Telecom Churn Case Study

Problem Statement

Business problem overview

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

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

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

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

Understanding and defining churn

There are two main models of payment in the telecom industry - **`postpaid`** (customers pay a monthly/annual bill after using the services) and **`prepaid`** (customers pay/recharge with a certain amount in advance and then use the services).

In the postpaid model, when customers want to switch to another operator, they usually inform the existing operator to terminate the services, and you directly know that this is an instance of churn.

However, in the prepaid model, customers who want to switch to another network can simply stop using the services without any notice, and it is hard to know whether someone has actually churned or is simply not using the services temporarily (e.g. someone may be on a trip abroad for a month or two and then intend to resume using the services again).

Thus, churn prediction is usually more critical (and non-trivial) for prepaid customers, and the term ‘churn’ should be defined carefully. Also, prepaid is the most common model in India and Southeast Asia, while postpaid is more common in Europe in North America.

This project is based on the Indian and Southeast Asian market.

Definitions of churn

There are various ways to define churn, such as:

`Revenue-based churn`: Customers who have not utilised any revenue-generating facilities such as mobile internet, outgoing calls, SMS etc. over a given period of time. One could also use aggregate metrics such as ‘customers who have generated less than INR 4 per month in total/average/median revenue’.

The main shortcoming of this definition is that there are customers who only receive calls/SMSes from their wage-earning counterparts, i.e. they don't generate revenue but use the services. For example, many users in rural areas only receive calls from their wage-earning siblings in urban areas.

`Usage-based churn`: Customers who have not done any usage, either incoming or outgoing - in terms of calls, internet etc. over a period of time.

A potential shortcoming of this definition is that when the customer has stopped using the services for a while, it may be too late to take any corrective actions to retain them. For e.g., if you define churn based on a 'two-months zero usage' period, predicting churn could be useless since by that time the customer would have already switched to another operator.

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

High-value 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.

In this project, you will define high-value customers based on a certain metric (mentioned later below) and predict churn only on high-value customers.

Understanding the business objective and the data

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

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

Understanding customer behaviour during churn

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

- The ***`'good'`*** phase: In this phase, the customer is happy with the service and behaves as usual.
- The ***`'action'`*** phase: The customer experience starts to sore in this phase, for e.g. he/she gets a compelling offer from a competitor, faces unjust charges, becomes unhappy with service quality etc. In this phase, the customer usually shows different behaviour than the 'good' months. Also, it is crucial to identify high-churn-risk customers in this phase, since some corrective actions can be taken at this point (such as matching the competitor's offer/improving the service quality etc.)
- The ***`'churn'`*** phase: In this phase, the customer is said to have churned. You define churn based on this phase. Also, it is important to note that at the time of prediction (i.e. the action months), this data is not available to you for prediction. Thus, after **`tagging`**

churn as 1/0 based on this phase, you discard all data corresponding to this phase.

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

Importing Libraries

```
# Basic libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import time

# Supressing the warnings generated
import warnings
warnings.filterwarnings('ignore')

# Importing Pandas EDA tool
import pandas_profiling as pp
from pandas_profiling import ProfileReport

# Displaying all Columns without restrictions
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
pd.set_option('display.max_colwidth', -1)
```

Importing the Dataset

```
# Reading the csv data file.
telecom_data = pd.read_csv("telecom_churn_data.csv")
# Displaying the first 10 field with all columns in the dataset
telecom_data.head(10)
# Checking the dimensions of the dataset
telecom_data.shape
(99999, 226)
# Checking the informations regarding the dataset
telecom_data.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Data columns (total 226 columns):
 #     Column                    Dtype
---    ------                    -----
 0     mobile_number             int64
 1     circle_id                 int64
 2     loc_og_t2o_mou            float64
 3     std_og_t2o_mou            float64
 4     loc_ic_t2o_mou            float64
```

```
5    last_date_of_month_6      object
6    last_date_of_month_7      object
7    last_date_of_month_8      object
8    last_date_of_month_9      object
9    arpu_6                    float64
10   arpu_7                    float64
11   arpu_8                    float64
12   arpu_9                    float64
13   onnet_mou_6               float64
14   onnet_mou_7               float64
15   onnet_mou_8               float64
16   onnet_mou_9               float64
17   offnet_mou_6              float64
18   offnet_mou_7              float64
19   offnet_mou_8              float64
20   offnet_mou_9              float64
21   roam_ic_mou_6             float64
22   roam_ic_mou_7             float64
23   roam_ic_mou_8             float64
24   roam_ic_mou_9             float64
25   roam_og_mou_6             float64
26   roam_og_mou_7             float64
27   roam_og_mou_8             float64
28   roam_og_mou_9             float64
29   loc_og_t2t_mou_6          float64
30   loc_og_t2t_mou_7          float64
31   loc_og_t2t_mou_8          float64
32   loc_og_t2t_mou_9          float64
33   loc_og_t2m_mou_6          float64
34   loc_og_t2m_mou_7          float64
35   loc_og_t2m_mou_8          float64
36   loc_og_t2m_mou_9          float64
37   loc_og_t2f_mou_6          float64
38   loc_og_t2f_mou_7          float64
39   loc_og_t2f_mou_8          float64
40   loc_og_t2f_mou_9          float64
41   loc_og_t2c_mou_6          float64
42   loc_og_t2c_mou_7          float64
43   loc_og_t2c_mou_8          float64
44   loc_og_t2c_mou_9          float64
45   loc_og_mou_6              float64
46   loc_og_mou_7              float64
47   loc_og_mou_8              float64
```

```
48   loc_og_mou_9            float64
49   std_og_t2t_mou_6        float64
50   std_og_t2t_mou_7        float64
51   std_og_t2t_mou_8        float64
52   std_og_t2t_mou_9        float64
53   std_og_t2m_mou_6        float64
54   std_og_t2m_mou_7        float64
55   std_og_t2m_mou_8        float64
56   std_og_t2m_mou_9        float64
57   std_og_t2f_mou_6        float64
58   std_og_t2f_mou_7        float64
59   std_og_t2f_mou_8        float64
60   std_og_t2f_mou_9        float64
61   std_og_t2c_mou_6        float64
62   std_og_t2c_mou_7        float64
63   std_og_t2c_mou_8        float64
64   std_og_t2c_mou_9        float64
65   std_og_mou_6            float64
66   std_og_mou_7            float64
67   std_og_mou_8            float64
68   std_og_mou_9            float64
69   isd_og_mou_6            float64
70   isd_og_mou_7            float64
71   isd_og_mou_8            float64
72   isd_og_mou_9            float64
73   spl_og_mou_6            float64
74   spl_og_mou_7            float64
75   spl_og_mou_8            float64
76   spl_og_mou_9            float64
77   og_others_6             float64
78   og_others_7             float64
79   og_others_8             float64
80   og_others_9             float64
81   total_og_mou_6          float64
82   total_og_mou_7          float64
83   total_og_mou_8          float64
84   total_og_mou_9          float64
85   loc_ic_t2t_mou_6        float64
86   loc_ic_t2t_mou_7        float64
87   loc_ic_t2t_mou_8        float64
88   loc_ic_t2t_mou_9        float64
89   loc_ic_t2m_mou_6        float64
90   loc_ic_t2m_mou_7        float64
```

91	loc_ic_t2m_mou_8	float64
92	loc_ic_t2m_mou_9	float64
93	loc_ic_t2f_mou_6	float64
94	loc_ic_t2f_mou_7	float64
95	loc_ic_t2f_mou_8	float64
96	loc_ic_t2f_mou_9	float64
97	loc_ic_mou_6	float64
98	loc_ic_mou_7	float64
99	loc_ic_mou_8	float64
100	loc_ic_mou_9	float64
101	std_ic_t2t_mou_6	float64
102	std_ic_t2t_mou_7	float64
103	std_ic_t2t_mou_8	float64
104	std_ic_t2t_mou_9	float64
105	std_ic_t2m_mou_6	float64
106	std_ic_t2m_mou_7	float64
107	std_ic_t2m_mou_8	float64
108	std_ic_t2m_mou_9	float64
109	std_ic_t2f_mou_6	float64
110	std_ic_t2f_mou_7	float64
111	std_ic_t2f_mou_8	float64
112	std_ic_t2f_mou_9	float64
113	std_ic_t2o_mou_6	float64
114	std_ic_t2o_mou_7	float64
115	std_ic_t2o_mou_8	float64
116	std_ic_t2o_mou_9	float64
117	std_ic_mou_6	float64
118	std_ic_mou_7	float64
119	std_ic_mou_8	float64
120	std_ic_mou_9	float64
121	total_ic_mou_6	float64
122	total_ic_mou_7	float64
123	total_ic_mou_8	float64
124	total_ic_mou_9	float64
125	spl_ic_mou_6	float64
126	spl_ic_mou_7	float64
127	spl_ic_mou_8	float64
128	spl_ic_mou_9	float64
129	isd_ic_mou_6	float64
130	isd_ic_mou_7	float64
131	isd_ic_mou_8	float64
132	isd_ic_mou_9	float64
133	ic_others_6	float64

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134  ic_others_7               float64
135  ic_others_8               float64
136  ic_others_9               float64
137  total_rech_num_6          int64
138  total_rech_num_7          int64
139  total_rech_num_8          int64
140  total_rech_num_9          int64
141  total_rech_amt_6          int64
142  total_rech_amt_7          int64
143  total_rech_amt_8          int64
144  total_rech_amt_9          int64
145  max_rech_amt_6            int64
146  max_rech_amt_7            int64
147  max_rech_amt_8            int64
148  max_rech_amt_9            int64
149  date_of_last_rech_6       object
150  date_of_last_rech_7       object
151  date_of_last_rech_8       object
152  date_of_last_rech_9       object
153  last_day_rch_amt_6        int64
154  last_day_rch_amt_7        int64
155  last_day_rch_amt_8        int64
156  last_day_rch_amt_9        int64
157  date_of_last_rech_data_6  object
158  date_of_last_rech_data_7  object
159  date_of_last_rech_data_8  object
160  date_of_last_rech_data_9  object
161  total_rech_data_6         float64
162  total_rech_data_7         float64
163  total_rech_data_8         float64
164  total_rech_data_9         float64
165  max_rech_data_6           float64
166  max_rech_data_7           float64
167  max_rech_data_8           float64
168  max_rech_data_9           float64
169  count_rech_2g_6           float64
170  count_rech_2g_7           float64
171  count_rech_2g_8           float64
172  count_rech_2g_9           float64
173  count_rech_3g_6           float64
174  count_rech_3g_7           float64
175  count_rech_3g_8           float64
176  count_rech_3g_9           float64
```

177	av_rech_amt_data_6	float64
178	av_rech_amt_data_7	float64
179	av_rech_amt_data_8	float64
180	av_rech_amt_data_9	float64
181	vol_2g_mb_6	float64
182	vol_2g_mb_7	float64
183	vol_2g_mb_8	float64
184	vol_2g_mb_9	float64
185	vol_3g_mb_6	float64
186	vol_3g_mb_7	float64
187	vol_3g_mb_8	float64
188	vol_3g_mb_9	float64
189	arpu_3g_6	float64
190	arpu_3g_7	float64
191	arpu_3g_8	float64
192	arpu_3g_9	float64
193	arpu_2g_6	float64
194	arpu_2g_7	float64
195	arpu_2g_8	float64
196	arpu_2g_9	float64
197	night_pck_user_6	float64
198	night_pck_user_7	float64
199	night_pck_user_8	float64
200	night_pck_user_9	float64
201	monthly_2g_6	int64
202	monthly_2g_7	int64
203	monthly_2g_8	int64
204	monthly_2g_9	int64
205	sachet_2g_6	int64
206	sachet_2g_7	int64
207	sachet_2g_8	int64
208	sachet_2g_9	int64
209	monthly_3g_6	int64
210	monthly_3g_7	int64
211	monthly_3g_8	int64
212	monthly_3g_9	int64
213	sachet_3g_6	int64
214	sachet_3g_7	int64
215	sachet_3g_8	int64
216	sachet_3g_9	int64
217	fb_user_6	float64
218	fb_user_7	float64
219	fb_user_8	float64

```
 220   fb_user_9                  float64
 221   aon                        int64
 222   aug_vbc_3g                 float64
 223   jul_vbc_3g                 float64
 224   jun_vbc_3g                 float64
 225   sep_vbc_3g                 float64
dtypes: float64(179), int64(35), object(12)
memory usage: 172.4+ MB
```

This telecom dataset has 99999 rows and 226 columns

Checking the terms used in the data from data dictionary provided.

```
# Importing the excel file of the dictionary.
telecom_data_dict = pd.read_excel("Data+Dictionary-+Telecom+Churn+Case+Study.xlsx")
# Displaying the dictionary items
telecom_data_dict
```

0	MOBILE_NUMBER	Customer phone number
1	CIRCLE_ID	Telecom circle area to which the customer belongs to
2	LOC	Local calls - within same telecom circle
3	STD	STD calls - outside the calling circle
4	IC	Incoming calls
5	OG	Outgoing calls
6	T2T	Operator T to T, i.e. within same operator (mobile to mobile)
7	T2M	Operator T to other operator mobile
8	T2O	Operator T to other operator fixed line
9	T2F	Operator T to fixed lines of T
10	T2C	Operator T to it's own call center
11	ARPU	Average revenue per user
12	MOU	Minutes of usage - voice calls

13	AON	Age on network - number of days the customer is using the operator T network
14	ONNET	All kind of calls within the same operator network
15	OFFNET	All kind of calls outside the operator T network
16	ROAM	Indicates that customer is in roaming zone during the cal
17	SPL	Special calls
18	ISD	ISD calls
19	RECH	Recharge
20	NUM	Number
21	AMT	Amount in local currency
22	MAX	Maximum
23	DATA	Mobile internet
24	3G	3G network
25	AV	Average
26	VOL	Mobile internet usage volume (in MB)
27	2G	2G network
28	PCK	Prepaid service schemes called - PACKS

29	NIGHT	Scheme to use during specific night hours only
30	MONTHLY	Service schemes with validity equivalent to a month
31	SACHET	Service schemes with validity smaller than a month
32	*.6	KPI for the month of June
33	*.7	KPI for the month of July
34	*.8	KPI for the month of August
35	*.9	KPI for the month of September
36	FB_USER	Service scheme to avail services of Facebook and similar social networking sites

37 VBC Volume based cost - when no specific scheme is not purchased and paid as per usage

Initial Statistical Analysis of the Data

