 |              0 |   24228 | 88.3653    |             24228 |
88.3653 |
|  1 |              1 |    2825 | 10.3035    |             27053 |
98.6688 |
|  2 |              2 |     334 |  1.21818   |             27387 |
99.8869 |
|  3 |                3 |       26 |  0.0948282 |                27413 |
99.9818 |
|  4 |                4 |        5 |  0.0182362 |                27418 |
100       |
+----+----------------+---------+------------+--------------------+-------
-----------------------+

+----+----------------+---------+-------------+--------------------+------
-------------------------+
|    |   monthly_2g_7 |   count |     percent |   cumulative_count |   cum
ulative_percent |
|----+----------------+---------+-------------+--------------------+------
-------------------------|
|  0 |                0 |   24079 | 87.8219     |                24079 |
87.8219 |
|  1 |                1 |    2909 | 10.6098     |                26988 |
98.4317 |
|  2 |                2 |     394 |  1.43701    |                27382 |
99.8687 |
|  3 |                3 |      29 |  0.10577    |                27411 |
99.9745 |
|  4 |                4 |       5 |  0.0182362  |                27416 |
99.9927 |
|  5 |                5 |       2 |  0.00729448 |                27418 |
100       |
+----+----------------+---------+-------------+--------------------+------
-------------------------+

+----+----------------+---------+-------------+--------------------+------
-------------------------+
|    |   monthly_2g_8 |   count |     percent |   cumulative_count |   cum
ulative_percent |
|----+----------------+---------+-------------+--------------------+------
-------------------------|
|  0 |                0 |   24383 | 88.9306     |                24383 |
88.9306 |
|  1 |                1 |    2724 |  9.93508    |                27107 |
98.8657 |
|  2 |                2 |     282 |  1.02852    |                27389 |
99.8942 |
|  3 |                3 |      22 |  0.0802393  |                27411 |
99.9745 |
|  4 |                4 |       5 |  0.0182362  |                27416 |
99.9927 |
|  5 |                5 |       2 |  0.00729448 |                27418 |
100       |
+----+----------------+---------+-------------+--------------------+------
-------------------------+
```



monthly_3g_6, monthly_3g_7, monthly_3g_8

In [79]:
```
columns = ['monthly_3g_6', 'monthly_3g_7', 'monthly_3g_8']
cat_univariate_analysis(columns)
```

```
Customers who churned (Churn : 1)
+----+---------------+--------+-----------+-------------------+-------
----------------------+
|    |   monthly_3g_6 |   count |    percent |   cumulative_count |   cumu
lative_percent |
|----+---------------+--------+-----------+-------------------+-------
----------------------|
|  0 |              0 |    2352 | 90.7057    |               2352 |
90.7057 |
|  1 |              1 |     170 |  6.55611   |               2522 |
97.2619 |
|  2 |              2 |      49 |  1.8897    |               2571 |
99.1516 |
|  3 |              3 |      13 |  0.50135   |               2584 |
99.6529 |
|  4 |              5 |       4 |  0.154261  |               2588 |
99.8072 |
|  5 |              4 |       4 |  0.154261  |               2592 |
99.9614 |
|  6 |              6 |       1 |  0.0385654 |               2593 |
100      |
+----+---------------+--------+-----------+-------------------+-------
----------------------+

+----+---------------+--------+-----------+-------------------+-------
----------------------+
|    |   monthly_3g_7 |   count |    percent |   cumulative_count |   cumu
lative_percent |
|----+---------------+--------+-----------+-------------------+-------
----------------------|
|  0 |              0 |    2399 | 92.5183    |               2399 |
92.5183 |
|  1 |              1 |     136 |  5.24489   |               2535 |
97.7632 |
|  2 |              2 |      48 |  1.85114   |               2583 |
99.6143 |
|  3 |              3 |       9 |  0.347088  |               2592 |
99.9614 |
|  4 |              5 |       1 |  0.0385654 |               2593 |
100      |
+----+---------------+--------+-----------+-------------------+-------
----------------------+

+----+---------------+--------+-----------+-------------------+-------
----------------------+
|    |   monthly_3g_8 |   count |    percent |   cumulative_count |   cumu
lative_percent |
|----+---------------+--------+-----------+-------------------+-------
----------------------|
|  0 |              0 |    2524 | 97.339     |               2524 |
97.339  |
|  1 |              1 |      56 |  2.15966   |               2580 |
99.4987 |
|  2 |              2 |       8 |  0.308523  |               2588 |
99.8072 |
|  3 |              3 |       4 |  0.154261  |               2592 |
99.9614 |
|  4 |              4 |       1 |  0.0385654 |               2593 |
100      |
+----+---------------+--------+-----------+-------------------+-------
----------------------+
Customers who did not churn (Churn : 0)
+----+----------------+---------+-------------+--------------------+------
------------------------+
|    |   monthly_3g_6 |   count |     percent |   cumulative_count |   cum
ulative_percent |
|----+----------------+---------+-------------+--------------------+------
------------------------|
|  0 |              0 |   24080 | 87.8255     |              24080 |
87.8255 |
|  1 |              1 |    2371 |  8.6476     |              26451 |
96.4731 |
|  2 |              2 |     648 |  2.36341    |              27099 |
98.8365 |
|  3 |              3 |     194 |  0.707564   |              27293 |
99.5441 |
|  4 |              4 |      70 |  0.255307   |              27363 |
99.7994 |
|  5 |              5 |      28 |  0.102123   |              27391 |
99.9015 |
|  6 |              6 |      10 |  0.0364724  |              27401 |
99.938  |
|  7 |              7 |       9 |  0.0328252  |              27410 |
99.9708 |
|  8 |              8 |       3 |  0.0109417  |              27413 |
99.9818 |
|  9 |             11 |       2 |  0.00729448 |              27415 |
99.9891 |
| 10 |              9 |       2 |  0.00729448 |              27417 |
99.9964 |
| 11 |             14 |       1 |  0.00364724 |              27418 |
100     |
+----+----------------+---------+-------------+--------------------+------
------------------------+

+----+----------------+---------+-------------+--------------------+------
------------------------+
|    |   monthly_3g_7 |   count |     percent |   cumulative_count |   cum
ulative_percent |
|----+----------------+---------+-------------+--------------------+------
------------------------|
|  0 |              0 |   23962 | 87.3951     |              23962 |
87.3951 |
|  1 |              1 |    2330 |  8.49807    |              26292 |
95.8932 |
|  2 |              2 |     774 |  2.82296    |              27066 |
98.7162 |
|  3 |              3 |     198 |  0.722153   |              27264 |
99.4383 |
|  4 |              4 |      68 |  0.248012   |              27332 |
99.6863 |
|  5 |              5 |      38 |  0.138595   |              27370 |
99.8249 |
|  6 |              6 |      23 |  0.0838865  |              27393 |
99.9088 |
|  7 |              7 |      10 |  0.0364724  |              27403 |
99.9453 |
|  8 |              8 |       5 |  0.0182362  |              27408 |
99.9635 |
|  9 |              9 |       4 |  0.014589   |              27412 |
99.9781 |
| 10 |              11 |        2 | 0.00729448 |                27414 |
99.9854 |
| 11 |              16 |        1 | 0.00364724 |                27415 |
99.9891 |
| 12 |              14 |        1 | 0.00364724 |                27416 |
99.9927 |
| 13 |              12 |        1 | 0.00364724 |                27417 |
99.9964 |
| 14 |              10 |        1 | 0.00364724 |                27418 |
100      |
+----+----------------+---------+-------------+--------------------+------
-------------------------+

+----+----------------+---------+-------------+--------------------+------
-------------------------+
|    |   monthly_3g_8 |   count |     percent |   cumulative_count |   cum
ulative_percent |
|----+----------------+---------+-------------+--------------------+------
-------------------------|
|  0 |              0 |   24002 | 87.541      |                24002 |
87.541   |
|  1 |              1 |    2347 |  8.56007    |                26349 |
96.1011 |
|  2 |              2 |     728 |  2.65519    |                27077 |
98.7563 |
|  3 |              3 |     193 |  0.703917   |                27270 |
99.4602 |
|  4 |              4 |      86 |  0.313663   |                27356 |
99.7739 |
|  5 |              5 |      30 |  0.109417   |                27386 |
99.8833 |
|  6 |              6 |      14 |  0.0510613  |                27400 |
99.9343 |
|  7 |              7 |       9 |  0.0328252  |                27409 |
99.9672 |
|  8 |              9 |       3 |  0.0109417  |                27412 |
99.9781 |
|  9 |              8 |       3 |  0.0109417  |                27415 |
99.9891 |
| 10 |             10 |       2 |  0.00729448 |                27417 |
99.9964 |
| 11 |             16 |       1 |  0.00364724 |                27418 |
100      |
+----+----------------+---------+-------------+--------------------+------
-------------------------+
```



sachet_3g_6, sachet_3g_7, sachet_3g_8

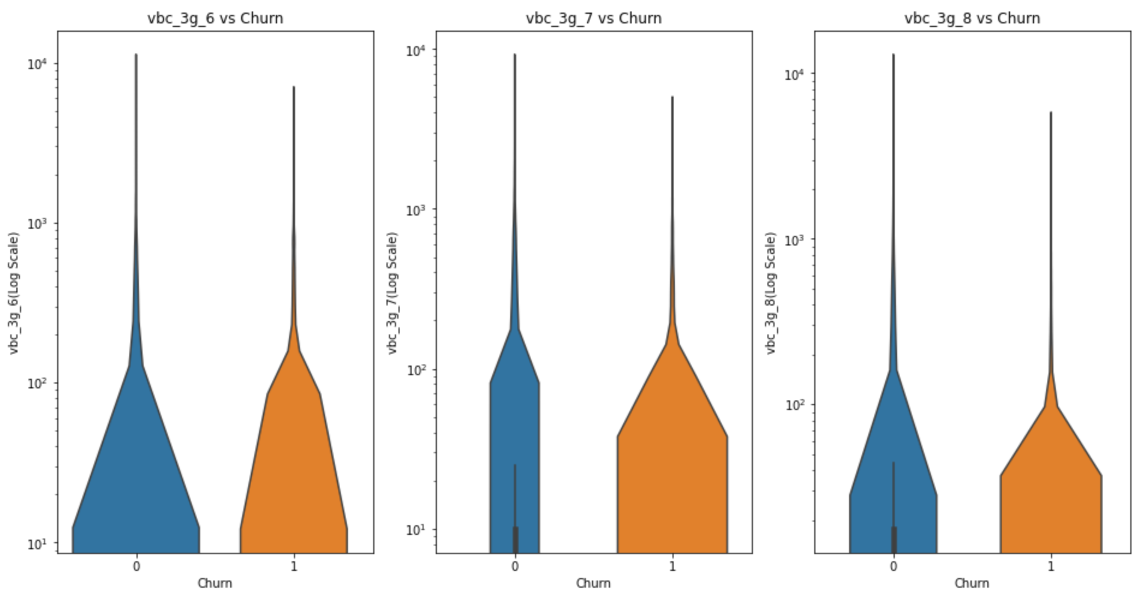
```
In [1]: columns = ['sachet_3g_6', 'sachet_3g_7','sachet_3g_8']
        print(data[columns].dtypes)
        cat_univariate_analysis(columns)
```

```
---------------------------------------------------------------------------
-
NameError                                 Traceback (most recent call las
t)
<ipython-input-1-43696c0d750b> in <module>
      1 columns = ['sachet_3g_6', 'sachet_3g_7','sachet_3g_8']
----> 2 print(data[columns].dtypes)
      3 cat_univariate_analysis(columns)

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

aug_vbc_3g, jul_vbc_3g, jun_vbc_3g

```
In [81]: columns = [ 'vbc_3g_6', 'vbc_3g_7','vbc_3g_8']
         num_univariate_analysis(columns, 'log')
```

```
Customers who churned (Churn : 1)
          vbc_3g_6     vbc_3g_7     vbc_3g_8
count  2593.000000  2593.000000  2593.000000
mean     81.564601    71.143880    32.610659
std     320.898511   284.882601   197.998246
min       0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000
max    6931.810000  4908.270000  5738.740000

Customers who did not churn (Churn : 0)
           vbc_3g_6      vbc_3g_7      vbc_3g_8
count  27418.000000  27418.000000  27418.000000
mean     125.124167    141.178182    138.597023
std      395.413666    417.292310    402.761779
min        0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000
75%        0.000000      9.940000     17.675000
max    11166.210000   9165.600000  12916.220000
```



Bivariate Analysis

In [96]:
```
data.head()
```

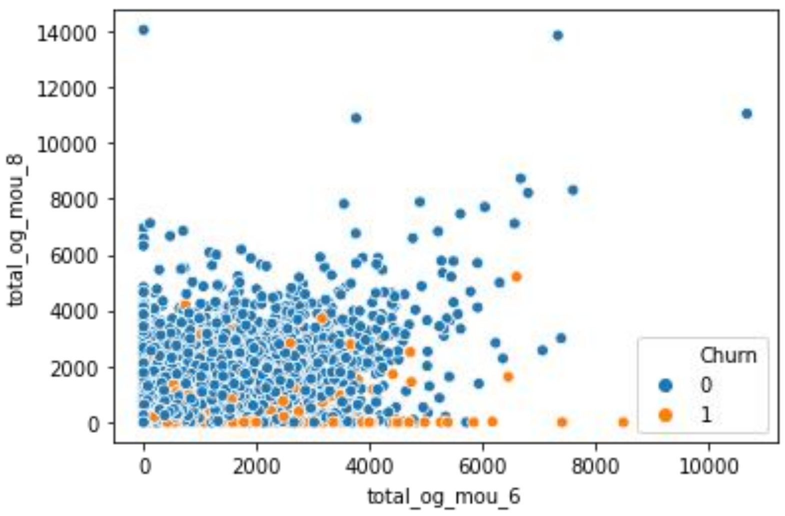
Out[96]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	off
mobile_number							
7000701601	1069.180	1349.850	3171.480	57.84	54.68	52.29	
7001524846	378.721	492.223	137.362	413.69	351.03	35.08	
7002191713	492.846	205.671	593.260	501.76	108.39	534.24	
7000875565	430.975	299.869	187.894	50.51	74.01	70.61	
7000187447	690.008	18.980	25.499	1185.91	9.28	7.79	

'total_og_mou_6' vs 'total_og_mou_8' with respect to Churn.

In [123]:
```
sns.scatterplot(x=data['total_og_mou_6'],y=data['total_og_mou_8'],hue=data
['Churn'])
```

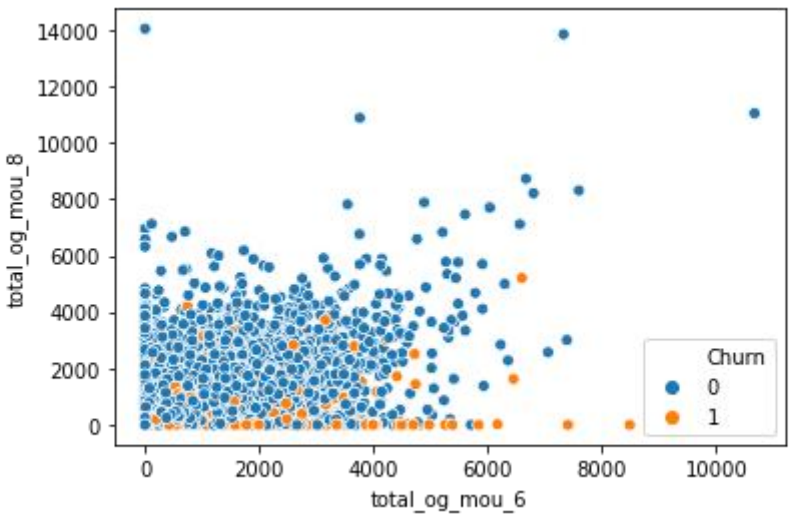
Out[123]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ffc15cc7190>
```



'total_og_mou_7' vs 'total_og_mou_8' with respect to Churn.

```
In [122]: sns.scatterplot(x=data['total_og_mou_6'],y=data['total_og_mou_8'],hue=data
          ['Churn'])
```

```
Out[122]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffc1a6f59a0>
```

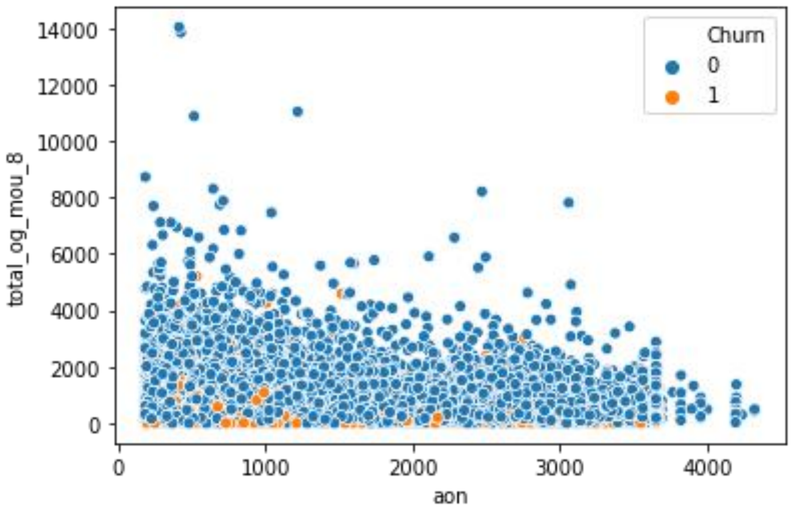


- The customers with lower total_og_mou in 6th and 8th months are more likely to Churn compared to the ones with higher total_og_mou.

'aon' vs 'total_og_mou_8' with respect to Churn.

```
In [119]: sns.scatterplot(x=data['aon'],y=data['total_og_mou_8'],hue=data['Churn'])
```

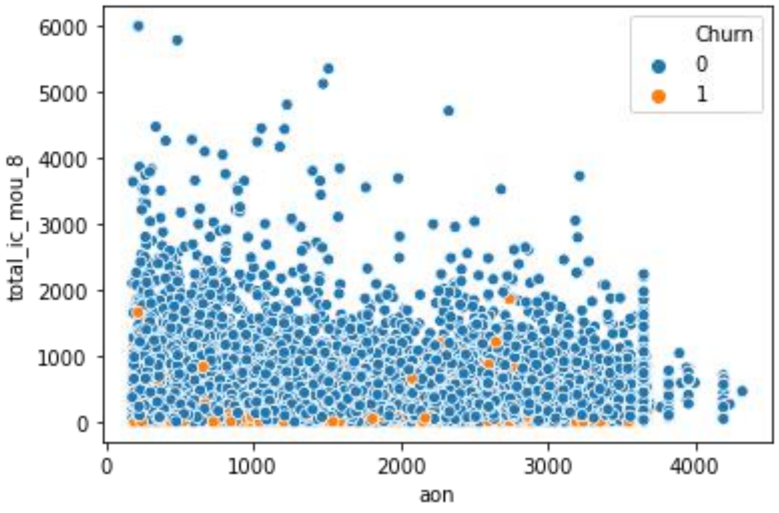
```
Out[119]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffc128bd790>
```



- The customers with lesser total_og_mou_8 and aon are more likely to churn compared to the one with higher total_og_mou_8 and aon.

In [120]:
```
sns.scatterplot(x=data['aon'],y=data['total_ic_mou_8'],hue=data['Churn'])
```

Out[120]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ffc197fbdc0>
```

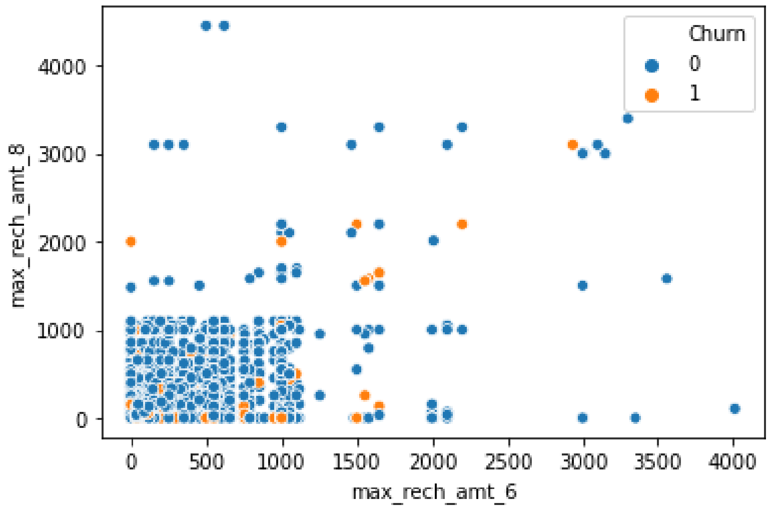


- The customers with less total_ic_mou_8 are more likely to churn irrespective of aon.
- The customers with total_ic_mou_8 > 2000 are very less likely to churn.