```
# Statistical analysis of the numercial features
telecom_data.describe().T
```

	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**
mobile_number	99999.0	7.001207e+09	695669.386290	7.000000e+09	7.000606e+09	7.001205e+09	7.001812e+09	7.002411e+09
circle_id	99999.0	1.090000e+02	0.000000	1.090000e+02	1.090000e+02	1.090000e+02	1.090000e+02	1.090000e+02
loc_og_t2o_mou	98981.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
std_og_t2o_mou	98981.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00

	98981.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
arpu_6	99999.0	2.829874e+02	328.439770	-2.258709e+03	9.341150e+01	1.977040e+02	3.710600e+02	2.773109e+04
arpu_7	99999.0	2.785366e+02	338.156291	-2.014045e+03	8.698050e+01	1.916400e+02	3.653445e+02	3.514583e+04
arpu_8	99999.0	2.791547e+02	344.474791	-9.458080e+02	8.412600e+01	1.920800e+02	3.693705e+02	3.354362e+04
	99999.0	2.616451e+02	341.998630	-1.899505e+03	6.268500e+01	1.768490e+02	3.534665e+02	3.880562e+04
onnet_mou_6	96062.0	1.323959e+02	297.207406	0.000000e+00	7.380000e+00	3.431000e+01	1.187400e+02	7.376710e+03
onnet_mou_7	96140.0	1.336708e+02	308.794148	0.000000e+00	6.660000e+00	3.233000e+01	1.155950e+02	8.157780e+03
onnet_mou_8	94621.0	1.330181e+02	308.951589	0.000000e+00	6.460000e+00	3.236000e+01	1.158600e+02	1.075256e+04
onnet_mou_9	92254.0	1.303023e+02	308.477668	0.000000e+00	5.330000e+00	2.984000e+01	1.121300e+02	1.042746e+04
	96062.0	1.979356e+02	316.851613	0.000000e+00	3.473000e+01	9.631000e+01	2.318600e+02	8.362360e+03
offnet_mou_7	96140.0	1.970451e+02	325.862803	0.000000e+00	3.219000e+01	9.173500e+01	2.268150e+02	9.667130e+03
offnet_mou_8	94621.0	1.965748e+02	327.170662	0.000000e+00	3.163000e+01	9.214000e+01	2.282600e+02	1.400734e+04
offnet_mou_9	92254.0	1.903372e+02	319.396092	0.000000e+00	2.713000e+01	8.729000e+01	2.205050e+02	1.031076e+04
roam_ic_mou_6	96062.0	9.950013e+00	72.825411	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.372438e+04
roam_ic_mou_7	96140.0	7.149898e+00	73.447948	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.537104e+04

roam_ic_mou_8	94621.0	7.292981e+00	68.402466	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.309536e+04
roam_ic_mou_9	92254.0	6.343841e+00	57.137537	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	8.464030e+03
roam_og_mou_6	96062.0	1.391134e+01	71.443196	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.775110e+03
roam_og_mou_7	96140.0	9.818732e+00	58.455762	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.812040e+03
roam_og_mou_8	94621.0	9.971890e+00	64.713221	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.337040e+03
roam_og_mou_9	92254.0	8.555519e+00	58.438186	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.428460e+03
loc_og_t2t_mou_6	96062.0	4.710076e+01	150.856393	0.000000e+00	1.660000e+00	1.191000e+01	4.096000e+01	6.431330e+03
loc_og_t2t_mou_7	96140.0	4.647301e+01	155.318705	0.000000e+00	1.630000e+00	1.161000e+01	3.991000e+01	7.400660e+03
loc_og_t2t_mou_8	94621.0	4.588781e+01	151.184830	0.000000e+00	1.600000e+00	1.173000e+01	4.011000e+01	1.075256e+04
loc_og_t2m_mou_6	96062.0	9.334209e+01	162.780544	0.000000e+00	9.880000e+00	4.103000e+01	1.103900e+02	4.729740e+03
loc_og_t2m_mou_7	96140.0	9.139713e+01	157.492308	0.000000e+00	1.002500e+01	4.043000e+01	1.075600e+02	4.557140e+03
loc_og_t2m_mou_8	94621.0	9.175513e+01	156.537048	0.000000e+00	9.810000e+00	4.036000e+01	1.090900e+02	4.961330e+03
loc_og_t2m_mou_9	92254.0	9.046319e+01	158.681454	0.000000e+00	8.810000e+00	3.912000e+01	1.068100e+02	4.429880e+03
loc_og_t2f_mou_6	96062.0	3.751013e+00	14.230438	0.000000e+00	0.000000e+00	0.000000e+00	2.080000e+00	1.466030e+03
loc_og_t2f_mou_7	96140.0	3.792985e+00	14.264986	0.000000e+00	0.000000e+00	0.000000e+00	2.090000e+00	1.196430e+03

loc_og_t2f_mou_8	94621.0	3.677991e+00	13.270996	0.000000e+00	0.000000e+00	0.000000e+00	2.040000e+00	9.284900e+02
loc_og_t2f_mou_9	92254.0	3.655123e+00	13.457549	0.000000e+00	0.000000e+00	0.000000e+00	1.940000e+00	9.274100e+02
loc_og_t2c_mou_6	96062.0	1.123056e+00	5.448946	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.428600e+02
loc_og_t2c_mou_7	96140.0	1.368500e+00	7.533445	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	9.162400e+02

loc_og_mou_8	94621.0	1.413282e+02	245.914311	0.000000e+00	1.711000e+01	6.373000e+01	1.661100e+02	1.103991e+04
loc_og_mou_9	92254.0	1.387100e+02	245.934517	0.000000e+00	1.556000e+01	6.184000e+01	1.622250e+02	1.109926e+04

std_og_t2t_mou_6	96062.0	7.982987e+01	252.476533	0.000000e+00	0.000000e+00	0.000000e+00	3.080750e+01	7.366580e+03
std_og_t2t_mou_7	96140.0	8.329960e+01	263.631042	0.000000e+00	0.000000e+00	0.000000e+00	3.113250e+01	8.133660e+03
std_og_t2t_mou_8	94621.0	8.328267e+01	265.486090	0.000000e+00	0.000000e+00	0.000000e+00	3.058000e+01	8.014430e+03
std_og_t2t_mou_9	92254.0	8.234292e+01	267.184991	0.000000e+00	0.000000e+00	0.000000e+00	2.823000e+01	9.382580e+03

std_og_t2m_mou_6	96062.0	8.729962e+01	255.617850	0.000000e+00	0.000000e+00	3.950000e+00	5.329000e+01	8.314760e+03
std_og_t2m_mou_7	96140.0	9.080414e+01	269.347911	0.000000e+00	0.000000e+00	3.635000e+00	5.404000e+01	9.284740e+03
std_og_t2m_mou_8	94621.0	8.983839e+01	271.757783	0.000000e+00	0.000000e+00	3.310000e+00	5.249000e+01	1.395004e+04
std_og_t2m_mou_9	92254.0	8.627662e+01	261.407396	0.000000e+00	0.000000e+00	2.500000e+00	4.856000e+01	1.022343e+04
std_og_t2f_mou_6	96062.0	1.129011e+00	7.984970	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	6.285600e+02

std_og_t2f_mou_7	96140.0	1.115010e+00	8.599406	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.446300e+02
std_og_t2f_mou_8	94621.0	1.067792e+00	7.905971	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.169100e+02
std_og_t2f_mou_9	92254.0	1.042362e+00	8.261770	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	8.084900e+02
std_og_t2c_mou_6	96062.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
std_og_t2c_mou_7	96140.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
std_og_t2c_mou_8	94621.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
std_og_t2c_mou_9	92254.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
std_og_mou_6	96062.0	1.682612e+02	389.948499	0.000000e+00	0.000000e+00	1.164000e+01	1.448375e+02	8.432990e+03
std_og_mou_7	96140.0	1.752214e+02	408.922934	0.000000e+00	0.000000e+00	1.109000e+01	1.506150e+02	1.093673e+04
std_og_mou_8	94621.0	1.741915e+02	411.633049	0.000000e+00	0.000000e+00	1.041000e+01	1.479400e+02	1.398006e+04
std_og_mou_9	92254.0	1.696645e+02	405.138658	0.000000e+00	0.000000e+00	8.410000e+00	1.421050e+02	1.149531e+04
isd_og_mou_6	96062.0	7.982775e-01	25.765248	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.900660e+03
isd_og_mou_7	96140.0	7.765721e-01	25.603052	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.490280e+03
isd_og_mou_8	94621.0	7.912471e-01	25.544471	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.681540e+03
isd_og_mou_9	92254.0	7.238921e-01	21.310751	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.244530e+03

spl_og_mou_6	96062.0	3.916811e+00	14.936449	0.000000e+00	0.000000e+00	0.000000e+00	2.430000e+00	1.023210e+03
spl_og_mou_7	96140.0	4.978279e+00	20.661570	0.000000e+00	0.000000e+00	0.000000e+00	3.710000e+00	2.372510e+03
spl_og_mou_8	94621.0	5.053769e+00	17.855111	0.000000e+00	0.000000e+00	0.000000e+00	3.990000e+00	1.390880e+03

spl_og_mou_8	94621.0	5.053769e+00	17.855111	0.000000e+00	0.000000e+00	0.000000e+00	3.990000e+00	1.390880e+03
spl_og_mou_9	92254.0	4.412767e+00	16.328227	0.000000e+00	0.000000e+00	0.000000e+00	3.230000e+00	1.635710e+03
og_others_6	96062.0	4.541571e-01	4.125911	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	8.008900e+02
og_others_7	96140.0	3.023539e-02	2.161717	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.701300e+02
og_others_8	94621.0	3.337198e-02	2.323464	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.949300e+02
og_others_9	92254.0	4.745572e-02	3.635466	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	7.877900e+02

total_og_mou_6	99999.0	3.051334e+02	463.419481	0.000000e+00	4.474000e+01	1.451400e+02	3.728600e+02	1.067403e+04
total_og_mou_7	99999.0	3.102312e+02	480.031178	0.000000e+00	4.301000e+01	1.415300e+02	3.785700e+02	1.136531e+04
total_og_mou_8	99999.0	3.041195e+02	478.150031	0.000000e+00	3.858000e+01	1.386100e+02	3.699000e+02	1.404306e+04
total_og_mou_9	99999.0	2.892792e+02	468.980002	0.000000e+00	2.551000e+01	1.254600e+02	3.534800e+02	1.151773e+04

loc_ic_t2t_mou_6	96062.0	4.792237e+01	140.258485	0.000000e+00	2.990000e+00	1.569000e+01	4.684000e+01	6.626930e+03
loc_ic_t2t_mou_7	96140.0	4.799052e+01	145.795055	0.000000e+00	3.230000e+00	1.574000e+01	4.581000e+01	9.324660e+03

loc_ic_t2t_mou_8	94621.0	4.721136e+01	137.239552	0.000000e+00	3.280000e+00	1.603000e+01	4.629000e+01	1.069623e+04
loc_ic_t2t_mou_9	92254.0	4.628179e+01	140.130610	0.000000e+00	3.290000e+00	1.566000e+01	4.518000e+01	1.059883e+04
loc_ic_t2m_mou_6	96062.0	1.074757e+02	171.713903	0.000000e+00	1.729000e+01	5.649000e+01	1.323875e+02	4.693860e+03
loc_ic_t2m_mou_7	96140.0	1.071205e+02	169.423620	0.000000e+00	1.859000e+01	5.708000e+01	1.309600e+02	4.455830e+03
loc_ic_t2m_mou_8	94621.0	1.084605e+02	169.723759	0.000000e+00	1.893000e+01	5.824000e+01	1.339300e+02	6.274190e+03
loc_ic_t2m_mou_9	92254.0	1.061555e+02	165.492803	0.000000e+00	1.856000e+01	5.661000e+01	1.304900e+02	5.463780e+03
loc_ic_t2f_mou_6	96062.0	1.208430e+01	40.140895	0.000000e+00	0.000000e+00	8.800000e-01	8.140000e+00	1.872340e+03
loc_ic_t2f_mou_7	96140.0	1.259970e+01	42.977442	0.000000e+00	0.000000e+00	9.300000e-01	8.282500e+00	1.983010e+03
loc_ic_t2f_mou_8	94621.0	1.175183e+01	39.125379	0.000000e+00	0.000000e+00	9.300000e-01	8.110000e+00	2.433060e+03
loc_ic_t2f_mou_9	92254.0	1.217310e+01	43.840776	0.000000e+00	0.000000e+00	9.600000e-01	8.140000e+00	4.318280e+03
loc_ic_mou_6	96062.0	1.674911e+02	254.124029	0.000000e+00	3.039000e+01	9.216000e+01	2.080750e+02	7.454630e+03
loc_ic_mou_7	96140.0	1.677195e+02	256.242707	0.000000e+00	3.246000e+01	9.255000e+01	2.058375e+02	9.669910e+03
loc_ic_mou_8	94621.0	1.674326e+02	250.025523	0.000000e+00	3.274000e+01	9.383000e+01	2.072800e+02	1.083016e+04
loc_ic_mou_9	92254.0	1.646193e+02	249.845070	0.000000e+00	3.229000e+01	9.164000e+01	2.027375e+02	1.079629e+04

std_ic_t2t_mou_6	96062.0	9.575993e+00	54.330607	0.000000e+00	0.000000e+00	0.000000e+00	4.060000e+00	5.459560e+03
std_ic_t2t_mou_7	96140.0	1.001190e+01	57.411971	0.000000e+00	0.000000e+00	0.000000e+00	4.230000e+00	5.800930e+03
std_ic_t2t_mou_8	94621.0	9.883921e+00	55.073186	0.000000e+00	0.000000e+00	0.000000e+00	4.080000e+00	4.309290e+03
std_ic_t2t_mou_9	92254.0	9.432479e+00	53.376273	0.000000e+00	0.000000e+00	0.000000e+00	3.510000e+00	3.819830e+03
std_ic_t2m_mou_6	96062.0	2.072224e+01	80.793414	0.000000e+00	0.000000e+00	2.030000e+00	1.503000e+01	5.647160e+03
std_ic_t2m_mou_7	96140.0	2.165641e+01	86.521393	0.000000e+00	0.000000e+00	2.040000e+00	1.574000e+01	6.141880e+03
std_ic_t2m_mou_8	94621.0	2.118321e+01	83.683565	0.000000e+00	0.000000e+00	2.030000e+00	1.536000e+01	5.645860e+03
std_ic_t2m_mou_9	92254.0	1.962091e+01	74.913050	0.000000e+00	0.000000e+00	1.740000e+00	1.426000e+01	5.689760e+03
std_ic_t2f_mou_6	96062.0	2.156397e+00	16.495594	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.351110e+03
std_ic_t2f_mou_7	96140.0	2.216923e+00	16.454061	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.136080e+03
std_ic_t2f_mou_8	94621.0	2.085004e+00	15.812580	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.394890e+03
std_ic_t2f_mou_9	92254.0	2.173419e+00	15.978601	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.431960e+03
std_ic_t2o_mou_6	96062.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
std_ic_t2o_mou_7	96140.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
std_ic_t2o_mou_8	94621.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00

std_ic_t2o_mou_9	92254.0	0.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
std_ic_mou_6	96062.0	3.245718e+01	106.283386	0.000000e+00	0.000000e+00	5.890000e+00	2.693000e+01	5.712110e+03
std_ic_mou_7	96140.0	3.388783e+01	113.720168	0.000000e+00	0.000000e+00	5.960000e+00	2.831000e+01	6.745760e+03
std_ic_mou_8	94621.0	3.315474e+01	110.127008	0.000000e+00	1.000000e-02	5.880000e+00	2.771000e+01	5.957140e+03
std_ic_mou_9	92254.0	3.122934e+01	101.982303	0.000000e+00	0.000000e+00	5.380000e+00	2.569000e+01	5.956660e+03
total_ic_mou_6	99999.0	2.001300e+02	291.651671	0.000000e+00	3.853000e+01	1.147400e+02	2.516700e+02	7.716140e+03
total_ic_mou_7	99999.0	2.028531e+02	298.124954	0.000000e+00	4.119000e+01	1.163400e+02	2.506600e+02	9.699010e+03
total_ic_mou_8	99999.0	1.987508e+02	289.321094	0.000000e+00	3.829000e+01	1.146600e+02	2.489900e+02	1.083038e+04
total_ic_mou_9	99999.0	1.892143e+02	284.823024	0.000000e+00	3.237000e+01	1.058900e+02	2.363200e+02	1.079659e+04
spl_ic_mou_6	96062.0	6.155660e-02	0.160920	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.976000e+01
spl_ic_mou_7	96140.0	3.358477e-02	0.155725	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.133000e+01
spl_ic_mou_8	94621.0	4.036134e-02	0.146147	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.686000e+01
spl_ic_mou_9	92254.0	1.631370e-01	0.527860	0.000000e+00	0.000000e+00	0.000000e+00	6.000000e-02	6.238000e+01
isd_ic_mou_6	96062.0	7.460608e+00	59.722948	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	6.789410e+03

isd_ic_mou_7	96140.0	8.334936e+00	65.219829	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.289540e+03
isd_ic_mou_8	94621.0	8.442001e+00	63.813098	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.127010e+03
isd_ic_mou_9	92254.0	8.063003e+00	63.505379	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.057740e+03
ic_others_6	96062.0	8.546555e-01	11.955164	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.362940e+03
ic_others_7	96140.0	1.012960e+00	12.673099	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.495940e+03
ic_others_8	94621.0	9.708005e-01	13.284348	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.327510e+03
ic_others_9	92254.0	1.017162e+00	12.381172	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.005230e+03
total_rech_num_6	99999.0	7.558806e+00	7.078405	0.000000e+00	3.000000e+00	6.000000e+00	9.000000e+00	3.070000e+02
total_rech_num_7	99999.0	7.700367e+00	7.070422	0.000000e+00	3.000000e+00	6.000000e+00	1.000000e+01	1.380000e+02
total_rech_num_8	99999.0	7.212912e+00	7.203753	0.000000e+00	3.000000e+00	5.000000e+00	9.000000e+00	1.960000e+02
total_rech_num_9	99999.0	6.893019e+00	7.096261	0.000000e+00	3.000000e+00	5.000000e+00	9.000000e+00	1.310000e+02
total_rech_amt_6	99999.0	3.275146e+02	398.019701	0.000000e+00	1.090000e+02	2.300000e+02	4.375000e+02	3.519000e+04
total_rech_amt_7	99999.0	3.229630e+02	408.114237	0.000000e+00	1.000000e+02	2.200000e+02	4.280000e+02	4.033500e+04
total_rech_amt_8	99999.0	3.241571e+02	416.540455	0.000000e+00	9.000000e+01	2.250000e+02	4.345000e+02	4.532000e+04
total_rech_amt_9	99999.0	3.033457e+02	404.588583	0.000000e+00	5.200000e+01	2.000000e+02	4.150000e+02	3.723500e+04

max_rech_amt_6	99999.0	1.046375e+02	120.614894	0.000000e+00	3.000000e+01	1.100000e+02	1.200000e+02	4.010000e+03
max_rech_amt_7	99999.0	1.047524e+02	124.523970	0.000000e+00	3.000000e+01	1.100000e+02	1.280000e+02	4.010000e+03
max_rech_amt_8	99999.0	1.077282e+02	126.902505	0.000000e+00	3.000000e+01	9.800000e+01	1.440000e+02	4.449000e+03
max_rech_amt_9	99999.0	1.019439e+02	125.375109	0.000000e+00	2.800000e+01	6.100000e+01	1.440000e+02	3.399000e+03
last_day_rch_amt_6	99999.0	6.315625e+01	97.356649	0.000000e+00	0.000000e+00	3.000000e+01	1.100000e+02	4.010000e+03
last_day_rch_amt_7	99999.0	5.938580e+01	95.915385	0.000000e+00	0.000000e+00	3.000000e+01	1.100000e+02	4.010000e+03
last_day_rch_amt_8	99999.0	6.264172e+01	104.431816	0.000000e+00	0.000000e+00	3.000000e+01	1.300000e+02	4.449000e+03
last_day_rch_amt_9	99999.0	4.390125e+01	90.809712	0.000000e+00	0.000000e+00	0.000000e+00	5.000000e+01	3.399000e+03
total_rech_data_6	25153.0	2.463802e+00	2.789128	1.000000e+00	1.000000e+00	1.000000e+00	3.000000e+00	6.100000e+01
total_rech_data_7	25571.0	2.666419e+00	3.031593	1.000000e+00	1.000000e+00	1.000000e+00	3.000000e+00	5.400000e+01
total_rech_data_8	26339.0	2.651999e+00	3.074987	1.000000e+00	1.000000e+00	1.000000e+00	3.000000e+00	6.000000e+01
total_rech_data_9	25922.0	2.441170e+00	2.516339	1.000000e+00	1.000000e+00	2.000000e+00	3.000000e+00	8.400000e+01
max_rech_data_6	25153.0	1.263934e+02	108.477235	1.000000e+00	2.500000e+01	1.450000e+02	1.770000e+02	1.555000e+03
max_rech_data_7	25571.0	1.267295e+02	109.765267	1.000000e+00	2.500000e+01	1.450000e+02	1.770000e+02	1.555000e+03
max_rech_data_8	26339.0	1.257173e+02	109.437851	1.000000e+00	2.500000e+01	1.450000e+02	1.790000e+02	1.555000e+03

max_rech_data_9	25922.0	1.249414e+02	111.363760	1.000000e+00	2.500000e+01	1.450000e+02	1.790000e+02	1.555000e+03
count_rech_2g_6	25153.0	1.864668e+00	2.570254	0.000000e+00	1.000000e+00	1.000000e+00	2.000000e+00	4.200000e+01
count_rech_2g_7	25571.0	2.044699e+00	2.768332	0.000000e+00	1.000000e+00	1.000000e+00	2.000000e+00	4.800000e+01
count_rech_2g_8	26339.0	2.016288e+00	2.720132	0.000000e+00	1.000000e+00	1.000000e+00	2.000000e+00	4.400000e+01
count_rech_2g_9	25922.0	1.781807e+00	2.214701	0.000000e+00	1.000000e+00	1.000000e+00	2.000000e+00	4.000000e+01
count_rech_3g_6	25153.0	5.991333e-01	1.274428	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	2.900000e+01
count_rech_3g_7	25571.0	6.217199e-01	1.394524	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	3.500000e+01
count_rech_3g_8	26339.0	6.357113e-01	1.422827	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	4.500000e+01
count_rech_3g_9	25922.0	6.593627e-01	1.411513	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	4.900000e+01
av_rech_amt_data_6	25153.0	1.926010e+02	192.646318	1.000000e+00	8.200000e+01	1.540000e+02	2.520000e+02	7.546000e+03
av_rech_amt_data_7	25571.0	2.009813e+02	196.791224	5.000000e-01	9.200000e+01	1.540000e+02	2.520000e+02	4.365000e+03
av_rech_amt_data_8	26339.0	1.975265e+02	191.301305	5.000000e-01	8.700000e+01	1.540000e+02	2.520000e+02	4.076000e+03
av_rech_amt_data_9	25922.0	1.927343e+02	188.400286	1.000000e+00	6.900000e+01	1.640000e+02	2.520000e+02	4.061000e+03
vol_2g_mb_6	99999.0	5.190496e+01	213.356445	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.028590e+04
vol_2g_mb_7	99999.0	5.122994e+01	212.302217	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	7.873550e+03

vol_2g_mb_8	99999.0	5.017015e+01	212.347892	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.111761e+04
vol_2g_mb_9	99999.0	4.471970e+01	198.653570	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	8.993950e+03
vol_3g_mb_6	99999.0	1.213962e+02	544.247227	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.573540e+04
vol_3g_mb_7	99999.0	1.289958e+02	541.494013	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.814412e+04
vol_3g_mb_8	99999.0	1.354107e+02	558.775335	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.003606e+04
vol_3g_mb_9	99999.0	1.360566e+02	577.394194	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.922127e+04
arpu_3g_6	25153.0	8.955506e+01	193.124653	-3.082000e+01	0.000000e+00	4.800000e-01	1.220700e+02	6.362280e+03
arpu_3g_7	25571.0	8.938412e+01	195.893924	-2.604000e+01	0.000000e+00	4.200000e-01	1.195600e+02	4.980900e+03
arpu_3g_8	26339.0	9.117385e+01	188.180936	-2.449000e+01	0.000000e+00	8.800000e-01	1.220700e+02	3.716900e+03
arpu_3g_9	25922.0	1.002641e+02	216.291992	-7.109000e+01	0.000000e+00	2.605000e+00	1.400100e+02	1.388431e+04
arpu_2g_6	25153.0	8.639800e+01	172.767523	-3.583000e+01	0.000000e+00	1.083000e+01	1.220700e+02	6.433760e+03
arpu_2g_7	25571.0	8.591445e+01	176.379871	-1.548000e+01	0.000000e+00	8.810000e+00	1.220700e+02	4.809360e+03
arpu_2g_8	26339.0	8.659948e+01	168.247852	-5.583000e+01	0.000000e+00	9.270000e+00	1.220700e+02	3.483170e+03
arpu_2g_9	25922.0	9.371203e+01	171.384224	-4.574000e+01	0.000000e+00	1.480000e+01	1.400100e+02	3.467170e+03
night_pck_user_6	25153.0	2.508647e-02	0.156391	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00

night_pck_user_7	25571.0	2.303391e-02	0.150014	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
night_pck_user_8	26339.0	2.084362e-02	0.142863	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
night_pck_user_9	25922.0	1.597099e-02	0.125366	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
monthly_2g_6	99999.0	7.964080e-02	0.295058	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.000000e+00
monthly_2g_7	99999.0	8.322083e-02	0.304395	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.000000e+00
monthly_2g_8	99999.0	8.100081e-02	0.299568	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.000000e+00
monthly_2g_9	99999.0	6.878069e-02	0.278120	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.000000e+00
sachet_2g_6	99999.0	3.893839e-01	1.497320	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.200000e+01
sachet_2g_7	99999.0	4.396344e-01	1.636230	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.800000e+01
sachet_2g_8	99999.0	4.500745e-01	1.630263	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.400000e+01
sachet_2g_9	99999.0	3.931039e-01	1.347140	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.000000e+01
monthly_3g_6	99999.0	7.592076e-02	0.363371	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.400000e+01
monthly_3g_7	99999.0	7.858079e-02	0.387231	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.600000e+01
monthly_3g_8	99999.0	8.294083e-02	0.384947	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.600000e+01
monthly_3g_9	99999.0	8.634086e-02	0.384978	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.100000e+0

sachet_3g_6	99999.0	7.478075e-02	0.568344	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.900000e+01
sachet_3g_7	99999.0	8.040080e-02	0.628334	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.500000e+01
sachet_3g_8	99999.0	8.450085e-02	0.660234	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.100000e+01
sachet_3g_9	99999.0	8.458085e-02	0.650457	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.900000e+01
fb_user_6	25153.0	9.144038e-01	0.279772	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
fb_user_7	25571.0	9.087638e-01	0.287950	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
fb_user_8	26339.0	8.908083e-01	0.311885	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
fb_user_9	25922.0	8.609675e-01	0.345987	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+0
aon	99999.0	1.219855e+03	954.733842	1.800000e+02	4.670000e+02	8.630000e+02	1.807500e+03	4.337000e+03
aug_vbc_3g	99999.0	6.817025e+01	267.580450	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.291622e+04
jul_vbc_3g	99999.0	6.683906e+01	271.201856	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	9.165600e+03

```
# lets check the columns unique values and drop such columns with its value as 1
unique_1_col=[]
for i in telecom_data.columns:
    if telecom_data[i].nunique() == 1:
        unique_1_col.append(i)
    else:
        pass

telecom_data.drop(unique_1_col, axis=1, inplace = True)
```

```
print("\n The following Columns are dropped from the dataset as their unique value is 1. (i.e.)It has no variance in the model\n",
    unique_1_col)
```

```
 The following Columns are dropped from the dataset as their unique value is 1. (i.e.)It has no variance in the model
 ['circle_id', 'loc_og_t2o_mou', 'std_og_t2o_mou', 'loc_ic_t2o_mou', 'last_date_of_month_6', 'last_date_of_month_7', 'last_date_of_month_8', 'last_date_of_month_9', 'std_og_t2c_mou_6', 'std_og_t2c_mou_7', 'std_og_t2c_mou_8', 'std_og_t2c_mou_9', 'std_ic_t2o_mou_6', 'std_ic_t2o_mou_7', 'std_ic_t2o_mou_8', 'std_ic_t2o_mou_9']
```

```
# The curent dimensions of the dataset
telecom_data.shape
(99999, 210)
# Checkng the overall missing values in the dataset
((telecom_data.isnull().sum()/telecom_data.shape[0])*100).round(2).sort_values(ascending=False)
max_rech_data_6          74.85
fb_user_6                74.85
count_rech_3g_6          74.85
count_rech_2g_6          74.85
night_pck_user_6         74.85
arpu_3g_6                74.85
total_rech_data_6        74.85
av_rech_amt_data_6       74.85
arpu_2g_6                74.85
date_of_last_rech_data_6 74.85
arpu_3g_7                74.43
night_pck_user_7         74.43
total_rech_data_7        74.43
date_of_last_rech_data_7 74.43
av_rech_amt_data_7       74.43
max_rech_data_7          74.43
fb_user_7                74.43
count_rech_3g_7          74.43
arpu_2g_7                74.43
count_rech_2g_7          74.43
count_rech_3g_9          74.08
date_of_last_rech_data_9 74.08
count_rech_2g_9          74.08
fb_user_9                74.08
total_rech_data_9        74.08
max_rech_data_9          74.08
night_pck_user_9         74.08
arpu_2g_9                74.08
av_rech_amt_data_9       74.08
arpu_3g_9                74.08
arpu_3g_8                73.66
```

fb_user_8	73.66
total_rech_data_8	73.66
count_rech_2g_8	73.66
arpu_2g_8	73.66
date_of_last_rech_data_8	73.66
count_rech_3g_8	73.66
max_rech_data_8	73.66
av_rech_amt_data_8	73.66
night_pck_user_8	73.66
loc_og_t2t_mou_9	7.75
std_ic_t2m_mou_9	7.75
isd_og_mou_9	7.75
roam_og_mou_9	7.75
std_ic_t2t_mou_9	7.75
spl_og_mou_9	7.75
loc_ic_mou_9	7.75
og_others_9	7.75
roam_ic_mou_9	7.75
ic_others_9	7.75
offnet_mou_9	7.75
loc_ic_t2f_mou_9	7.75
loc_og_t2m_mou_9	7.75
loc_ic_t2t_mou_9	7.75
loc_ic_t2m_mou_9	7.75
spl_ic_mou_9	7.75
std_ic_t2f_mou_9	7.75
std_og_mou_9	7.75
std_og_t2m_mou_9	7.75
loc_og_mou_9	7.75
loc_og_t2c_mou_9	7.75
std_og_t2t_mou_9	7.75
isd_ic_mou_9	7.75
loc_og_t2f_mou_9	7.75
onnet_mou_9	7.75
std_ic_mou_9	7.75
std_og_t2f_mou_9	7.75
std_ic_t2t_mou_8	5.38
offnet_mou_8	5.38
std_ic_mou_8	5.38
loc_ic_mou_8	5.38
onnet_mou_8	5.38
loc_ic_t2m_mou_8	5.38
isd_ic_mou_8	5.38
std_ic_t2f_mou_8	5.38
loc_ic_t2f_mou_8	5.38
spl_ic_mou_8	5.38
std_ic_t2m_mou_8	5.38
ic_others_8	5.38
loc_og_t2m_mou_8	5.38
std_og_t2m_mou_8	5.38

roam_og_mou_8	5.38
loc_og_mou_8	5.38
std_og_t2t_mou_8	5.38
isd_og_mou_8	5.38
loc_og_t2t_mou_8	5.38
spl_og_mou_8	5.38
loc_og_t2c_mou_8	5.38
std_og_mou_8	5.38
og_others_8	5.38
roam_ic_mou_8	5.38
std_og_t2f_mou_8	5.38
loc_og_t2f_mou_8	5.38
loc_ic_t2t_mou_8	5.38
date_of_last_rech_9	4.76
std_og_t2t_mou_6	3.94
onnet_mou_6	3.94
std_og_t2m_mou_6	3.94
spl_ic_mou_6	3.94
loc_ic_t2m_mou_6	3.94
isd_ic_mou_6	3.94
loc_og_t2m_mou_6	3.94
ic_others_6	3.94
loc_og_t2c_mou_6	3.94
loc_og_t2f_mou_6	3.94
loc_og_mou_6	3.94
std_ic_mou_6	3.94
std_og_t2f_mou_6	3.94
offnet_mou_6	3.94
loc_ic_t2f_mou_6	3.94
std_og_mou_6	3.94
loc_og_t2t_mou_6	3.94
std_ic_t2f_mou_6	3.94
isd_og_mou_6	3.94
std_ic_t2m_mou_6	3.94
og_others_6	3.94
std_ic_t2t_mou_6	3.94
roam_og_mou_6	3.94
loc_ic_mou_6	3.94
loc_ic_t2t_mou_6	3.94
roam_ic_mou_6	3.94
spl_og_mou_6	3.94
loc_ic_mou_7	3.86
std_ic_t2t_mou_7	3.86
isd_og_mou_7	3.86
og_others_7	3.86
std_og_mou_7	3.86
loc_ic_t2t_mou_7	3.86
loc_ic_t2m_mou_7	3.86
loc_ic_t2f_mou_7	3.86
std_og_t2f_mou_7	3.86

std_ic_t2m_mou_7	3.86
std_ic_t2f_mou_7	3.86
std_ic_mou_7	3.86
std_og_t2m_mou_7	3.86
std_og_t2t_mou_7	3.86
loc_og_mou_7	3.86
spl_ic_mou_7	3.86
isd_ic_mou_7	3.86
ic_others_7	3.86
loc_og_t2c_mou_7	3.86
loc_og_t2f_mou_7	3.86
loc_og_t2m_mou_7	3.86
loc_og_t2t_mou_7	3.86
roam_og_mou_7	3.86
roam_ic_mou_7	3.86
offnet_mou_7	3.86
onnet_mou_7	3.86
spl_og_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
aug_vbc_3g	0.00
jul_vbc_3g	0.00
jun_vbc_3g	0.00
monthly_3g_8	0.00
aon	0.00
monthly_2g_8	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00
monthly_2g_9	0.00
monthly_2g_7	0.00
monthly_3g_7	0.00
monthly_3g_9	0.00
monthly_2g_6	0.00
sachet_3g_6	0.00
sachet_3g_7	0.00
sachet_3g_8	0.00
sachet_3g_9	0.00
mobile_number	0.00
total_ic_mou_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
total_rech_num_9	0.00
total_rech_num_8	0.00
total_rech_num_7	0.00
total_rech_num_6	0.00
total_ic_mou_9	0.00