'max_rech_amt_6' vs 'max_rech_amt_8' with respect to 'Churn'.

In [124]:
```
sns.scatterplot(x=data['max_rech_amt_6'],y=data['max_rech_amt_8'],hue=data
['Churn'])
```

Out[124]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ffc1b2ad970>
```



Correlation Analysis

In [186]:
```
# function to correlate variables
def correlation(dataframe) :

    columnsForAnalysis = set(dataframe.columns.values) - {'Churn'}
    cor0=dataframe[columnsForAnalysis].corr()
    type(cor0)
    cor0.where(np.triu(np.ones(cor0.shape),k=1).astype(np.bool))
    cor0=cor0.unstack().reset_index()
    cor0.columns=['VAR1','VAR2','CORR']
    cor0.dropna(subset=['CORR'], inplace=True)
    cor0.CORR=round(cor0['CORR'],2)
    cor0.CORR=cor0.CORR.abs()
    cor0.sort_values(by=['CORR'],ascending=False)
    cor0=cor0[~(cor0['VAR1']==cor0['VAR2'])]

    # removing duplicate correlations
    cor0['pair'] = cor0[['VAR1', 'VAR2']].apply(lambda x: '{}-{}'.format(*s
orted((x[0], x[1]))), axis=1)

    cor0 = cor0.drop_duplicates(subset=['pair'], keep='first')
    cor0 = cor0[['VAR1', 'VAR2','CORR']]
    return pd.DataFrame(cor0.sort_values(by=['CORR'],ascending=False))
```

In [187]:
```
# Correlations for Churn : 0  - non churn customers
# Absolute values are reported
pd.set_option('precision', 2)
cor_0 = correlation(non_churned_customers)

# filtering for correlations >= 40%
condition = cor_0['CORR'] > 0.4
cor_0 = cor_0[condition]
cor_0.style.background_gradient(cmap='GnBu').hide_index()
```

Out[187]:

VAR1	VAR2	CORR
isd_og_mou_8	isd_og_mou_7	0.96
isd_og_mou_8	isd_og_mou_6	0.95
arpu_8	total_rech_amt_8	0.95
isd_og_mou_7	isd_og_mou_6	0.95
arpu_6	total_rech_amt_6	0.94
total_rech_amt_7	arpu_7	0.94
Average_rech_amt_6n7	arpu_7	0.91
total_rech_amt_7	Average_rech_amt_6n7	0.91
total_ic_mou_6	loc_ic_mou_6	0.90
Average_rech_amt_6n7	total_rech_amt_6	0.90
arpu_6	Average_rech_amt_6n7	0.89
loc_ic_mou_8	total_ic_mou_8	0.89
loc_ic_mou_7	total_ic_mou_7	0.88
loc_ic_mou_7	loc_ic_mou_8	0.85
std_og_t2t_mou_8	onnet_mou_8	0.85
loc_ic_mou_8	loc_ic_t2m_mou_8	0.85
loc_ic_t2m_mou_6	loc_ic_mou_6	0.85
std_og_t2m_mou_8	offnet_mou_8	0.85
std_og_t2t_mou_7	onnet_mou_7	0.84
std_og_mou_8	total_og_mou_8	0.84
loc_og_mou_8	loc_og_mou_7	0.84
std_ic_mou_8	std_ic_t2m_mou_8	0.84
std_og_t2t_mou_6	onnet_mou_6	0.84
offnet_mou_7	std_og_t2m_mou_7	0.84
total_og_mou_7	std_og_mou_7	0.83
loc_ic_mou_7	loc_ic_mou_6	0.83
total_ic_mou_7	total_ic_mou_8	0.83
loc_og_t2t_mou_8	loc_og_t2t_mou_7	0.83
loc_ic_mou_7	loc_ic_t2m_mou_7	0.83
loc_ic_t2m_mou_7	loc_ic_t2m_mou_8	0.82
loc_og_t2f_mou_8	loc_og_t2f_mou_7	0.82
loc_og_t2m_mou_8	loc_og_t2m_mou_7	0.82
onnet_mou_7	onnet_mou_8	0.82
std_ic_t2m_mou_6	std_ic_mou_6	0.82
std_og_t2t_mou_7	std_og_t2t_mou_8	0.82
std_ic_t2m_mou_7	std_ic_mou_7	0.81
loc_ic_t2t_mou_6	loc_ic_t2t_mou_7	0.81
std_og_mou_8	std_og_mou_7	0.81

VAR1	VAR2	CORR
offnet_mou_6	std_og_t2m_mou_6	0.81
total_ic_mou_6	total_ic_mou_7	0.81
loc_ic_t2t_mou_8	loc_ic_t2t_mou_7	0.81
total_og_mou_6	std_og_mou_6	0.80
loc_og_mou_6	loc_og_mou_7	0.80
loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	0.80
loc_og_t2t_mou_6	loc_og_t2t_mou_7	0.80
std_og_t2m_mou_8	std_og_t2m_mou_7	0.79
loc_og_t2f_mou_7	loc_og_t2f_mou_6	0.79
loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	0.79
loc_og_mou_6	loc_og_t2m_mou_6	0.79
total_rech_num_8	total_rech_num_7	0.78
loc_og_t2m_mou_7	loc_og_t2m_mou_6	0.78
arpu_8	Average_rech_amt_6n7	0.78
offnet_mou_7	offnet_mou_8	0.78
loc_og_t2t_mou_8	loc_og_mou_8	0.77
arpu_7	total_rech_amt_8	0.77
arpu_8	arpu_7	0.77
arpu_8	total_rech_amt_7	0.77
loc_og_t2m_mou_8	loc_og_mou_8	0.77
total_og_mou_7	total_og_mou_8	0.77
std_og_t2f_mou_7	std_og_t2f_mou_8	0.77
loc_og_mou_7	loc_og_t2t_mou_7	0.77
total_ic_mou_8	loc_ic_t2m_mou_8	0.76
std_ic_mou_8	std_ic_mou_7	0.76
loc_ic_t2m_mou_6	total_ic_mou_6	0.76
isd_ic_mou_7	isd_ic_mou_6	0.75
isd_ic_mou_8	isd_ic_mou_7	0.75
loc_og_mou_6	loc_og_t2t_mou_6	0.75
std_ic_mou_6	std_ic_mou_7	0.75
loc_ic_mou_7	total_ic_mou_8	0.75
loc_og_t2m_mou_7	loc_og_mou_7	0.75
loc_ic_mou_8	loc_ic_mou_6	0.75
total_ic_mou_7	loc_ic_mou_8	0.75
Average_rech_amt_6n7	total_rech_amt_8	0.75
loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	0.75
vol_3g_mb_8	vol_3g_mb_7	0.75
std_og_t2m_mou_6	std_og_t2m_mou_7	0.75
std_og_mou_8	std_og_t2m_mou_8	0.75

VAR1	VAR2	CORR
std_og_t2m_mou_6	std_og_mou_6	0.74
std_og_mou_8	std_og_t2t_mou_8	0.74
std_ic_t2f_mou_7	std_ic_t2f_mou_6	0.74
std_og_t2m_mou_7	std_og_mou_7	0.74
loc_ic_mou_7	total_ic_mou_6	0.74
loc_ic_t2m_mou_7	total_ic_mou_7	0.74
std_og_mou_6	std_og_t2t_mou_6	0.74
std_ic_t2t_mou_6	std_ic_t2t_mou_7	0.74
std_ic_t2t_mou_8	std_ic_t2t_mou_7	0.73
loc_og_t2f_mou_8	loc_og_t2f_mou_6	0.73
std_og_t2t_mou_7	std_og_t2t_mou_6	0.73
std_ic_t2m_mou_7	std_ic_t2m_mou_8	0.73
onnet_mou_7	onnet_mou_6	0.73
total_rech_amt_7	total_rech_amt_8	0.73
loc_og_mou_6	loc_og_mou_8	0.73
total_ic_mou_6	total_ic_mou_8	0.73
std_og_t2t_mou_7	std_og_mou_7	0.73
std_og_mou_6	std_og_mou_7	0.73
total_ic_mou_7	loc_ic_mou_6	0.72
std_ic_t2f_mou_7	std_ic_t2f_mou_8	0.72
offnet_mou_6	offnet_mou_7	0.72
loc_ic_t2m_mou_6	loc_ic_t2m_mou_8	0.72
loc_ic_t2m_mou_7	loc_ic_mou_8	0.72
total_og_mou_8	offnet_mou_8	0.72
std_ic_t2m_mou_7	std_ic_t2m_mou_6	0.72
loc_og_t2t_mou_8	loc_og_t2t_mou_6	0.72
total_og_mou_8	onnet_mou_8	0.71
vbc_3g_8	vbc_3g_7	0.71
vol_3g_mb_6	vol_3g_mb_7	0.71
std_og_t2f_mou_6	std_og_t2f_mou_7	0.71
total_og_mou_7	onnet_mou_7	0.71
ic_others_8	ic_others_7	0.71
total_og_mou_6	offnet_mou_6	0.70
total_rech_amt_6	arpu_7	0.70
total_og_mou_7	offnet_mou_7	0.70
std_ic_t2t_mou_7	std_ic_mou_7	0.70
arpu_6	arpu_7	0.70
total_og_mou_6	onnet_mou_6	0.70
loc_ic_t2t_mou_6	loc_ic_t2t_mou_8	0.70

VAR1	VAR2	CORR
loc_ic_mou_7	loc_ic_t2m_mou_8	0.70
last_day_rch_amt_8	max_rech_amt_8	0.69
std_og_t2t_mou_7	onnet_mou_8	0.69
vbc_3g_7	vbc_3g_6	0.69
loc_og_t2m_mou_8	loc_og_t2m_mou_6	0.69
loc_ic_t2m_mou_7	loc_ic_mou_6	0.69
total_rech_num_6	total_rech_num_7	0.69
vol_2g_mb_7	vol_2g_mb_8	0.69
std_og_t2t_mou_8	onnet_mou_7	0.69
loc_ic_mou_7	loc_ic_t2m_mou_6	0.68
arpu_6	total_rech_amt_7	0.68
loc_ic_mou_7	loc_ic_t2t_mou_7	0.68
total_ic_mou_6	loc_ic_mou_8	0.68
std_ic_t2f_mou_8	std_ic_t2f_mou_6	0.67
ic_others_7	ic_others_6	0.67
loc_ic_t2t_mou_6	loc_ic_mou_6	0.67
loc_ic_t2t_mou_8	loc_ic_mou_8	0.67
vol_2g_mb_7	vol_2g_mb_6	0.67
loc_ic_t2f_mou_6	loc_ic_t2f_mou_8	0.67
total_og_mou_6	total_og_mou_7	0.67
vol_3g_mb_8	vol_3g_mb_6	0.67
std_ic_t2t_mou_6	std_ic_mou_6	0.67
total_ic_mou_8	loc_ic_mou_6	0.66
std_ic_t2t_mou_8	std_ic_mou_8	0.66
total_og_mou_7	std_og_mou_8	0.66
std_og_t2m_mou_8	offnet_mou_7	0.66
std_ic_mou_8	std_ic_mou_6	0.66
vbc_3g_7	vol_3g_mb_7	0.65
max_rech_amt_6	last_day_rch_amt_6	0.65
std_og_t2m_mou_7	offnet_mou_8	0.65
std_og_t2f_mou_6	std_og_t2f_mou_8	0.65
loc_og_t2t_mou_8	loc_og_mou_7	0.65
arpu_6	total_rech_amt_8	0.64
arpu_6	arpu_8	0.64
total_og_mou_8	std_og_mou_7	0.64
std_og_t2m_mou_8	total_og_mou_8	0.64
loc_ic_t2m_mou_6	loc_ic_mou_8	0.64
roam_og_mou_6	roam_ic_mou_6	0.64
std_ic_t2m_mou_7	std_ic_mou_8	0.64

VAR1	VAR2	CORR
loc_og_mou_8	loc_og_t2t_mou_7	0.64
loc_ic_t2m_mou_7	total_ic_mou_8	0.64
total_rech_amt_7	total_rech_amt_6	0.64
total_ic_mou_7	loc_ic_t2m_mou_8	0.63
vol_3g_mb_6	vbc_3g_6	0.63
vbc_3g_8	vol_3g_mb_8	0.63
total_ic_mou_6	loc_ic_t2m_mou_7	0.63
roam_ic_mou_7	roam_og_mou_7	0.63
onnet_mou_8	onnet_mou_6	0.63
loc_og_t2m_mou_8	loc_og_mou_7	0.63
arpu_8	total_rech_amt_6	0.63
std_og_t2t_mou_8	std_og_t2t_mou_6	0.63
loc_ic_t2m_mou_8	loc_ic_mou_6	0.63
loc_og_t2t_mou_6	loc_og_mou_7	0.63
total_og_mou_7	std_og_t2m_mou_7	0.63
ic_others_8	ic_others_6	0.63
std_ic_t2m_mou_7	std_ic_mou_6	0.63
loc_og_mou_8	loc_og_t2m_mou_7	0.63
std_ic_t2m_mou_6	std_ic_t2m_mou_8	0.63
total_rech_amt_6	total_rech_amt_8	0.63
isd_ic_mou_8	isd_ic_mou_6	0.62
std_og_t2t_mou_8	std_og_mou_7	0.62
total_og_mou_8	std_og_t2t_mou_8	0.61
loc_og_t2m_mou_6	loc_og_mou_7	0.61
onnet_mou_7	std_og_t2t_mou_6	0.61
vbc_3g_8	vbc_3g_6	0.61
loc_og_mou_6	loc_og_t2m_mou_7	0.61
std_og_mou_8	onnet_mou_8	0.61
std_ic_t2m_mou_8	std_ic_mou_7	0.61
last_day_rch_amt_7	max_rech_amt_7	0.61
std_og_t2m_mou_6	offnet_mou_7	0.61
std_og_mou_8	std_og_mou_6	0.61
max_rech_amt_6	max_rech_amt_8	0.60
std_og_mou_8	std_og_t2m_mou_7	0.60
total_rech_num_8	total_rech_num_6	0.60
total_ic_mou_7	loc_ic_t2t_mou_7	0.60
loc_ic_t2m_mou_6	total_ic_mou_7	0.60
roam_og_mou_8	roam_ic_mou_8	0.60
std_og_t2t_mou_7	onnet_mou_6	0.60

VAR1	VAR2	CORR
total_og_mou_7	std_og_t2t_mou_7	0.60
std_og_mou_8	std_og_t2t_mou_7	0.60
loc_og_mou_6	loc_og_t2t_mou_7	0.60
total_og_mou_6	std_og_t2m_mou_6	0.60
std_og_mou_8	offnet_mou_8	0.60
std_og_t2m_mou_8	std_og_t2m_mou_6	0.60
std_og_mou_6	onnet_mou_6	0.59
loc_ic_t2t_mou_8	total_ic_mou_8	0.59
onnet_mou_7	std_og_mou_7	0.59
total_ic_mou_6	loc_ic_t2t_mou_6	0.59
std_og_t2m_mou_8	std_og_mou_7	0.59
offnet_mou_6	offnet_mou_8	0.59
std_ic_t2t_mou_6	std_ic_t2t_mou_8	0.59
loc_ic_mou_7	loc_ic_t2t_mou_8	0.59
total_og_mou_7	onnet_mou_8	0.58
std_ic_t2m_mou_6	std_ic_mou_7	0.58
total_og_mou_6	std_og_t2t_mou_6	0.58
offnet_mou_6	std_og_t2m_mou_7	0.58
roam_og_mou_8	roam_og_mou_7	0.58
total_ic_mou_6	loc_ic_t2m_mou_8	0.58
spl_og_mou_7	spl_og_mou_8	0.57
total_og_mou_7	std_og_mou_6	0.57
offnet_mou_7	std_og_mou_7	0.57
loc_ic_mou_7	loc_ic_t2t_mou_6	0.57
loc_og_t2t_mou_8	loc_og_mou_6	0.57
std_og_t2m_mou_6	std_og_mou_7	0.56
max_rech_amt_7	max_rech_amt_8	0.56
loc_ic_t2m_mou_6	total_ic_mou_8	0.56
spl_og_mou_7	spl_og_mou_6	0.56
roam_ic_mou_7	roam_ic_mou_8	0.56
std_ic_t2m_mou_8	std_ic_mou_6	0.56
loc_og_mou_8	loc_og_t2t_mou_6	0.56
loc_ic_mou_8	loc_ic_t2t_mou_7	0.56
loc_og_mou_8	loc_og_t2m_mou_6	0.56
total_og_mou_8	onnet_mou_7	0.56
total_og_mou_6	total_og_mou_8	0.55
loc_og_t2m_mou_8	loc_og_mou_6	0.55
std_ic_t2t_mou_6	std_ic_mou_7	0.55
loc_ic_t2t_mou_7	loc_ic_mou_6	0.55

VAR1	VAR2	CORR
total_og_mou_7	offnet_mou_8	0.54
std_og_t2t_mou_7	std_og_mou_6	0.54
std_ic_mou_8	std_ic_t2m_mou_6	0.54
offnet_mou_6	std_og_mou_6	0.54
std_og_mou_6	std_og_t2m_mou_7	0.54
total_og_mou_8	offnet_mou_7	0.54
spl_og_mou_7	loc_og_t2c_mou_7	0.53
std_og_t2t_mou_6	std_og_mou_7	0.53
total_og_mou_6	std_og_mou_7	0.53
std_og_t2t_mou_6	onnet_mou_8	0.53
std_ic_t2t_mou_8	std_ic_mou_7	0.53
loc_og_t2c_mou_8	loc_og_t2c_mou_7	0.53
Average_rech_amt_6n7	isd_og_mou_7	0.53
std_og_t2t_mou_8	onnet_mou_6	0.52
vol_2g_mb_8	vol_2g_mb_6	0.52
isd_og_mou_7	arpu_7	0.52
loc_ic_t2t_mou_8	loc_ic_mou_6	0.51
arpu_8	total_og_mou_8	0.51
total_ic_mou_7	loc_ic_t2t_mou_8	0.51
vol_3g_mb_7	vbc_3g_6	0.51
vbc_3g_8	vol_3g_mb_7	0.51
total_og_mou_6	arpu_6	0.51
total_rech_amt_7	isd_og_mou_7	0.50
roam_og_mou_7	roam_og_mou_6	0.50
onnet_mou_8	std_og_mou_7	0.50
Average_rech_amt_6n7	isd_og_mou_6	0.50
loc_ic_t2t_mou_6	total_ic_mou_7	0.50
loc_ic_t2t_mou_6	loc_ic_mou_8	0.50
std_ic_t2t_mou_7	std_ic_mou_6	0.50
max_rech_amt_6	max_rech_amt_7	0.50
isd_og_mou_8	Average_rech_amt_6n7	0.50
std_ic_mou_8	std_ic_t2t_mou_7	0.50
loc_ic_t2m_mou_6	loc_og_t2m_mou_6	0.50
total_og_mou_6	total_rech_amt_6	0.49
loc_ic_t2t_mou_7	total_ic_mou_8	0.49
total_og_mou_7	std_og_t2m_mou_8	0.49
isd_og_mou_8	total_rech_amt_8	0.49
total_og_mou_7	std_og_t2t_mou_8	0.49
total_og_mou_8	total_rech_amt_8	0.49

VAR1	VAR2	CORR
loc_og_t2m_mou_7	loc_ic_t2m_mou_7	0.49
total_ic_mou_6	loc_ic_t2t_mou_7	0.49
vbc_3g_7	vol_3g_mb_8	0.49
std_og_mou_8	onnet_mou_7	0.49
loc_og_t2m_mou_8	loc_ic_t2m_mou_8	0.49
total_og_mou_7	onnet_mou_6	0.48
total_og_mou_7	offnet_mou_6	0.48
std_og_t2m_mou_6	offnet_mou_8	0.48
total_og_mou_7	arpu_7	0.48
max_rech_amt_8	total_rech_amt_8	0.48
isd_og_mou_8	arpu_7	0.48
total_og_mou_8	std_og_t2m_mou_7	0.48
arpu_6	isd_og_mou_6	0.48
total_og_mou_6	onnet_mou_7	0.48
isd_og_mou_7	total_rech_amt_8	0.48
isd_og_mou_8	arpu_8	0.48
loc_og_t2c_mou_6	spl_og_mou_6	0.48
offnet_mou_6	std_og_t2m_mou_8	0.47
vol_3g_mb_8	vbc_3g_6	0.47
total_rech_amt_6	isd_og_mou_6	0.47
onnet_mou_7	loc_og_t2t_mou_7	0.47
std_og_t2t_mou_8	std_og_mou_6	0.47
arpu_6	isd_og_mou_7	0.47
total_og_mou_6	offnet_mou_7	0.47
offnet_mou_6	loc_og_t2m_mou_6	0.47
std_og_t2t_mou_7	total_og_mou_8	0.47
loc_og_t2t_mou_6	onnet_mou_6	0.47
arpu_8	offnet_mou_8	0.47
roam_ic_mou_7	roam_ic_mou_6	0.46
arpu_7	isd_og_mou_6	0.46
offnet_mou_8	total_rech_amt_8	0.46
total_og_mou_7	total_rech_amt_7	0.46
spl_og_mou_8	loc_og_t2c_mou_8	0.46
isd_og_mou_8	arpu_6	0.46
isd_og_mou_7	total_rech_amt_6	0.46
std_og_mou_8	std_og_t2m_mou_6	0.46
arpu_8	isd_og_mou_7	0.46
std_ic_mou_8	total_ic_mou_8	0.46
total_rech_amt_7	max_rech_amt_7	0.46

VAR1	VAR2	CORR
vbc_3g_7	vol_3g_mb_6	0.46
total_og_mou_8	std_og_mou_6	0.46
loc_og_t2t_mou_8	onnet_mou_8	0.46
arpu_6	offnet_mou_6	0.46
isd_og_mou_8	total_rech_amt_7	0.46
offnet_mou_6	total_rech_amt_6	0.45
total_ic_mou_6	loc_ic_t2t_mou_8	0.45
total_ic_mou_7	std_ic_mou_7	0.45
std_og_mou_8	offnet_mou_7	0.45
isd_og_mou_8	total_rech_amt_6	0.45
total_og_mou_7	std_og_t2m_mou_6	0.45
std_og_mou_8	std_og_t2t_mou_6	0.45
loc_og_mou_6	loc_ic_mou_6	0.45
total_ic_mou_6	std_ic_mou_6	0.44
loc_og_t2m_mou_8	loc_ic_mou_8	0.44
loc_og_t2m_mou_8	offnet_mou_8	0.44
total_og_mou_6	loc_og_mou_6	0.44
total_og_mou_6	std_og_mou_8	0.44
isd_og_mou_6	total_rech_amt_8	0.44
std_og_mou_7	offnet_mou_8	0.44
std_og_t2m_mou_8	std_og_mou_6	0.44
loc_og_t2m_mou_6	loc_ic_mou_6	0.44
std_ic_t2t_mou_6	std_ic_mou_8	0.44
loc_og_mou_8	loc_ic_mou_8	0.44
offnet_mou_7	arpu_7	0.44
arpu_8	isd_og_mou_6	0.43
loc_og_t2m_mou_7	loc_ic_t2m_mou_8	0.43
max_rech_amt_6	total_rech_amt_6	0.43
loc_og_t2m_mou_8	loc_ic_t2m_mou_7	0.43
total_rech_amt_7	isd_og_mou_6	0.43
vbc_3g_8	vol_3g_mb_6	0.43
total_rech_amt_7	offnet_mou_7	0.43
loc_ic_t2t_mou_6	total_ic_mou_8	0.43
onnet_mou_7	std_og_mou_6	0.43
loc_og_mou_8	total_og_mou_8	0.42
loc_ic_t2m_mou_7	loc_og_t2m_mou_6	0.42
total_og_mou_6	Average_rech_amt_6n7	0.42
loc_ic_mou_7	loc_og_mou_7	0.42
loc_ic_mou_7	loc_og_t2m_mou_7	0.42

VAR1	VAR2	CORR
total_og_mou_7	Average_rech_amt_6n7	0.42
last_day_rch_amt_6	max_rech_amt_8	0.42
std_ic_t2t_mou_8	std_ic_mou_6	0.42
loc_ic_t2m_mou_6	loc_og_t2m_mou_7	0.42
loc_og_t2m_mou_7	offnet_mou_7	0.42
total_og_mou_6	onnet_mou_8	0.42
spl_og_mou_8	spl_og_mou_6	0.41
last_day_rch_amt_8	max_rech_amt_7	0.41
offnet_mou_6	Average_rech_amt_6n7	0.41
max_rech_amt_6	last_day_rch_amt_8	0.41
loc_ic_t2m_mou_6	loc_og_mou_6	0.41
total_og_mou_8	onnet_mou_6	0.41

In [188]:
```
# Correlations for Churn : 1  - churned customers
# Absolute values are reported
pd.set_option('precision', 2)
cor_1 = correlation(churned_customers)

# filtering for correlations >= 40%
condition = cor_1['CORR'] > 0.4
cor_1 = cor_1[condition]
cor_1.style.background_gradient(cmap='GnBu').hide_index()
```

Out[188]:

VAR1	VAR2	CORR
og_others_7	og_others_8	1.00
arpu_8	total_rech_amt_8	0.96
arpu_6	total_rech_amt_6	0.95
std_og_mou_8	total_og_mou_8	0.95
total_rech_amt_7	arpu_7	0.95
std_og_t2t_mou_7	onnet_mou_7	0.95
total_og_mou_7	std_og_mou_7	0.94
og_others_8	loc_og_t2f_mou_6	0.93
std_og_t2t_mou_8	onnet_mou_8	0.93
loc_og_t2f_mou_7	loc_og_t2f_mou_6	0.93
og_others_7	loc_og_t2f_mou_6	0.93
total_og_mou_6	std_og_mou_6	0.92
offnet_mou_6	std_og_t2m_mou_6	0.92
offnet_mou_7	std_og_t2m_mou_7	0.92
std_og_t2t_mou_6	onnet_mou_6	0.92
std_ic_mou_8	std_ic_t2m_mou_8	0.92
loc_og_t2f_mou_7	og_others_8	0.91
loc_og_t2f_mou_7	og_others_7	0.91
loc_ic_mou_8	loc_ic_t2m_mou_8	0.90
loc_ic_t2m_mou_6	loc_ic_mou_6	0.90
loc_ic_mou_8	total_ic_mou_8	0.89
loc_og_t2m_mou_8	loc_og_mou_8	0.88
total_ic_mou_6	loc_ic_mou_6	0.87
std_og_t2m_mou_8	offnet_mou_8	0.87
loc_ic_mou_7	total_ic_mou_7	0.86
loc_ic_mou_7	loc_ic_t2m_mou_7	0.84
loc_og_t2m_mou_7	loc_og_mou_7	0.84
std_ic_t2m_mou_7	std_ic_mou_7	0.82
total_ic_mou_8	loc_ic_t2m_mou_8	0.81
std_og_mou_8	std_og_t2t_mou_8	0.79
std_ic_t2t_mou_6	std_ic_t2t_mou_7	0.78
Average_rech_amt_6n7	arpu_7	0.77
loc_og_mou_6	loc_og_t2m_mou_6	0.77
loc_ic_t2m_mou_6	total_ic_mou_6	0.77
std_ic_t2m_mou_6	std_ic_mou_6	0.77
total_rech_amt_7	Average_rech_amt_6n7	0.76
Average_rech_amt_6n7	total_rech_amt_6	0.76
loc_og_mou_6	loc_og_t2t_mou_6	0.75

VAR1	VAR2	CORR
total_og_mou_8	std_og_t2t_mou_8	0.75
std_og_t2m_mou_7	std_og_mou_7	0.74
std_og_mou_8	onnet_mou_8	0.74
total_og_mou_8	onnet_mou_8	0.74
arpu_6	Average_rech_amt_6n7	0.73
loc_og_t2t_mou_8	loc_og_t2t_mou_7	0.73
loc_ic_t2t_mou_8	loc_ic_mou_8	0.73
loc_ic_t2t_mou_6	loc_ic_mou_6	0.72
max_rech_amt_6	last_day_rch_amt_6	0.72
std_og_t2m_mou_6	std_og_mou_6	0.72
std_ic_t2t_mou_6	std_ic_mou_6	0.72
roam_ic_mou_7	roam_ic_mou_8	0.72
total_og_mou_7	offnet_mou_7	0.72
loc_ic_t2m_mou_7	total_ic_mou_7	0.72
std_og_mou_8	std_og_t2m_mou_8	0.71
total_og_mou_8	offnet_mou_8	0.70
last_day_rch_amt_8	max_rech_amt_8	0.70
loc_og_mou_7	loc_og_t2t_mou_7	0.69
std_og_t2t_mou_7	std_og_mou_7	0.69
total_og_mou_7	std_og_t2m_mou_7	0.69
loc_ic_mou_7	loc_ic_t2t_mou_7	0.69
loc_og_t2t_mou_8	loc_og_mou_8	0.68
total_og_mou_6	offnet_mou_6	0.68
std_og_mou_6	std_og_t2t_mou_6	0.68
std_og_t2m_mou_8	total_og_mou_8	0.68
max_rech_amt_8	total_rech_amt_8	0.68
spl_og_mou_7	loc_og_t2c_mou_7	0.68
loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	0.67
vol_3g_mb_8	vol_3g_mb_7	0.67
std_og_t2t_mou_7	std_og_t2t_mou_6	0.67
total_og_mou_6	std_og_t2m_mou_6	0.67
offnet_mou_7	std_og_mou_7	0.66
total_og_mou_7	onnet_mou_7	0.66
onnet_mou_7	std_og_mou_7	0.65
loc_og_mou_8	loc_ic_mou_8	0.65
std_ic_t2t_mou_7	std_ic_mou_7	0.65
loc_og_t2m_mou_8	loc_ic_t2m_mou_8	0.65
roam_og_mou_8	roam_og_mou_7	0.65
total_og_mou_6	onnet_mou_6	0.65

VAR1	VAR2	CORR
total_og_mou_7	std_og_t2t_mou_7	0.64
loc_ic_t2t_mou_8	total_ic_mou_8	0.64
onnet_mou_7	onnet_mou_6	0.64
loc_og_mou_8	loc_ic_t2m_mou_8	0.64
onnet_mou_7	std_og_t2t_mou_6	0.63
loc_og_mou_8	loc_og_mou_7	0.63
total_ic_mou_6	loc_ic_t2t_mou_6	0.63
offnet_mou_6	std_og_mou_6	0.63
roam_og_mou_6	roam_ic_mou_6	0.63
std_og_mou_8	offnet_mou_8	0.63
roam_ic_mou_7	roam_ic_mou_6	0.62
arpu_8	max_rech_amt_8	0.62
std_og_t2m_mou_6	std_og_t2m_mou_7	0.62
total_og_mou_6	std_og_t2t_mou_6	0.62
vol_3g_mb_6	vbc_3g_6	0.62
onnet_mou_7	onnet_mou_8	0.62
loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	0.62
loc_og_mou_8	total_ic_mou_8	0.61
vbc_3g_8	vbc_3g_7	0.61
loc_og_t2m_mou_7	loc_og_t2m_mou_6	0.61
std_og_t2t_mou_7	onnet_mou_6	0.61
roam_og_mou_7	roam_og_mou_6	0.61
std_og_t2t_mou_7	std_og_t2t_mou_8	0.61
std_og_mou_6	onnet_mou_6	0.61
std_og_t2t_mou_8	onnet_mou_7	0.60
std_ic_mou_6	std_ic_mou_7	0.60
loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	0.60
arpu_8	total_og_mou_8	0.60
std_og_t2f_mou_7	std_og_t2f_mou_8	0.60
isd_og_mou_8	isd_og_mou_7	0.60
loc_og_mou_6	loc_og_mou_7	0.59
loc_og_t2m_mou_8	loc_og_t2m_mou_7	0.59
last_day_rch_amt_7	max_rech_amt_7	0.59
arpu_8	offnet_mou_8	0.59
std_og_mou_8	std_og_mou_7	0.58
total_og_mou_8	total_rech_amt_8	0.58
loc_og_t2m_mou_7	loc_ic_t2m_mou_7	0.58
loc_og_t2m_mou_8	loc_ic_mou_8	0.58
loc_ic_mou_7	loc_ic_mou_8	0.58

VAR1	VAR2	CORR
std_og_t2m_mou_8	std_og_t2m_mou_7	0.58
total_ic_mou_7	loc_ic_t2t_mou_7	0.58
offnet_mou_8	total_rech_amt_8	0.58
std_og_mou_6	std_og_mou_7	0.58
spl_og_mou_8	loc_og_t2c_mou_8	0.57
loc_ic_mou_7	loc_ic_mou_6	0.57
isd_ic_mou_7	isd_ic_mou_6	0.57
offnet_mou_6	offnet_mou_7	0.57
offnet_mou_7	offnet_mou_8	0.57
vol_3g_mb_6	vol_3g_mb_7	0.57
isd_og_mou_7	arpu_7	0.57
loc_ic_t2m_mou_7	loc_ic_t2m_mou_8	0.57
total_rech_num_8	total_og_mou_8	0.57
loc_og_t2t_mou_6	loc_og_t2t_mou_7	0.56
std_og_t2t_mou_7	onnet_mou_8	0.56
total_og_mou_7	total_og_mou_8	0.56
vbc_3g_7	vol_3g_mb_7	0.56
total_rech_amt_7	isd_og_mou_7	0.56
std_ic_mou_8	total_ic_mou_8	0.56
loc_ic_t2t_mou_8	loc_ic_t2t_mou_7	0.56
loc_og_t2c_mou_6	spl_og_mou_6	0.56
std_og_t2m_mou_6	offnet_mou_7	0.55
ic_others_7	ic_others_6	0.55
total_og_mou_7	std_og_mou_8	0.55
total_ic_mou_6	total_ic_mou_7	0.55
total_rech_num_8	total_rech_amt_8	0.55
arpu_8	total_rech_num_8	0.54
loc_ic_t2m_mou_7	loc_ic_mou_6	0.54
std_ic_t2t_mou_8	std_ic_mou_8	0.54
loc_og_t2c_mou_6	loc_og_t2c_mou_7	0.54
std_og_t2m_mou_8	offnet_mou_7	0.54
total_rech_num_8	total_rech_num_7	0.54
total_ic_mou_7	std_ic_mou_7	0.54
std_ic_t2t_mou_7	std_ic_mou_6	0.54
loc_ic_mou_7	loc_ic_t2m_mou_6	0.54
offnet_mou_6	std_og_t2m_mou_7	0.54
std_og_mou_8	total_rech_num_8	0.54
loc_og_t2m_mou_8	total_ic_mou_8	0.54
total_ic_mou_7	total_ic_mou_8	0.54

VAR1	VAR2	CORR
std_ic_t2t_mou_8	std_ic_t2t_mou_7	0.54
total_ic_mou_6	std_ic_mou_6	0.53
vol_2g_mb_7	vol_2g_mb_6	0.53
vbc_3g_7	vbc_3g_6	0.53
arpu_6	isd_og_mou_6	0.53
total_og_mou_8	std_og_mou_7	0.52
std_ic_mou_8	std_ic_mou_7	0.52
total_rech_amt_6	isd_og_mou_6	0.52
loc_og_mou_8	loc_og_t2m_mou_7	0.52
arpu_8	std_og_mou_8	0.51
loc_og_t2m_mou_8	loc_og_mou_7	0.51
loc_ic_t2m_mou_7	loc_og_mou_7	0.51
loc_og_t2m_mou_6	loc_og_mou_7	0.51
arpu_8	total_rech_amt_7	0.51
total_og_mou_7	arpu_7	0.51
total_og_mou_6	total_og_mou_7	0.51
roam_ic_mou_7	roam_og_mou_7	0.51
loc_ic_t2m_mou_7	loc_ic_mou_8	0.51
total_og_mou_7	std_og_mou_6	0.51
loc_ic_t2m_mou_6	loc_og_t2m_mou_6	0.50
std_ic_t2m_mou_7	std_ic_t2m_mou_8	0.50
std_ic_t2m_mou_7	std_ic_t2m_mou_6	0.50
total_og_mou_6	std_og_mou_7	0.50
total_rech_amt_7	max_rech_amt_7	0.50
std_og_t2m_mou_7	offnet_mou_8	0.50
arpu_8	onnet_mou_8	0.50
onnet_mou_8	total_rech_amt_8	0.50
loc_ic_mou_7	loc_og_mou_7	0.50
total_ic_mou_7	loc_ic_mou_8	0.50
std_og_mou_8	total_rech_amt_8	0.50
loc_ic_mou_7	loc_ic_t2m_mou_8	0.50
last_day_rch_amt_8	total_rech_amt_8	0.50
std_og_t2f_mou_7	loc_og_t2f_mou_7	0.50
loc_og_t2t_mou_8	loc_og_mou_7	0.50
arpu_8	arpu_7	0.50
loc_ic_mou_7	total_ic_mou_6	0.49
std_ic_t2t_mou_6	std_ic_t2t_mou_8	0.49
loc_ic_mou_7	loc_og_t2m_mou_7	0.49
loc_ic_mou_7	total_ic_mou_8	0.49

VAR1	VAR2	CORR
vol_2g_mb_7	vol_2g_mb_8	0.49
vbc_3g_8	vol_3g_mb_8	0.49
loc_ic_mou_8	loc_ic_t2f_mou_8	0.49
arpu_7	total_rech_amt_8	0.48
std_og_t2f_mou_7	og_others_8	0.48
loc_og_t2t_mou_8	loc_ic_t2t_mou_8	0.48
vol_3g_mb_8	vol_3g_mb_6	0.48
std_ic_t2t_mou_6	std_ic_mou_7	0.48
isd_og_mou_7	isd_ic_mou_7	0.48
isd_ic_mou_8	isd_ic_mou_7	0.48
std_ic_t2m_mou_8	total_ic_mou_8	0.48
total_og_mou_7	total_rech_amt_7	0.48
std_og_t2f_mou_7	og_others_7	0.48
std_og_t2f_mou_7	loc_og_t2f_mou_6	0.48
loc_og_mou_8	total_og_mou_8	0.47
total_rech_num_8	onnet_mou_8	0.47
total_ic_mou_6	loc_ic_t2m_mou_7	0.47
loc_ic_mou_7	loc_ic_t2t_mou_8	0.47
total_og_mou_6	arpu_6	0.47
std_og_mou_8	std_og_t2t_mou_7	0.46
Average_rech_amt_6n7	isd_og_mou_7	0.46
spl_og_mou_7	spl_og_mou_8	0.46
loc_ic_t2f_mou_6	loc_ic_t2f_mou_8	0.46
roam_og_mou_8	last_day_rch_amt_8	0.46
total_og_mou_7	total_rech_num_7	0.46
total_og_mou_6	total_rech_amt_6	0.46
total_ic_mou_7	loc_ic_mou_6	0.46
std_ic_t2m_mou_7	std_ic_mou_8	0.46
loc_og_mou_8	loc_og_t2t_mou_7	0.46
max_rech_amt_6	total_rech_amt_6	0.46
arpu_8	roam_og_mou_8	0.45
loc_og_t2m_mou_6	loc_ic_mou_6	0.45
total_rech_num_8	std_og_t2t_mou_8	0.45
loc_og_mou_6	loc_og_t2t_mou_7	0.45
std_ic_t2m_mou_8	std_ic_mou_7	0.45
std_ic_t2m_mou_7	total_ic_mou_7	0.45
total_rech_num_6	total_rech_num_7	0.45
offnet_mou_7	arpu_7	0.45
loc_og_mou_6	loc_ic_mou_6	0.45

VAR1	VAR2	CORR
std_ic_t2f_mou_7	std_ic_t2f_mou_6	0.45
max_rech_amt_7	max_rech_amt_8	0.45
total_rech_amt_7	total_rech_amt_8	0.45
loc_og_mou_6	loc_og_t2m_mou_7	0.45
std_og_t2m_mou_8	std_og_mou_7	0.44
arpu_8	Average_rech_amt_6n7	0.44
total_ic_mou_7	loc_og_mou_7	0.44
std_og_mou_8	onnet_mou_7	0.44
loc_og_t2c_mou_8	loc_og_t2c_mou_7	0.44
roam_og_mou_8	roam_ic_mou_8	0.44
loc_ic_t2m_mou_6	total_ic_mou_7	0.44
roam_og_mou_8	total_rech_amt_8	0.44
arpu_8	last_day_rch_amt_8	0.44
ic_others_6	isd_ic_mou_6	0.44
loc_og_t2m_mou_8	offnet_mou_8	0.44
loc_ic_t2m_mou_7	total_ic_mou_8	0.43
std_og_t2t_mou_8	std_og_mou_7	0.43
loc_og_mou_8	offnet_mou_8	0.43
total_og_mou_6	total_rech_num_6	0.43
total_og_mou_8	onnet_mou_7	0.43
std_ic_t2m_mou_6	total_ic_mou_6	0.43
total_rech_num_8	offnet_mou_8	0.43
spl_og_mou_7	spl_og_mou_6	0.43
total_ic_mou_8	loc_ic_t2f_mou_8	0.43
std_ic_t2f_mou_7	std_og_t2f_mou_7	0.43
loc_og_t2t_mou_8	loc_ic_mou_8	0.42
loc_ic_t2m_mou_6	loc_og_mou_6	0.42
loc_ic_mou_7	loc_ic_t2f_mou_7	0.42
total_ic_mou_7	loc_ic_t2m_mou_8	0.42
max_rech_amt_6	max_rech_amt_8	0.42
loc_og_mou_8	loc_ic_t2t_mou_8	0.42
std_og_t2t_mou_7	std_og_mou_6	0.42
std_ic_t2m_mou_6	std_ic_mou_7	0.42
arpu_8	total_ic_mou_8	0.42
loc_og_t2m_mou_8	loc_ic_t2m_mou_7	0.42
last_day_rch_amt_7	max_rech_amt_8	0.42
arpu_6	offnet_mou_6	0.42
total_rech_amt_7	offnet_mou_7	0.42
loc_og_t2m_mou_7	total_ic_mou_7	0.42

VAR1	VAR2	CORR
total_og_mou_7	std_og_t2m_mou_8	0.42
Average_rech_amt_6n7	total_rech_amt_8	0.42
std_og_mou_7	arpu_7	0.41
std_og_mou_6	std_og_t2m_mou_7	0.41
total_rech_num_7	std_og_mou_7	0.41
total_og_mou_7	offnet_mou_8	0.41
spl_ic_mou_8	spl_ic_mou_6	0.41
std_og_t2t_mou_6	std_og_mou_7	0.41
offnet_mou_6	total_rech_amt_6	0.41
loc_og_t2t_mou_8	loc_og_t2t_mou_6	0.41
std_og_t2t_mou_7	total_og_mou_8	0.41
total_og_mou_8	total_ic_mou_8	0.41
std_og_t2m_mou_6	std_og_mou_7	0.41

Data Preparation

Derived Variables

In [189]:
```
# Derived variables to measure change in usage