```
total_ic_mou_8          0.00
total_ic_mou_7          0.00
arpu_6                  0.00
total_og_mou_9          0.00
total_og_mou_8          0.00
total_og_mou_7          0.00
total_og_mou_6          0.00
arpu_9                  0.00
arpu_8                  0.00
arpu_7                  0.00
total_rech_amt_6        0.00
total_rech_amt_7        0.00
total_rech_amt_8        0.00
last_day_rch_amt_9      0.00
vol_3g_mb_7             0.00
vol_3g_mb_6             0.00
vol_2g_mb_9             0.00
vol_2g_mb_8             0.00
vol_2g_mb_7             0.00
vol_2g_mb_6             0.00
last_day_rch_amt_8      0.00
total_rech_amt_9        0.00
last_day_rch_amt_7      0.00
last_day_rch_amt_6      0.00
max_rech_amt_9          0.00
max_rech_amt_8          0.00
max_rech_amt_7          0.00
max_rech_amt_6          0.00
sep_vbc_3g              0.00
dtype: float64
```

As we can see that the columns with datetime values represented as object, they can be converted into datetime format

```
# selecting all the columns with datetime format
date_col= telecom_data.select_dtypes(include=['object'])
print("\nThese are the columns available with datetime format represented as object\n",date_col.columns)

# Converting the selected columns to datetime format
for i in date_col.columns:
    telecom_data[i] = pd.to_datetime(telecom_data[i])

# Current dimension of the dataset
telecom_data.shape
```

```
These are the columns available with datetime format represented as
object
 Index(['date_of_last_rech_6', 'date_of_last_rech_7',
'date_of_last_rech_8',
       'date_of_last_rech_9', 'date_of_last_rech_data_6',
```

```
       'date_of_last_rech_data_7', 'date_of_last_rech_data_8',
       'date_of_last_rech_data_9'],
      dtype='object')
```

(99999, 210)

```
# confirming the conversion of dtype
telecom_data.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Data columns (total 210 columns):
 #    Column                    Dtype  
---   ------                    -----  
 0    mobile_number             int64  
 1    arpu_6                    float64
 2    arpu_7                    float64
 3    arpu_8                    float64
 4    arpu_9                    float64
 5    onnet_mou_6               float64
 6    onnet_mou_7               float64
 7    onnet_mou_8               float64
 8    onnet_mou_9               float64
 9    offnet_mou_6              float64
 10   offnet_mou_7              float64
 11   offnet_mou_8              float64
 12   offnet_mou_9              float64
 13   roam_ic_mou_6             float64
 14   roam_ic_mou_7             float64
 15   roam_ic_mou_8             float64
 16   roam_ic_mou_9             float64
 17   roam_og_mou_6             float64
 18   roam_og_mou_7             float64
 19   roam_og_mou_8             float64
 20   roam_og_mou_9             float64
 21   loc_og_t2t_mou_6          float64
 22   loc_og_t2t_mou_7          float64
 23   loc_og_t2t_mou_8          float64
 24   loc_og_t2t_mou_9          float64
 25   loc_og_t2m_mou_6          float64
 26   loc_og_t2m_mou_7          float64
 27   loc_og_t2m_mou_8          float64
 28   loc_og_t2m_mou_9          float64
 29   loc_og_t2f_mou_6          float64
 30   loc_og_t2f_mou_7          float64
 31   loc_og_t2f_mou_8          float64
```

```
32   loc_og_t2f_mou_9          float64
33   loc_og_t2c_mou_6          float64
34   loc_og_t2c_mou_7          float64
35   loc_og_t2c_mou_8          float64
36   loc_og_t2c_mou_9          float64
37   loc_og_mou_6              float64
38   loc_og_mou_7              float64
39   loc_og_mou_8              float64
40   loc_og_mou_9              float64
41   std_og_t2t_mou_6          float64
42   std_og_t2t_mou_7          float64
43   std_og_t2t_mou_8          float64
44   std_og_t2t_mou_9          float64
45   std_og_t2m_mou_6          float64
46   std_og_t2m_mou_7          float64
47   std_og_t2m_mou_8          float64
48   std_og_t2m_mou_9          float64
49   std_og_t2f_mou_6          float64
50   std_og_t2f_mou_7          float64
51   std_og_t2f_mou_8          float64
52   std_og_t2f_mou_9          float64
53   std_og_mou_6              float64
54   std_og_mou_7              float64
55   std_og_mou_8              float64
56   std_og_mou_9              float64
57   isd_og_mou_6              float64
58   isd_og_mou_7              float64
59   isd_og_mou_8              float64
60   isd_og_mou_9              float64
61   spl_og_mou_6              float64
62   spl_og_mou_7              float64
63   spl_og_mou_8              float64
64   spl_og_mou_9              float64
65   og_others_6               float64
66   og_others_7               float64
67   og_others_8               float64
68   og_others_9               float64
69   total_og_mou_6            float64
70   total_og_mou_7            float64
71   total_og_mou_8            float64
72   total_og_mou_9            float64
73   loc_ic_t2t_mou_6          float64
74   loc_ic_t2t_mou_7          float64
```

75	loc_ic_t2t_mou_8	float64
76	loc_ic_t2t_mou_9	float64
77	loc_ic_t2m_mou_6	float64
78	loc_ic_t2m_mou_7	float64
79	loc_ic_t2m_mou_8	float64
80	loc_ic_t2m_mou_9	float64
81	loc_ic_t2f_mou_6	float64
82	loc_ic_t2f_mou_7	float64
83	loc_ic_t2f_mou_8	float64
84	loc_ic_t2f_mou_9	float64
85	loc_ic_mou_6	float64
86	loc_ic_mou_7	float64
87	loc_ic_mou_8	float64
88	loc_ic_mou_9	float64
89	std_ic_t2t_mou_6	float64
90	std_ic_t2t_mou_7	float64
91	std_ic_t2t_mou_8	float64
92	std_ic_t2t_mou_9	float64
93	std_ic_t2m_mou_6	float64
94	std_ic_t2m_mou_7	float64
95	std_ic_t2m_mou_8	float64
96	std_ic_t2m_mou_9	float64
97	std_ic_t2f_mou_6	float64
98	std_ic_t2f_mou_7	float64
99	std_ic_t2f_mou_8	float64
100	std_ic_t2f_mou_9	float64
101	std_ic_mou_6	float64
102	std_ic_mou_7	float64
103	std_ic_mou_8	float64
104	std_ic_mou_9	float64
105	total_ic_mou_6	float64
106	total_ic_mou_7	float64
107	total_ic_mou_8	float64
108	total_ic_mou_9	float64
109	spl_ic_mou_6	float64
110	spl_ic_mou_7	float64
111	spl_ic_mou_8	float64
112	spl_ic_mou_9	float64
113	isd_ic_mou_6	float64
114	isd_ic_mou_7	float64
115	isd_ic_mou_8	float64
116	isd_ic_mou_9	float64
117	ic_others_6	float64

```
118  ic_others_7                float64
119  ic_others_8                float64
120  ic_others_9                float64
121  total_rech_num_6           int64
122  total_rech_num_7           int64
123  total_rech_num_8           int64
124  total_rech_num_9           int64
125  total_rech_amt_6           int64
126  total_rech_amt_7           int64
127  total_rech_amt_8           int64
128  total_rech_amt_9           int64
129  max_rech_amt_6             int64
130  max_rech_amt_7             int64
131  max_rech_amt_8             int64
132  max_rech_amt_9             int64
133  date_of_last_rech_6        datetime64[ns]
134  date_of_last_rech_7        datetime64[ns]
135  date_of_last_rech_8        datetime64[ns]
136  date_of_last_rech_9        datetime64[ns]
137  last_day_rch_amt_6         int64
138  last_day_rch_amt_7         int64
139  last_day_rch_amt_8         int64
140  last_day_rch_amt_9         int64
141  date_of_last_rech_data_6   datetime64[ns]
142  date_of_last_rech_data_7   datetime64[ns]
143  date_of_last_rech_data_8   datetime64[ns]
144  date_of_last_rech_data_9   datetime64[ns]
145  total_rech_data_6          float64
146  total_rech_data_7          float64
147  total_rech_data_8          float64
148  total_rech_data_9          float64
149  max_rech_data_6            float64
150  max_rech_data_7            float64
151  max_rech_data_8            float64
152  max_rech_data_9            float64
153  count_rech_2g_6            float64
154  count_rech_2g_7            float64
155  count_rech_2g_8            float64
156  count_rech_2g_9            float64
157  count_rech_3g_6            float64
158  count_rech_3g_7            float64
159  count_rech_3g_8            float64
160  count_rech_3g_9            float64
```

161	av_rech_amt_data_6	float64
162	av_rech_amt_data_7	float64
163	av_rech_amt_data_8	float64
164	av_rech_amt_data_9	float64
165	vol_2g_mb_6	float64
166	vol_2g_mb_7	float64
167	vol_2g_mb_8	float64
168	vol_2g_mb_9	float64
169	vol_3g_mb_6	float64
170	vol_3g_mb_7	float64
171	vol_3g_mb_8	float64
172	vol_3g_mb_9	float64
173	arpu_3g_6	float64
174	arpu_3g_7	float64
175	arpu_3g_8	float64
176	arpu_3g_9	float64
177	arpu_2g_6	float64
178	arpu_2g_7	float64
179	arpu_2g_8	float64
180	arpu_2g_9	float64
181	night_pck_user_6	float64
182	night_pck_user_7	float64
183	night_pck_user_8	float64
184	night_pck_user_9	float64
185	monthly_2g_6	int64
186	monthly_2g_7	int64
187	monthly_2g_8	int64
188	monthly_2g_9	int64
189	sachet_2g_6	int64
190	sachet_2g_7	int64
191	sachet_2g_8	int64
192	sachet_2g_9	int64
193	monthly_3g_6	int64
194	monthly_3g_7	int64
195	monthly_3g_8	int64
196	monthly_3g_9	int64
197	sachet_3g_6	int64
198	sachet_3g_7	int64
199	sachet_3g_8	int64
200	sachet_3g_9	int64
201	fb_user_6	float64
202	fb_user_7	float64
203	fb_user_8	float64

```
 204   fb_user_9                 float64
 205   aon                       int64
 206   aug_vbc_3g                float64
 207   jul_vbc_3g                float64
 208   jun_vbc_3g                float64
 209   sep_vbc_3g                float64
dtypes: datetime64[ns](8), float64(168), int64(34)
memory usage: 160.2 MB
```

Handling missing values

Handling missing values of meaningful attribute column

```
# Handling missing values with respect to `data recharge` attributes
telecom_data[['date_of_last_rech_data_6','total_rech_data_6','max_rech_data_6']].head(10)
```

- Let us conside the column `date_of_last_rech_data` indicating the date of the last recharge made in any given month for mobile internet. Here it can deduced if the `total_rech_data` and the `max_rech_data` also has missing values, the missing values in all the columns mentioned can be considered as meaningful missing.
- Hence imputing 0 as their values.
- Meaningfull missing in this case represents the the customer has not done any recharge for mobile interenet.

Handling the missing values for the attributes `total_rech_data_*`, `max_rech_data_*` and for month 6,7,8 and 9

```
# Code for conditional imputation
start_time=time.time()
for i in range(len(telecom_data)):
  # Handling 'total_rech_data', 'max_rech_data' and for month 6
    if pd.isnull((telecom_data['total_rech_data_6'][i]) and (telecom_data['max_rech_data_6'][i])):
        if pd.isnull(telecom_data['date_of_last_rech_data_6'][i]):
            telecom_data['total_rech_data_6'][i]=0
            telecom_data['max_rech_data_6'][i]=0

  # Handling 'total_rech_data', 'max_rech_data' and for month 7
    if pd.isnull((telecom_data['total_rech_data_7'][i]) and (telecom_data['max_rech_data_7'][i])):
        if pd.isnull(telecom_data['date_of_last_rech_data_7'][i]):
            telecom_data['total_rech_data_7'][i]=0
            telecom_data['max_rech_data_7'][i]=0

  # Handling 'total_rech_data', 'max_rech_data' and for month 8
    if pd.isnull((telecom_data['total_rech_data_8'][i]) and (telecom_data['max_rech_data_8'][i])):
        if pd.isnull(telecom_data['date_of_last_rech_data_8'][i]):
            telecom_data['total_rech_data_8'][i]=0
            telecom_data['max_rech_data_8'][i]=0

  # Handling 'total_rech_data', 'max_rech_data' and for month 9
    if pd.isnull((telecom_data['total_rech_data_9'][i]) and (telecom_data['max_rech_data_9'][i])):
        if pd.isnull(telecom_data['date_of_last_rech_data_9'][i]):
            telecom_data['total_rech_data_9'][i]=0
```

```
        telecom_data['max_rech_data_9'][i]=0

end_time = time.time()
print("\nExecution Time = ", round(end_time-start_time,2),"seconds")
print("The columns \n'total_rech_data_6','total_rech_data_7','total_rech_data_8','total_rech_data_9'\n'max_rech_data_6','max_rech_data_7','max_rech_data_8','max_rech_data_9' are imputed with 0 based on the condition explained above")
```

```
Execution Time =  382.04 seconds
The columns
'total_rech_data_6','total_rech_data_7','total_rech_data_8','total_rech_data_9'
'max_rech_data_6','max_rech_data_7','max_rech_data_8','max_rech_data_9'
are imputed with 0 based on the condition explained above
```

Handling the missing values for the attributes `count_rech_2g_*`,`count_rech_3g_*` for month 6,7,8 and 9

```
# Checking the related columns values
telecom_data[['count_rech_2g_6','count_rech_3g_6','total_rech_data_6']].head(10)
```

From the above tablular the column values of `total_rech_data` for each month from 6 to 9 respectively is the sum of the columns values of `count_rech_2g` for each month from 6 to 9 respectively and `count_rech_3g` for each month from 6 to 9 respectively, which derives to a multicollinearity issue. In order to reduce the multicollinearity, we can drop the columns `count_rech_2g` for each month from 6 to 9 respectively and `count_rech_3g` for each month from 6 to 9 respectively.

```
# Dropping the columns 'count_rech_2g_*' & 'count_rech_3g_*' for the months 6,7,8 and 9
telecom_data.drop(['count_rech_2g_6','count_rech_3g_6',
                   'count_rech_2g_7','count_rech_3g_7',
                   'count_rech_2g_8','count_rech_3g_8',
                   'count_rech_2g_9','count_rech_3g_9'],axis=1, inplace=True)

print("The 'count_rech_2g_6','count_rech_3g_6','count_rech_2g_7','count_rech_3g_7','count_rech_2g_8','count_rech_3g_8','count_rech_2g_9','count_rech_3g_9' columns are dropped as they can be explained from the 'total_rech_data'column")
```

```
The
'count_rech_2g_6','count_rech_3g_6','count_rech_2g_7','count_rech_3g_7'
,'count_rech_2g_8','count_rech_3g_8','count_rech_2g_9','count_rech_3g_9
' columns are dropped as they can be explained from the
'total_rech_data'column
```

```
# The curent dimensions of the dataset
telecom_data.shape
```

(99999, 202)

Handling the missing values for the attributes `arpu_3g_*`,`arpu_2g_*` for month 6,7,8 and 9

```
# Checking the related columns values
```

```python
telecom_data[['arpu_3g_6','arpu_2g_6','av_rech_amt_data_6']].head(10)
# Checking the correlation between the above mentioned columns in tabular for months 6,7,8 and 9
print("Correlation table for month 6\n\n",
telecom_data[['arpu_3g_6','arpu_2g_6','av_rech_amt_data_6']].corr())
print("\nCorrelation table for month 7\n\n",
telecom_data[['arpu_3g_7','arpu_2g_7','av_rech_amt_data_7']].corr())
print("\nCorrelation table for month 8\n\n",
telecom_data[['arpu_3g_8','arpu_2g_8','av_rech_amt_data_8']].corr())
print("\nCorrelation table for month 9\n\n",
telecom_data[['arpu_3g_9','arpu_2g_9','av_rech_amt_data_9']].corr())
```

```
Correlation table for month 6

                    arpu_3g_6  arpu_2g_6  av_rech_amt_data_6
arpu_3g_6            1.000000   0.932232   0.809695
arpu_2g_6            0.932232   1.000000   0.834065
av_rech_amt_data_6   0.809695   0.834065   1.000000

Correlation table for month 7

                    arpu_3g_7  arpu_2g_7  av_rech_amt_data_7
arpu_3g_7            1.000000   0.930366   0.796131
arpu_2g_7            0.930366   1.000000   0.815933
av_rech_amt_data_7   0.796131   0.815933   1.000000

Correlation table for month 8

                    arpu_3g_8  arpu_2g_8  av_rech_amt_data_8
arpu_3g_8            1.000000   0.924925   0.787165
arpu_2g_8            0.924925   1.000000   0.805482
av_rech_amt_data_8   0.787165   0.805482   1.000000

Correlation table for month 9

                    arpu_3g_9  arpu_2g_9  av_rech_amt_data_9
arpu_3g_9            1.000000   0.852253   0.722932
arpu_2g_9            0.852253   1.000000   0.817815
av_rech_amt_data_9   0.722932   0.817815   1.000000
```

From the above correlation table between attributes `arpu_2g_*` and `arpu_3g_*` for each month from 6 to 9 respectively is highly correlated to the attribute `av_rech_amt_data_*` for each month from 6 to 9 respectively.
Considering the high correlation between them, it is safer to drop the attributes `arpu_2g_*` and `arpu_3g_*`.

```python
# Dropping the columns 'arpu_3g_*'&'arpu_2g_*' in month 6,7,8 and 9 datafrom the dataset
```

```
telecom_data.drop(['arpu_3g_6','arpu_2g_6',
            'arpu_3g_7','arpu_2g_7',
            'arpu_3g_8','arpu_2g_8',
            'arpu_3g_9','arpu_2g_9'],axis=1, inplace=True)
print("\nThe columns'arpu_3g_6','arpu_2g_6','arpu_3g_7','arpu_2g_7','arpu_3g_8','arpu_2g_8','arpu_3g_9','arpu_2g_9' are dropped from the dataset due to high corellation between their respective arpu_* variable in the dataset\n")
```

```
The
columns'arpu_3g_6','arpu_2g_6','arpu_3g_7','arpu_2g_7','arpu_3g_8','arpu_2g_8','arpu_3g_9','arpu_2g_9' are dropped from the dataset due to high corellation between their respective arpu_* variable in the dataset
```

```
# The curent dimensions of the dataset
telecom_data.shape
```

(99999, 194)

Handling the other attributes with higher missing value percentage

The column `fb_user_*` and `night_pck_user_*` for each month from 6 to 9 respectively has a missing values above 50% and does not seem to add any information to understand the data. Hence we can drop these columns for further analysis.

```
telecom_data.drop(['fb_user_6','fb_user_7','fb_user_8','fb_user_9',
            'night_pck_user_6','night_pck_user_7','night_pck_user_8','night_pck_user_9'],
            axis=1, inplace=True)
print("\nThe columns 'fb_user_6','fb_user_7','fb_user_8','fb_user_9','night_pck_user_6','night_pck_user_7','night_pck_user_8','night_pck_user_9' are dropped from the dataset as it has no meaning to the data snd has high missing values above 50%\n")
```

```
The columns
'fb_user_6','fb_user_7','fb_user_8','fb_user_9','night_pck_user_6','night_pck_user_7','night_pck_user_8','night_pck_user_9' are dropped from the dataset as it has no meaning to the data snd has high missing values above 50%
```

```
# The curent dimensions of the dataset
telecom_data.shape
```

(99999, 186)

Handling the missing values for the attributes `av_rech_amt_data_*` for month 6,7,8 and 9

```
# Checking the related columns values
telecom_data[['av_rech_amt_data_7','max_rech_data_7','total_rech_data_7']].head(10)
```

From the above tabular it is deduced that the missing values for the column `av_rech_amt_data_*` for each month from 6 to 9 can be replaced as 0 if the `total_rech_data_*` for each month from 6 to 9 respectively is 0. i.e. if the total recharge done is 0 then the average recharge amount shall also be 0.

```
# Code for conditional imputation
start_time = time.time()
for i in range(len(telecom_data)):
  # Handling `av_rech_amt_data`  for month 6
    if (pd.isnull(telecom_data['av_rech_amt_data_6'][i]) and (telecom_data['total_rech_data_6'][i]==0)):
        telecom_data['av_rech_amt_data_6'][i] = 0

  # Handling `av_rech_amt_data`  for month 7
    if (pd.isnull(telecom_data['av_rech_amt_data_7'][i]) and (telecom_data['total_rech_data_7'][i]==0)):
        telecom_data['av_rech_amt_data_7'][i] = 0

  # Handling `av_rech_amt_data`  for month 8
    if (pd.isnull(telecom_data['av_rech_amt_data_8'][i]) and (telecom_data['total_rech_data_8'][i]==0)):
        telecom_data['av_rech_amt_data_8'][i] = 0

  # Handling `av_rech_amt_data`  for month 9
    if (pd.isnull(telecom_data['av_rech_amt_data_9'][i]) and (telecom_data['total_rech_data_9'][i]==0)):
        telecom_data['av_rech_amt_data_9'][i] = 0


end_time=time.time()
print("\nExecution Time = ", round(end_time-start_time,2),"seconds")
print("\nThe columns 'av_rech_amt_data_6','av_rech_amt_data_7','av_rech_amt_data_8' and 'av_rech_amt_data_9' are imputed with 0 based on the condition explained above\n")
```

```
Execution Time =  189.69 seconds

The columns 'av_rech_amt_data_6','av_rech_amt_data_7','av_rech_amt_data_8' and 'av_rech_amt_data_9' are imputed with 0 based on the condition explained above
```

```
# Checkng the overall missing values in the dataset
((telecom_data.isnull().sum()/telecom_data.shape[0])*100).round(2).sort_values(ascending=False)
```