# Usage
data['delta_vol_2g'] = data['vol_2g_mb_8'] - data['vol_2g_mb_6'].add(data
['vol_2g_mb_7']).div(2)
data['delta_vol_3g'] = data['vol_3g_mb_8'] - data['vol_3g_mb_6'].add(data
['vol_3g_mb_7']).div(2)
data['delta_total_og_mou'] = data['total_og_mou_8'] - data['total_og_mou_
6'].add(data['total_og_mou_7']).div(2)
data['delta_total_ic_mou'] = data['total_ic_mou_8'] - data['total_ic_mou_
6'].add(data['total_ic_mou_7']).div(2)
data['delta_vbc_3g'] = data['vbc_3g_8'] - data['vbc_3g_6'].add(data['vbc_3g
_7']).div(2)

# Revenue
data['delta_arpu'] = data['arpu_8'] - data['arpu_6'].add(data['arpu_7']).di
v(2)
data['delta_total_rech_amt'] = data['total_rech_amt_8'] - data['total_rech_
amt_6'].add(data['total_rech_amt_7']).div(2)
```

In [190]:
```
# Removing variables used for derivation :
data.drop(columns=[
 'vol_2g_mb_8', 'vol_2g_mb_6', 'vol_2g_mb_7',
  'vol_3g_mb_8'  , 'vol_3g_mb_6', 'vol_3g_mb_7' ,
    'total_og_mou_8','total_og_mou_6', 'total_og_mou_7',
    'total_ic_mou_8','total_ic_mou_6', 'total_ic_mou_7',
    'vbc_3g_8','vbc_3g_6','vbc_3g_7',
    'arpu_8','arpu_6','arpu_7',
    'total_rech_amt_8', 'total_rech_amt_6', 'total_rech_amt_7'

], inplace=True)
```

Outlier Treatment

In [191]:
```
# Looking at quantiles from 0.90 to 1.
data.quantile(np.arange(0.9,1.01,0.01)).style.bar()
```

Out[191]:

	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7
0.9	794.98	824.38	723.61	915.58	935.69
0.91	848.97	878.35	783.49	966.74	984.02
0.92	909.05	941.99	848.96	1031.39	1038.09
0.93	990.48	1016.15	920.96	1094.77	1103.93
0.9400000000000001	1066.85	1097.12	1007.56	1168.09	1186.36
0.9500000000000001	1153.97	1208.17	1115.66	1271.47	1286.28
0.9600000000000001	1282.78	1344.04	1256.34	1406.07	1407.78
0.9700000000000001	1444.23	1497.25	1441.53	1578.82	1585.02
0.9800000000000001	1694.68	1772.62	1700.24	1837.93	1838.39
0.9900000000000001	2166.37	2220.37	2188.50	2326.29	2410.10
1.0	7376.71	8157.78	10752.56	8362.36	9667.13

In [192]:
```
# Looking at percentage change in quantiles from 0.90 to 1.
data.quantile(np.arange(0.9,1.01,0.01)).pct_change().mul(100).style.bar()
```

Out[192]:

	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7
0.9	nan	nan	nan	nan	nan
0.91	6.79	6.55	8.27	5.59	5.17
0.92	7.08	7.25	8.36	6.69	5.49
0.93	8.96	7.87	8.48	6.14	6.34
0.9400000000000001	7.71	7.97	9.40	6.70	7.47
0.9500000000000001	8.17	10.12	10.73	8.85	8.42
0.9600000000000001	11.16	11.25	12.61	10.59	9.45
0.9700000000000001	12.59	11.40	14.74	12.29	12.59
0.9800000000000001	17.34	18.39	17.95	16.41	15.99
0.9900000000000001	27.83	25.26	28.72	26.57	31.10
1.0	240.51	267.41	391.32	259.47	301.11

In [193]:
```
# Columns with outliers
pct_change_99_1 = data.quantile(np.arange(0.9,1.01,0.01)).pct_change().mul
(100).iloc[-1]
outlier_condition = pct_change_99_1 > 100
columns_with_outliers = pct_change_99_1[outlier_condition].index.values
print('Columns with outliers :\n', columns_with_outliers)
```

```
Columns with outliers :
 ['onnet_mou_6' 'onnet_mou_7' 'onnet_mou_8' 'offnet_mou_6' 'offnet_mou_7'
 'offnet_mou_8' 'roam_ic_mou_6' 'roam_ic_mou_7' 'roam_ic_mou_8'
 'roam_og_mou_6' 'roam_og_mou_7' 'roam_og_mou_8' 'loc_og_t2t_mou_6'
 'loc_og_t2t_mou_7' 'loc_og_t2t_mou_8' 'loc_og_t2m_mou_6'
 'loc_og_t2m_mou_7' 'loc_og_t2m_mou_8' 'loc_og_t2f_mou_6'
 'loc_og_t2f_mou_7' 'loc_og_t2f_mou_8' 'loc_og_t2c_mou_6'
 'loc_og_t2c_mou_7' 'loc_og_t2c_mou_8' 'loc_og_mou_6' 'loc_og_mou_7'
 'loc_og_mou_8' 'std_og_t2t_mou_6' 'std_og_t2t_mou_7' 'std_og_t2t_mou_8'
 'std_og_t2m_mou_6' 'std_og_t2m_mou_7' 'std_og_t2m_mou_8'
 'std_og_t2f_mou_6' 'std_og_t2f_mou_7' 'std_og_t2f_mou_8' 'std_og_mou_6'
 'std_og_mou_7' 'std_og_mou_8' 'isd_og_mou_6' 'isd_og_mou_7'
 'isd_og_mou_8' 'spl_og_mou_6' 'spl_og_mou_7' 'spl_og_mou_8' 'og_others_6'
 'og_others_7' 'og_others_8' 'loc_ic_t2t_mou_6' 'loc_ic_t2t_mou_7'
 'loc_ic_t2t_mou_8' 'loc_ic_t2m_mou_6' 'loc_ic_t2m_mou_7'
 'loc_ic_t2m_mou_8' 'loc_ic_t2f_mou_6' 'loc_ic_t2f_mou_7'
 'loc_ic_t2f_mou_8' 'loc_ic_mou_6' 'loc_ic_mou_7' 'loc_ic_mou_8'
 'std_ic_t2t_mou_6' 'std_ic_t2t_mou_7' 'std_ic_t2t_mou_8'
 'std_ic_t2m_mou_6' 'std_ic_t2m_mou_7' 'std_ic_t2m_mou_8'
 'std_ic_t2f_mou_6' 'std_ic_t2f_mou_7' 'std_ic_t2f_mou_8' 'std_ic_mou_6'
 'std_ic_mou_7' 'std_ic_mou_8' 'spl_ic_mou_6' 'spl_ic_mou_7'
 'spl_ic_mou_8' 'isd_ic_mou_6' 'isd_ic_mou_7' 'isd_ic_mou_8' 'ic_others_6'
 'ic_others_7' 'ic_others_8' 'total_rech_num_6' 'total_rech_num_7'
 'total_rech_num_8' 'max_rech_amt_6' 'max_rech_amt_7' 'max_rech_amt_8'
 'last_day_rch_amt_6' 'last_day_rch_amt_7' 'last_day_rch_amt_8'
 'Average_rech_amt_6n7' 'delta_vol_2g' 'delta_vol_3g' 'delta_total_og_mou'
 'delta_total_ic_mou' 'delta_vbc_3g' 'delta_arpu' 'delta_total_rech_amt']
```

In [194]:
```
# capping outliers to 99th percentile values
outlier_treatment = pd.DataFrame(columns=['Column', 'Outlier Threshold', 'O
utliers replaced'])
for col in columns_with_outliers :
    outlier_threshold = data[col].quantile(0.99)
    condition = data[col] > outlier_threshold
    outlier_treatment = outlier_treatment.append({'Column' : col , 'Outlier
Threshold' : outlier_threshold, 'Outliers replaced' : data.loc[condition,co
l].shape[0] }, ignore_index=True)
    data.loc[condition, col] = outlier_threshold
outlier_treatment
```

Out[194]:

	Column	Outlier Threshold	Outliers replaced
0	onnet_mou_6	2166.37	301
1	onnet_mou_7	2220.37	301
2	onnet_mou_8	2188.50	301
3	offnet_mou_6	2326.29	301
4	offnet_mou_7	2410.10	301
5	offnet_mou_8	2211.64	301
6	roam_ic_mou_6	349.35	301
7	roam_ic_mou_7	292.54	301
8	roam_ic_mou_8	288.49	301
9	roam_og_mou_6	543.71	301
10	roam_og_mou_7	448.13	301
11	roam_og_mou_8	432.74	301
12	loc_og_t2t_mou_6	1076.24	301
13	loc_og_t2t_mou_7	1059.88	301
14	loc_og_t2t_mou_8	956.50	301
15	loc_og_t2m_mou_6	1147.05	301
16	loc_og_t2m_mou_7	1112.66	301
17	loc_og_t2m_mou_8	1092.59	301
18	loc_og_t2f_mou_6	90.88	301
19	loc_og_t2f_mou_7	91.06	301
20	loc_og_t2f_mou_8	86.68	300
21	loc_og_t2c_mou_6	24.86	301
22	loc_og_t2c_mou_7	28.24	301
23	loc_og_t2c_mou_8	28.87	301
24	loc_og_mou_6	1806.94	301
25	loc_og_mou_7	1761.43	301
26	loc_og_mou_8	1689.07	301
27	std_og_t2t_mou_6	1885.20	301
28	std_og_t2t_mou_7	1919.19	301
29	std_og_t2t_mou_8	1938.13	301
30	std_og_t2m_mou_6	1955.61	301
31	std_og_t2m_mou_7	2112.66	301
32	std_og_t2m_mou_8	1905.81	301
33	std_og_t2f_mou_6	44.39	301
34	std_og_t2f_mou_7	43.89	301
35	std_og_t2f_mou_8	38.88	301
36	std_og_mou_6	2744.49	301
37	std_og_mou_7	2874.65	301

	Column	Outlier Threshold	Outliers replaced
38	std_og_mou_8	2800.87	301
39	isd_og_mou_6	41.25	301
40	isd_og_mou_7	40.43	301
41	isd_og_mou_8	31.24	300
42	spl_og_mou_6	71.36	301
43	spl_og_mou_7	79.87	301
44	spl_og_mou_8	74.11	301
45	og_others_6	9.31	301
46	og_others_7	0.00	164
47	og_others_8	0.00	180
48	loc_ic_t2t_mou_6	625.35	301
49	loc_ic_t2t_mou_7	648.79	301
50	loc_ic_t2t_mou_8	621.67	301
51	loc_ic_t2m_mou_6	1026.44	301
52	loc_ic_t2m_mou_7	1009.29	301
53	loc_ic_t2m_mou_8	976.09	301
54	loc_ic_t2f_mou_6	197.17	301
55	loc_ic_t2f_mou_7	205.25	301
56	loc_ic_t2f_mou_8	185.62	301
57	loc_ic_mou_6	1484.99	301
58	loc_ic_mou_7	1515.87	301
59	loc_ic_mou_8	1459.55	301
60	std_ic_t2t_mou_6	215.64	301
61	std_ic_t2t_mou_7	231.15	301
62	std_ic_t2t_mou_8	215.20	301
63	std_ic_t2m_mou_6	393.73	301
64	std_ic_t2m_mou_7	408.58	301
65	std_ic_t2m_mou_8	372.61	301
66	std_ic_t2f_mou_6	53.39	301
67	std_ic_t2f_mou_7	56.59	300
68	std_ic_t2f_mou_8	49.41	301
69	std_ic_mou_6	577.89	301
70	std_ic_mou_7	616.89	301
71	std_ic_mou_8	563.89	301
72	spl_ic_mou_6	0.68	278
73	spl_ic_mou_7	0.51	295
74	spl_ic_mou_8	0.61	293
75	isd_ic_mou_6	239.60	301
76	isd_ic_mou_7	240.13	301

	Column	Outlier Threshold	Outliers replaced
77	isd_ic_mou_8	249.89	301
78	ic_others_6	20.71	301
79	ic_others_7	25.26	301
80	ic_others_8	21.53	300
81	total_rech_num_6	48.00	283
82	total_rech_num_7	48.00	283
83	total_rech_num_8	46.00	287
84	max_rech_amt_6	1000.00	169
85	max_rech_amt_7	1000.00	204
86	max_rech_amt_8	951.00	289
87	last_day_rch_amt_6	655.00	284
88	last_day_rch_amt_7	655.00	300
89	last_day_rch_amt_8	619.00	283
90	Average_rech_amt_6n7	2216.30	301
91	delta_vol_2g	654.31	301
92	delta_vol_3g	1878.12	301
93	delta_total_og_mou	1465.10	301
94	delta_total_ic_mou	619.69	301
95	delta_vbc_3g	929.64	301
96	delta_arpu	864.34	301
97	delta_total_rech_amt	1036.40	301

In [195]:
```
categorical = data.dtypes == 'category'
categorical_vars = data.columns[categorical].to_list()
ind_categorical_vars = set(categorical_vars) - {'Churn'} #independent categ
orical variables
ind_categorical_vars
```

Out[195]:
```
{'monthly_2g_6',
 'monthly_2g_7',
 'monthly_2g_8',
 'monthly_3g_6',
 'monthly_3g_7',
 'monthly_3g_8',
 'sachet_2g_6',
 'sachet_2g_7',
 'sachet_2g_8',
 'sachet_3g_6',
 'sachet_3g_7',
 'sachet_3g_8'}
```

Grouping Categories with less Contribution

In [196]:
```
# Finding & Grouping categories with less than 1% contribution in each colu
mn into "Others"
for col in ind_categorical_vars :
    category_counts = 100*data[col].value_counts(normalize=True)
    print('\n',tabulate(pd.DataFrame(category_counts), headers='keys', tabl
efmt='psql'),'\n')
    low_count_categories = category_counts[category_counts <= 1].index.to_l
ist()
    print(f"Replaced {low_count_categories} in {col} with category : Other
s")
    data[col].replace(low_count_categories,'Others',inplace=True)
```

```
 +----+------------------+
|    |   sachet_3g_6 |
|----+------------------|
|  0 |   93.4091      |
|  1 |    4.35507     |
|  2 |    1.04295     |
|  3 |    0.396521    |
|  4 |    0.219919    |
|  5 |    0.123288    |
|  6 |    0.089967    |
|  7 |    0.0866349   |
|  8 |    0.0499817   |
|  9 |    0.0499817   |
| 10 |    0.0366532   |
| 11 |    0.0266569   |
| 15 |    0.0166606   |
| 12 |    0.0133284   |
| 19 |    0.0133284   |
| 13 |    0.00999633 |
| 14 |    0.00999633 |
| 18 |    0.00999633 |
| 23 |    0.00999633 |
| 16 |    0.00666422 |
| 22 |    0.00666422 |
| 29 |    0.00666422 |
| 28 |    0.00333211 |
| 17 |    0.00333211 |
| 21 |    0.00333211 |
+----+------------------+

Replaced [3, 4, 5, 6, 7, 8, 9, 10, 11, 15, 12, 19, 13, 14, 18, 23, 16, 22,
29, 28, 17, 21] in sachet_3g_6 with category : Others

 +----+-------------------+
|    |   monthly_2g_7 |
|----+-------------------|
|  0 |    88.4876      |
|  1 |    10.0397      |
|  2 |     1.35284     |
|  3 |     0.0966312   |
|  4 |     0.0166606   |
|  5 |     0.00666422 |
+----+-------------------+

Replaced [3, 4, 5] in monthly_2g_7 with category : Others

 +----+-------------------+
|    |   monthly_2g_8 |
|----+-------------------|
|  0 |    89.7604      |
|  1 |     9.19996     |
|  2 |     0.942988    |
|  3 |     0.0733065   |
|  4 |     0.0166606   |
|  5 |     0.00666422 |
+----+-------------------+

Replaced [2, 3, 4, 5] in monthly_2g_8 with category : Others

 +----+------------------+
|    |   sachet_3g_8 |
|----+------------------|
|  0 |   94.2388        |
|  1 |    3.52537       |
|  2 |    0.839692      |
|  3 |    0.429842      |
|  4 |    0.243244      |
|  5 |    0.219919      |
|  6 |    0.0866349     |
|  7 |    0.0766386     |
|  8 |    0.0733065     |
|  9 |    0.0399853     |
| 12 |    0.0366532     |
| 13 |    0.0333211     |
| 10 |    0.0333211     |
| 11 |    0.0199927     |
| 14 |    0.0199927     |
| 15 |    0.0166606     |
| 16 |    0.00999633    |
| 17 |    0.00666422    |
| 18 |    0.00666422    |
| 20 |    0.00666422    |
| 21 |    0.00666422    |
| 23 |    0.00666422    |
| 38 |    0.00333211    |
| 19 |    0.00333211    |
| 25 |    0.00333211    |
| 27 |    0.00333211    |
| 29 |    0.00333211    |
| 30 |    0.00333211    |
| 41 |    0.00333211    |
+----+------------------+

Replaced [2, 3, 4, 5, 6, 7, 8, 9, 12, 13, 10, 11, 14, 15, 16, 17, 18, 20,
21, 23, 38, 19, 25, 27, 29, 30, 41] in sachet_3g_8 with category : Others

 +----+-------------------+
|    |   monthly_3g_7    |
|----+-------------------|
|  0 |    87.8378        |
|  1 |     8.21699       |
|  2 |     2.739         |
|  3 |     0.689747      |
|  4 |     0.226584      |
|  5 |     0.129952      |
|  6 |     0.0766386     |
|  7 |     0.0333211     |
|  8 |     0.0166606     |
|  9 |     0.0133284     |
| 11 |     0.00666422    |
| 16 |     0.00333211    |
| 14 |     0.00333211    |
| 12 |     0.00333211    |
| 10 |     0.00333211    |
+----+-------------------+

Replaced [3, 4, 5, 6, 7, 8, 9, 11, 16, 14, 12, 10] in monthly_3g_7 with ca
tegory : Others

 +----+------------------+
|    |   sachet_2g_6    |
|----+------------------|
| 0 |   82.5631      |
| 1 |    7.87378     |
| 2 |    3.3621      |
| 3 |    2.0126      |
| 4 |    1.32951     |
| 5 |    0.703076    |
| 6 |    0.509813    |
| 7 |    0.356536    |
| 8 |    0.286562    |
| 9 |    0.239912    |
| 10 |   0.17327     |
| 12 |   0.146613    |
| 11 |   0.0999633   |
| 13 |   0.0566459   |
| 14 |   0.0533138   |
| 15 |   0.0433175   |
| 17 |   0.0366532   |
| 18 |   0.029989    |
| 19 |   0.029989    |
| 16 |   0.0233248   |
| 22 |   0.0133284   |
| 20 |   0.00999633  |
| 21 |   0.00999633  |
| 24 |   0.00999633  |
| 25 |   0.00999633  |
| 39 |   0.00333211  |
| 27 |   0.00333211  |
| 30 |   0.00333211  |
| 32 |   0.00333211  |
| 34 |   0.00333211  |
| 28 |   0           |
| 42 |   0           |
+----+-------------+

Replaced [5, 6, 7, 8, 9, 10, 12, 11, 13, 14, 15, 17, 18, 19, 16, 22, 20, 2
1, 24, 25, 39, 27, 30, 32, 34, 28, 42] in sachet_2g_6 with category : Othe
rs

 +----+-------------+
|    |  monthly_2g_6 |
|----+-------------|
|  0 |    88.9074    |
|  1 |     9.83306   |
|  2 |     1.14958   |
|  3 |     0.0866349 |
|  4 |     0.0233248 |
+----+-------------+

Replaced [3, 4] in monthly_2g_6 with category : Others

 +----+-------------+
|    |  sachet_2g_7 |
|----+-------------|
|  0 |   81.8033     |
|  1 |    7.24068    |
|  2 |    3.34877    |
|  3 |    1.96595    |
|  4 |    1.50945    |
|  5 |    1.20622    |
|  6 |    0.843024   |
|  7 |    0.543134   |
|  8 |    0.403185    |
| 10 |    0.239912    |
|  9 |    0.219919    |
| 11 |    0.159941    |
| 12 |    0.0966312   |
| 14 |    0.0799707   |
| 13 |    0.0666422   |
| 15 |    0.0499817   |
| 16 |    0.0366532   |
| 18 |    0.0333211   |
| 17 |    0.029989    |
| 20 |    0.0266569   |
| 19 |    0.0233248   |
| 21 |    0.00999633  |
| 26 |    0.00999633  |
| 27 |    0.00999633  |
| 22 |    0.00666422  |
| 23 |    0.00666422  |
| 30 |    0.00666422  |
| 42 |    0.00333211  |
| 24 |    0.00333211  |
| 25 |    0.00333211  |
| 29 |    0.00333211  |
| 32 |    0.00333211  |
| 35 |    0.00333211  |
| 48 |    0.00333211  |
| 28 |    0           |
+----+----------------+

Replaced [6, 7, 8, 10, 9, 11, 12, 14, 13, 15, 16, 18, 17, 20, 19, 21, 26,
27, 22, 23, 30, 42, 24, 25, 29, 32, 35, 48, 28] in sachet_2g_7 with catego
ry : Others

 +----+----------------+
|    |   sachet_3g_7  |
|----+----------------|
|  0 |   93.4757      |
|  1 |    4.10849     |
|  2 |    1.03962     |
|  3 |    0.383193    |
|  4 |    0.239912    |
|  5 |    0.219919    |
|  6 |    0.139949    |
|  7 |    0.059978    |
|  9 |    0.0533138   |
|  8 |    0.0466496   |
| 11 |    0.0433175   |
| 10 |    0.0333211   |
| 12 |    0.0333211   |
| 15 |    0.0166606   |
| 14 |    0.0166606   |
| 13 |    0.0133284   |
| 18 |    0.0133284   |
| 19 |    0.00999633  |
| 20 |    0.00999633  |
| 22 |    0.00999633  |
| 17 |    0.00666422  |
| 21 |    0.00666422  |
| 24 |    0.00666422  |
| 33 |    0.00333211  |
| 16 |    0.00333211  |
| 31 |    0.00333211 |
| 35 |    0.00333211 |
+----+---------------+

Replaced [3, 4, 5, 6, 7, 9, 8, 11, 10, 12, 15, 14, 13, 18, 19, 20, 22, 17,
21, 24, 33, 16, 31, 35] in sachet_3g_7 with category : Others

 +----+----------------+
|    |   monthly_3g_8 |
|----+----------------|
|  0 |    88.3876     |
|  1 |     8.00706    |
|  2 |     2.45243    |
|  3 |     0.656426   |
|  4 |     0.289894   |
|  5 |     0.0999633  |
|  6 |     0.0466496  |
|  7 |     0.029989   |
|  9 |     0.00999633 |
|  8 |     0.00999633 |
| 10 |     0.00666422 |
| 16 |     0.00333211 |
+----+----------------+

Replaced [3, 4, 5, 6, 7, 9, 8, 10, 16] in monthly_3g_8 with category : Oth
ers

 +----+----------------+
|    |   monthly_3g_6 |
|----+----------------|
|  0 |    88.0744     |
|  1 |     8.4669     |
|  2 |     2.32248    |
|  3 |     0.689747   |
|  4 |     0.246576   |
|  5 |     0.106628   |
|  6 |     0.0366532  |
|  7 |     0.029989   |
|  8 |     0.00999633 |
| 11 |     0.00666422 |
|  9 |     0.00666422 |
| 14 |     0.00333211 |
+----+----------------+

Replaced [3, 4, 5, 6, 7, 8, 11, 9, 14] in monthly_3g_6 with category : Oth
ers

 +----+---------------+
|    |   sachet_2g_8 |
|----+---------------|
|  0 |   79.7274     |
|  1 |    8.87008    |
|  2 |    3.25881    |
|  3 |    2.19253    |
|  4 |    1.81267    |
|  5 |    1.44947    |
|  6 |    0.88301    |
|  7 |    0.459831   |
|  8 |    0.313218   |
|  9 |    0.249908   |
| 10 |    0.169938   |
| 11 |     0.123288    |
| 12 |     0.113292    |
| 14 |     0.0766386   |
| 15 |     0.0566459   |
| 13 |     0.0499817   |
| 16 |     0.0433175   |
| 18 |     0.0266569   |
| 17 |     0.0233248   |
| 19 |     0.0233248   |
| 20 |     0.0133284   |
| 34 |     0.00666422  |
| 29 |     0.00666422  |
| 27 |     0.00666422  |
| 24 |     0.00666422  |
| 22 |     0.00666422  |
| 21 |     0.00666422  |
| 23 |     0.00333211  |
| 25 |     0.00333211  |
| 26 |     0.00333211  |
| 31 |     0.00333211  |
| 32 |     0.00333211  |
| 33 |     0.00333211  |
| 44 |     0.00333211  |
+----+-----------------------+

Replaced [6, 7, 8, 9, 10, 11, 12, 14, 15, 13, 16, 18, 17, 19, 20, 34, 29,
27, 24, 22, 21, 23, 25, 26, 31, 32, 33, 44] in sachet_2g_8 with category :
Others
```

Creating Dummy Variables

In [197]:
```
dummy_vars = pd.get_dummies(data[ind_categorical_vars], drop_first=False, p
refix=ind_categorical_vars, prefix_sep='_')
dummy_vars.head()
```

Out[197]:

	sachet_3g_6_0	sachet_3g_6_1	sachet_3g_6_2	sachet_3g_6_Others	monthly_
mobile_number					
7000701601	1	0	0	0	
7001524846	1	0	0	0	
7002191713	1	0	0	0	
7000875565	1	0	0	0	
7000187447	1	0	0	0	

In [ ]:

In [198]:
```
reference_cols = dummy_vars.filter(regex='.*Others$').columns.to_list() # U
sing category 'Others' in each column as reference.
dummy_vars.drop(columns=reference_cols, inplace=True)
reference_cols
```

Out[198]:
```
['sachet_3g_6_Others',
 'monthly_2g_7_Others',
 'monthly_2g_8_Others',
 'sachet_3g_8_Others',
 'monthly_3g_7_Others',
 'sachet_2g_6_Others',
 'monthly_2g_6_Others',
 'sachet_2g_7_Others',
 'sachet_3g_7_Others',
 'monthly_3g_8_Others',
 'monthly_3g_6_Others',
 'sachet_2g_8_Others']
```

In [199]:
```
# concatenating dummy variables with original 'data'
data.drop(columns=ind_categorical_vars, inplace=True) # dropping original c
ategorical columns
data = pd.concat([data, dummy_vars], axis=1)
data.head()
```

Out[199]:

	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offn
mobile_number						
7000701601	57.84	54.68	52.29	453.43	567.16	
7001524846	413.69	351.03	35.08	94.66	80.63	
7002191713	501.76	108.39	534.24	413.31	119.28	
7000875565	50.51	74.01	70.61	296.29	229.74	
7000187447	1185.91	9.28	7.79	61.64	0.00	

In [200]:
```
dummy_cols = dummy_vars.columns.to_list()
data[dummy_cols] = data[dummy_cols].astype('category')
```

In [201]:
```
data.shape
```

Out[201]:
```
(30011, 142)
```

----joint

This following section contains

- Test Train Split
- Class Imbalance
- Standardization
- Modelling
    - Model 1 : Logistic Regression with RFE & Manual Elimination (Interpretable Model)
    - Model 2 : PCA + Logistic Regression
    - Model 3 : PCA + Random Forest Classifier
    - Model 4 : PCA + XGBoost

Train-Test Split

In [3]:
```
y = data.pop('Churn') # Predicted / Target Variable
X = data # Predictor variables
```

In [4]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7, ra
ndom_state=42)
```

Class Imbalance

In [5]:
```
y.value_counts(normalize=True).to_frame()
```

Out[5]:

	Churn
0	0.913598
1	0.086402

In [6]:
```
# Ratio of classes
class_0 = y[y == 0].count()
class_1 = y[y == 1].count()

print(f'Class Imbalance Ratio : {round(class_1/class_0,3)}')
```

```
Class Imbalance Ratio : 0.095
```

- To account for class imbalance, Synthetic Minority Class Oversampling Technique (SMOTE) could be used.

Using SMOTE

In [7]:
```
#!pip install imblearn
from imblearn.over_sampling import SMOTE
smt = SMOTE(random_state=42, k_neighbors=5)

# Resampling Train set to account for class imbalance

X_train_resampled, y_train_resampled= smt.fit_resample(X_train, y_train)
X_train_resampled.head()
```

Out[7]:

	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roa
0	53.01	52.64	37.48	316.01	195.74	68.36	
1	91.39	216.14	150.58	504.19	301.98	434.41	
2	11.96	14.13	0.40	1.51	0.00	0.00	
3	532.66	537.31	738.21	49.03	71.64	39.43	
4	122.68	105.51	149.33	302.23	211.44	264.11	

Standardizing Columns

In [8]:
```
# columns with numerical data
condition1 = data.dtypes == 'int'
condition2 = data.dtypes == 'float'
numerical_vars = data.columns[condition1 | condition2].to_list()
```

In [9]:
```
# Standard scaling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

# Fit and transform train set
X_train_resampled[numerical_vars] = scaler.fit_transform(X_train_resampled
[numerical_vars])

# Transform test set
X_test[numerical_vars] = scaler.transform(X_test[numerical_vars])
```

In [10]:
```
# summary statistics of standardized variables
round(X_train_resampled.describe(),2)
```

Out[10]:

	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8
count	38374.00	38374.00	38374.00	38374.00	38374.00	38374.00
mean	-0.00	-0.00	0.00	0.00	-0.00	-0.00
std	1.00	1.00	1.00	1.00	1.00	1.00
min	-0.73	-0.68	-0.53	-0.94	-0.89	-0.70
25%	-0.63	-0.60	-0.52	-0.66	-0.65	-0.66
50%	-0.42	-0.41	-0.40	-0.33	-0.33	-0.36
75%	0.20	0.15	0.01	0.27	0.26	0.23
max	4.09	4.46	5.67	4.02	4.45	5.24

Modelling

Model 1 : Interpretable Model : Logistic Regression

Baseline Logistic Regression Model

In [11]:
```
from sklearn.linear_model import LogisticRegression


baseline_model = LogisticRegression(random_state=100, class_weight='balance
d') # `weight of class` balancing technique used
baseline_model = baseline_model.fit(X_train, y_train)

y_train_pred = baseline_model.predict_proba(X_train)[:,1]
y_test_pred  = baseline_model.predict_proba(X_test)[:,1]
```

In [12]:
```
y_train_pred = pd.Series(y_train_pred,index = X_train.index, ) # converting
test and train to a series to preserve index
y_test_pred = pd.Series(y_test_pred,index = X_test.index)
```

Baseline Performance

In [13]:
```
# Function for Baseline Performance Metrics
import math
def model_metrics(matrix) :
    TN = matrix[0][0]
    TP = matrix[1][1]
    FP = matrix[0][1]
    FN = matrix[1][0]
    accuracy = round((TP + TN)/float(TP+TN+FP+FN),3)
    print('Accuracy :' ,accuracy )
    sensitivity = round(TP/float(FN + TP),3)
    print('Sensitivity / True Positive Rate / Recall :', sensitivity)
    specificity = round(TN/float(TN + FP),3)
    print('Specificity / True Negative Rate : ', specificity)
    precision = round(TP/float(TP + FP),3)
    print('Precision / Positive Predictive Value :', precision)
    print('F1-score :', round(2*precision*sensitivity/(precision + sensitiv
ity),3))
```

In [14]:
```
# Prediction at threshold of 0.5
classification_threshold = 0.5

y_train_pred_classified = y_train_pred.map(lambda x : 1 if x > classificati
on_threshold else 0)
y_test_pred_classified = y_test_pred.map(lambda x : 1 if x > classification
_threshold else 0)
```

In [15]:
```
from sklearn.metrics import confusion_matrix
train_matrix = confusion_matrix(y_train, y_train_pred_classified)
print('Confusion Matrix for train:\n', train_matrix)
test_matrix = confusion_matrix(y_test, y_test_pred_classified)
print('\nConfusion Matrix for test: \n', test_matrix)
```

```
Confusion Matrix for train:
 [[16001  3186]
 [  326  1494]]

Confusion Matrix for test:
 [[6090 2141]
 [ 149  624]]
```

In [16]:
```
# Baseline Model Performance :

print('Train Performance : \n')
model_metrics(train_matrix)

print('\n\nTest Performance : \n')
model_metrics(test_matrix)
```

```
Train Performance :

Accuracy : 0.833
Sensitivity / True Positive Rate / Recall : 0.821
Specificity / True Negative Rate :  0.834
Precision / Positive Predictive Value : 0.319
F1-score : 0.459


Test Performance :

Accuracy : 0.746
Sensitivity / True Positive Rate / Recall : 0.807
Specificity / True Negative Rate :  0.74
Precision / Positive Predictive Value : 0.226
F1-score : 0.353
```

Baseline Performance - Finding Optimum Probability Cutoff

In [17]:
```
# Specificity / Sensitivity Tradeoff

# Classification at probability thresholds between 0 and 1
y_train_pred_thres = pd.DataFrame(index=X_train.index)
thresholds = [float(x)/10 for x in range(10)]

def thresholder(x, thresh) :
    if x > thresh :
        return 1
    else :
        return 0


for i in thresholds:
    y_train_pred_thres[i]= y_train_pred.map(lambda x : thresholder(x,i))
y_train_pred_thres.head()
```

Out[17]:

	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
mobile_number										
7000166926	1	1	1	1	1	0	0	0	0	0
7001343085	1	1	1	0	0	0	0	0	0	0
7001863283	1	1	0	0	0	0	0	0	0	0
7002275981	1	1	1	0	0	0	0	0	0	0
7001086221	1	0	0	0	0	0	0	0	0	0

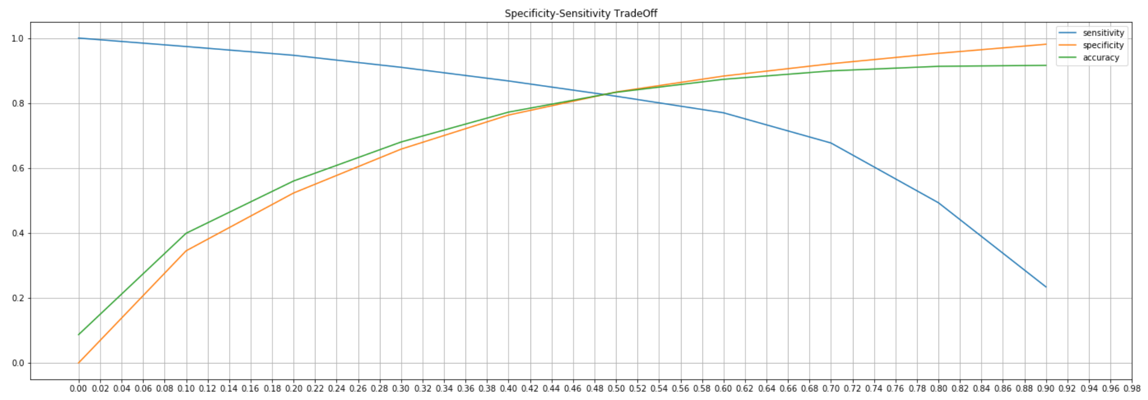
In [18]:

```
# # sensitivity, specificity, accuracy for each threshold
metrics_df = pd.DataFrame(columns=['sensitivity', 'specificity', 'accurac
y'])

# Function for calculation of metrics for each threshold
def model_metrics_thres(matrix) :
    TN = matrix[0][0]
    TP = matrix[1][1]
    FP = matrix[0][1]
    FN = matrix[1][0]
    accuracy = round((TP + TN)/float(TP+TN+FP+FN),3)
    sensitivity = round(TP/float(FN + TP),3)
    specificity = round(TN/float(TN + FP),3)
    return sensitivity,specificity,accuracy

# generating a data frame for metrics for each threshold
for thres,column in zip(thresholds,y_train_pred_thres.columns.to_list()) :
    confusion = confusion_matrix(y_train, y_train_pred_thres.loc[:,column])
    sensitivity,specificity,accuracy = model_metrics_thres(confusion)

    metrics_df =  metrics_df.append({
        'sensitivity' :sensitivity,
        'specificity' : specificity,
        'accuracy' : accuracy
    }, ignore_index = True)

metrics_df.index = thresholds
metrics_df
```