```
date_of_last_rech_data_6    74.85
date_of_last_rech_data_7    74.43
date_of_last_rech_data_9    74.08
date_of_last_rech_data_8    73.66
og_others_9                  7.75
loc_og_t2f_mou_9             7.75
```

loc_og_t2t_mou_9	7.75
loc_ic_t2f_mou_9	7.75
std_ic_mou_9	7.75
std_og_t2f_mou_9	7.75
loc_og_t2m_mou_9	7.75
loc_ic_mou_9	7.75
std_og_t2m_mou_9	7.75
std_ic_t2f_mou_9	7.75
std_ic_t2t_mou_9	7.75
loc_og_t2c_mou_9	7.75
std_ic_t2m_mou_9	7.75
std_og_t2t_mou_9	7.75
loc_og_mou_9	7.75
std_og_mou_9	7.75
spl_ic_mou_9	7.75
roam_og_mou_9	7.75
spl_og_mou_9	7.75
loc_ic_t2t_mou_9	7.75
isd_og_mou_9	7.75
roam_ic_mou_9	7.75
loc_ic_t2m_mou_9	7.75
isd_ic_mou_9	7.75
onnet_mou_9	7.75
ic_others_9	7.75
offnet_mou_9	7.75
og_others_8	5.38
std_ic_t2t_mou_8	5.38
std_og_t2m_mou_8	5.38
loc_ic_t2m_mou_8	5.38
spl_og_mou_8	5.38
loc_ic_t2f_mou_8	5.38
loc_ic_mou_8	5.38
std_og_t2f_mou_8	5.38
isd_og_mou_8	5.38
std_og_mou_8	5.38
std_og_t2t_mou_8	5.38
loc_ic_t2t_mou_8	5.38
std_ic_t2m_mou_8	5.38
loc_og_t2t_mou_8	5.38
onnet_mou_8	5.38
ic_others_8	5.38
offnet_mou_8	5.38
roam_ic_mou_8	5.38
isd_ic_mou_8	5.38
roam_og_mou_8	5.38
loc_og_mou_8	5.38
spl_ic_mou_8	5.38
loc_og_t2m_mou_8	5.38
std_ic_mou_8	5.38
loc_og_t2f_mou_8	5.38

loc_og_t2c_mou_8	5.38
std_ic_t2f_mou_8	5.38
date_of_last_rech_9	4.76
loc_ic_mou_6	3.94
spl_ic_mou_6	3.94
std_ic_mou_6	3.94
loc_ic_t2f_mou_6	3.94
isd_ic_mou_6	3.94
loc_ic_t2t_mou_6	3.94
ic_others_6	3.94
std_ic_t2t_mou_6	3.94
loc_ic_t2m_mou_6	3.94
std_ic_t2f_mou_6	3.94
std_ic_t2m_mou_6	3.94
loc_og_t2c_mou_6	3.94
spl_og_mou_6	3.94
std_og_t2t_mou_6	3.94
loc_og_t2f_mou_6	3.94
std_og_t2m_mou_6	3.94
onnet_mou_6	3.94
std_og_t2f_mou_6	3.94
loc_og_t2m_mou_6	3.94
std_og_mou_6	3.94
isd_og_mou_6	3.94
loc_og_t2t_mou_6	3.94
loc_og_mou_6	3.94
roam_og_mou_6	3.94
og_others_6	3.94
roam_ic_mou_6	3.94
offnet_mou_6	3.94
offnet_mou_7	3.86
loc_og_t2c_mou_7	3.86
onnet_mou_7	3.86
loc_og_t2f_mou_7	3.86
std_ic_mou_7	3.86
isd_ic_mou_7	3.86
loc_og_t2m_mou_7	3.86
roam_og_mou_7	3.86
loc_og_t2t_mou_7	3.86
roam_ic_mou_7	3.86
std_ic_t2f_mou_7	3.86
ic_others_7	3.86
spl_ic_mou_7	3.86
loc_og_mou_7	3.86
std_og_t2f_mou_7	3.86
loc_ic_t2t_mou_7	3.86
og_others_7	3.86
loc_ic_t2m_mou_7	3.86
spl_og_mou_7	3.86
loc_ic_t2f_mou_7	3.86

std_og_mou_7	3.86
loc_ic_mou_7	3.86
isd_og_mou_7	3.86
std_og_t2m_mou_7	3.86
std_ic_t2t_mou_7	3.86
std_og_t2t_mou_7	3.86
std_ic_t2m_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
jun_vbc_3g	0.00
vol_2g_mb_8	0.00
vol_3g_mb_6	0.00
av_rech_amt_data_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_7	0.00
vol_3g_mb_8	0.00
av_rech_amt_data_7	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_8	0.00
av_rech_amt_data_9	0.00
aug_vbc_3g	0.00
jul_vbc_3g	0.00
vol_3g_mb_7	0.00
sachet_3g_9	0.00
vol_3g_mb_9	0.00
monthly_3g_6	0.00
sachet_3g_7	0.00
aon	0.00
max_rech_data_8	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00
sachet_3g_8	0.00
monthly_2g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00
monthly_2g_9	0.00
monthly_2g_8	0.00
monthly_2g_7	0.00
max_rech_data_9	0.00
mobile_number	0.00
max_rech_data_7	0.00
arpu_6	0.00
total_rech_num_7	0.00
total_rech_num_6	0.00
total_ic_mou_9	0.00

```
total_ic_mou_8           0.00
total_ic_mou_7           0.00
total_ic_mou_6           0.00
total_og_mou_9           0.00
total_rech_num_9         0.00
total_og_mou_8           0.00
total_og_mou_7           0.00
total_og_mou_6           0.00
arpu_9                   0.00
arpu_8                   0.00
arpu_7                   0.00
total_rech_num_8         0.00
total_rech_amt_6         0.00
max_rech_data_6          0.00
last_day_rch_amt_7       0.00
total_rech_data_9        0.00
total_rech_data_8        0.00
total_rech_data_7        0.00
total_rech_data_6        0.00
last_day_rch_amt_9       0.00
last_day_rch_amt_8       0.00
last_day_rch_amt_6       0.00
total_rech_amt_7         0.00
max_rech_amt_9           0.00
max_rech_amt_8           0.00
max_rech_amt_7           0.00
max_rech_amt_6           0.00
total_rech_amt_9         0.00
total_rech_amt_8         0.00
sep_vbc_3g               0.00
dtype: float64
```

```
telecom_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Columns: 186 entries, mobile_number to sep_vbc_3g
dtypes: datetime64[ns](8), float64(144), int64(34)
memory usage: 141.9 MB
```

From the above results, we can conclude, the `date_of_last_rech_data_*` corresponding to months 6,7,8 and 9 are of no value after the conditional imputation of of columns `total_rech_data_*`, `max_rech_data_*`are completes.
Also the missing value percentage is high for these columns and can be dropped from the dataset.

```
# Dropping the columns related to datetime dtype from the dataset
telecom_data.drop(["date_of_last_rech_data_6","date_of_last_rech_data_7",
                   "date_of_last_rech_data_8","date_of_last_rech_data_9"], axis=1, inplace=True)
```

```
print("\nThe columns 'date_of_last_rech_data_6','date_of_last_rech_data_7','date_of_last_rech_data_8','date_of_last_rech_data_9' are dropped as it has no significance to the data\n")
```

```
The columns
'date_of_last_rech_data_6','date_of_last_rech_data_7','date_of_last_rech_data_8','date_of_last_rech_data_9' are dropped as it has no significance to the data
```

As we can no more utilise the datetime column, we can drop the `date_of_last_rech_data_*` column corresponding to months 6,7,8 and 9 respectively.

```
# Dropping the columns related to datetime dtype from the dataset
telecom_data.drop(["date_of_last_rech_6","date_of_last_rech_7",
                "date_of_last_rech_8","date_of_last_rech_9"], axis=1, inplace=True)
print("\nThe columns 'date_of_last_rech_6','date_of_last_rech_7','date_of_last_rech_8','date_of_last_rech_9' are dropped as it has no significance to the data\n")
```

```
The columns
'date_of_last_rech_6','date_of_last_rech_7','date_of_last_rech_8','date_of_last_rech_9' are dropped as it has no significance to the data
```

```
# The curent dimensions of the dataset
telecom_data.shape
```

(99999, 178)

Since the columns used to determine the High Value Customer is clear of null values, we can filter the overall data and then handle the remaining missing values for each column

Filtering the High Value Customer from Good Phase

```
# Filtering the data
 # We are filtering the data in accordance to total revenue generated per customer.

 # first we need the total amount recharge amount done for data alone, we have average rechage amount done.

 # Calculating the total recharge amount done for data alone in months 6,7,8 and 9
telecom_data['total_rech_amt_data_6']=telecom_data['av_rech_amt_data_6'] * telecom_data['total_rech_data_6']
telecom_data['total_rech_amt_data_7']=telecom_data['av_rech_amt_data_7'] * telecom_data['total_rech_data_7']

# Calculating the overall recharge amount for the months 6,7,8 and 9
telecom_data['overall_rech_amt_6'] = telecom_data['total_rech_amt_data_6'] + telecom_data['total_rech_amt_6']
telecom_data['overall_rech_amt_7'] = telecom_data['total_rech_amt_data_7'] + telecom_data['total_rech_amt_7']
```

```
# Calculating the average recharge done by customer in months June and July(i.e. 6th and 7th month)
telecom_data['avg_rech_amt_6_7'] = (telecom_data['overall_rech_amt_6'] +
telecom_data['overall_rech_amt_7'])/2

# Finding the value of 70th percentage in the overall revenues defining the high value customer creteria for the company
cut_off = telecom_data['avg_rech_amt_6_7'].quantile(0.70)
print("\nThe 70th quantile value to determine the High Value Customer is: ",cut_off,"\n")

# Filtering the data to the top 30% considered as High Value Customer
telecom_data = telecom_data[telecom_data['avg_rech_amt_6_7'] >= cut_off]
```

```
The 70th quantile value to determine the High Value Customer is:  478.0
```

```
# The curent dimension of the dataset
telecom_data.shape
```

(30001, 183)

The total number of customers is now limited to ~30k who lies under the High Value customer criteria basen upon which the model is built.

```
# Let us check the missing values percentages again for the HVC group
    # Checkng the overall missing values in the dataset
((telecom_data.isnull().sum()/telecom_data.shape[0])*100).round(2).sort_values(ascending=False)
```

```
loc_ic_t2f_mou_9       6.34
spl_og_mou_9           6.34
loc_og_t2m_mou_9       6.34
loc_og_t2f_mou_9       6.34
loc_ic_t2t_mou_9       6.34
isd_og_mou_9           6.34
loc_og_t2t_mou_9       6.34
loc_ic_t2m_mou_9       6.34
std_og_t2t_mou_9       6.34
roam_og_mou_9          6.34
std_og_mou_9           6.34
loc_ic_mou_9           6.34
std_ic_t2t_mou_9       6.34
roam_ic_mou_9          6.34
loc_og_t2c_mou_9       6.34
std_ic_t2m_mou_9       6.34
offnet_mou_9           6.34
std_ic_t2f_mou_9       6.34
std_og_t2f_mou_9       6.34
std_ic_mou_9           6.34
onnet_mou_9            6.34
spl_ic_mou_9           6.34
loc_og_mou_9           6.34
isd_ic_mou_9           6.34
```

std_og_t2m_mou_9	6.34
ic_others_9	6.34
og_others_9	6.34
std_og_mou_8	3.91
isd_og_mou_8	3.91
std_og_t2f_mou_8	3.91
std_ic_t2t_mou_8	3.91
og_others_8	3.91
loc_ic_t2t_mou_8	3.91
loc_ic_t2m_mou_8	3.91
loc_ic_t2f_mou_8	3.91
loc_ic_mou_8	3.91
std_ic_t2m_mou_8	3.91
std_ic_t2f_mou_8	3.91
std_ic_mou_8	3.91
spl_ic_mou_8	3.91
isd_ic_mou_8	3.91
ic_others_8	3.91
std_og_t2m_mou_8	3.91
spl_og_mou_8	3.91
std_og_t2t_mou_8	3.91
offnet_mou_8	3.91
loc_og_t2t_mou_8	3.91
loc_og_t2f_mou_8	3.91
roam_og_mou_8	3.91
roam_ic_mou_8	3.91
loc_og_t2c_mou_8	3.91
loc_og_t2m_mou_8	3.91
loc_og_mou_8	3.91
onnet_mou_8	3.91
offnet_mou_6	1.82
std_og_t2m_mou_6	1.82
loc_ic_t2m_mou_6	1.82
loc_og_t2m_mou_6	1.82
ic_others_6	1.82
loc_ic_t2f_mou_6	1.82
loc_og_t2t_mou_6	1.82
onnet_mou_6	1.82
std_ic_t2t_mou_6	1.82
isd_ic_mou_6	1.82
std_ic_mou_6	1.82
roam_og_mou_6	1.82
std_ic_t2m_mou_6	1.82
loc_ic_t2t_mou_6	1.82
spl_ic_mou_6	1.82
roam_ic_mou_6	1.82
std_ic_t2f_mou_6	1.82
loc_ic_mou_6	1.82
loc_og_mou_6	1.82
std_og_t2t_mou_6	1.82

loc_og_t2c_mou_6	1.82
std_og_t2f_mou_6	1.82
isd_og_mou_6	1.82
loc_og_t2f_mou_6	1.82
spl_og_mou_6	1.82
std_og_mou_6	1.82
og_others_6	1.82
std_ic_mou_7	1.79
roam_ic_mou_7	1.79
std_ic_t2f_mou_7	1.79
std_og_mou_7	1.79
offnet_mou_7	1.79
std_ic_t2m_mou_7	1.79
loc_og_mou_7	1.79
ic_others_7	1.79
std_og_t2m_mou_7	1.79
std_og_t2f_mou_7	1.79
spl_ic_mou_7	1.79
onnet_mou_7	1.79
isd_og_mou_7	1.79
loc_og_t2c_mou_7	1.79
std_og_t2t_mou_7	1.79
loc_og_t2t_mou_7	1.79
loc_ic_t2t_mou_7	1.79
loc_og_t2m_mou_7	1.79
loc_ic_t2m_mou_7	1.79
loc_og_t2f_mou_7	1.79
og_others_7	1.79
loc_ic_t2f_mou_7	1.79
isd_ic_mou_7	1.79
loc_ic_mou_7	1.79
spl_og_mou_7	1.79
roam_og_mou_7	1.79
std_ic_t2t_mou_7	1.79
monthly_2g_9	0.00
monthly_2g_8	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_8	0.00
sachet_2g_6	0.00
sachet_2g_7	0.00
av_rech_amt_data_9	0.00
vol_3g_mb_6	0.00
monthly_2g_7	0.00
monthly_2g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
vol_2g_mb_9	0.00
vol_3g_mb_7	0.00
sachet_2g_9	0.00
vol_2g_mb_7	0.00

vol_2g_mb_8	0.00
sachet_2g_8	0.00
jul_vbc_3g	0.00
monthly_3g_6	0.00
monthly_3g_7	0.00
overall_rech_amt_7	0.00
overall_rech_amt_6	0.00
total_rech_amt_data_7	0.00
total_rech_amt_data_6	0.00
sep_vbc_3g	0.00
jun_vbc_3g	0.00
av_rech_amt_data_6	0.00
aug_vbc_3g	0.00
aon	0.00
sachet_3g_9	0.00
sachet_3g_8	0.00
sachet_3g_7	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
av_rech_amt_data_7	0.00
mobile_number	0.00
max_rech_data_9	0.00
total_rech_amt_6	0.00
total_rech_num_8	0.00
total_rech_num_7	0.00
total_rech_num_6	0.00
total_ic_mou_9	0.00
total_ic_mou_8	0.00
total_ic_mou_7	0.00
total_ic_mou_6	0.00
arpu_6	0.00
total_og_mou_9	0.00
total_og_mou_8	0.00
total_og_mou_7	0.00
total_og_mou_6	0.00
arpu_9	0.00
arpu_8	0.00
arpu_7	0.00
total_rech_num_9	0.00
total_rech_amt_7	0.00
max_rech_data_8	0.00
total_rech_amt_8	0.00
max_rech_data_7	0.00
max_rech_data_6	0.00
total_rech_data_9	0.00
total_rech_data_8	0.00
total_rech_data_7	0.00
total_rech_data_6	0.00
last_day_rch_amt_9	0.00

```
last_day_rch_amt_8      0.00
last_day_rch_amt_7      0.00
last_day_rch_amt_6      0.00
max_rech_amt_9          0.00
max_rech_amt_8          0.00
max_rech_amt_7          0.00
max_rech_amt_6          0.00
total_rech_amt_9        0.00
avg_rech_amt_6_7        0.00
dtype: float64
```

*** The remaining attributes with missing value can be imputed using the advanced imputation technique like `KNNImputer`.***

```
# Numerical columns available
num_col = telecom_data.select_dtypes(include = ['int64','float64']).columns.tolist()
# Importing the libraries for Scaling and Imputation
from sklearn.impute import KNNImputer
from sklearn.preprocessing import MinMaxScaler

# Calling the Scaling function
scalar = MinMaxScaler()

# Scaling and transforming the data for the columns that are numerical
telecom_data[num_col]=scalar.fit_transform(telecom_data[num_col])

# Calling the KNN Imputer function
knn=KNNImputer(n_neighbors=3)

# Imputing the NaN values using KNN Imputer
start_time=time.time()

telecom_data_knn = pd.DataFrame(knn.fit_transform(telecom_data[num_col]))
telecom_data_knn.columns=telecom_data[num_col].columns

end_time=time.time()
print("\nExecution Time = ", round(end_time-start_time,2),"seconds\n")
```

```
Execution Time =  170.72 seconds
```

```
# check for any null values after imputation for numerical columns
telecom_data_knn.isnull().sum().sum()
0
```

The KNN Imputer has replaced all the null values in the numerical column usingK-means algorithm sucessfully

```
# Since we sclaed the numerical columns for the purpose of handling the null values,
  #we can restore the sclaed alues to its original form.

# Converting the scaled data back to the original data
telecom_data[num_col]=scalar.inverse_transform(telecom_data_knn)
```

```
# Checking the top 10 data
telecom_data.head(10)
# Checking the overall missing values in the dataset
((telecom_data.isnull().sum()/telecom_data.shape[0])*100).round(2).sort_values(ascending=Fals
e)
mobile_number          0.0
isd_ic_mou_8           0.0
ic_others_6            0.0
ic_others_7            0.0
ic_others_8            0.0
ic_others_9            0.0
total_rech_num_6       0.0
total_rech_num_7       0.0
total_rech_num_8       0.0
total_rech_num_9       0.0
total_rech_amt_6       0.0
total_rech_amt_7       0.0
total_rech_amt_8       0.0
total_rech_amt_9       0.0
max_rech_amt_6         0.0
max_rech_amt_7         0.0
max_rech_amt_8         0.0
max_rech_amt_9         0.0
last_day_rch_amt_6     0.0
last_day_rch_amt_7     0.0
last_day_rch_amt_8     0.0
isd_ic_mou_9           0.0
isd_ic_mou_7           0.0
total_rech_data_6      0.0
isd_ic_mou_6           0.0
std_ic_t2m_mou_7       0.0
std_ic_t2m_mou_8       0.0
std_ic_t2m_mou_9       0.0
std_ic_t2f_mou_6       0.0
std_ic_t2f_mou_7       0.0
std_ic_t2f_mou_8       0.0
std_ic_t2f_mou_9       0.0
std_ic_mou_6           0.0
std_ic_mou_7           0.0
std_ic_mou_8           0.0
std_ic_mou_9           0.0
total_ic_mou_6         0.0
total_ic_mou_7         0.0
total_ic_mou_8         0.0
total_ic_mou_9         0.0
spl_ic_mou_6           0.0
spl_ic_mou_7           0.0
spl_ic_mou_8           0.0
spl_ic_mou_9           0.0
```

last_day_rch_amt_9 0.0
total_rech_data_7 0.0
std_ic_t2t_mou_9 0.0
sachet_2g_6 0.0
sachet_2g_8 0.0
sachet_2g_9 0.0
monthly_3g_6 0.0
monthly_3g_7 0.0
monthly_3g_8 0.0
monthly_3g_9 0.0
sachet_3g_6 0.0
sachet_3g_7 0.0
sachet_3g_8 0.0
sachet_3g_9 0.0
aon 0.0
aug_vbc_3g 0.0
jul_vbc_3g 0.0
jun_vbc_3g 0.0
sep_vbc_3g 0.0
total_rech_amt_data_6 0.0
total_rech_amt_data_7 0.0
overall_rech_amt_6 0.0
overall_rech_amt_7 0.0
sachet_2g_7 0.0
monthly_2g_9 0.0
total_rech_data_8 0.0
monthly_2g_8 0.0
total_rech_data_9 0.0
max_rech_data_6 0.0
max_rech_data_7 0.0
max_rech_data_8 0.0
max_rech_data_9 0.0
av_rech_amt_data_6 0.0
av_rech_amt_data_7 0.0
av_rech_amt_data_8 0.0
av_rech_amt_data_9 0.0
vol_2g_mb_6 0.0
vol_2g_mb_7 0.0
vol_2g_mb_8 0.0
vol_2g_mb_9 0.0
vol_3g_mb_6 0.0
vol_3g_mb_7 0.0
vol_3g_mb_8 0.0
vol_3g_mb_9 0.0
monthly_2g_6 0.0
monthly_2g_7 0.0
std_ic_t2m_mou_6 0.0
std_ic_t2t_mou_8 0.0
arpu_6 0.0
loc_og_t2t_mou_8 0.0

loc_og_t2m_mou_6	0.0
loc_og_t2m_mou_7	0.0
loc_og_t2m_mou_8	0.0
loc_og_t2m_mou_9	0.0
loc_og_t2f_mou_6	0.0
loc_og_t2f_mou_7	0.0
loc_og_t2f_mou_8	0.0
loc_og_t2f_mou_9	0.0
loc_og_t2c_mou_6	0.0
loc_og_t2c_mou_7	0.0
loc_og_t2c_mou_8	0.0
loc_og_t2c_mou_9	0.0
loc_og_mou_6	0.0
loc_og_mou_7	0.0
loc_og_mou_8	0.0
loc_og_mou_9	0.0
std_og_t2t_mou_6	0.0
std_og_t2t_mou_7	0.0
std_og_t2t_mou_8	0.0
loc_og_t2t_mou_9	0.0
loc_og_t2t_mou_7	0.0
std_og_t2m_mou_6	0.0
loc_og_t2t_mou_6	0.0
arpu_7	0.0
arpu_8	0.0
arpu_9	0.0
onnet_mou_6	0.0
onnet_mou_7	0.0
onnet_mou_8	0.0
onnet_mou_9	0.0
offnet_mou_6	0.0
offnet_mou_7	0.0
offnet_mou_8	0.0
offnet_mou_9	0.0
roam_ic_mou_6	0.0
roam_ic_mou_7	0.0
roam_ic_mou_8	0.0
roam_ic_mou_9	0.0
roam_og_mou_6	0.0
roam_og_mou_7	0.0
roam_og_mou_8	0.0
roam_og_mou_9	0.0
std_og_t2t_mou_9	0.0
std_og_t2m_mou_7	0.0
std_ic_t2t_mou_7	0.0
total_og_mou_6	0.0
total_og_mou_8	0.0
total_og_mou_9	0.0
loc_ic_t2t_mou_6	0.0
loc_ic_t2t_mou_7	0.0

```
loc_ic_t2t_mou_8      0.0
loc_ic_t2t_mou_9      0.0
loc_ic_t2m_mou_6      0.0
loc_ic_t2m_mou_7      0.0
loc_ic_t2m_mou_8      0.0
loc_ic_t2m_mou_9      0.0
loc_ic_t2f_mou_6      0.0
loc_ic_t2f_mou_7      0.0
loc_ic_t2f_mou_8      0.0
loc_ic_t2f_mou_9      0.0
loc_ic_mou_6          0.0
loc_ic_mou_7          0.0
loc_ic_mou_8          0.0
loc_ic_mou_9          0.0
std_ic_t2t_mou_6      0.0
total_og_mou_7        0.0
og_others_9           0.0
std_og_t2m_mou_8      0.0
og_others_8           0.0
std_og_t2m_mou_9      0.0
std_og_t2f_mou_6      0.0
std_og_t2f_mou_7      0.0
std_og_t2f_mou_8      0.0
std_og_t2f_mou_9      0.0
std_og_mou_6          0.0
std_og_mou_7          0.0
std_og_mou_8          0.0
std_og_mou_9          0.0
isd_og_mou_6          0.0
isd_og_mou_7          0.0
isd_og_mou_8          0.0
isd_og_mou_9          0.0
spl_og_mou_6          0.0
spl_og_mou_7          0.0
spl_og_mou_8          0.0
spl_og_mou_9          0.0
og_others_6           0.0
og_others_7           0.0
avg_rech_amt_6_7      0.0
dtype: float64
```

```
# Reconfirming for missing values if any
telecom_data.isnull().sum().sum()
```

0

Defining Churn variable

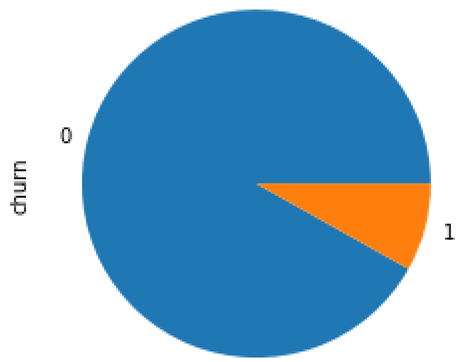
As explained above in the introduction, we are deriving based on usage based for this model.

For that, we need to find the derive churn variable using `total_ic_mou_9`,`total_og_mou_9`,`vol_2g_mb_9` and `vol_3g_mb_9` attributes

```
# Selecting the columns to define churn variable (i.e. TARGET Variable)
churn_col=['total_ic_mou_9','total_og_mou_9','vol_2g_mb_9','vol_3g_mb_9']
```

```
telecom_data[churn_col].info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30001 entries, 0 to 99997
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   total_ic_mou_9  30001 non-null  float64
 1   total_og_mou_9  30001 non-null  float64
 2   vol_2g_mb_9     30001 non-null  float64
 3   vol_3g_mb_9     30001 non-null  float64
dtypes: float64(4)
memory usage: 1.1 MB
```

```
# Initializing the churn variable.
telecom_data['churn']=0

# Imputing the churn values based on the condition
telecom_data['churn'] = np.where(telecom_data[churn_col].sum(axis=1) == 0, 1, 0)
# Checking the top 10 data
telecom_data.head(10)
# lets find out churn/non churn percentage
print((telecom_data['churn'].value_counts()/len(telecom_data))*100)
((telecom_data['churn'].value_counts()/len(telecom_data))*100).plot(kind="pie")
plt.show()
0    91.863605
1     8.136395
Name: churn, dtype: float64
```



As we can see that 91% of the customers do not churn, there is a possibility of class imbalance

Since this variable `churn` is the target variable, all the columns relating to this variable(i.e. all columns with suffix _9) can be dropped forn the dataset.

```
# Selecting all the churn phase columns in order to drop then

churn_phase_cols = [col for col in telecom_data.columns if '_9' in col]
```

```
print("The columns from churn phase are:\n",churn_phase_cols)
```

```
The columns from churn phase are:
 ['arpu_9', 'onnet_mou_9', 'offnet_mou_9', 'roam_ic_mou_9',
'roam_og_mou_9', 'loc_og_t2t_mou_9', 'loc_og_t2m_mou_9',
'loc_og_t2f_mou_9', 'loc_og_t2c_mou_9', 'loc_og_mou_9',
'std_og_t2t_mou_9', 'std_og_t2m_mou_9', 'std_og_t2f_mou_9',
'std_og_mou_9', 'isd_og_mou_9', 'spl_og_mou_9', 'og_others_9',
'total_og_mou_9', 'loc_ic_t2t_mou_9', 'loc_ic_t2m_mou_9',
'loc_ic_t2f_mou_9', 'loc_ic_mou_9', 'std_ic_t2t_mou_9',
'std_ic_t2m_mou_9', 'std_ic_t2f_mou_9', 'std_ic_mou_9',
'total_ic_mou_9', 'spl_ic_mou_9', 'isd_ic_mou_9', 'ic_others_9',
'total_rech_num_9', 'total_rech_amt_9', 'max_rech_amt_9',
'last_day_rch_amt_9', 'total_rech_data_9', 'max_rech_data_9',
'av_rech_amt_data_9', 'vol_2g_mb_9', 'vol_3g_mb_9', 'monthly_2g_9',
'sachet_2g_9', 'monthly_3g_9', 'sachet_3g_9']
```

```
# Dropping the selected churn phase columns
telecom_data.drop(churn_phase_cols, axis=1, inplace=True)

# The curent dimension of the dataset after dropping the churn related columns
telecom_data.shape
```

(30001, 141)

We can still clean the data by few possible columns relating to the good phase.

As we derived few columns in the good phase earlier, we can drop those related columns during creation.

```
# telecom_data['total_rech_amt_data_6']=telecom_data['av_rech_amt_data_6'] * telecom_data['total_rech_data_6']
# telecom_data['total_rech_amt_data_7']=telecom_data['av_rech_amt_data_7'] * telecom_data['total_rech_data_7']

# # Calculating the overall recharge amount for the months 6,7,8 and 9
# telecom_data['overall_rech_amt_6'] = telecom_data['total_rech_amt_data_6'] + telecom_data['total_rech_amt_6']
# telecom_data['overall_rech_amt_7'] = telecom_data['total_rech_amt_data_7'] + telecom_data['total_rech_amt_7']

telecom_data.drop(['total_rech_amt_data_6','av_rech_amt_data_6',
                   'total_rech_data_6','total_rech_amt_6',
                  'total_rech_amt_data_7','av_rech_amt_data_7',
                   'total_rech_data_7','total_rech_amt_7'], axis=1, inplace=True)
```

We can also create new columns for the defining the good phase variables and drop the seperate 6th and 7 month variables.

Before proceding to check the remaining missing value handling, let us check the collineartity of the indepedent variables and try to understand their dependencies.

```
# creating a list of column names for each month
mon_6_cols = [col for col in telecom_data.columns if '_6' in col]
```

```
mon_7_cols = [col for col in telecom_data.columns if '_7' in col]
mon_8_cols = [col for col in telecom_data.columns if '_8' in col]
# lets check the correlation amongst the independent variables, drop the highly correlated ones
telecom_data_corr = telecom_data.corr()
telecom_data_corr.loc[:,:] = np.tril(telecom_data_corr, k=-1)
telecom_data_corr = telecom_data_corr.stack()
telecom_data_corr
telecom_data_corr[(telecom_data_corr > 0.80) | (telecom_data_corr <
-0.80)].sort_values(ascending=False)
total_rech_amt_8    arpu_8              0.955351
isd_og_mou_8        isd_og_mou_7        0.943433
                    isd_og_mou_6        0.919641
isd_og_mou_7        isd_og_mou_6        0.916237
sachet_2g_8         total_rech_data_8   0.900629
total_ic_mou_6      loc_ic_mou_6        0.895099
total_ic_mou_8      loc_ic_mou_8        0.893072
total_ic_mou_7      loc_ic_mou_7        0.883070
std_og_t2t_mou_8    onnet_mou_8         0.860483
std_og_t2t_mou_7    onnet_mou_7         0.860275
std_og_t2t_mou_6    onnet_mou_6         0.859593
avg_rech_amt_6_7    overall_rech_amt_7  0.856275
std_og_t2m_mou_7    offnet_mou_7        0.854685
std_og_t2m_mou_8    offnet_mou_8        0.851049
total_og_mou_8      std_og_mou_8        0.848858
total_og_mou_7      std_og_mou_7        0.848825
loc_ic_mou_8        loc_ic_t2m_mou_8    0.847512
std_ic_mou_8        std_ic_t2m_mou_8    0.845590
loc_ic_mou_6        loc_ic_t2m_mou_6    0.844418
loc_og_mou_8        loc_og_mou_7        0.844245
loc_ic_mou_8        loc_ic_mou_7        0.842908
avg_rech_amt_6_7    overall_rech_amt_6  0.842748
loc_og_t2t_mou_8    loc_og_t2t_mou_7    0.834612
loc_ic_mou_7        loc_ic_t2m_mou_7    0.834557
total_og_mou_6      std_og_mou_6        0.831720
std_og_t2m_mou_6    offnet_mou_6        0.830433
loc_og_t2m_mou_8    loc_og_t2m_mou_7    0.826720
loc_ic_mou_7        loc_ic_mou_6        0.821979
total_ic_mou_8      total_ic_mou_7      0.820529
std_ic_mou_7        std_ic_t2m_mou_7    0.819316
loc_ic_t2m_mou_8    loc_ic_t2m_mou_7    0.814748
std_ic_mou_6        std_ic_t2m_mou_6    0.814081
loc_og_t2f_mou_7    loc_og_t2f_mou_6    0.809471
onnet_mou_8         onnet_mou_7         0.808507
loc_ic_t2t_mou_8    loc_ic_t2t_mou_7    0.808102
loc_og_mou_7        loc_og_mou_6        0.807980
std_og_t2t_mou_8    std_og_t2t_mou_7    0.804607
loc_og_mou_6        loc_og_t2m_mou_6    0.803954
loc_ic_t2t_mou_7    loc_ic_t2t_mou_6    0.803421
total_ic_mou_7      total_ic_mou_6      0.803042
av_rech_amt_data_8  max_rech_data_8     0.801613
```

dtype: float64
col_to_drop=['total_rech_amt_8','isd_og_mou_8','isd_og_mou_7','sachet_2g_8','total_ic_mou_6',

'total_ic_mou_8','total_ic_mou_7','std_og_t2t_mou_6','std_og_t2t_mou_8','std_og_t2t_mou_7',
'std_og_t2m_mou_7','std_og_t2m_mou_8',]

These columns can be dropped as they are highly collinered with other predictor variables.
criteria set is for collinearity of 85%

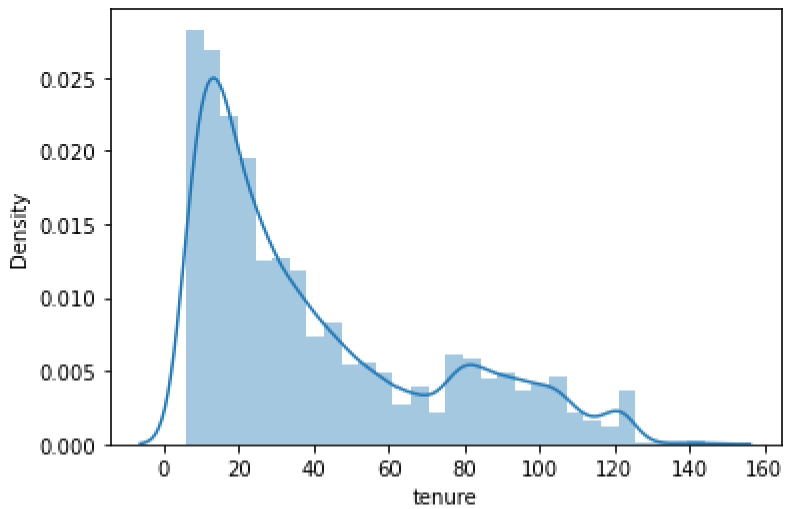
# dropping these column
telecom_data.drop(col_to_drop, axis=1, inplace=True)
# The curent dimension of the dataset after dropping few unwanted columns
telecom_data.shape
(30001, 121)
Deriving new variables to understand the data
We have a column called 'aon'

we can derive new variables from this to explain the data w.r.t churn.

creating a new variable 'tenure'
telecom_data['tenure'] = (telecom_data['aon']/30).round(0)

# Since we derived a new column from 'aon', we can drop it
telecom_data.drop('aon',axis=1, inplace=True)
# Checking the distribution of he tenure variable

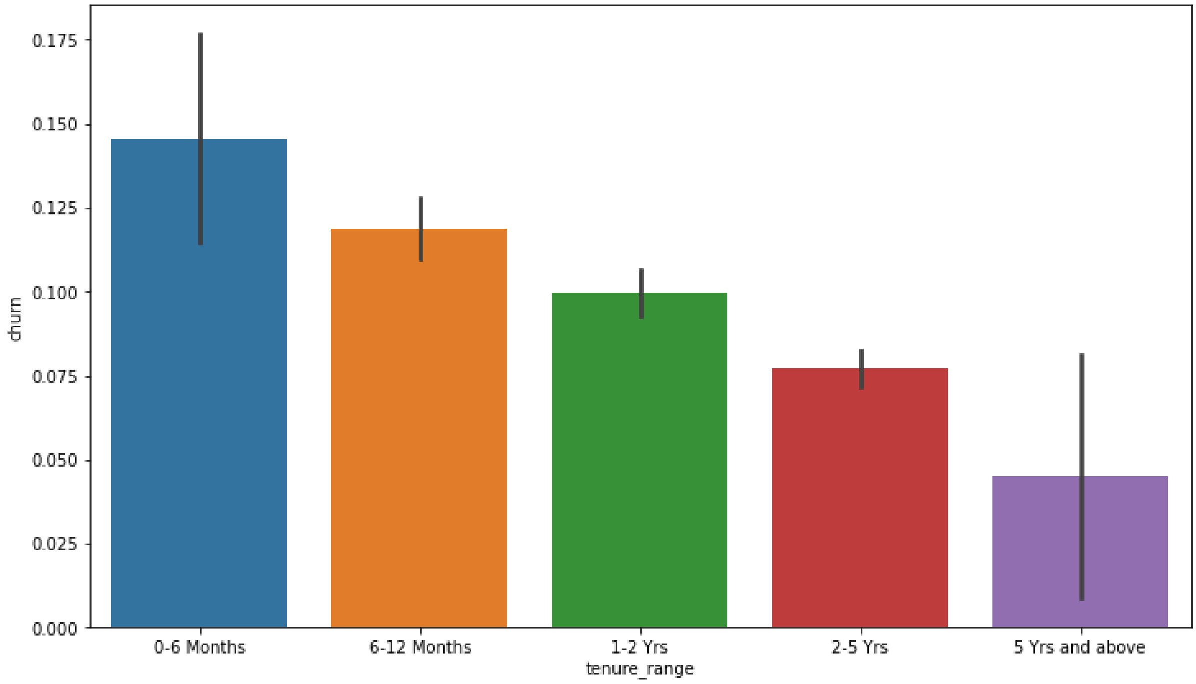
sns.distplot(telecom_data['tenure'],bins=30)
plt.show()



tn_range = [0, 6, 12, 24, 60, 61]
tn_label = ['0-6 Months', '6-12 Months', '1-2 Yrs', '2-5 Yrs', '5 Yrs and above']
telecom_data['tenure_range'] = pd.cut(telecom_data['tenure'], tn_range, labels=tn_label)
telecom_data['tenure_range'].head()
0 2-5 Yrs
7 2-5 Yrs
8 6-12 Months

21   1-2 Yrs
23   1-2 Yrs
Name: tenure_range, dtype: category
Categories (5, object): ['0-6 Months' < '6-12 Months' < '1-2 Yrs' < '2-5 Yrs' < '5 Yrs and above']

```
# Plotting a bar plot for tenure range
plt.figure(figsize=[12,7])
sns.barplot(x='tenure_range',y='churn', data=telecom_data)
plt.show()
```



It can be seen that the maximum churn rate happens within 0-6 month, but it gradually decreases as the customer retains in the network.

The average revenue per user is good phase of customer is given by arpu_6 and arpu_7. since we have two seperate averages, lets take an average to these two and drop the other columns.

```
telecom_data["avg_arpu_6_7"]= (telecom_data['arpu_6']+telecom_data['arpu_7'])/2
telecom_data['avg_arpu_6_7'].head()
```

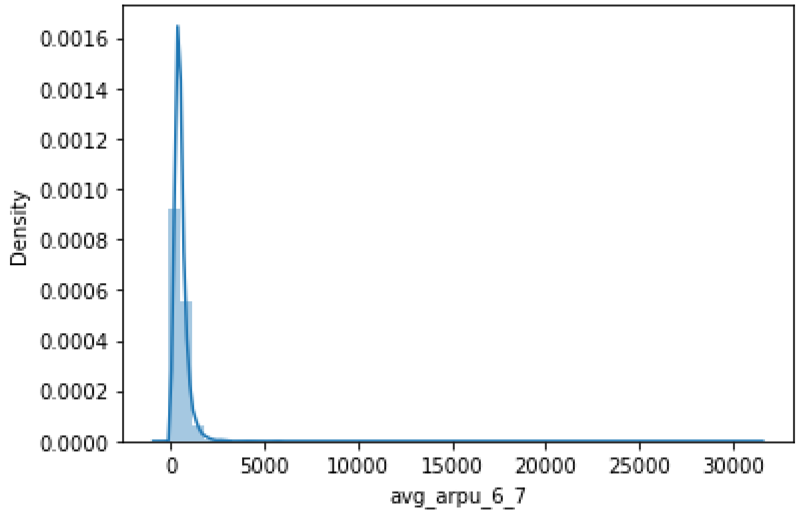
0   206.1005
7   1209.5150
8   435.4720
21   556.1030
23   134.1235
Name: avg_arpu_6_7, dtype: float64

```
# Lets drop the original columns as they are derived to a new column for better understanding of the data

telecom_data.drop(['arpu_6','arpu_7'], axis=1, inplace=True)


# The curent dimension of the dataset after dropping few unwanted columns
telecom_data.shape
```

(30001, 121)

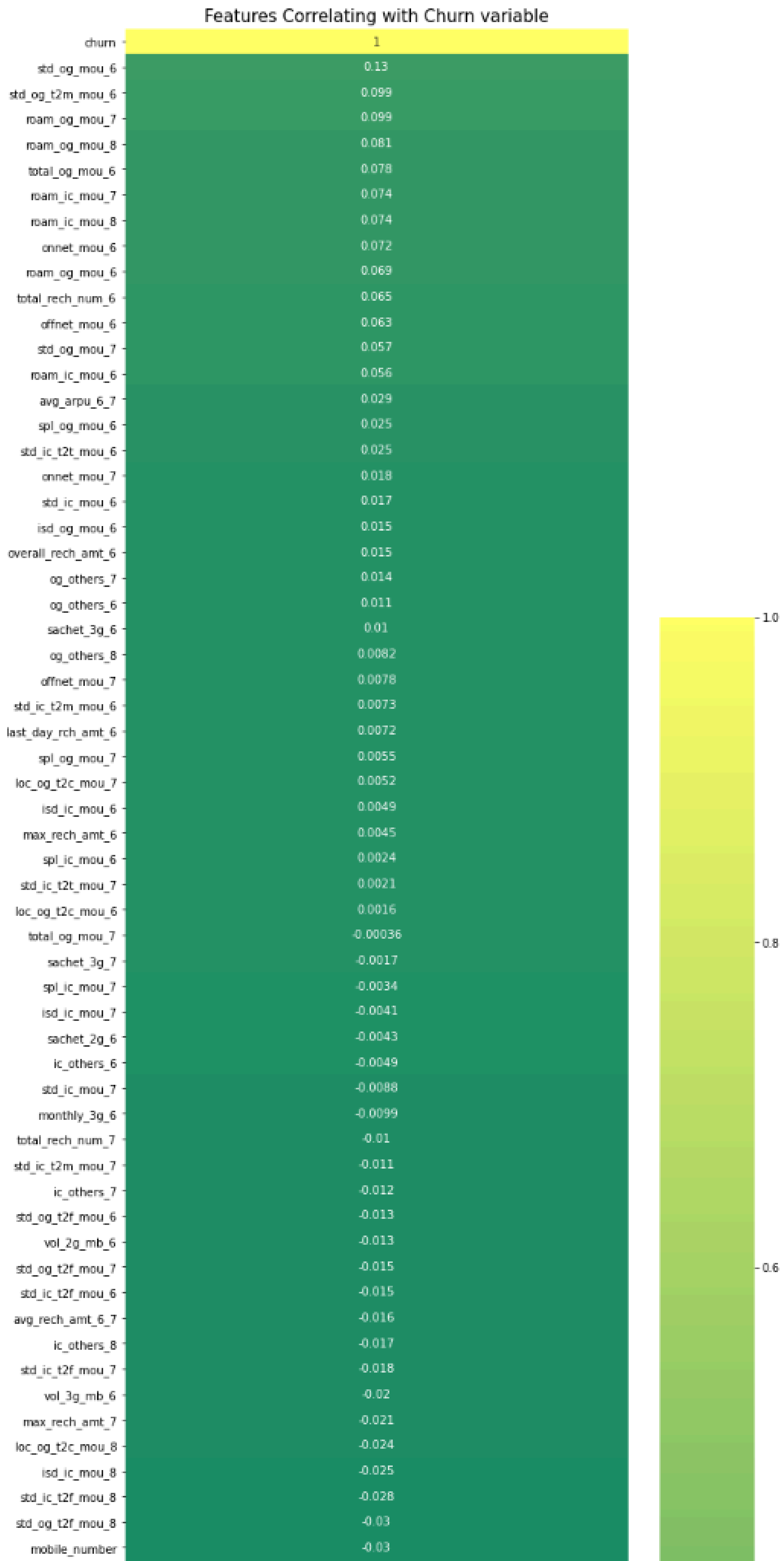
```
# Visualizing the column created
sns.distplot(telecom_data['avg_arpu_6_7'])
```

```
plt.show()
```



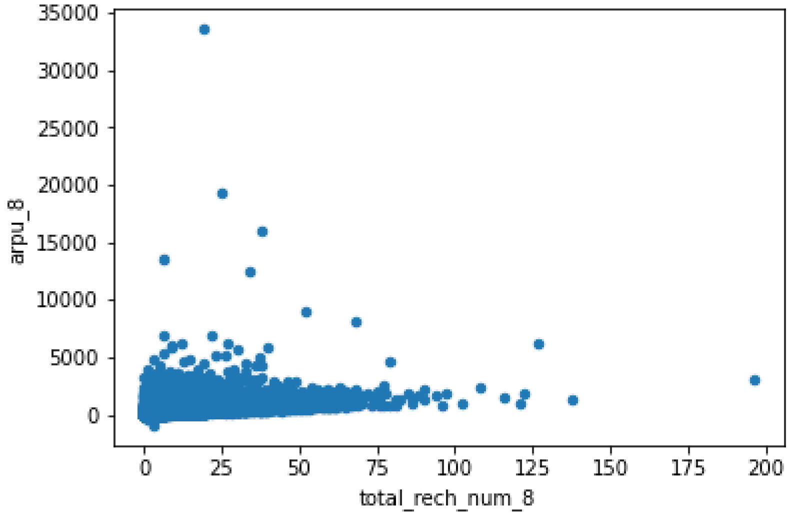

```
# Checking Correlation between target variable(SalePrice) with the other variable in the dataset
plt.figure(figsize=(10,50))
heatmap_churn = sns.heatmap(telecom_data.corr()[['churn']].sort_values(ascending=False,
by='churn'),annot=True,
                          cmap='summer')
heatmap_churn.set_title("Features Correlating with Churn variable", fontsize=15)
```

Text(0.5, 1.0, 'Features Correlating with Churn variable')

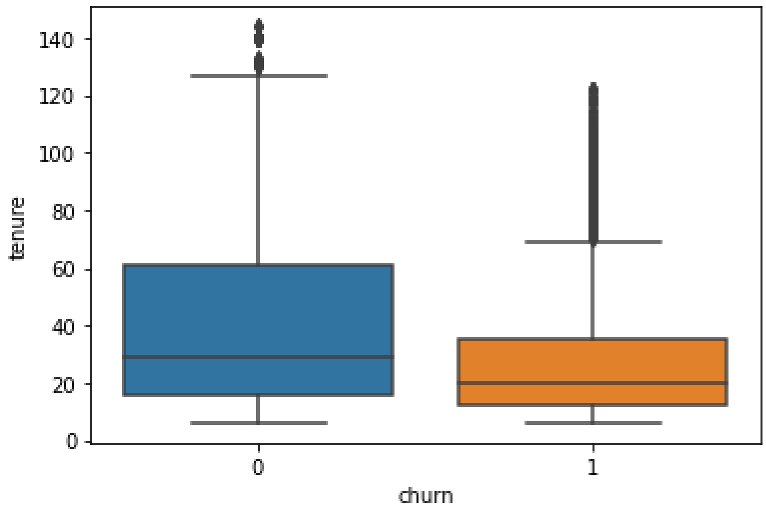

Features Correlating with Churn variable
churn
1
std_og_mou_6
0.13
std_og_t2m_mou_6
0.099
roam_og_mou_7
0.099
roam_og_mou_8
0.081
total_og_mou_6
0.078
roam_ic_mou_7
0.074
roam_ic_mou_8
0.074
onnet_mou_6
0.072
roam_og_mou_6
0.069
total_rech_num_6
0.065
offnet_mou_6
0.063
std_og_mou_7
0.057
roam_ic_mou_6
0.056
avg_arpu_6_7
0.029
spl_og_mou_6
0.025
std_ic_t2t_mou_6
0.025
onnet_mou_7
0.018
std_ic_mou_6
0.017
isd_og_mou_6
0.015
overall_rech_amt_6
0.015
og_others_7
0.014
og_others_6
0.011
sachet_3g_6
0.01
og_others_8
0.0082
offnet_mou_7
0.0078
std_ic_t2m_mou_6
0.0073
last_day_rch_amt_6
0.0072
spl_og_mou_7
0.0055
loc_og_t2c_mou_7
0.0052
isd_ic_mou_6
0.0049
max_rech_amt_6
0.0045
spl_ic_mou_6
0.0024
std_ic_t2t_mou_7
0.0021
loc_og_t2c_mou_6
0.0016
total_og_mou_7
-0.00036
sachet_3g_7
-0.0017
spl_ic_mou_7
-0.0034
isd_ic_mou_7
-0.0041
sachet_2g_6
-0.0043
ic_others_6
-0.0049
std_ic_mou_7
-0.0088
monthly_3g_6
-0.0099
total_rech_num_7
-0.01
std_ic_t2m_mou_7
-0.011
ic_others_7
-0.012
std_og_t2f_mou_6
-0.013
vol_2g_mb_6
-0.013
std_og_t2f_mou_7
-0.015
std_ic_t2f_mou_6
-0.015
avg_rech_amt_6_7
-0.016
ic_others_8
-0.017
std_ic_t2f_mou_7
-0.018
vol_3g_mb_6
-0.02
max_rech_amt_7
-0.021
loc_og_t2c_mou_8
-0.024
isd_ic_mou_8
-0.025
std_ic_t2f_mou_8
-0.028
std_og_t2f_mou_8
-0.03
mobile_number
-0.03
1.0
0.8
0.6

- Avg Outgoing Calls & calls on romaning for 6 & 7th months are positively correlated with churn.
- Avg Revenue, No. Of Recharge for 8th month has negative correlation with churn.