Out[18]:

	sensitivity	specificity	accuracy
0.0	1.000	0.000	0.087
0.1	0.974	0.345	0.399
0.2	0.947	0.523	0.560
0.3	0.910	0.658	0.680
0.4	0.868	0.763	0.772
0.5	0.821	0.834	0.833
0.6	0.770	0.883	0.873
0.7	0.677	0.921	0.899
0.8	0.493	0.953	0.913
0.9	0.234	0.981	0.916

In [19]:
```
metrics_df.plot(kind='line', figsize=(24,8), grid=True, xticks=np.arange(0,
1,0.02),
                title='Specificity-Sensitivity TradeOff');
```



Baseline Performance at Optimum Cutoff

In [20]:
```
optimum_cutoff = 0.49
y_train_pred_final = y_train_pred.map(lambda x : 1 if x > optimum_cutoff el
se 0)
y_test_pred_final = y_test_pred.map(lambda x : 1 if x > optimum_cutoff else
0)

train_matrix = confusion_matrix(y_train, y_train_pred_final)
print('Confusion Matrix for train:\n', train_matrix)
test_matrix = confusion_matrix(y_test, y_test_pred_final)
print('\nConfusion Matrix for test: \n', test_matrix)
```

```
Confusion Matrix for train:
 [[15888  3299]
 [  318  1502]]

Confusion Matrix for test:
 [[1329 6902]
 [  16  757]]
```

In [21]:
```
print('Train Performance: \n')
model_metrics(train_matrix)

print('\n\nTest Performance : \n')
model_metrics(test_matrix)
```

```
Train Performance:

Accuracy : 0.828
Sensitivity / True Positive Rate / Recall : 0.825
Specificity / True Negative Rate :  0.828
Precision / Positive Predictive Value : 0.313
F1-score : 0.454


Test Performance :

Accuracy : 0.232
Sensitivity / True Positive Rate / Recall : 0.979
Specificity / True Negative Rate :  0.161
Precision / Positive Predictive Value : 0.099
F1-score : 0.18
```

In [22]:
```
# ROC_AUC score
from sklearn.metrics import roc_auc_score
print('ROC AUC score for Train : ',round(roc_auc_score(y_train, y_train_pre
d),3), '\n' )
print('ROC AUC score for Test : ',round(roc_auc_score(y_test, y_test_pred),
3) )
```

```
ROC AUC score for Train :  0.891

ROC AUC score for Test :  0.838
```

Feature Selection using RFE

In [23]:
```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(random_state=100 , class_weight='balanced')
rfe = RFE(lr, 15)
results = rfe.fit(X_train,y_train)
results.support_
```

Out[23]:
```
array([False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False,  True,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False,  True, False, False, False, False, False, False,
       False, False, False, False,  True,  True, False, False, False,
       False, False, False, False, False, False, False, False, False,
        True, False,  True, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
        True, False, False,  True, False, False,  True, False, False,
       False,  True, False, False,  True, False, False, False, False,
        True, False, False,  True, False, False, False, False, False,
       False, False, False,  True, False, False, False, False, False,
        True, False, False, False, False, False])
```

In [24]:
```
# DataFrame with features supported by RFE
rfe_support = pd.DataFrame({'Column' : X.columns.to_list(), 'Rank' : rfe.ra
nking_,
                                      'Support' :  rfe.support_}).sort_valu
es(by=
                                       'Rank', ascending=True)
rfe_support
```

Out[24]:

	Column	Rank	Support
99	sachet_3g_6_0	1	True
120	sachet_2g_7_0	1	True
102	monthly_2g_7_0	1	True
135	sachet_2g_8_0	1	True
81	total_rech_num_6	1	True
129	monthly_3g_8_0	1	True
105	monthly_2g_8_0	1	True
83	total_rech_num_8	1	True
117	monthly_2g_6_0	1	True
68	std_ic_t2f_mou_8	1	True
67	std_ic_t2f_mou_7	1	True
112	sachet_2g_6_0	1	True
109	monthly_3g_7_0	1	True
56	loc_ic_t2f_mou_8	1	True
35	std_og_t2f_mou_8	1	True
40	isd_og_mou_7	2	False
53	loc_ic_t2m_mou_8	3	False
19	loc_og_t2f_mou_7	4	False
62	std_ic_t2t_mou_8	5	False
61	std_ic_t2t_mou_7	6	False
107	sachet_3g_8_0	7	False
41	isd_og_mou_8	8	False
89	last_day_rch_amt_8	9	False
11	roam_og_mou_8	10	False
132	monthly_3g_6_0	11	False
39	isd_og_mou_6	12	False
79	ic_others_7	13	False
50	loc_ic_t2t_mou_8	14	False
7	roam_ic_mou_7	15	False
58	loc_ic_mou_7	16	False
71	std_ic_mou_8	17	False
75	isd_ic_mou_6	18	False
33	std_og_t2f_mou_6	19	False
38	std_og_mou_8	20	False
66	std_ic_t2f_mou_6	21	False
29	std_og_t2t_mou_8	22	False
32	std_og_t2m_mou_8	23	False
78	ic_others_6	24	False

	Column	Rank	Support
44	spl_og_mou_8	25	False
97	delta_arpu	26	False
85	max_rech_amt_7	27	False
70	std_ic_mou_7	28	False
64	std_ic_t2m_mou_7	29	False
30	std_og_t2m_mou_6	30	False
42	spl_og_mou_6	31	False
27	std_og_t2t_mou_6	32	False
18	loc_og_t2f_mou_6	33	False
60	std_ic_t2t_mou_6	34	False
36	std_og_mou_6	35	False
51	loc_ic_t2m_mou_6	36	False
15	loc_og_t2m_mou_6	37	False
94	delta_total_og_mou	38	False
69	std_ic_mou_6	39	False
65	std_ic_t2m_mou_8	40	False
2	onnet_mou_8	41	False
55	loc_ic_t2f_mou_7	42	False
28	std_og_t2t_mou_7	43	False
13	loc_og_t2t_mou_7	44	False
1	onnet_mou_7	45	False
9	roam_og_mou_6	46	False
21	loc_og_t2c_mou_6	47	False
14	loc_og_t2t_mou_8	48	False
84	max_rech_amt_6	49	False
26	loc_og_mou_8	50	False
8	roam_ic_mou_8	51	False
10	roam_og_mou_7	52	False
48	loc_ic_t2t_mou_6	53	False
57	loc_ic_mou_6	54	False
6	roam_ic_mou_6	55	False
106	monthly_2g_8_1	56	False
87	last_day_rch_amt_6	57	False
49	loc_ic_t2t_mou_7	58	False
98	delta_total_rech_amt	59	False
88	last_day_rch_amt_7	60	False
34	std_og_t2f_mou_7	61	False
126	sachet_3g_7_0	62	False
23	loc_og_t2c_mou_8	63	False

	Column	Rank	Support
103	monthly_2g_7_1	64	False
118	monthly_2g_6_1	65	False
92	delta_vol_2g	66	False
16	loc_og_t2m_mou_7	67	False
4	offnet_mou_7	68	False
43	spl_og_mou_7	69	False
130	monthly_3g_8_1	70	False
20	loc_og_t2f_mou_8	71	False
17	loc_og_t2m_mou_8	72	False
63	std_ic_t2m_mou_6	73	False
93	delta_vol_3g	74	False
76	isd_ic_mou_7	75	False
24	loc_og_mou_6	76	False
12	loc_og_t2t_mou_6	77	False
54	loc_ic_t2f_mou_6	78	False
0	onnet_mou_6	79	False
3	offnet_mou_6	80	False
77	isd_ic_mou_8	81	False
5	offnet_mou_8	82	False
22	loc_og_t2c_mou_7	83	False
95	delta_total_ic_mou	84	False
52	loc_ic_t2m_mou_7	85	False
59	loc_ic_mou_8	86	False
90	aon	87	False
74	spl_ic_mou_8	88	False
136	sachet_2g_8_1	89	False
121	sachet_2g_7_1	90	False
113	sachet_2g_6_1	91	False
108	sachet_3g_8_1	92	False
80	ic_others_8	93	False
137	sachet_2g_8_2	94	False
138	sachet_2g_8_3	95	False
114	sachet_2g_6_2	96	False
123	sachet_2g_7_3	97	False
133	monthly_3g_6_1	98	False
125	sachet_2g_7_5	99	False
131	monthly_3g_8_2	100	False
119	monthly_2g_6_2	101	False
25	loc_og_mou_7	102	False

	Column	Rank	Support
104	monthly_2g_7_2	103	False
110	monthly_3g_7_1	104	False
100	sachet_3g_6_1	105	False
139	sachet_2g_8_4	106	False
134	monthly_3g_6_2	107	False
111	monthly_3g_7_2	108	False
37	std_og_mou_7	109	False
31	std_og_t2m_mou_7	110	False
140	sachet_2g_8_5	111	False
101	sachet_3g_6_2	112	False
72	spl_ic_mou_6	113	False
86	max_rech_amt_8	114	False
73	spl_ic_mou_7	115	False
96	delta_vbc_3g	116	False
82	total_rech_num_7	117	False
115	sachet_2g_6_3	118	False
124	sachet_2g_7_4	119	False
127	sachet_3g_7_1	120	False
91	Average_rech_amt_6n7	121	False
45	og_others_6	122	False
116	sachet_2g_6_4	123	False
128	sachet_3g_7_2	124	False
122	sachet_2g_7_2	125	False
47	og_others_8	126	False
46	og_others_7	127	False

```
In [25]: # RFE Selected columns
         rfe_selected_columns = rfe_support.loc[rfe_support['Rank'] == 1,'Column'].t
         o_list()
         rfe_selected_columns
```

```
Out[25]: ['sachet_3g_6_0',
          'sachet_2g_7_0',
          'monthly_2g_7_0',
          'sachet_2g_8_0',
          'total_rech_num_6',
          'monthly_3g_8_0',
          'monthly_2g_8_0',
          'total_rech_num_8',
          'monthly_2g_6_0',
          'std_ic_t2f_mou_8',
          'std_ic_t2f_mou_7',
          'sachet_2g_6_0',
          'monthly_3g_7_0',
          'loc_ic_t2f_mou_8',
          'std_og_t2f_mou_8']
```

Logistic Regression with RFE Selected Columns

Model I

In [26]:
```
# Logistic Regression Model with RFE columns
import statsmodels.api as sm

# Note that the SMOTE resampled Train set is used with statsmodels.api.GLM
since it doesnot support class_weight
logr = sm.GLM(y_train_resampled,(sm.add_constant(X_train_resampled[rfe_sele
cted_columns])), family = sm.families.Binomial())
logr_fit = logr.fit()
logr_fit.summary()
```

Out[26]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	38374
Model:	GLM	**Df Residuals:**	38358
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-19485.
Date:	Mon, 30 Nov 2020	**Deviance:**	38969.
Time:	21:57:09	**Pearson chi2:**	2.80e+05
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.2334	0.015	-15.657	0.000	-0.263	-0.204
sachet_3g_6_0	-0.0396	0.014	-2.886	0.004	-0.066	-0.013
sachet_2g_7_0	-0.0980	0.016	-6.201	0.000	-0.129	-0.067
monthly_2g_7_0	0.0096	0.016	0.594	0.552	-0.022	0.041
sachet_2g_8_0	0.0489	0.015	3.359	0.001	0.020	0.077
total_rech_num_6	0.6047	0.017	35.547	0.000	0.571	0.638
monthly_3g_8_0	0.3993	0.017	23.439	0.000	0.366	0.433
monthly_2g_8_0	0.3697	0.018	21.100	0.000	0.335	0.404
total_rech_num_8	-1.2013	0.019	-62.378	0.000	-1.239	-1.164
monthly_2g_6_0	-0.0194	0.015	-1.262	0.207	-0.050	0.011
std_ic_t2f_mou_8	-0.3364	0.026	-12.792	0.000	-0.388	-0.285
std_ic_t2f_mou_7	0.1535	0.019	8.148	0.000	0.117	0.190
sachet_2g_6_0	-0.1117	0.016	-6.847	0.000	-0.144	-0.080
monthly_3g_7_0	-0.2094	0.017	-12.602	0.000	-0.242	-0.177
loc_ic_t2f_mou_8	-1.2743	0.038	-33.599	0.000	-1.349	-1.200
std_og_t2f_mou_8	-0.2476	0.021	-11.621	0.000	-0.289	-0.206

Logistic Regression with Manual Feature Elimination

In [27]:
```
# Using P-value and vif for manual feature elimination

from statsmodels.stats.outliers_influence import variance_inflation_factor
def vif(X_train_resampled, logr_fit, selected_columns) :
    vif = pd.DataFrame()
    vif['Features'] = rfe_selected_columns
    vif['VIF'] = [variance_inflation_factor(X_train_resampled[selected_colu
mns].values, i) for i in range(X_train_resampled[selected_columns].shape
[1])]
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.set_index('Features')
    vif['P-value'] = round(logr_fit.pvalues,4)
    vif = vif.sort_values(by = ["VIF",'P-value'], ascending = [False,Fals
e])
    return vif

vif(X_train_resampled, logr_fit, rfe_selected_columns)
```

Out[27]:

Features	VIF	P-value
std_ic_t2f_mou_8	1.66	0.0000
sachet_2g_6_0	1.64	0.0000
sachet_2g_7_0	1.57	0.0000
std_ic_t2f_mou_7	1.56	0.0000
monthly_2g_7_0	1.54	0.5524
monthly_3g_7_0	1.54	0.0000
monthly_3g_8_0	1.52	0.0000
monthly_2g_8_0	1.43	0.0000
monthly_2g_6_0	1.38	0.2069
sachet_2g_8_0	1.36	0.0008
total_rech_num_6	1.27	0.0000
total_rech_num_8	1.25	0.0000
std_og_t2f_mou_8	1.20	0.0000
sachet_3g_6_0	1.12	0.0039
loc_ic_t2f_mou_8	1.09	0.0000

- 'monthly_2g_7_0' has the very p-value. Hence, this feature could be eliminated

In [28]:
```
selected_columns = rfe_selected_columns
selected_columns.remove('monthly_2g_7_0')
selected_columns
```

Out[28]:
```
['sachet_3g_6_0',
 'sachet_2g_7_0',
 'sachet_2g_8_0',
 'total_rech_num_6',
 'monthly_3g_8_0',
 'monthly_2g_8_0',
 'total_rech_num_8',
 'monthly_2g_6_0',
 'std_ic_t2f_mou_8',
 'std_ic_t2f_mou_7',
 'sachet_2g_6_0',
 'monthly_3g_7_0',
 'loc_ic_t2f_mou_8',
 'std_og_t2f_mou_8']
```

Model II

In [29]:
```
logr2 = sm.GLM(y_train_resampled,(sm.add_constant(X_train_resampled[selecte
d_columns])), family = sm.families.Binomial())
logr2_fit = logr2.fit()
logr2_fit.summary()
```

Out[29]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	38374
Model:	GLM	**Df Residuals:**	38359
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-19485.
Date:	Mon, 30 Nov 2020	**Deviance:**	38970.
Time:	21:57:09	**Pearson chi2:**	2.80e+05
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.2335	0.015	-15.662	0.000	-0.263	-0.204
sachet_3g_6_0	-0.0395	0.014	-2.881	0.004	-0.066	-0.013
sachet_2g_7_0	-0.0982	0.016	-6.217	0.000	-0.129	-0.067
sachet_2g_8_0	0.0491	0.015	3.372	0.001	0.021	0.078
total_rech_num_6	0.6049	0.017	35.566	0.000	0.572	0.638
monthly_3g_8_0	0.4000	0.017	23.521	0.000	0.367	0.433
monthly_2g_8_0	0.3733	0.016	22.696	0.000	0.341	0.406
total_rech_num_8	-1.2012	0.019	-62.375	0.000	-1.239	-1.163
monthly_2g_6_0	-0.0163	0.014	-1.128	0.259	-0.045	0.012
std_ic_t2f_mou_8	-0.3361	0.026	-12.784	0.000	-0.388	-0.285
std_ic_t2f_mou_7	0.1532	0.019	8.136	0.000	0.116	0.190
sachet_2g_6_0	-0.1111	0.016	-6.823	0.000	-0.143	-0.079
monthly_3g_7_0	-0.2098	0.017	-12.633	0.000	-0.242	-0.177
loc_ic_t2f_mou_8	-1.2749	0.038	-33.622	0.000	-1.349	-1.201
std_og_t2f_mou_8	-0.2476	0.021	-11.620	0.000	-0.289	-0.206

In [30]:
```
# vif and p-values
vif(X_train_resampled, logr2_fit, selected_columns)
```

Out[30]:

Features	VIF	P-value
std_ic_t2f_mou_8	1.66	0.0000
sachet_2g_6_0	1.63	0.0000
sachet_2g_7_0	1.57	0.0000
std_ic_t2f_mou_7	1.56	0.0000
monthly_3g_7_0	1.54	0.0000
monthly_3g_8_0	1.52	0.0000
sachet_2g_8_0	1.36	0.0007
total_rech_num_6	1.27	0.0000
total_rech_num_8	1.25	0.0000
monthly_2g_8_0	1.23	0.0000
monthly_2g_6_0	1.21	0.2595
std_og_t2f_mou_8	1.20	0.0000
sachet_3g_6_0	1.12	0.0040
loc_ic_t2f_mou_8	1.09	0.0000

- 'monthly_2g_6_0' has very high p-value. Hence, this feature could be eliminated

In [31]:
```
selected_columns.remove('monthly_2g_6_0')
selected_columns
```

Out[31]:
```
['sachet_3g_6_0',
 'sachet_2g_7_0',
 'sachet_2g_8_0',
 'total_rech_num_6',
 'monthly_3g_8_0',
 'monthly_2g_8_0',
 'total_rech_num_8',
 'std_ic_t2f_mou_8',
 'std_ic_t2f_mou_7',
 'sachet_2g_6_0',
 'monthly_3g_7_0',
 'loc_ic_t2f_mou_8',
 'std_og_t2f_mou_8']
```

Model III

In [32]:
```
logr3 = sm.GLM(y_train_resampled,(sm.add_constant(X_train_resampled[selecte
d_columns])), family = sm.families.Binomial())
logr3_fit = logr3.fit()
logr3_fit.summary()
```

Out[32]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	38374
Model:	GLM	**Df Residuals:**	38360
Model Family:	Binomial	**Df Model:**	13
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-19486.
Date:	Mon, 30 Nov 2020	**Deviance:**	38971.
Time:	21:57:10	**Pearson chi2:**	2.79e+05
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.2336	0.015	-15.667	0.000	-0.263	-0.204
sachet_3g_6_0	-0.0399	0.014	-2.916	0.004	-0.067	-0.013
sachet_2g_7_0	-0.0987	0.016	-6.249	0.000	-0.130	-0.068
sachet_2g_8_0	0.0488	0.015	3.354	0.001	0.020	0.077
total_rech_num_6	0.6053	0.017	35.581	0.000	0.572	0.639
monthly_3g_8_0	0.3994	0.017	23.494	0.000	0.366	0.433
monthly_2g_8_0	0.3666	0.015	23.953	0.000	0.337	0.397
total_rech_num_8	-1.2033	0.019	-62.720	0.000	-1.241	-1.166
std_ic_t2f_mou_8	-0.3363	0.026	-12.788	0.000	-0.388	-0.285
std_ic_t2f_mou_7	0.1532	0.019	8.137	0.000	0.116	0.190
sachet_2g_6_0	-0.1108	0.016	-6.810	0.000	-0.143	-0.079
monthly_3g_7_0	-0.2099	0.017	-12.640	0.000	-0.242	-0.177
loc_ic_t2f_mou_8	-1.2736	0.038	-33.621	0.000	-1.348	-1.199
std_og_t2f_mou_8	-0.2474	0.021	-11.617	0.000	-0.289	-0.206

In [33]:
```
# vif and p-values
vif(X_train_resampled, logr3_fit, selected_columns)
```

Out[33]:

	VIF	P-value
Features		
std_ic_t2f_mou_8	1.66	0.0000
sachet_2g_6_0	1.63	0.0000
sachet_2g_7_0	1.57	0.0000
std_ic_t2f_mou_7	1.56	0.0000
monthly_3g_7_0	1.54	0.0000
monthly_3g_8_0	1.52	0.0000
sachet_2g_8_0	1.36	0.0008
total_rech_num_6	1.27	0.0000
total_rech_num_8	1.24	0.0000
std_og_t2f_mou_8	1.20	0.0000
sachet_3g_6_0	1.12	0.0035
loc_ic_t2f_mou_8	1.09	0.0000
monthly_2g_8_0	1.03	0.0000

- All features have low p-values(<0.05) and VIF (<5)
- This model could be used as the interpretable logistic regression model.