```
# lets now draw a scatter plot between total recharge and avg revenue for the 8th month
telecom_data[['total_rech_num_8', 'arpu_8']].plot.scatter(x = 'total_rech_num_8',
                                                          y='arpu_8')
plt.show()
```



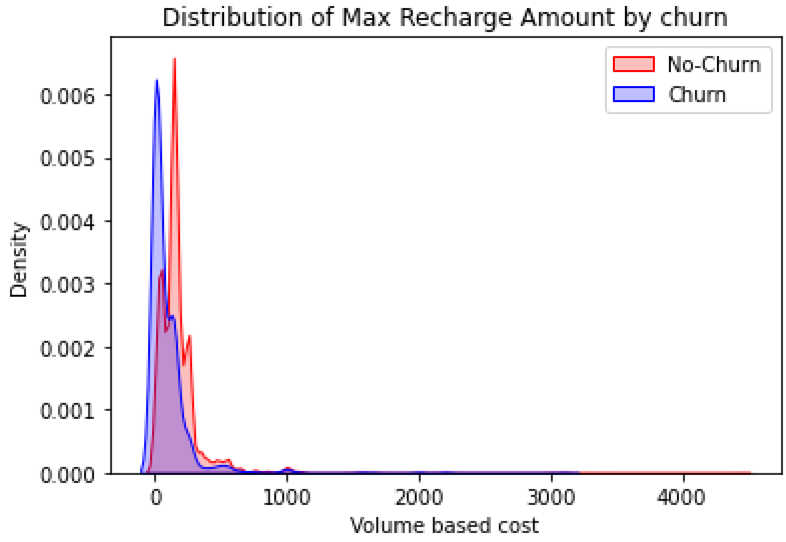

```
sns.boxplot(x = telecom_data.churn, y = telecom_data.tenure)

plt.show()
```



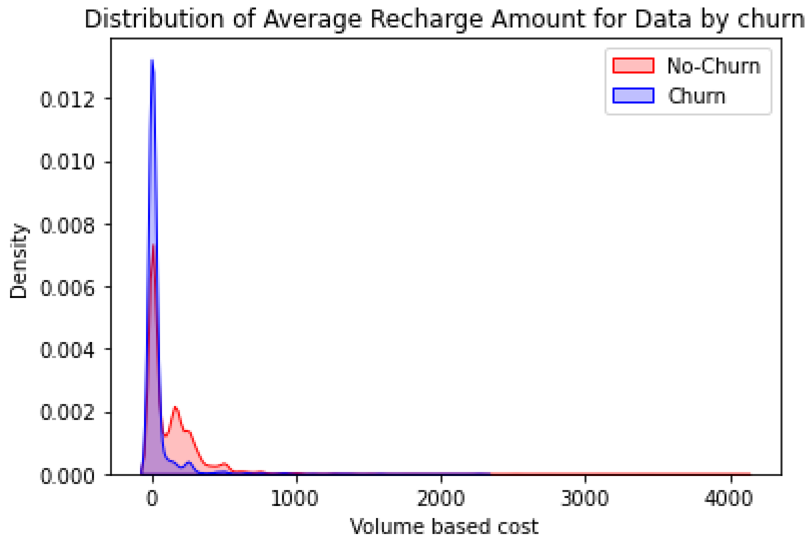
From the above plot , its clear tenured customers do no churn and they keep availing telecom services

```
# Plot between churn vs max rechare amount
ax = sns.kdeplot(telecom_data.max_rech_amt_8[(telecom_data["churn"] == 0)],
            color="Red", shade = True)
ax = sns.kdeplot(telecom_data.max_rech_amt_8[(telecom_data["churn"] == 1)],
            ax =ax, color="Blue", shade= True)
ax.legend(["No-Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Volume based cost')
```

```
ax.set_title('Distribution of Max Recharge Amount by churn')
plt.show()
```



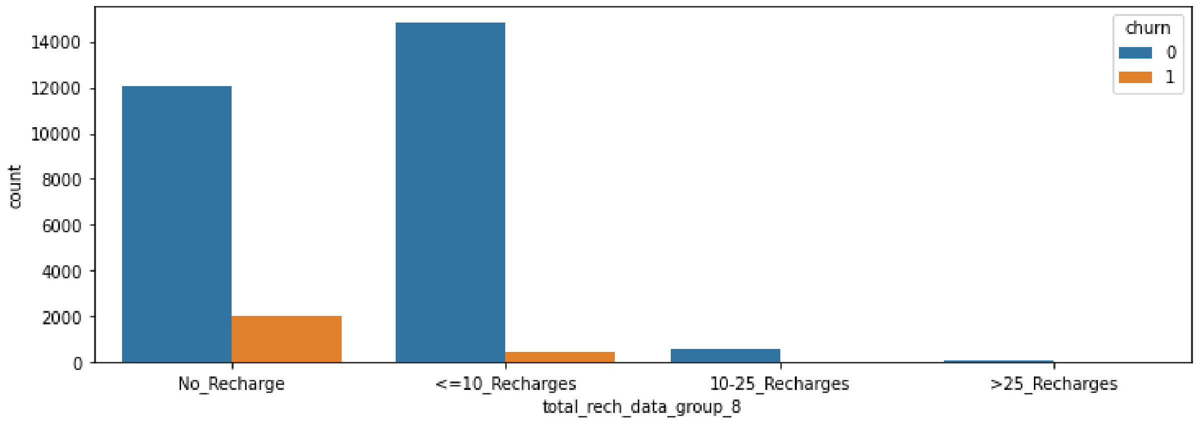

```
# churn vs max rechare amount
ax = sns.kdeplot(telecom_data.av_rech_amt_data_8[(telecom_data["churn"] == 0)],
            color="Red", shade = True)
ax = sns.kdeplot(telecom_data.av_rech_amt_data_8[(telecom_data["churn"] == 1)],
            ax =ax, color="Blue", shade= True)
ax.legend(["No-Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Volume based cost')
ax.set_title('Distribution of Average Recharge Amount for Data by churn')
plt.show()
```



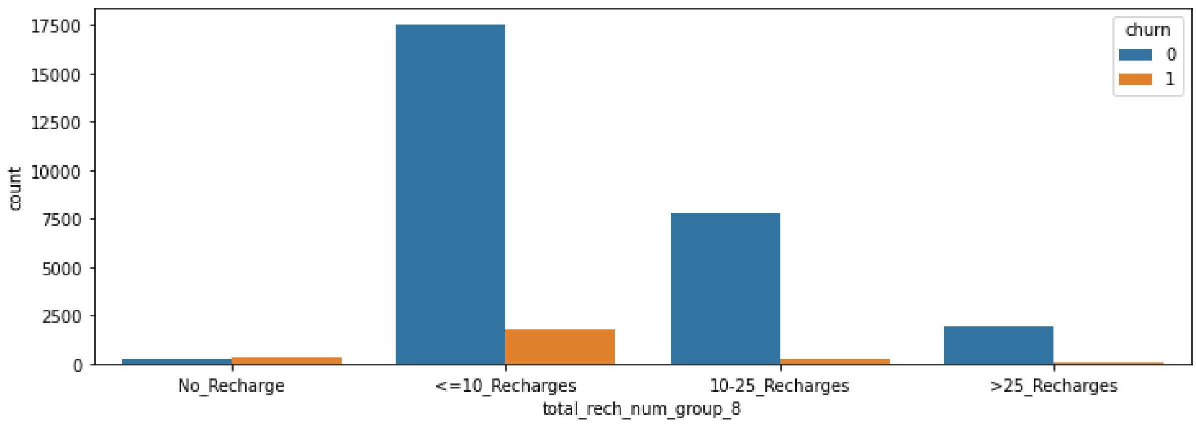

```
# Creating categories for month 8 column totalrecharge and their count
telecom_data['total_rech_data_group_8']=pd.cut(telecom_data['total_rech_data_8'],[-1,0,10,25,1
00],labels=["No_Recharge","<=10_Recharges","10-25_Recharges",">25_Recharges"])
telecom_data['total_rech_num_group_8']=pd.cut(telecom_data['total_rech_num_8'],[-1,0,10,25,1
000],labels=["No_Recharge","<=10_Recharges","10-25_Recharges",">25_Recharges"])
# Plotting the results
```

```
plt.figure(figsize=[12,4])
sns.countplot(data=telecom_data,x="total_rech_data_group_8",hue="churn")
print("\t\t\t\t\tDistribution of total_rech_data_8
variable\n",telecom_data['total_rech_data_group_8'].value_counts())
plt.show()
plt.figure(figsize=[12,4])
sns.countplot(data=telecom_data,x="total_rech_num_group_8",hue="churn")
print("\t\t\t\t\tDistribution of total_rech_num_8
variable\n",telecom_data['total_rech_num_group_8'].value_counts())
plt.show()
```

```
                                        Distribution of total_rech_data_8 variable
 <=10_Recharges     15307
No_Recharge        14048
10-25_Recharges    608
>25_Recharges      38
Name: total_rech_data_group_8, dtype: int64
```




```
                                        Distribution of total_rech_num_8 variable
 <=10_Recharges     19349
10-25_Recharges    8073
>25_Recharges      1996
No_Recharge        583
Name: total_rech_num_group_8, dtype: int64
```



As the number of recharge rate increases, the churn rate decreases clearly.

```
# Creating a dummy variable for some of the categorical variables and dropping the first one.
dummy =
pd.get_dummies(telecom_data[['total_rech_data_group_8','total_rech_num_group_8','tenure_ran
ge']], drop_first=True)
dummy.head()
# Adding the results to the master dataframe
telecom_data = pd.concat([telecom_data, dummy], axis=1)
telecom_data.head()
# Creating a copy of the filtered dataframe

df=telecom_data[:].copy()

# Dropping unwanted columns
df.drop(['tenure_range','mobile_number','total_rech_data_group_8','total_rech_num_group_8','se
p_vbc_3g','tenure'], axis=1, inplace=True)
# Cheking the dataset
df.head()
# lets create X dataset for model building.
X = df.drop(['churn'],axis=1)
X.head()
# lets create y dataset for model building.
y=df['churn']
y.head()
0    1
7    1
8    0
21    0
23    0
Name: churn, dtype: int32
# split the dateset into train and test datasets
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, train_size=0.7,
random_state=1)
print("Dimension of X_train:", X_train.shape)
print("Dimension of X_test:", X_test.shape)
Dimension of X_train: (21000, 126)
Dimension of X_test: (9001, 126)

X_train.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21000 entries, 15709 to 99093
Data columns (total 126 columns):
 #    Column                                       Dtype
---   ------                                       -----
 0    arpu_8                                       float64
 1    onnet_mou_6                                  float64
```

```
2    onnet_mou_7                                  float64
3    onnet_mou_8                                  float64
4    offnet_mou_6                                 float64
5    offnet_mou_7                                 float64
6    offnet_mou_8                                 float64
7    roam_ic_mou_6                                float64
8    roam_ic_mou_7                                float64
9    roam_ic_mou_8                                float64
10   roam_og_mou_6                                float64
11   roam_og_mou_7                                float64
12   roam_og_mou_8                                float64
13   loc_og_t2t_mou_6                             float64
14   loc_og_t2t_mou_7                             float64
15   loc_og_t2t_mou_8                             float64
16   loc_og_t2m_mou_6                             float64
17   loc_og_t2m_mou_7                             float64
18   loc_og_t2m_mou_8                             float64
19   loc_og_t2f_mou_6                             float64
20   loc_og_t2f_mou_7                             float64
21   loc_og_t2f_mou_8                             float64
22   loc_og_t2c_mou_6                             float64
23   loc_og_t2c_mou_7                             float64
24   loc_og_t2c_mou_8                             float64
25   loc_og_mou_6                                 float64
26   loc_og_mou_7                                 float64
27   loc_og_mou_8                                 float64
28   std_og_t2m_mou_6                             float64
29   std_og_t2f_mou_6                             float64
30   std_og_t2f_mou_7                             float64
31   std_og_t2f_mou_8                             float64
32   std_og_mou_6                                 float64
33   std_og_mou_7                                 float64
34   std_og_mou_8                                 float64
35   isd_og_mou_6                                 float64
36   spl_og_mou_6                                 float64
37   spl_og_mou_7                                 float64
38   spl_og_mou_8                                 float64
39   og_others_6                                  float64
40   og_others_7                                  float64
41   og_others_8                                  float64
42   total_og_mou_6                               float64
43   total_og_mou_7                               float64
44   total_og_mou_8                               float64
```

45	loc_ic_t2t_mou_6	float64
46	loc_ic_t2t_mou_7	float64
47	loc_ic_t2t_mou_8	float64
48	loc_ic_t2m_mou_6	float64
49	loc_ic_t2m_mou_7	float64
50	loc_ic_t2m_mou_8	float64
51	loc_ic_t2f_mou_6	float64
52	loc_ic_t2f_mou_7	float64
53	loc_ic_t2f_mou_8	float64
54	loc_ic_mou_6	float64
55	loc_ic_mou_7	float64
56	loc_ic_mou_8	float64
57	std_ic_t2t_mou_6	float64
58	std_ic_t2t_mou_7	float64
59	std_ic_t2t_mou_8	float64
60	std_ic_t2m_mou_6	float64
61	std_ic_t2m_mou_7	float64
62	std_ic_t2m_mou_8	float64
63	std_ic_t2f_mou_6	float64
64	std_ic_t2f_mou_7	float64
65	std_ic_t2f_mou_8	float64
66	std_ic_mou_6	float64
67	std_ic_mou_7	float64
68	std_ic_mou_8	float64
69	spl_ic_mou_6	float64
70	spl_ic_mou_7	float64
71	spl_ic_mou_8	float64
72	isd_ic_mou_6	float64
73	isd_ic_mou_7	float64
74	isd_ic_mou_8	float64
75	ic_others_6	float64
76	ic_others_7	float64
77	ic_others_8	float64
78	total_rech_num_6	float64
79	total_rech_num_7	float64
80	total_rech_num_8	float64
81	max_rech_amt_6	float64
82	max_rech_amt_7	float64
83	max_rech_amt_8	float64
84	last_day_rch_amt_6	float64
85	last_day_rch_amt_7	float64
86	last_day_rch_amt_8	float64
87	total_rech_data_8	float64

```
 88   max_rech_data_6                          float64
 89   max_rech_data_7                          float64
 90   max_rech_data_8                          float64
 91   av_rech_amt_data_8                       float64
 92   vol_2g_mb_6                              float64
 93   vol_2g_mb_7                              float64
 94   vol_2g_mb_8                              float64
 95   vol_3g_mb_6                              float64
 96   vol_3g_mb_7                              float64
 97   vol_3g_mb_8                              float64
 98   monthly_2g_6                             float64
 99   monthly_2g_7                             float64
 100  monthly_2g_8                             float64
 101  sachet_2g_6                              float64
 102  sachet_2g_7                              float64
 103  monthly_3g_6                             float64
 104  monthly_3g_7                             float64
 105  monthly_3g_8                             float64
 106  sachet_3g_6                              float64
 107  sachet_3g_7                              float64
 108  sachet_3g_8                              float64
 109  aug_vbc_3g                               float64
 110  jul_vbc_3g                               float64
 111  jun_vbc_3g                               float64
 112  overall_rech_amt_6                       float64
 113  overall_rech_amt_7                       float64
 114  avg_rech_amt_6_7                         float64
 115  avg_arpu_6_7                             float64
 116  total_rech_data_group_8_<=10_Recharges   uint8
 117  total_rech_data_group_8_10-25_Recharges  uint8
 118  total_rech_data_group_8_>25_Recharges    uint8
 119  total_rech_num_group_8_<=10_Recharges    uint8
 120  total_rech_num_group_8_10-25_Recharges   uint8
 121  total_rech_num_group_8_>25_Recharges     uint8
 122  tenure_range_6-12 Months                 uint8
 123  tenure_range_1-2 Yrs                     uint8
 124  tenure_range_2-5 Yrs                     uint8
 125  tenure_range_5 Yrs and above             uint8
dtypes: float64(116), uint8(10)
memory usage: 18.9 MB
```

```
num_col = X_train.select_dtypes(include = ['int64','float64']).columns.tolist()
# apply scaling on the dataset
from sklearn import preprocessing
```

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X_train[num_col] = scaler.fit_transform(X_train[num_col])
X_train.head()
```

Data Imbalance Handling

Using SMOTE method, we can balance the data w.r.t. churn variable and proceed further

```
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=42)
X_train_sm,y_train_sm = sm.fit_resample(X_train,y_train)
print("Dimension of X_train_sm Shape:", X_train_sm.shape)
print("Dimension of y_train_sm Shape:", y_train_sm.shape)
```

```
Dimension of X_train_sm Shape: (38576, 126)
Dimension of y_train_sm Shape: (38576,)
```

Logistic Regression

```
# Importing necessary libraries for Model creation
import statsmodels.api as sm
# Logistic regression model
logm1 = sm.GLM(y_train_sm,(sm.add_constant(X_train_sm)), family = sm.families.Binomial())
logm1.fit().summary()
```

Logistic Regression using Feature Selection (RFE method)

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()

from sklearn.feature_selection import RFE

# running RFE with 20 variables as output
rfe = RFE(logreg, 20)
rfe = rfe.fit(X_train_sm, y_train_sm)
rfe.support_
```

```
array([ True, False, False, False, False, False, False, False,  True,
       False, False, False,  True, False, False, False, False, False,
        True, 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,
       False, False,  True, False, False,  True, False, False, False,
        True, False,  True, False, False, False, False, False, False,
       False, False, False, False, False,  True, False, False,  True,
       False, False, False, False, False, False, False, False,  True,
       False, False, False, False, False,  True,  True, False, False,
       False,  True, False, False,  True, False, False, False, False,
       False,  True, False, False, False, False, False, False, False,
       False,  True, False, False, False, False, False,  True, False,
       False, False, False, False, False, False, False, False, False])
```

```
rfe_columns=X_train_sm.columns[rfe.support_]
print("The selected columns by RFE for modelling are: \n\n",rfe_columns)
```

```
The selected columns by RFE for modelling are:
```

```
Index(['arpu_8', 'roam_ic_mou_7', 'roam_og_mou_8', 'loc_og_t2m_mou_8',
       'std_og_mou_7', 'total_og_mou_8', 'loc_ic_t2t_mou_8',
       'loc_ic_t2m_mou_8', 'loc_ic_mou_6', 'loc_ic_mou_8',
'std_ic_mou_8',
       'spl_ic_mou_8', 'total_rech_num_8', 'last_day_rch_amt_8',
       'total_rech_data_8', 'av_rech_amt_data_8', 'vol_2g_mb_8',
       'monthly_2g_8', 'aug_vbc_3g', 'avg_arpu_6_7'],
      dtype='object')
```

```
list(zip(X_train_sm.columns, rfe.support_, rfe.ranking_))
[('arpu_8', True, 1),
 ('onnet_mou_6', False, 22),
 ('onnet_mou_7', False, 37),
 ('onnet_mou_8', False, 42),
 ('offnet_mou_6', False, 35),
 ('offnet_mou_7', False, 21),
 ('offnet_mou_8', False, 26),
 ('roam_ic_mou_6', False, 13),
 ('roam_ic_mou_7', True, 1),
 ('roam_ic_mou_8', False, 60),
 ('roam_og_mou_6', False, 69),
 ('roam_og_mou_7', False, 33),
 ('roam_og_mou_8', True, 1),
 ('loc_og_t2t_mou_6', False, 65),
 ('loc_og_t2t_mou_7', False, 99),
 ('loc_og_t2t_mou_8', False, 19),
 ('loc_og_t2m_mou_6', False, 67),
 ('loc_og_t2m_mou_7', False, 74),
 ('loc_og_t2m_mou_8', True, 1),
 ('loc_og_t2f_mou_6', False, 107),
 ('loc_og_t2f_mou_7', False, 5),
 ('loc_og_t2f_mou_8', False, 25),
 ('loc_og_t2c_mou_6', False, 7),
 ('loc_og_t2c_mou_7', False, 66),
 ('loc_og_t2c_mou_8', False, 104),
 ('loc_og_mou_6', False, 48),
 ('loc_og_mou_7', False, 105),
 ('loc_og_mou_8', False, 2),
 ('std_og_t2m_mou_6', False, 93),
 ('std_og_t2f_mou_6', False, 79),
 ('std_og_t2f_mou_7', False, 27),
 ('std_og_t2f_mou_8', False, 4),
 ('std_og_mou_6', False, 46),
 ('std_og_mou_7', True, 1),
 ('std_og_mou_8', False, 64),
 ('isd_og_mou_6', False, 14),
 ('spl_og_mou_6', False, 87),
 ('spl_og_mou_7', False, 51),
 ('spl_og_mou_8', False, 36),
```

('og_others_6', False, 23),
('og_others_7', False, 82),
('og_others_8', False, 98),
('total_og_mou_6', False, 47),
('total_og_mou_7', False, 90),
('total_og_mou_8', True, 1),
('loc_ic_t2t_mou_6', False, 45),
('loc_ic_t2t_mou_7', False, 77),
('loc_ic_t2t_mou_8', True, 1),
('loc_ic_t2m_mou_6', False, 6),
('loc_ic_t2m_mou_7', False, 28),
('loc_ic_t2m_mou_8', True, 1),
('loc_ic_t2f_mou_6', False, 52),
('loc_ic_t2f_mou_7', False, 83),
('loc_ic_t2f_mou_8', False, 11),
('loc_ic_mou_6', True, 1),
('loc_ic_mou_7', False, 57),
('loc_ic_mou_8', True, 1),
('std_ic_t2t_mou_6', False, 59),
('std_ic_t2t_mou_7', False, 32),
('std_ic_t2t_mou_8', False, 12),
('std_ic_t2m_mou_6', False, 38),
('std_ic_t2m_mou_7', False, 39),
('std_ic_t2m_mou_8', False, 8),
('std_ic_t2f_mou_6', False, 95),
('std_ic_t2f_mou_7', False, 50),
('std_ic_t2f_mou_8', False, 34),
('std_ic_mou_6', False, 9),
('std_ic_mou_7', False, 73),
('std_ic_mou_8', True, 1),
('spl_ic_mou_6', False, 102),
('spl_ic_mou_7', False, 92),
('spl_ic_mou_8', True, 1),
('isd_ic_mou_6', False, 54),
('isd_ic_mou_7', False, 40),
('isd_ic_mou_8', False, 55),
('ic_others_6', False, 53),
('ic_others_7', False, 70),
('ic_others_8', False, 78),
('total_rech_num_6', False, 103),
('total_rech_num_7', False, 3),
('total_rech_num_8', True, 1),
('max_rech_amt_6', False, 81),
('max_rech_amt_7', False, 16),
('max_rech_amt_8', False, 72),
('last_day_rch_amt_6', False, 89),
('last_day_rch_amt_7', False, 15),
('last_day_rch_amt_8', True, 1),
('total_rech_data_8', True, 1),
('max_rech_data_6', False, 41),

('max_rech_data_7', False, 61),
('max_rech_data_8', False, 100),
('av_rech_amt_data_8', True, 1),
('vol_2g_mb_6', False, 43),
('vol_2g_mb_7', False, 17),
('vol_2g_mb_8', True, 1),
('vol_3g_mb_6', False, 97),
('vol_3g_mb_7', False, 62),
('vol_3g_mb_8', False, 71),
('monthly_2g_6', False, 44),
('monthly_2g_7', False, 18),
('monthly_2g_8', True, 1),
('sachet_2g_6', False, 63),
('sachet_2g_7', False, 106),
('monthly_3g_6', False, 84),
('monthly_3g_7', False, 49),
('monthly_3g_8', False, 75),
('sachet_3g_6', False, 10),
('sachet_3g_7', False, 24),
('sachet_3g_8', False, 76),
('aug_vbc_3g', True, 1),
('jul_vbc_3g', False, 58),
('jun_vbc_3g', False, 88),
('overall_rech_amt_6', False, 85),
('overall_rech_amt_7', False, 86),
('avg_rech_amt_6_7', False, 101),
('avg_arpu_6_7', True, 1),
('total_rech_data_group_8_<=10_Recharges', False, 68),
('total_rech_data_group_8_10-25_Recharges', False, 20),
('total_rech_data_group_8_>25_Recharges', False, 80),
('total_rech_num_group_8_<=10_Recharges', False, 31),
('total_rech_num_group_8_10-25_Recharges', False, 30),
('total_rech_num_group_8_>25_Recharges', False, 29),
('tenure_range_6-12 Months', False, 91),
('tenure_range_1-2 Yrs', False, 94),
('tenure_range_2-5 Yrs', False, 96),
('tenure_range_5 Yrs and above', False, 56)]

Assessing the model with StatsModels

```
X_train_SM = sm.add_constant(X_train_sm[rfe_columns])
logm2 = sm.GLM(y_train_sm,X_train_SM, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
# From the p-value of the individual columns,
   # we can drop the column 'loc_ic_t2t_mou_8' as it has high p-value of 0.80
rfe_columns_1=rfe_columns.drop('loc_ic_t2t_mou_8',1)
print("\nThe new set of edited featured are:\n",rfe_columns_1)
```

```
The new set of columns are:
 Index(['arpu_8', 'roam_ic_mou_7', 'roam_og_mou_8', 'loc_og_t2m_mou_8',
```

```
       'std_og_mou_7', 'total_og_mou_8', 'loc_ic_t2m_mou_8',
'loc_ic_mou_6',
       'loc_ic_mou_8', 'std_ic_mou_8', 'spl_ic_mou_8',
'total_rech_num_8',
       'last_day_rch_amt_8', 'total_rech_data_8', 'av_rech_amt_data_8',
       'vol_2g_mb_8', 'monthly_2g_8', 'aug_vbc_3g', 'avg_arpu_6_7'],
      dtype='object')
```

```
# Training the model with the edited feature list
X_train_SM = sm.add_constant(X_train_sm[rfe_columns_1])
logm2 = sm.GLM(y_train_sm,X_train_SM, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
# From the p-value of the individual columns,
  # we can drop the column 'loc_ic_t2m_mou_8' as it has high p-value of 0.80
rfe_columns_2=rfe_columns_1.drop('loc_ic_t2m_mou_8',1)
print("\nThe new set of edited featured are:\n",rfe_columns_2)
```

```
The new set of edited featured are:
 Index(['arpu_8', 'roam_ic_mou_7', 'roam_og_mou_8', 'loc_og_t2m_mou_8',
       'std_og_mou_7', 'total_og_mou_8', 'loc_ic_mou_6',
'loc_ic_mou_8',
       'std_ic_mou_8', 'spl_ic_mou_8', 'total_rech_num_8',
       'last_day_rch_amt_8', 'total_rech_data_8', 'av_rech_amt_data_8',
       'vol_2g_mb_8', 'monthly_2g_8', 'aug_vbc_3g', 'avg_arpu_6_7'],
      dtype='object')
```

```
# Training the model with the edited feature list
X_train_SM = sm.add_constant(X_train_sm[rfe_columns_2])
logm2 = sm.GLM(y_train_sm,X_train_SM, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
# Getting the predicted values on the train set
y_train_sm_pred = res.predict(X_train_SM)
y_train_sm_pred = y_train_sm_pred.values.reshape(-1)
y_train_sm_pred[:10]
array([1.38574250e-01, 4.01121753e-01, 3.24275768e-01, 4.14619020e-01,
     5.08729618e-01, 4.31066021e-01, 2.12010834e-05, 2.27844968e-01,
     5.14992869e-02, 7.08374581e-01])
```

Creating a dataframe with the actual churn flag and the predicted probabilities

```
y_train_sm_pred_final = pd.DataFrame({'Converted':y_train_sm.values,
'Converted_prob':y_train_sm_pred})
y_train_sm_pred_final.head()
```

Creating new column 'churn_pred' with 1 if Churn_Prob > 0.5 else 0

```
y_train_sm_pred_final['churn_pred'] = y_train_sm_pred_final.Converted_prob.map(lambda x: 1 if
x > 0.5 else 0)
```

```python
# Viewing the prediction results
y_train_sm_pred_final.head()
from sklearn import metrics

# Confusion matrix
confusion = metrics.confusion_matrix(y_train_sm_pred_final.Converted,
y_train_sm_pred_final.churn_pred )
print(confusion)
```

```
[[15661  3627]
 [ 2775 16513]]
```

```python
# Predicted     not_churn    churn
# Actual
# not_churn        15661      3627
# churn            2775       16513
# Checking the overall accuracy.
print("The overall accuracy of the model
is:",metrics.accuracy_score(y_train_sm_pred_final.Converted,
y_train_sm_pred_final.churn_pred))
```

```
The overall accuracy of the model is: 0.8340418913313977
```

```python
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor
# Create a dataframe that will contain the names of all the feature variables and their respective
VIFs
vif = pd.DataFrame()
vif['Features'] = X_train_sm[rfe_columns_2].columns
vif['VIF'] = [variance_inflation_factor(X_train_sm[rfe_columns].values, i) for i in
range(X_train_sm[rfe_columns_2].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Metrics beyond simply accuracy

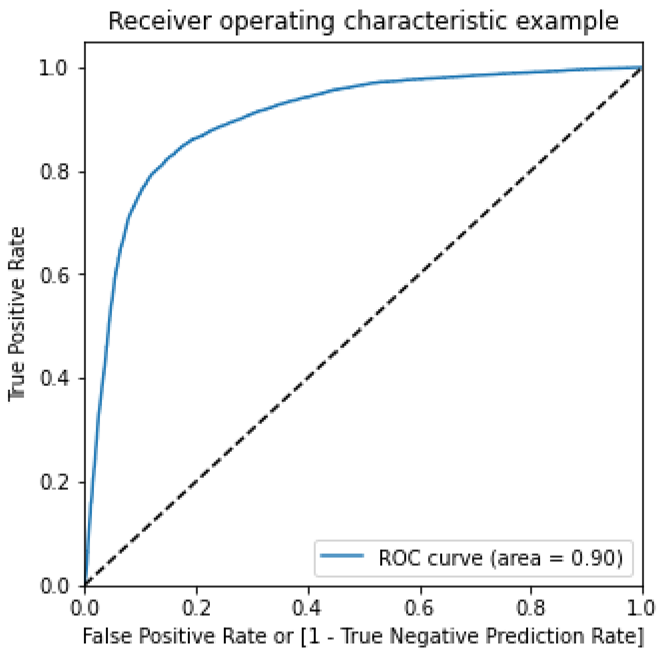
```python
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives
# Let's see the sensitivity of our logistic regression model
print("Sensitivity = ",TP / float(TP+FN))

# Let us calculate specificity
print("Specificity = ",TN / float(TN+FP))

# Calculate false postive rate - predicting churn when customer does not have churned
print("False Positive Rate = ",FP/ float(TN+FP))

# positive predictive value
print ("Precision = ",TP / float(TP+FP))
```

```python
# Negative predictive value
print ("True Negative Prediction Rate = ",TN / float(TN+ FN))
```

```
Sensitivity =  0.8561281625881377
Specificity =  0.8119556200746578
False Positive Rate =  0.18804437992534218
Precision =  0.8199106256206554
True Negative Prediction Rate =  0.8494792796702104
```

Plotting the ROC Curve

```python
# Defining a function to plot the roc curve
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Prediction Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return None
# Defining the variables to plot the curve
fpr, tpr, thresholds = metrics.roc_curve( y_train_sm_pred_final.Converted,
y_train_sm_pred_final.Converted_prob, drop_intermediate = False )
# Plotting the curve for the obtained metrics
draw_roc(y_train_sm_pred_final.Converted, y_train_sm_pred_final.Converted_prob)
```

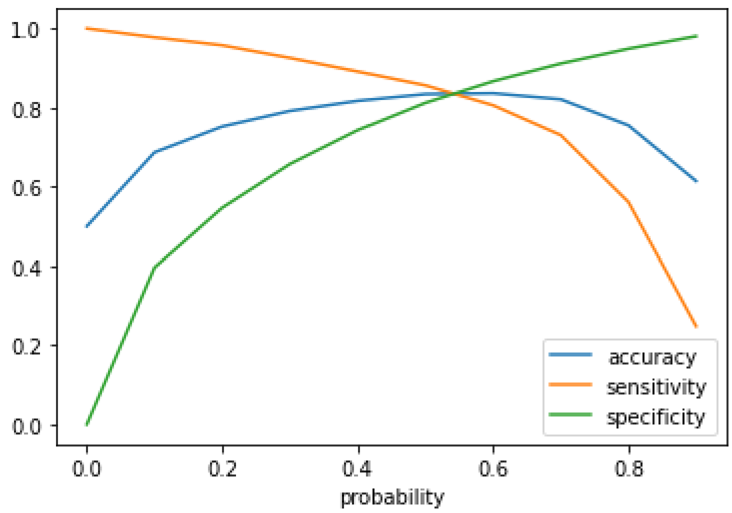


Finding Optimal Cutoff Point

```
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_sm_pred_final[i]= y_train_sm_pred_final.Converted_prob.map(lambda x: 1 if x > i else
0)
y_train_sm_pred_final.head()
# Now let's calculate accuracy sensitivity and specificity for various probability cutoffs.
cutoff_df = pd.DataFrame( columns = ['probability','accuracy','sensitivity','specificity'])
from sklearn.metrics import confusion_matrix

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

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

    specificity = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensitivity = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensitivity,specificity]
print(cutoff_df)
```

	probability	accuracy	sensitivity	specificity
0.0	0.0	0.500000	1.000000	0.000000
0.1	0.1	0.686696	0.977603	0.395790
0.2	0.2	0.751996	0.957538	0.546454
0.3	0.3	0.791321	0.925653	0.656989
0.4	0.4	0.816881	0.891176	0.742586
0.5	0.5	0.834042	0.856128	0.811956
0.6	0.6	0.836116	0.805682	0.866549
0.7	0.7	0.820795	0.730350	0.911240
0.8	0.8	0.755003	0.561230	0.948776
0.9	0.9	0.614294	0.248185	0.980402

```
# plotting accuracy sensitivity and specificity for various probabilities calculated above.
cutoff_df.plot.line(x='probability', y=['accuracy','sensitivity','specificity'])
plt.show()
<Figure size 1080x1080 with 0 Axes>
```



Initially we selected the optimm point of classification as 0.5.

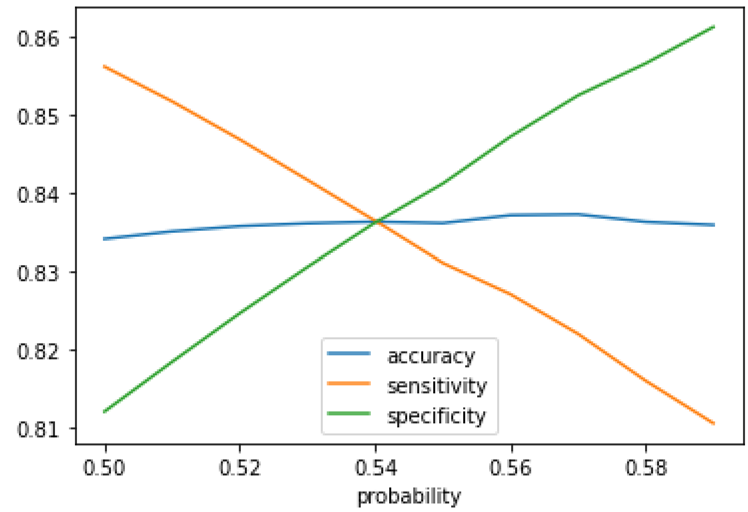
From the above graph, we can see the optimum cutoff is slightly higher than 0.5 but lies lower than 0.6. So lets tweek a little more within this range.

```
# Let's create columns with refined probability cutoffs
numbers = [0.50,0.51,0.52,0.53,0.54,0.55,0.56,0.57,0.58,0.59]
for i in numbers:
    y_train_sm_pred_final[i]= y_train_sm_pred_final.Converted_prob.map(lambda x: 1 if x > i else 
0)
y_train_sm_pred_final.head()
# Now let's calculate accuracy sensitivity and specificity for various probability cutoffs.
cutoff_df = pd.DataFrame( columns = ['probability','accuracy','sensitivity','specificity'])
from sklearn.metrics import confusion_matrix

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

num = [0.50,0.51,0.52,0.53,0.54,0.55,0.56,0.57,0.58,0.59]
for i in num:
    cm1 = metrics.confusion_matrix(y_train_sm_pred_final.Converted, y_train_sm_pred_final[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1

    specificity = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensitivity = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensitivity,specificity]
print(cutoff_df)
```

```
     probability  accuracy  sensitivity  specificity
0.50  0.50         0.834042  0.856128     0.811956
0.51  0.51         0.835001  0.851669     0.818333
0.52  0.52         0.835675  0.846796     0.824554
0.53  0.53         0.836038  0.841611     0.830465
```

```
0.54  0.54          0.836245  0.836375     0.836116
0.55  0.55          0.836064  0.830983     0.841145
0.56  0.56          0.837075  0.826991     0.847159
0.57  0.57          0.837179  0.821910     0.852447
0.58  0.58          0.836219  0.815896     0.856543
0.59  0.59          0.835831  0.810452     0.861209
```

```
# plotting accuracy sensitivity and specificity for various probabilities calculated above.
cutoff_df.plot.line(x='probability', y=['accuracy','sensitivity','specificity'])
plt.show()
```



From the above graph we can conclude, the optimal cutoff point in the probability to define the predicted churn variabe converges at `0.54`

```
#### From the curve above, 0.2 is the optimum point to take it as a cutoff probability.

y_train_sm_pred_final['final_churn_pred'] = y_train_sm_pred_final.Converted_prob.map( lambda
x: 1 if x > 0.54 else 0)

y_train_sm_pred_final.head()
# Calculating the ovearall accuracy again
print("The overall accuracy of the model now
is:",metrics.accuracy_score(y_train_sm_pred_final.Converted,
y_train_sm_pred_final.final_churn_pred))
```

```
The overall accuracy of the model now is: 0.8362453338863542
```

```
confusion2 = metrics.confusion_matrix(y_train_sm_pred_final.Converted,
y_train_sm_pred_final.final_churn_pred )
print(confusion2)
```

```
[[16127  3161]
 [ 3156 16132]]
```

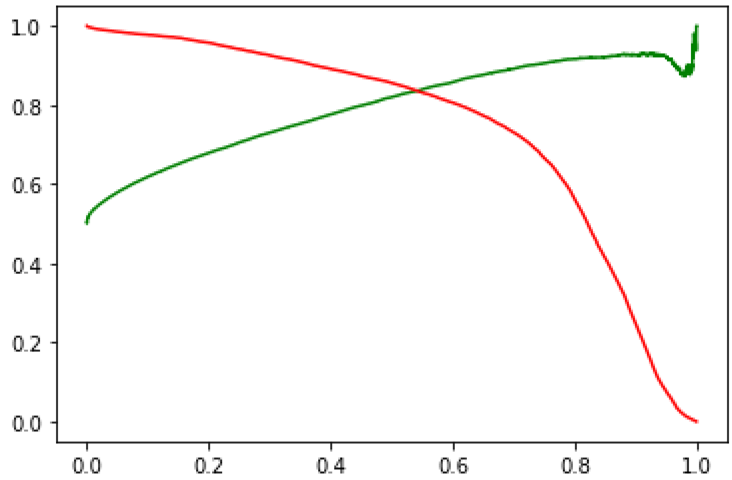
```
TP2 = confusion2[1,1] # true positive
TN2 = confusion2[0,0] # true negatives
FP2 = confusion2[0,1] # false positives
```

```
FN2 = confusion2[1,0] # false negatives

# Let's see the sensitivity of our logistic regression model
print("Sensitivity = ",TP2 / float(TP2+FN2))

# Let us calculate specificity
print("Specificity = ",TN2 / float(TN2+FP2))

# Calculate false postive rate - predicting churn when customer does not have churned
print("False Positive Rate = ",FP2/ float(TN2+FP2))

# positive predictive value
print ("Precision = ",TP2 / float(TP2+FP2))

# Negative predictive value
print ("True Negative Prediction Rate = ",TN2 / float(TN2 + FN2))
```

```
Sensitivity =  0.8363749481542928
Specificity =  0.8361157196184156
False Positive Rate =  0.1638842803815844
Precision =  0.8361581920903954
True Negative Prediction Rate =  0.8363325208733081
```

Precision and recall tradeoff

```
from sklearn.metrics import precision_recall_curve
p, r, thresholds = precision_recall_curve(y_train_sm_pred_final.Converted, y_train_sm_pred_final.Converted_prob)

# Plotting the curve
plt.plot(thresholds, p[:-1], "g-")
plt.plot(thresholds, r[:-1], "r-")
plt.show()
```



Making predictions on the test set

Transforming and feature selection for test data

```
# Scaling the test data
X_test[num_col] = scaler.transform(X_test[num_col])
```

```
X_test.head()
# Feature selection
X_test=X_test[rfe_columns_2]
X_test.head()
# Adding constant to the test model.
X_test_SM = sm.add_constant(X_test)
```

Predicting the target variable

```
y_test_pred = res.predict(X_test_SM)
print("\n The first ten probability value of the prediction are:\n",y_test_pred[:10])
35865    0.772260
41952    0.516558
98938    0.000325
29459    0.128443
70682    0.007754
58317    0.237200
4860     0.007990
16890    0.702931
61329    0.652452
94332    0.491091
dtype: float64
y_pred = pd.DataFrame(y_test_pred)
y_pred.head()
y_pred=y_pred.rename(columns = {0:"Conv_prob"})
y_test_df = pd.DataFrame(y_test)
y_test_df.head()
y_pred_final = pd.concat([y_test_df,y_pred],axis=1)
y_pred_final.head()
y_pred_final['test_churn_pred'] = y_pred_final.Conv_prob.map(lambda x: 1 if x>0.54 else 0)
y_pred_final.head()
# Checking the overall accuracy of the predicted set.
metrics.accuracy_score(y_pred_final.churn, y_pred_final.test_churn_pred)
0.8270192200866571
```

Metrics Evaluation

```
# Confusion Matrix
confusion2_test = metrics.confusion_matrix(y_pred_final.churn, y_pred_final.test_churn_pred)
print("Confusion Matrix\n",confusion2_test)
Confusion Matrix
 [[6860 1412]
 [ 145  584]]

# Calculating model validation parameters
TP3 = confusion2_test[1,1] # true positive
TN3 = confusion2_test[0,0] # true negatives
FP3 = confusion2_test[0,1] # false positives
FN3 = confusion2_test[1,0] # false negatives
# Let's see the sensitivity of our logistic regression model
print("Sensitivity = ",TP3 / float(TP3+FN3))

# Let us calculate specificity
```

```python
print("Specificity = ",TN3 / float(TN3+FP3))

# Calculate false postive rate - predicting churn when customer does not have churned
print("False Positive Rate = ",FP3/ float(TN3+FP3))

# positive predictive value
print ("Precision = ",TP3 / float(TP3+FP3))

# Negative predictive value
print ("True Negative Prediction Rate = ",TN3 / float(TN3+FN3))
```

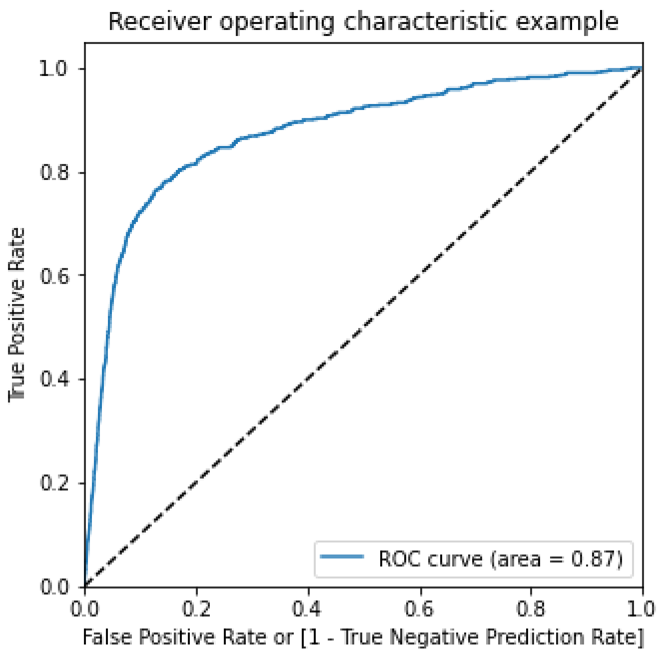
```
Sensitivity =  0.8010973936899863
Specificity =  0.8293036750483559
False Positive Rate =  0.1706963249516441
Precision =  0.2925851703406814
True Negative Prediction Rate =  0.979300499643112
```

Explaining the results

```python
print("The accuracy of the predicted model is: ",round(metrics.accuracy_score(y_pred_final.churn, y_pred_final.test_churn_pred),2)*100,"%")
print("The sensitivity of the predicted model is: ",round(TP3 / float(TP3+FN3),2)*100,"%")

print("\nAs the model created is based on a sentivity model, i.e. the True positive rate is given more importance as the actual and prediction of churn by a customer\n")
```

```
The accuracy of the predicted model is:  83.0 %
The sensitivity of the predicted model is:  80.0 %

As the model created is based on a sentivity model, i.e. the True
positive rate is given more importance as the actual and prediction of
churn by a customer
```

```python
# ROC curve for the test dataset

# Defining the variables to plot the curve
fpr, tpr, thresholds = metrics.roc_curve(y_pred_final.churn,y_pred_final.Conv_prob, drop_intermediate = False )
# Plotting the curve for the obtained metrics
draw_roc(y_pred_final.churn,y_pred_final.Conv_prob)
```



The AUC score for train dataset is 0.90 and the test dataset is 0.87.
This model can be considered as a good model.