Final Logistic Regression Model with RFE and Manual Elimination

In [34]:
```
logr3_fit.summary()
```

Out[34]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	38374
Model:	GLM	**Df Residuals:**	38360
Model Family:	Binomial	**Df Model:**	13
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-19486.
Date:	Mon, 30 Nov 2020	**Deviance:**	38971.
Time:	21:57:10	**Pearson chi2:**	2.79e+05
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.2336	0.015	-15.667	0.000	-0.263	-0.204
sachet_3g_6_0	-0.0399	0.014	-2.916	0.004	-0.067	-0.013
sachet_2g_7_0	-0.0987	0.016	-6.249	0.000	-0.130	-0.068
sachet_2g_8_0	0.0488	0.015	3.354	0.001	0.020	0.077
total_rech_num_6	0.6053	0.017	35.581	0.000	0.572	0.639
monthly_3g_8_0	0.3994	0.017	23.494	0.000	0.366	0.433
monthly_2g_8_0	0.3666	0.015	23.953	0.000	0.337	0.397
total_rech_num_8	-1.2033	0.019	-62.720	0.000	-1.241	-1.166
std_ic_t2f_mou_8	-0.3363	0.026	-12.788	0.000	-0.388	-0.285
std_ic_t2f_mou_7	0.1532	0.019	8.137	0.000	0.116	0.190
sachet_2g_6_0	-0.1108	0.016	-6.810	0.000	-0.143	-0.079
monthly_3g_7_0	-0.2099	0.017	-12.640	0.000	-0.242	-0.177
loc_ic_t2f_mou_8	-1.2736	0.038	-33.621	0.000	-1.348	-1.199
std_og_t2f_mou_8	-0.2474	0.021	-11.617	0.000	-0.289	-0.206

In [35]:
```
selected_columns
```

Out[35]:
```
['sachet_3g_6_0',
 'sachet_2g_7_0',
 'sachet_2g_8_0',
 'total_rech_num_6',
 'monthly_3g_8_0',
 'monthly_2g_8_0',
 'total_rech_num_8',
 'std_ic_t2f_mou_8',
 'std_ic_t2f_mou_7',
 'sachet_2g_6_0',
 'monthly_3g_7_0',
 'loc_ic_t2f_mou_8',
 'std_og_t2f_mou_8']
```

In [36]:
```
# Prediction
y_train_pred_lr = logr3_fit.predict(sm.add_constant(X_train_resampled[selec
ted_columns]))
y_train_pred_lr.head()
```

Out[36]:
```
0    0.118916
1    0.343873
2    0.381230
3    0.015277
4    0.001595
dtype: float64
```

In [37]:
```
y_test_pred_lr = logr3_fit.predict(sm.add_constant(X_test[selected_column
s]))
y_test_pred_lr.head()
```

Out[37]:
```
mobile_number
7002242818    0.013556
7000517161    0.903162
7002162382    0.247123
7002152271    0.330787
7002058655    0.056105
dtype: float64
```

Performance

Finding Optimum Probability Cutoff

In [38]:
```
# Specificity / Sensitivity Tradeoff

# Classification at probability thresholds between 0 and 1
y_train_pred_thres = pd.DataFrame(index=X_train_resampled.index)
thresholds = [float(x)/10 for x in range(10)]

def thresholder(x, thresh) :
    if x > thresh :
        return 1
    else :
        return 0


for i in thresholds:
    y_train_pred_thres[i]= y_train_pred_lr.map(lambda x : thresholder(x,i))
y_train_pred_thres.head()
```

Out[38]:

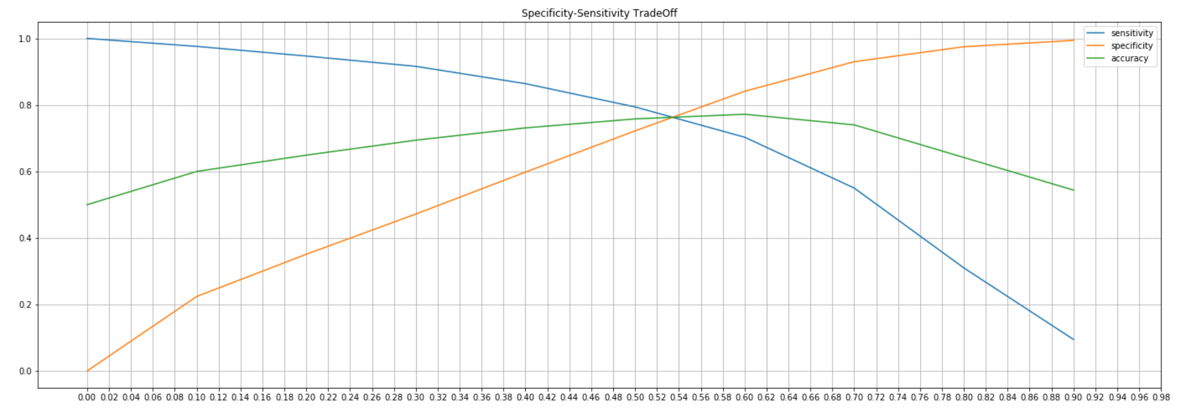
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	1	1	0	0	0	0	0	0	0	0
1	1	1	1	1	0	0	0	0	0	0
2	1	1	1	1	0	0	0	0	0	0
3	1	0	0	0	0	0	0	0	0	0
4	1	0	0	0	0	0	0	0	0	0

In [39]:
```
# DataFrame for Performance metrics at each threshold

logr_metrics_df = pd.DataFrame(columns=['sensitivity', 'specificity', 'accu
racy'])
for thres,column in zip(thresholds,y_train_pred_thres.columns.to_list()) :
    confusion = confusion_matrix(y_train_resampled, y_train_pred_thres.loc
[:,column])
    sensitivity,specificity,accuracy = model_metrics_thres(confusion)
    logr_metrics_df =  logr_metrics_df.append({
        'sensitivity' :sensitivity,
        'specificity' : specificity,
        'accuracy' : accuracy
    }, ignore_index = True)

logr_metrics_df.index = thresholds
logr_metrics_df
```

Out[39]:

	sensitivity	specificity	accuracy
0.0	1.000	0.000	0.500
0.1	0.976	0.224	0.600
0.2	0.947	0.351	0.649
0.3	0.916	0.472	0.694
0.4	0.864	0.598	0.731
0.5	0.794	0.722	0.758
0.6	0.703	0.841	0.772
0.7	0.550	0.930	0.740
0.8	0.310	0.975	0.642
0.9	0.095	0.994	0.544

In [40]:
```
logr_metrics_df.plot(kind='line', figsize=(24,8), grid=True, xticks=np.aran
ge(0,1,0.02),
                    title='Specificity-Sensitivity TradeOff');
```



- The optimum probability cutoff for Logistic regression model is 0.53

In [41]:
```
optimum_cutoff = 0.53
y_train_pred_lr_final = y_train_pred_lr.map(lambda x : 1 if x > optimum_cut
off else 0)
y_test_pred_lr_final = y_test_pred_lr.map(lambda x : 1 if x > optimum_cutof
f else 0)

train_matrix = confusion_matrix(y_train_resampled, y_train_pred_lr_final)
print('Confusion Matrix for train:\n', train_matrix)
test_matrix = confusion_matrix(y_test, y_test_pred_lr_final)
print('\nConfusion Matrix for test: \n', test_matrix)
```

```
Confusion Matrix for train:
 [[14531  4656]
 [ 4411 14776]]

Confusion Matrix for test:
 [[6313 1918]
 [ 191  582]]
```

In [42]:
```
print('Train Performance: \n')
model_metrics(train_matrix)

print('\n\nTest Performance : \n')
model_metrics(test_matrix)
```

```
Train Performance:

Accuracy : 0.764
Sensitivity / True Positive Rate / Recall : 0.77
Specificity / True Negative Rate :  0.757
Precision / Positive Predictive Value : 0.76
F1-score : 0.765


Test Performance :

Accuracy : 0.766
Sensitivity / True Positive Rate / Recall : 0.753
Specificity / True Negative Rate :  0.767
Precision / Positive Predictive Value : 0.233
F1-score : 0.356
```

In [43]:
```
# ROC_AUC score
print('ROC AUC score for Train : ',round(roc_auc_score(y_train_resampled, y
_train_pred_lr),3), '\n' )
print('ROC AUC score for Test : ',round(roc_auc_score(y_test, y_test_pred_l
r),3) )
```

```
ROC AUC score for Train :  0.843

ROC AUC score for Test :  0.828
```

Model 1 : Logistic Regression (Interpretable Model Summary)

In [44]:
```
lr_summary_html = logr3_fit.summary().tables[1].as_html()
lr_results = pd.read_html(lr_summary_html, header=0, index_col=0)[0]
coef_column = lr_results.columns[0]
print('Most important predictors of Churn , in order of importance and thei
r coefficients are as follows : \n')
lr_results.sort_values(by=coef_column, key=lambda x: abs(x), ascending=Fals
e)['coef']
```

```
Most important predictors of Churn , in order of importance and their coef
ficients are as follows :
```

Out[44]:
```
loc_ic_t2f_mou_8     -1.2736
total_rech_num_8     -1.2033
total_rech_num_6      0.6053
monthly_3g_8_0        0.3994
monthly_2g_8_0        0.3666
std_ic_t2f_mou_8     -0.3363
std_og_t2f_mou_8     -0.2474
const                -0.2336
monthly_3g_7_0       -0.2099
std_ic_t2f_mou_7      0.1532
sachet_2g_6_0        -0.1108
sachet_2g_7_0        -0.0987
sachet_2g_8_0         0.0488
sachet_3g_6_0        -0.0399
Name: coef, dtype: float64
```

- The above model could be used as the interpretable model for predicting telecom churn.

PCA

In [45]:
```
from sklearn.decomposition import PCA
pca = PCA(random_state = 42)
pca.fit(X_train) # note that pca is fit on original train set instead of re
sampled train set.
pca.components_
```

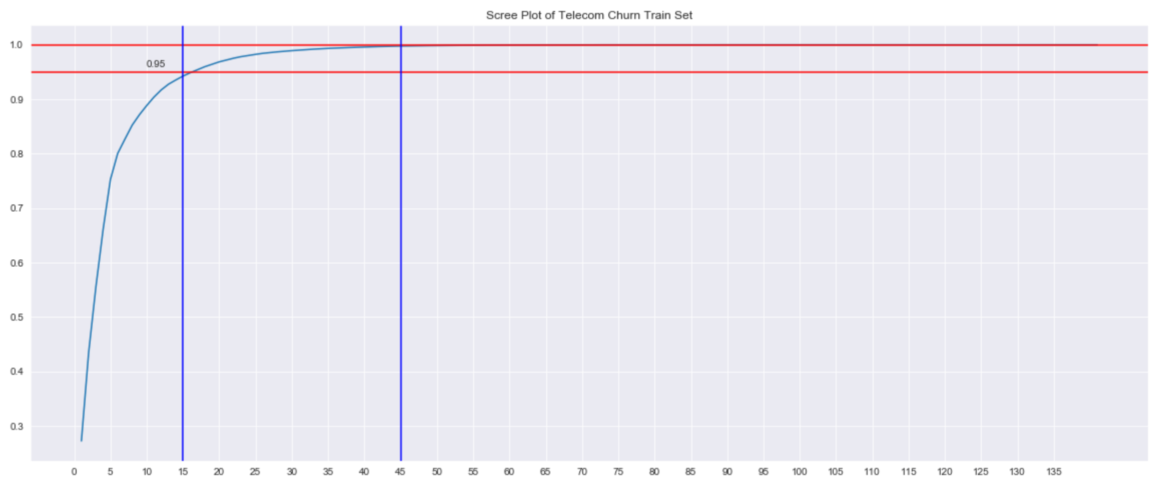
Out[45]:
```
array([[ 1.64887430e-01,  1.93987506e-01,  1.67239205e-01, ...,
         1.43967238e-06, -1.55704675e-06, -1.88892194e-06],
       [ 6.48591961e-02,  9.55966684e-02,  1.20775174e-01, ...,
        -2.12841595e-06, -1.47944145e-06, -3.90881587e-07],
       [ 2.38415388e-01,  2.73645507e-01,  2.38436263e-01, ...,
        -1.25598531e-06, -4.37900299e-07,  6.19889336e-07],
       ...,
       [ 1.68015588e-06,  1.93600851e-06, -1.82065762e-06, ...,
         4.25473944e-03,  2.56738368e-03,  3.51118176e-03],
       [ 0.00000000e+00, -1.11533905e-16,  1.57807487e-16, ...,
         1.73764144e-15,  6.22907679e-16,  1.45339158e-16],
       [ 0.00000000e+00,  4.98537742e-16, -6.02718139e-16, ...,
         1.27514583e-15,  1.25772226e-15,  3.41773342e-16]])
```

In [46]:
```
pca.explained_variance_ratio_
```

Out[46]:
```
array([2.72067612e-01, 1.62438240e-01, 1.20827535e-01, 1.06070063e-01,
       9.11349433e-02, 4.77504400e-02, 2.63978655e-02, 2.56843982e-02,
       1.91789343e-02, 1.68045932e-02, 1.55523468e-02, 1.31676589e-02,
       1.04552128e-02, 7.72970448e-03, 7.22746863e-03, 6.14494838e-03,
       5.62073089e-03, 5.44579273e-03, 4.59009989e-03, 4.38488162e-03,
       3.46703626e-03, 3.27941490e-03, 2.78099200e-03, 2.13444270e-03,
       2.07542043e-03, 1.89794720e-03, 1.41383936e-03, 1.30240760e-03,
       1.15369576e-03, 1.05262500e-03, 9.64293417e-04, 9.16686049e-04,
       8.84067044e-04, 7.62966236e-04, 6.61794767e-04, 5.69667265e-04,
       5.12585166e-04, 5.04441248e-04, 4.82396680e-04, 4.46889495e-04,
       4.36441254e-04, 4.10389488e-04, 3.51844810e-04, 3.12626195e-04,
       2.51673027e-04, 2.34723896e-04, 1.96950034e-04, 1.71296745e-04,
       1.59882693e-04, 1.48330353e-04, 1.45919483e-04, 1.08583729e-04,
       1.04038518e-04, 8.90621848e-05, 8.53009223e-05, 7.60704088e-05,
       7.57150133e-05, 6.16615717e-05, 6.07777411e-05, 5.70517541e-05,
       5.36161089e-05, 5.28495367e-05, 5.14887086e-05, 4.73768570e-05,
       4.71283394e-05, 4.11523975e-05, 4.10392906e-05, 2.86090257e-05,
       2.19793282e-05, 1.58203581e-05, 1.50969788e-05, 1.42865579e-05,
       1.34537530e-05, 1.33026062e-05, 1.10239870e-05, 8.27539516e-06,
       7.55845974e-06, 6.45372276e-06, 6.22570067e-06, 3.42288900e-06,
       3.20804681e-06, 3.09270863e-06, 2.86608967e-06, 2.44898003e-06,
       2.08230568e-06, 1.85144734e-06, 1.64714248e-06, 1.45630245e-06,
       1.35265729e-06, 1.05472047e-06, 9.89133015e-07, 8.65864423e-07,
       7.45065121e-07, 3.66727807e-07, 6.49277820e-08, 6.13357428e-08,
       4.35995018e-08, 2.28152900e-08, 2.00441141e-08, 1.84235145e-08,
       1.66102335e-08, 1.47870989e-08, 1.23390691e-08, 1.12094165e-08,
       1.09702422e-08, 9.51924270e-09, 8.61596309e-09, 7.38051070e-09,
       7.15370081e-09, 6.29095319e-09, 5.00739371e-09, 4.68791660e-09,
       4.23376173e-09, 4.04558169e-09, 3.75847771e-09, 3.71213838e-09,
       3.32806929e-09, 3.23527525e-09, 3.12734302e-09, 2.82062311e-09,
       2.72602311e-09, 2.66103741e-09, 2.46562734e-09, 2.20243536e-09,
       2.15044476e-09, 1.59498492e-09, 1.47087974e-09, 1.06159357e-09,
       9.33938436e-10, 8.10080735e-10, 8.04656028e-10, 6.12994365e-10,
       4.82074297e-10, 4.02577318e-10, 3.58059984e-10, 3.28374076e-10,
       3.03687605e-10, 7.12091816e-11, 6.13978255e-11, 1.04375208e-33,
       1.04375208e-33])
```

Scree Plot

In [47]:
```
var_cum = np.cumsum(pca.explained_variance_ratio_)
plt.figure(figsize=(20,8))
sns.set_style('darkgrid')
sns.lineplot(np.arange(1,len(var_cum) + 1), var_cum)
plt.xticks(np.arange(0,140,5))
plt.axhline(0.95,color='r')
plt.axhline(1.0,color='r')
plt.axvline(15,color='b')
plt.axvline(45,color='b')
plt.text(10,0.96,'0.95')

plt.title('Scree Plot of Telecom Churn Train Set');
```



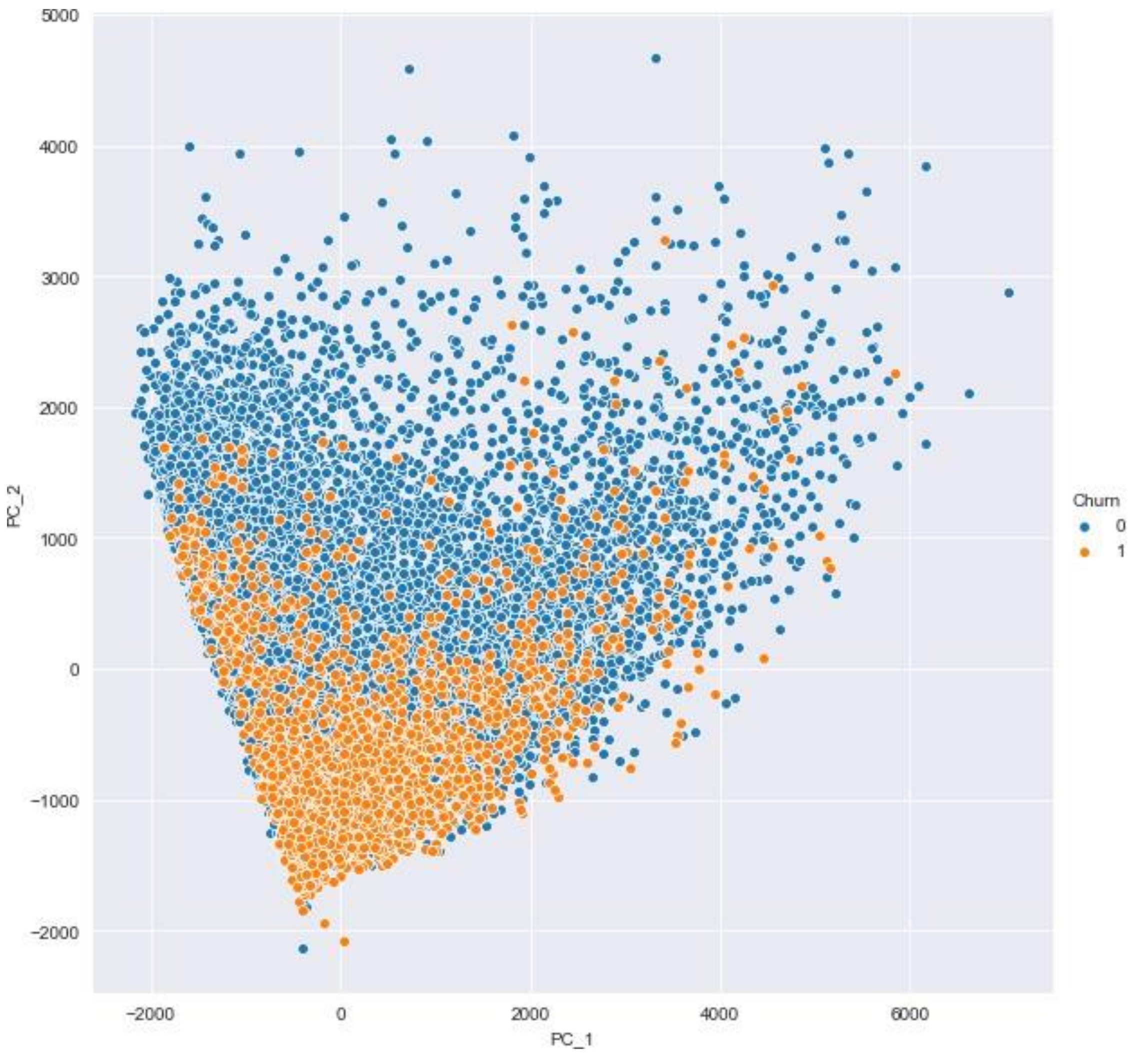
- From the above scree plot, it is clear that 95% of variance in the train set can be explained by first 16 principal components and 100% of variance is explained by the first 45 principal components.