Logistic Regression using PCA

```
# split the dateset into train and test datasets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, train_size=0.7,
random_state=1)
print("Dimension of X_train:", X_train.shape)
print("Dimension of X_test:", X_test.shape)

# apply scaling on the dataset

scaler = MinMaxScaler()
X_train[num_col] = scaler.fit_transform(X_train[num_col])
X_test[num_col] = scaler.transform(X_test[num_col])

# Applying SMOTE technique for data imbalance correction

sm = SMOTE(random_state=42)
X_train_sm,y_train_sm = sm.fit_resample(X_train,y_train)
print("Dimension of X_train_sm Shape:", X_train_sm.shape)
print("Dimension of y_train_sm Shape:", y_train_sm.shape)

X_train_sm.head()
```

```
Dimension of X_train: (21000, 126)
Dimension of X_test: (9001, 126)
Dimension of X_train_sm Shape: (38576, 126)
Dimension of y_train_sm Shape: (38576,)
```

```
# importing PCA
```

```
from sklearn.decomposition import PCA
pca = PCA(random_state=42)

# applying PCA on train data
pca.fit(X_train_sm)
PCA(random_state=42)
X_train_sm_pca=pca.fit_transform(X_train_sm)
print("Dimension of X_train_sm_pca: ",X_train_sm_pca.shape)

X_test_pca=pca.transform(X_test)
print("Dimension of X_test_pca: ",X_test_pca.shape)
Dimension of X_train_sm_pca:  (38576, 126)
Dimension of X_test_pca:  (9001, 126)

#Viewing the PCA components
pca.components_
array([[ 1.77080250e-02,  5.62945551e-03,  1.28071557e-02, ...,
        -8.33377373e-02,  2.03169293e-01, -2.25884463e-04],
       [ 1.17884332e-03,  1.36226801e-04,  2.66567649e-03, ...,
         6.62002105e-01, -7.17541378e-01,  1.93966990e-04],
       [ 8.31908962e-03, -2.32698646e-02, -1.53378013e-02, ...,
         7.54642802e-02,  5.50287343e-02,  1.26734621e-03],
       ...,
       [-3.94307290e-07,  1.32661563e-06, -2.21287988e-06, ...,
        -3.76725866e-08, -1.42403279e-08,  2.74517957e-08],
       [ 2.29473384e-07, -1.88640723e-06,  1.53383133e-06, ...,
        -3.64244933e-08, -2.71775061e-08, -3.24942343e-08],
       [-0.00000000e+00, -1.20429354e-16, -2.26455538e-17, ...,
         3.32681843e-18, -2.16312073e-18, -2.01305223e-17]])
```

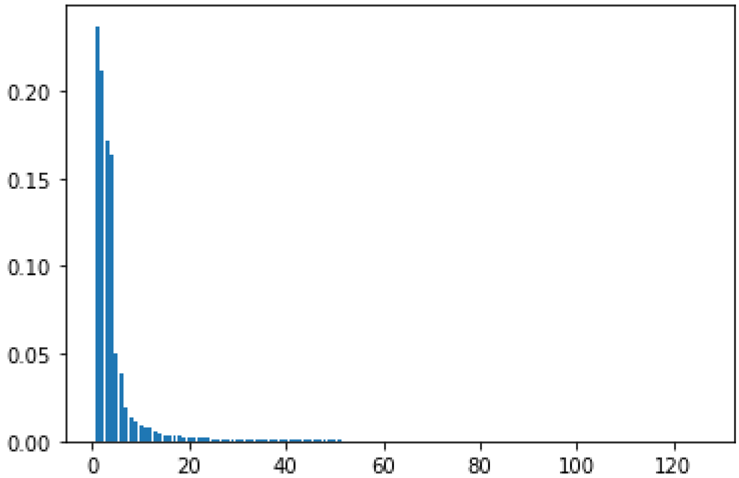
Performing Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
logreg_pca = LogisticRegression()
logreg_pca.fit(X_train_sm_pca, y_train_sm)

# making the predictions
y_pred = logreg_pca.predict(X_test_pca)

# converting the prediction into a dataframe
y_pred_df = pd.DataFrame(y_pred)
print("Dimension of y_pred_df:", y_pred_df.shape)
Dimension of y_pred_df: (9001, 1)

from sklearn.metrics import confusion_matrix, accuracy_score

# Checking the Confusion matrix
print("Confusion Matirx for y_test & y_pred\n",confusion_matrix(y_test,y_pred),"\n")

# Checking the Accuracy of the Predicted model.
```

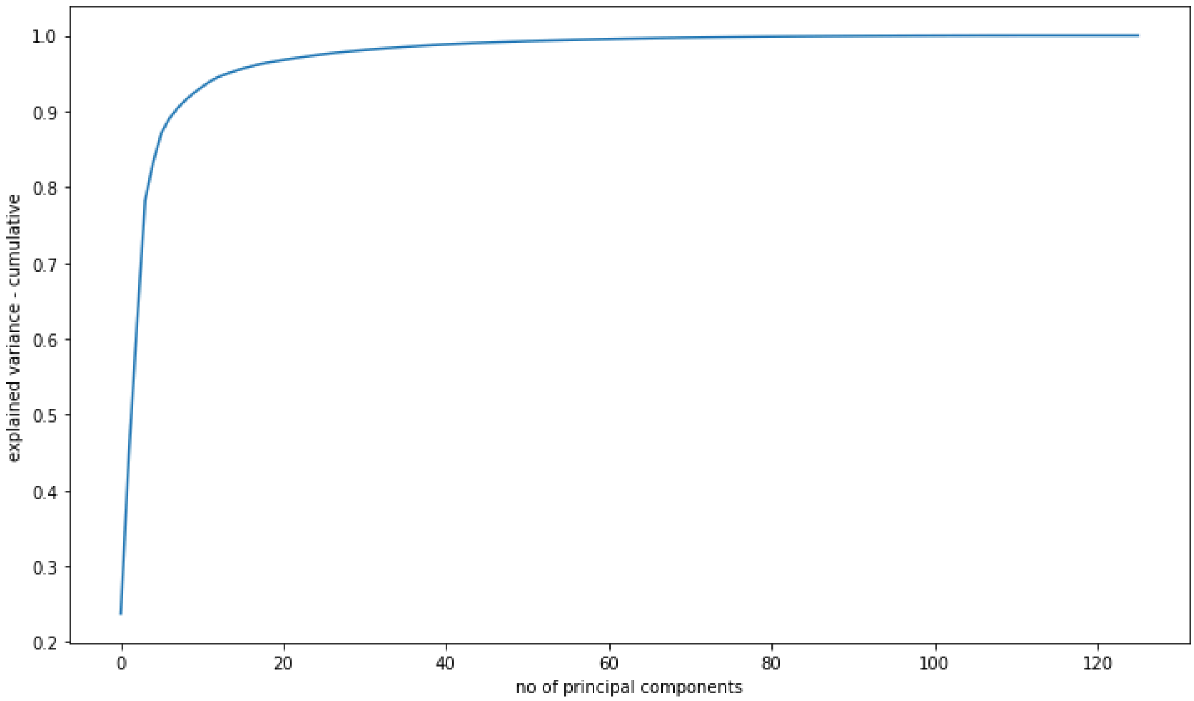
```
print("Accuracy of the logistic regression model with PCA: ",accuracy_score(y_test,y_pred))
```

```
Confusion Matirx for y_test & y_pred
 [[6761 1511]
 [ 126  603]]

Accuracy of the logistic regression model with PCA:  0.818131318742362
```

```
plt.bar(range(1,len(pca.explained_variance_ratio_)+1),pca.explained_variance_ratio_)
plt.show()
```




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

# Making a scree plot
fig = plt.figure(figsize=[12,7])
plt.plot(var_cumu)
plt.xlabel('no of principal components')
plt.ylabel('explained variance - cumulative')
plt.show()
```




```
np.cumsum(np.round(pca.explained_variance_ratio_, decimals=3)*100)
array([23.7, 44.8, 62. , 78.3, 83.3, 87.1, 89. , 90.4, 91.5, 92.4, 93.2,
       93.9, 94.5, 94.9, 95.3, 95.6, 95.9, 96.2, 96.4, 96.6, 96.8, 97. ,
       97.2, 97.4, 97.5, 97.6, 97.7, 97.8, 97.9, 98. , 98.1, 98.2, 98.3,
       98.4, 98.5, 98.6, 98.7, 98.8, 98.9, 99. , 99.1, 99.2, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3])
```

90% of the data can be explained with 8 PCA components

Fitting the dataset with the 8 explainable components

```
pca_8 = PCA(n_components=15)

train_pca_8 = pca_8.fit_transform(X_train_sm)
print("Dimension for Train dataset using PCA: ", train_pca_8.shape)

test_pca_8 = pca_8.transform(X_test)
print("Dimension for Test dataset using PCA: ", test_pca_8.shape)
```

```
Dimension for Train dataset using PCA:  (38576, 15)
Dimension for Test dataset using PCA:  (9001, 15)
```

```
logreg_pca_8 = LogisticRegression()
logreg_pca_8.fit(train_pca_8, y_train_sm)

# making the predictions
y_pred_8 = logreg_pca_8.predict(test_pca_8)
```

```
# converting the prediction into a dataframe
y_pred_df_8 = pd.DataFrame(y_pred_8)
print("Dimension of y_pred_df_8: ", y_pred_df_8.shape)
```

```
Dimension of y_pred_df_8:  (9001, 1)
```

```
# Checking the Confusion matrix
print("Confusion Matirx for y_test & y_pred\n",confusion_matrix(y_test,y_pred_8),"\n")

# Checking the Accuracy of the Predicted model.
print("Accuracy of the logistic regression model with PCA: ",accuracy_score(y_test,y_pred_8))
```

```
Confusion Matirx for y_test & y_pred
 [[6250 2022]
 [ 185  544]]

Accuracy of the logistic regression model with PCA:  0.7548050216642596
```

```
# df_pca = pd.DataFrame(newdata, columns=["PC1", "PC2"])
# df.head()
```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/
telecom-churn-case-study
Updated 3 years ago
Run

Telecom Churn Case Study

Problem Statement

Business problem overview

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

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

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

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

Understanding and defining churn

There are two main models of payment in the telecom industry - **`postpaid`** (customers pay a monthly/annual bill after using the services) and **`prepaid`** (customers pay/recharge with a certain amount in advance and then use the services).

In the postpaid model, when customers want to switch to another operator, they usually inform the existing operator to terminate the services, and you directly know that this is an instance of churn.

However, in the prepaid model, customers who want to switch to another network can simply stop using the services without any notice, and it is hard to know whether someone has actually churned or is simply not using the services temporarily (e.g. someone may be on a trip abroad for a month or two and then intend to resume using the services again).

Thus, churn prediction is usually more critical (and non-trivial) for prepaid customers, and the term 'churn' should be defined carefully. Also, prepaid is the most common model in India and Southeast Asia, while postpaid is more common in Europe in North America.

This project is based on the Indian and Southeast Asian market.

Definitions of churn

There are various ways to define churn, such as:

`Revenue-based churn`: Customers who have not utilised any revenue-generating facilities such as mobile internet, outgoing calls, SMS etc. over a given period of time. One could also use aggregate metrics such as 'customers who have generated less than INR 4 per month in total/average/median revenue'.

The main shortcoming of this definition is that there are customers who only receive calls/SMSes from their wage-earning counterparts, i.e. they don't generate revenue but use the services. For example, many users in rural areas only receive calls from their wage-earning siblings in urban areas.

`Usage-based churn`: Customers who have not done any usage, either incoming or outgoing - in terms of calls, internet etc. over a period of time.

A potential shortcoming of this definition is that when the customer has stopped using the services for a while, it may be too late to take any corrective actions to retain them. For e.g., if you define churn based on a ‘two-months zero usage’ period, predicting churn could be useless since by that time the customer would have already switched to another operator.

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

High-value 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.

In this project, you will define high-value customers based on a certain metric (mentioned later below) and predict churn only on high-value customers.

Understanding the business objective and the data

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

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

Understanding customer behaviour during churn

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

- The ***`‘good’`*** phase: In this phase, the customer is happy with the service and behaves as usual.
- The ***`‘action’`*** phase: The customer experience starts to sore in this phase, for e.g. he/she gets a compelling offer from a competitor, faces unjust charges, becomes unhappy with service quality etc. In this phase, the customer usually shows different behaviour than the ‘good’ months. Also, it is crucial to identify high-churn-risk customers in this phase, since some corrective actions can be taken at this point (such as matching the competitor’s offer/improving the service quality etc.)
- The ***`‘churn’`*** phase: In this phase, the customer is said to have churned. You define churn based on this phase. Also, it is important to note that at the time of prediction (i.e. the action months), this data is not available to you for prediction. Thus, after **`tagging churn as 1/0 based on this phase`**, you discard all data corresponding to this phase.

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

```
# Basic libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
%matplotlib inline
import time

# Supressing the warnings generated
import warnings
warnings.filterwarnings('ignore')

# Importing Pandas EDA tool
import pandas_profiling as pp
from pandas_profiling import ProfileReport

# Displaying all Columns without restrictions
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
pd.set_option('display.max_colwidth', -1)
```

Importing the Dataset

```
# Reading the csv data file.
telecom_data = pd.read_csv("telecom_churn_data.csv")
# Displaying the first 10 field with all columns in the dataset
telecom_data.head(10)
# Checking the dimensions of the dataset
telecom_data.shape
(99999, 226)
# Checking the informations regarding the dataset
telecom_data.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Data columns (total 226 columns):
 #    Column                        Dtype
---   ------                        -----
 0    mobile_number                 int64
 1    circle_id                     int64
 2    loc_og_t2o_mou                float64
 3    std_og_t2o_mou                float64
 4    loc_ic_t2o_mou                float64
 5    last_date_of_month_6          object
 6    last_date_of_month_7          object
 7    last_date_of_month_8          object
 8    last_date_of_month_9          object
 9    arpu_6                        float64
 10   arpu_7                        float64
 11   arpu_8                        float64
 12   arpu_9                        float64
 13   onnet_mou_6                   float64
 14   onnet_mou_7                   float64
 15   onnet_mou_8                   float64
```

16	onnet_mou_9	float64
17	offnet_mou_6	float64
18	offnet_mou_7	float64
19	offnet_mou_8	float64
20	offnet_mou_9	float64
21	roam_ic_mou_6	float64
22	roam_ic_mou_7	float64
23	roam_ic_mou_8	float64
24	roam_ic_mou_9	float64
25	roam_og_mou_6	float64
26	roam_og_mou_7	float64
27	roam_og_mou_8	float64
28	roam_og_mou_9	float64
29	loc_og_t2t_mou_6	float64
30	loc_og_t2t_mou_7	float64
31	loc_og_t2t_mou_8	float64
32	loc_og_t2t_mou_9	float64
33	loc_og_t2m_mou_6	float64
34	loc_og_t2m_mou_7	float64
35	loc_og_t2m_mou_8	float64
36	loc_og_t2m_mou_9	float64
37	loc_og_t2f_mou_6	float64
38	loc_og_t2f_mou_7	float64
39	loc_og_t2f_mou_8	float64
40	loc_og_t2f_mou_9	float64
41	loc_og_t2c_mou_6	float64
42	loc_og_t2c_mou_7	float64
43	loc_og_t2c_mou_8	float64
44	loc_og_t2c_mou_9	float64
45	loc_og_mou_6	float64
46	loc_og_mou_7	float64
47	loc_og_mou_8	float64
48	loc_og_mou_9	float64
49	std_og_t2t_mou_6	float64
50	std_og_t2t_mou_7	float64
51	std_og_t2t_mou_8	float64
52	std_og_t2t_mou_9	float64
53	std_og_t2m_mou_6	float64
54	std_og_t2m_mou_7	float64
55	std_og_t2m_mou_8	float64
56	std_og_t2m_mou_9	float64
57	std_og_t2f_mou_6	float64
58	std_og_t2f_mou_7	float64

59	std_og_t2f_mou_8	float64
60	std_og_t2f_mou_9	float64
61	std_og_t2c_mou_6	float64
62	std_og_t2c_mou_7	float64
63	std_og_t2c_mou_8	float64
64	std_og_t2c_mou_9	float64
65	std_og_mou_6	float64
66	std_og_mou_7	float64
67	std_og_mou_8	float64
68	std_og_mou_9	float64
69	isd_og_mou_6	float64
70	isd_og_mou_7	float64
71	isd_og_mou_8	float64
72	isd_og_mou_9	float64
73	spl_og_mou_6	float64
74	spl_og_mou_7	float64
75	spl_og_mou_8	float64
76	spl_og_mou_9	float64
77	og_others_6	float64
78	og_others_7	float64
79	og_others_8	float64
80	og_others_9	float64
81	total_og_mou_6	float64
82	total_og_mou_7	float64
83	total_og_mou_8	float64
84	total_og_mou_9	float64
85	loc_ic_t2t_mou_6	float64
86	loc_ic_t2t_mou_7	float64
87	loc_ic_t2t_mou_8	float64
88	loc_ic_t2t_mou_9	float64
89	loc_ic_t2m_mou_6	float64
90	loc_ic_t2m_mou_7	float64
91	loc_ic_t2m_mou_8	float64
92	loc_ic_t2m_mou_9	float64
93	loc_ic_t2f_mou_6	float64
94	loc_ic_t2f_mou_7	float64
95	loc_ic_t2f_mou_8	float64
96	loc_ic_t2f_mou_9	float64
97	loc_ic_mou_6	float64
98	loc_ic_mou_7	float64
99	loc_ic_mou_8	float64
100	loc_ic_mou_9	float64
101	std_ic_t2t_mou_6	float64

```
102  std_ic_t2t_mou_7          float64
103  std_ic_t2t_mou_8          float64
104  std_ic_t2t_mou_9          float64
105  std_ic_t2m_mou_6          float64
106  std_ic_t2m_mou_7          float64
107  std_ic_t2m_mou_8          float64
108  std_ic_t2m_mou_9          float64
109  std_ic_t2f_mou_6          float64
110  std_ic_t2f_mou_7          float64
111  std_ic_t2f_mou_8          float64
112  std_ic_t2f_mou_9          float64
113  std_ic_t2o_mou_6          float64
114  std_ic_t2o_mou_7          float64
115  std_ic_t2o_mou_8          float64
116  std_ic_t2o_mou_9          float64
117  std_ic_mou_6              float64
118  std_ic_mou_7              float64
119  std_ic_mou_8              float64
120  std_ic_mou_9              float64
121  total_ic_mou_6            float64
122  total_ic_mou_7            float64
123  total_ic_mou_8            float64
124  total_ic_mou_9            float64
125  spl_ic_mou_6              float64
126  spl_ic_mou_7              float64
127  spl_ic_mou_8              float64
128  spl_ic_mou_9              float64
129  isd_ic_mou_6              float64
130  isd_ic_mou_7              float64
131  isd_ic_mou_8              float64
132  isd_ic_mou_9              float64
133  ic_others_6               float64
134  ic_others_7               float64
135  ic_others_8               float64
136  ic_others_9               float64
137  total_rech_num_6          int64
138  total_rech_num_7          int64
139  total_rech_num_8          int64
140  total_rech_num_9          int64
141  total_rech_amt_6          int64
142  total_rech_amt_7          int64
143  total_rech_amt_8          int64
144  total_rech_amt_9          int64
```

```
145  max_rech_amt_6            int64
146  max_rech_amt_7            int64
147  max_rech_amt_8            int64
148  max_rech_amt_9            int64
149  date_of_last_rech_6       object
150  date_of_last_rech_7       object
151  date_of_last_rech_8       object
152  date_of_last_rech_9       object
153  last_day_rch_amt_6        int64
154  last_day_rch_amt_7        int64
155  last_day_rch_amt_8        int64
156  last_day_rch_amt_9        int64
157  date_of_last_rech_data_6  object
158  date_of_last_rech_data_7  object
159  date_of_last_rech_data_8  object
160  date_of_last_rech_data_9  object
161  total_rech_data_6         float64
162  total_rech_data_7         float64
163  total_rech_data_8         float64
164  total_rech_data_9         float64
165  max_rech_data_6           float64
166  max_rech_data_7           float64
167  max_rech_data_8           float64
168  max_rech_data_9           float64
169  count_rech_2g_6           float64
170  count_rech_2g_7           float64
171  count_rech_2g_8           float64
172  count_rech_2g_9           float64
173  count_rech_3g_6           float64
174  count_rech_3g_7           float64
175  count_rech_3g_8           float64
176  count_rech_3g_9           float64
177  av_rech_amt_data_6        float64
178  av_rech_amt_data_7        float64
179  av_rech_amt_data_8        float64
180  av_rech_amt_data_9        float64
181  vol_2g_mb_6               float64
182  vol_2g_mb_7               float64
183  vol_2g_mb_8               float64
184  vol_2g_mb_9               float64
185  vol_3g_mb_6               float64
186  vol_3g_mb_7               float64
187  vol_3g_mb_8               float64
```

```
 188  vol_3g_mb_9                float64
 189  arpu_3g_6                  float64
 190  arpu_3g_7                  float64
 191  arpu_3g_8                  float64
 192  arpu_3g_9                  float64
 193  arpu_2g_6                  float64
 194  arpu_2g_7                  float64
 195  arpu_2g_8                  float64
 196  arpu_2g_9                  float64
 197  night_pck_user_6           float64
 198  night_pck_user_7           float64
 199  night_pck_user_8           float64
 200  night_pck_user_9           float64
 201  monthly_2g_6               int64
 202  monthly_2g_7               int64
 203  monthly_2g_8               int64
 204  monthly_2g_9               int64
 205  sachet_2g_6                int64
 206  sachet_2g_7                int64
 207  sachet_2g_8                int64
 208  sachet_2g_9                int64
 209  monthly_3g_6               int64
 210  monthly_3g_7               int64
 211  monthly_3g_8               int64
 212  monthly_3g_9               int64
 213  sachet_3g_6                int64
 214  sachet_3g_7                int64
 215  sachet_3g_8                int64
 216  sachet_3g_9                int64
 217  fb_user_6                  float64
 218  fb_user_7                  float64
 219  fb_user_8                  float64
 220  fb_user_9                  float64
 221  aon                        int64
 222  aug_vbc_3g                 float64
 223  jul_vbc_3g                 float64
 224  jun_vbc_3g                 float64
 225  sep_vbc_3g                 float64
dtypes: float64(179), int64(35), object(12)
memory usage: 172.4+ MB
```

This telecom dataset has 99999 rows and 226 columns

Checking the terms used in the data from data dictionary provided.

 # Importing the excel file of the dictionary.

```
telecom_data_dict = pd.read_excel("Data+Dictionary-+Telecom+Churn+Case+Study.xlsx")
# Displaying the dictionary items
telecom_data_dict
```

Initial Statistical Analysis of the Data

```
# Statistical analysis of the numercial features
telecom_data.describe().T
# lets check the columns unique values and drop such columns with its value as 1
unique_1_col=[]
for i in telecom_data.columns:
    if telecom_data[i].nunique() == 1:
        unique_1_col.append(i)
    else:
        pass

telecom_data.drop(unique_1_col, axis=1, inplace = True)
print("\n The following Columns are dropped from the dataset as their unique value is 1. (i.e.)It has no variance in the model\n",
     unique_1_col)
```

```
 The following Columns are dropped from the dataset as their unique value is 1. (i.e.)It has no variance in the model
 ['circle_id', 'loc_og_t2o_mou', 'std_og_t2o_mou', 'loc_ic_t2o_mou', 'last_date_of_month_6', 'last_date_of_month_7', 'last_date_of_month_8', 'last_date_of_month_9', 'std_og_t2c_mou_6', 'std_og_t2c_mou_7', 'std_og_t2c_mou_8', 'std_og_t2c_mou_9', 'std_ic_t2o_mou_6', 'std_ic_t2o_mou_7', 'std_ic_t2o_mou_8', 'std_ic_t2o_mou_9']
```

```
# The curent dimensions of the dataset
telecom_data.shape
```

(99999, 210)

```
# Checkng the overall missing values in the dataset
((telecom_data.isnull().sum()/telecom_data.shape[0])*100).round(2).sort_values(ascending=False)
```

```
max_rech_data_6          74.85
fb_user_6                74.85
count_rech_3g_6          74.85
count_rech_2g_6          74.85
night_pck_user_6         74.85
arpu_3g_6                74.85
total_rech_data_6        74.85
av_rech_amt_data_6       74.85
arpu_2g_6                74.85
date_of_last_rech_data_6    74.85
arpu_3g_7                74.43
night_pck_user_7         74.43
total_rech_data_7        74.43
date_of_last_rech_data_7    74.43
av_rech_amt_data_7       74.43
```

max_rech_data_7	74.43
fb_user_7	74.43
count_rech_3g_7	74.43
arpu_2g_7	74.43
count_rech_2g_7	74.43
count_rech_3g_9	74.08
date_of_last_rech_data_9	74.08
count_rech_2g_9	74.08
fb_user_9	74.08
total_rech_data_9	74.08
max_rech_data_9	74.08
night_pck_user_9	74.08
arpu_2g_9	74.08
av_rech_amt_data_9	74.08
arpu_3g_9	74.08
arpu_3g_8	73.66
fb_user_8	73.66
total_rech_data_8	73.66
count_rech_2g_8	73.66
arpu_2g_8	73.66
date_of_last_rech_data_8	73.66
count_rech_3g_8	73.66
max_rech_data_8	73.66
av_rech_amt_data_8	73.66
night_pck_user_8	73.66
loc_og_t2t_mou_9	7.75
std_ic_t2m_mou_9	7.75
isd_og_mou_9	7.75
roam_og_mou_9	7.75
std_ic_t2t_mou_9	7.75
spl_og_mou_9	7.75
loc_ic_mou_9	7.75
og_others_9	7.75
roam_ic_mou_9	7.75
ic_others_9	7.75
offnet_mou_9	7.75
loc_ic_t2f_mou_9	7.75
loc_og_t2m_mou_9	7.75
loc_ic_t2t_mou_9	7.75
loc_ic_t2m_mou_9	7.75
spl_ic_mou_9	7.75
std_ic_t2f_mou_9	7.75
std_og_mou_9	7.75
std_og_t2m_mou_9	7.75
loc_og_mou_9	7.75
loc_og_t2c_mou_9	7.75
std_og_t2t_mou_9	7.75
isd_ic_mou_9	7.75
loc_og_t2f_mou_9	7.75
onnet_mou_9	7.75

std_ic_mou_9	7.75
std_og_t2f_mou_9	7.75
std_ic_t2t_mou_8	5.38
offnet_mou_8	5.38
std_ic_mou_8	5.38
loc_ic_mou_8	5.38
onnet_mou_8	5.38
loc_ic_t2m_mou_8	5.38
isd_ic_mou_8	5.38
std_ic_t2f_mou_8	5.38
loc_ic_t2f_mou_8	5.38
spl_ic_mou_8	5.38
std_ic_t2m_mou_8	5.38
ic_others_8	5.38
loc_og_t2m_mou_8	5.38
std_og_t2m_mou_8	5.38
roam_og_mou_8	5.38
loc_og_mou_8	5.38
std_og_t2t_mou_8	5.38
isd_og_mou_8	5.38
loc_og_t2t_mou_8	5.38
spl_og_mou_8	5.38
loc_og_t2c_mou_8	5.38
std_og_mou_8	5.38
og_others_8	5.