In [48]:
```
# Perform PCA using the first 45 components
pca_final = PCA(n_components=45, random_state=42)
transformed_data = pca_final.fit_transform(X_train)
X_train_pca = pd.DataFrame(transformed_data, columns=["PC_"+str(x) for x in
range(1,46)], index = X_train.index)
data_train_pca = pd.concat([X_train_pca, y_train], axis=1)

data_train_pca.head()
```

Out[48]:

	PC_1	PC_2	PC_3	PC_4	PC_5	PC
mobile_number						
7000166926	-907.572208	-342.923676	13.094442	58.813506	-95.616159	-1050.5352
7001343085	573.898045	-902.385767	-424.839214	-331.153508	-148.987005	-36.9557
7001863283	-1538.198366	514.032564	846.865497	57.032319	-1126.228705	-84.2095
7002275981	486.830772	-224.929803	1130.460535	-496.189015	6.009139	81.1068
7001086221	-1420.949314	794.071749	99.221352	155.118564	145.349456	784.7235

In [49]:
```
## Plotting principal components
sns.pairplot(data=data_train_pca, x_vars=["PC_1"], y_vars=["PC_2"], hue =
"Churn", size=8);
```



Model 2 : PCA + Logistic Regression Model

In [50]:
```
# X,y Split
y_train_pca = data_train_pca.pop('Churn')
X_train_pca = data_train_pca

# Transforming test set with pca ( 45 components)
X_test_pca = pca_final.transform(X_test)

# Logistic Regression
lr_pca = LogisticRegression(random_state=100, class_weight='balanced')
lr_pca.fit(X_train_pca,y_train_pca )
```

Out[50]:
```
LogisticRegression(class_weight='balanced', random_state=100)
```

In [51]:
```
# y_train predictions
y_train_pred_lr_pca = lr_pca.predict(X_train_pca)
y_train_pred_lr_pca[:5]
```

Out[51]:
```
array([1, 0, 0, 0, 0])
```

In [52]:
```
# Test Prediction
X_test_pca = pca_final.transform(X_test)
y_test_pred_lr_pca = lr_pca.predict(X_test_pca)
y_test_pred_lr_pca[:5]
```

Out[52]:
```
array([1, 1, 1, 1, 1])
```

Baseline Performance

In [53]:
```
train_matrix = confusion_matrix(y_train, y_train_pred_lr_pca)
test_matrix = confusion_matrix(y_test, y_test_pred_lr_pca)

print('Train Performance :\n')
model_metrics(train_matrix)

print('\nTest Performance :\n')
model_metrics(test_matrix)
```

```
Train Performance :

Accuracy : 0.645
Sensitivity / True Positive Rate / Recall : 0.905
Specificity / True Negative Rate :  0.62
Precision / Positive Predictive Value : 0.184
F1-score : 0.306

Test Performance :

Accuracy : 0.086
Sensitivity / True Positive Rate / Recall : 1.0
Specificity / True Negative Rate :  0.0
Precision / Positive Predictive Value : 0.086
F1-score : 0.158
```

Hyperparameter Tuning

In [54]:
```
# Creating a Logistic regression model using pca transformed train set
from sklearn.pipeline import Pipeline
lr_pca = LogisticRegression(random_state=100, class_weight='balanced')
```

In [55]:
```
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV , Stra
tifiedKFold
params = {
    'penalty' : ['l1','l2','none'],
    'C' : [0,1,2,3,4,5,10,50]
}
folds = StratifiedKFold(n_splits=4, shuffle=True, random_state=100)

search = GridSearchCV(cv=folds, estimator = lr_pca, param_grid=params,scori
ng='roc_auc', verbose=True, n_jobs=-1)
search.fit(X_train_pca, y_train_pca)
```

```
Fitting 4 folds for each of 24 candidates, totalling 96 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:    4.0s
[Parallel(n_jobs=-1)]: Done  96 out of  96 | elapsed:    6.9s finished
```

Out[55]:
```
GridSearchCV(cv=StratifiedKFold(n_splits=4, random_state=100, shuffle=Tru
e),
             estimator=LogisticRegression(class_weight='balanced',
                                          random_state=100),
             n_jobs=-1,
             param_grid={'C': [0, 1, 2, 3, 4, 5, 10, 50],
                         'penalty': ['l1', 'l2', 'none']},
             scoring='roc_auc', verbose=True)
```

In [56]:
```
# Optimum Hyperparameters
print('Best ROC-AUC score :', search.best_score_)
print('Best Parameters :', search.best_params_)
```

```
Best ROC-AUC score : 0.8763924253372933
Best Parameters : {'C': 0, 'penalty': 'none'}
```

In [57]:
```
# Modelling using the best LR-PCA estimator
lr_pca_best = search.best_estimator_
lr_pca_best_fit = lr_pca_best.fit(X_train_pca, y_train_pca)

# Prediction on Train set
y_train_pred_lr_pca_best = lr_pca_best_fit.predict(X_train_pca)
y_train_pred_lr_pca_best[:5]
```

Out[57]:
```
array([1, 1, 0, 0, 0])
```

In [58]:
```
# Prediction on test set
y_test_pred_lr_pca_best = lr_pca_best_fit.predict(X_test_pca)
y_test_pred_lr_pca_best[:5]
```

Out[58]:
```
array([1, 1, 1, 1, 1])
```

In [59]:
```
## Model Performance after Hyper Parameter Tuning

train_matrix = confusion_matrix(y_train, y_train_pred_lr_pca_best)
test_matrix = confusion_matrix(y_test, y_test_pred_lr_pca_best)

print('Train Performance :\n')
model_metrics(train_matrix)

print('\nTest Performance :\n')
model_metrics(test_matrix)
```

```
Train Performance :

Accuracy : 0.627
Sensitivity / True Positive Rate / Recall : 0.918
Specificity / True Negative Rate :  0.599
Precision / Positive Predictive Value : 0.179
F1-score : 0.3

Test Performance :

Accuracy : 0.086
Sensitivity / True Positive Rate / Recall : 1.0
Specificity / True Negative Rate :  0.0
Precision / Positive Predictive Value : 0.086
F1-score : 0.158
```

Model 3 : PCA + Random Forest

In [60]:
```
from sklearn.ensemble import RandomForestClassifier

# creating a random forest classifier using pca output

pca_rf = RandomForestClassifier(random_state=42, class_weight= {0 : class_
1/(class_0 + class_1) , 1 : class_0/(class_0 + class_1) } , oob_score=True,
n_jobs=-1,verbose=1)
pca_rf
```

Out[60]:
```
RandomForestClassifier(class_weight={0: 0.08640165272733331,
                                     1: 0.9135983472726666},
                       n_jobs=-1, oob_score=True, random_state=42, verbose
=1)
```

In [68]:
```
# Hyper parameter Tuning
params = {
    'n_estimators'  : [30,40,50,100],
    'max_depth' : [3,4,5,6,7],
    'min_samples_leaf' : [15,20,25,30]
}
folds = StratifiedKFold(n_splits=4, shuffle=True, random_state=42)
pca_rf_model_search = GridSearchCV(estimator=pca_rf, param_grid=params,
                                   cv=folds, scoring='roc_auc', verbose=Tru
e, n_jobs=-1 )

pca_rf_model_search.fit(X_train_pca, y_train)
```

```
Fitting 4 folds for each of 80 candidates, totalling 320 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:   23.2s
[Parallel(n_jobs=-1)]: Done 192 tasks      | elapsed:  2.7min
[Parallel(n_jobs=-1)]: Done 320 out of 320 | elapsed:  5.5min finished
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 4 concurrent wo
rkers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:    1.2s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:    2.6s finished
```

Out[68]:
```
GridSearchCV(cv=StratifiedKFold(n_splits=4, random_state=42, shuffle=Tru
e),
             estimator=RandomForestClassifier(class_weight={0: 0.086401652
72733331,
                                                              1: 0.913598347
2726666},
                                                n_jobs=-1, oob_score=True,
                                                random_state=42, verbose=1),
             n_jobs=-1,
             param_grid={'max_depth': [3, 4, 5, 6, 7],
                         'min_samples_leaf': [15, 20, 25, 30],
                         'n_estimators': [30, 40, 50, 100]},
             scoring='roc_auc', verbose=True)
```

In [69]:
```
# Optimum Hyperparameters
print('Best ROC-AUC score :', pca_rf_model_search.best_score_)
print('Best Parameters :', pca_rf_model_search.best_params_)
```

```
Best ROC-AUC score : 0.8861621751601011
Best Parameters : {'max_depth': 7, 'min_samples_leaf': 20, 'n_estimators':
100}
```

In [70]:
```
# Modelling using the best PCA-RandomForest Estimator
pca_rf_best = pca_rf_model_search.best_estimator_
pca_rf_best_fit = pca_rf_best.fit(X_train_pca, y_train)

# Prediction on Train set
y_train_pred_pca_rf_best = pca_rf_best_fit.predict(X_train_pca)
y_train_pred_pca_rf_best[:5]
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 4 concurrent wo
rkers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:    1.1s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:    2.7s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent wor
kers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.0s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    0.1s finished
```

Out[70]:
```
array([0, 0, 0, 0, 0])
```

In [71]:
```
# Prediction on test set
y_test_pred_pca_rf_best = pca_rf_best_fit.predict(X_test_pca)
y_test_pred_pca_rf_best[:5]
```

```
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent wor
kers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.1s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    0.1s finished
```

Out[71]:
```
array([0, 0, 0, 0, 0])
```

In [72]:
```
## PCA - RandomForest Model Performance - Hyper Parameter Tuned

train_matrix = confusion_matrix(y_train, y_train_pred_pca_rf_best)
test_matrix = confusion_matrix(y_test, y_test_pred_pca_rf_best)

print('Train Performance :\n')
model_metrics(train_matrix)

print('\nTest Performance :\n')
model_metrics(test_matrix)
```

```
Train Performance :

Accuracy : 0.882
Sensitivity / True Positive Rate / Recall : 0.816
Specificity / True Negative Rate :  0.888
Precision / Positive Predictive Value : 0.408
F1-score : 0.544

Test Performance :

Accuracy : 0.86
Sensitivity / True Positive Rate / Recall : 0.80
Specificity / True Negative Rate :  0.78
Precision / Positive Predictive Value : 0.37
F1-score : 0.51
```

```
In [67]: ## out of bag error
         pca_rf_best_fit.oob_score_

Out[67]: 0.8625220164707003
```

Model 4 : PCA + XGBoost

```
In [74]: import xgboost as xgb
         pca_xgb = xgb.XGBClassifier(random_state=42, scale_pos_weight= class_0/clas
         s_1 ,
                                     tree_method='hist',
                                    objective='binary:logistic',


                                   )  # scale_pos_weight takes care of class
         imbalance
         pca_xgb.fit(X_train_pca, y_train)

Out[74]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                       colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
                       importance_type='gain', interaction_constraints='',
                       learning_rate=0.300000012, max_delta_step=0, max_depth=6,
                       min_child_weight=1, missing=nan, monotone_constraints='()',
                       n_estimators=100, n_jobs=0, num_parallel_tree=1, random_stat
         e=42,
                       reg_alpha=0, reg_lambda=1, scale_pos_weight=10.5738526802930
         97,
                       subsample=1, tree_method='hist', validate_parameters=1,
                       verbosity=None)
```

```
In [75]: print('Baseline Train AUC Score')
         roc_auc_score(y_train, pca_xgb.predict_proba(X_train_pca)[:, 1])

         Baseline Train AUC Score

Out[75]: 0.9999996277241286
```

```
In [76]: print('Baseline Test AUC Score')
         roc_auc_score(y_test, pca_xgb.predict_proba(X_test_pca)[:, 1])

         Baseline Test AUC Score

Out[76]: 0.46093390352284136
```

In [77]:
```
## Hyper parameter Tuning
parameters = {
              'learning_rate': [0.1, 0.2, 0.3],
              'gamma' : [10,20,50],
              'max_depth': [2,3,4],
              'min_child_weight': [25,50],
              'n_estimators': [150,200,500]}
pca_xgb_search = GridSearchCV(estimator=pca_xgb , param_grid=parameters,sco
ring='roc_auc', cv=folds, n_jobs=-1, verbose=1)
pca_xgb_search.fit(X_train_pca, y_train)
```

```
Fitting 4 folds for each of 162 candidates, totalling 648 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:   28.3s
[Parallel(n_jobs=-1)]: Done 192 tasks      | elapsed:  2.1min
[Parallel(n_jobs=-1)]: Done 442 tasks      | elapsed:  4.8min
[Parallel(n_jobs=-1)]: Done 648 out of 648 | elapsed:  8.0min finished
```

Out[77]:
```
GridSearchCV(cv=StratifiedKFold(n_splits=4, random_state=42, shuffle=Tru
e),
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     colsample_bylevel=1, colsample_bynode
=1,
                                     colsample_bytree=1, gamma=0, gpu_id=-
1,
                                     importance_type='gain',
                                     interaction_constraints='',
                                     learning_rate=0.300000012,
                                     max_delta_step=0, max_depth=6,
                                     min_child_weight=1, missing=nan,
                                     monotone_...
                                     n_estimators=100, n_jobs=0,
                                     num_parallel_tree=1, random_state=42,
                                     reg_alpha=0, reg_lambda=1,
                                     scale_pos_weight=10.573852680293097,
                                     subsample=1, tree_method='hist',
                                     validate_parameters=1, verbosity=Non
e),
             n_jobs=-1,
             param_grid={'gamma': [10, 20, 50],
                         'learning_rate': [0.1, 0.2, 0.3],
                         'max_depth': [2, 3, 4], 'min_child_weight': [25,
50],
                         'n_estimators': [150, 200, 500]},
             scoring='roc_auc', verbose=1)
```

In [78]:
```
# Optimum Hyperparameters
print('Best ROC-AUC score :', pca_xgb_search.best_score_)
print('Best Parameters :', pca_xgb_search.best_params_)
```

```
Best ROC-AUC score : 0.8955777259491308
Best Parameters : {'gamma': 10, 'learning_rate': 0.1, 'max_depth': 2, 'min
_child_weight': 50, 'n_estimators': 500}
```

In [79]:
```
# Modelling using the best PCA-XGBoost Estimator
pca_xgb_best = pca_xgb_search.best_estimator_
pca_xgb_best_fit = pca_xgb_best.fit(X_train_pca, y_train)

# Prediction on Train set
y_train_pred_pca_xgb_best = pca_xgb_best_fit.predict(X_train_pca)
y_train_pred_pca_xgb_best[:5]
```

Out[79]:
```
array([0, 0, 0, 0, 0])
```

In [84]:
```
X_train_pca.head()
```

Out[84]:

	PC_1	PC_2	PC_3	PC_4	PC_5	PC
mobile_number						
7000166926	-907.572208	-342.923676	13.094442	58.813506	-95.616159	-1050.5352
7001343085	573.898045	-902.385767	-424.839214	-331.153508	-148.987005	-36.9557
7001863283	-1538.198366	514.032564	846.865497	57.032319	-1126.228705	-84.2095
7002275981	486.830772	-224.929803	1130.460535	-496.189015	6.009139	81.1068
7001086221	-1420.949314	794.071749	99.221352	155.118564	145.349456	784.7235

In [85]:
```
# Prediction on test set
X_test_pca = pca_final.transform(X_test)
X_test_pca = pd.DataFrame(X_test_pca, index=X_test.index, columns = X_train
_pca.columns)
y_test_pred_pca_xgb_best = pca_xgb_best_fit.predict(X_test_pca)
y_test_pred_pca_xgb_best[:5]
```

Out[85]:
```
array([1, 1, 1, 1, 1])
```

In [86]:
```
## PCA - XGBOOST [Hyper parameter tuned] Model Performance

train_matrix = confusion_matrix(y_train, y_train_pred_pca_xgb_best)
test_matrix = confusion_matrix(y_test, y_test_pred_pca_xgb_best)

print('Train Performance :\n')
model_metrics(train_matrix)

print('\nTest Performance :\n')
model_metrics(test_matrix)
```

```
Train Performance :

Accuracy : 0.873
Sensitivity / True Positive Rate / Recall : 0.887
Specificity / True Negative Rate :  0.872
Precision / Positive Predictive Value : 0.396
F1-score : 0.548

Test Performance :

Accuracy : 0.086
Sensitivity / True Positive Rate / Recall : 1.0
Specificity / True Negative Rate :  0.0
Precision / Positive Predictive Value : 0.086
F1-score : 0.158
```

In [87]:
```
## PCA - XGBOOST [Hyper parameter tuned] Model Performance
print('Train AUC Score')
print(roc_auc_score(y_train, pca_xgb_best.predict_proba(X_train_pca)[:,
1]))
print('Test AUC Score')
print(roc_auc_score(y_test, pca_xgb_best.predict_proba(X_test_pca)[:, 1]))
```

```
Train AUC Score
0.9442462043611259
Test AUC Score
0.6353301334697982
```

Recommendations

In [88]:
```
print('Most Important Predictors of churn , in the order of importance are : ')
lr_results.sort_values(by=coef_column, key=lambda x: abs(x), ascending=False)['coef']
```

```
Most Important Predictors of churn , in the order of importance are :
```

Out[88]:
```
loc_ic_t2f_mou_8   -1.2736
total_rech_num_8   -1.2033
total_rech_num_6    0.6053
monthly_3g_8_0      0.3994
monthly_2g_8_0      0.3666
std_ic_t2f_mou_8   -0.3363
std_og_t2f_mou_8   -0.2474
const              -0.2336
monthly_3g_7_0     -0.2099
std_ic_t2f_mou_7    0.1532
sachet_2g_6_0      -0.1108
sachet_2g_7_0      -0.0987
sachet_2g_8_0       0.0488
sachet_3g_6_0      -0.0399
Name: coef, dtype: float64
```

From the above, the following are the strongest indicators of churn

- Customers who churn show lower average monthly local incoming calls from fixed line in the action period by 1.27 standard deviations , compared to users who don't churn , when all other factors are held constant. This is the strongest indicator of churn.
- Customers who churn show lower number of recharges done in action period by 1.20 standard deviations, when all other factors are held constant. This is the second strongest indicator of churn.
- Further customers who churn have done 0.6 standard deviations higher recharge than non-churn customers. This factor when coupled with above factors is a good indicator of churn.
- Customers who churn are more likely to be users of 'monthly 2g package-0 / monthly 3g package-0' in action period (approximately 0.3 std deviations higher than other packages), when all other factors are held constant.

Based on the above indicators the recommendations to the telecom company are :

- Concentrate on users with 1.27 std devations lower than average incoming calls from fixed line. They are most likely to churn.
- Concentrate on users who recharge less number of times (less than 1.2 std deviations compared to avg) in the 8th month. They are second most likely to churn.
- Models with high sensitivity are the best for predicting churn. Use the PCA + Logistic Regression model to predict churn. It has an ROC score of 0.87, test sensitivity of 100%

In [ ]:

In [ ]: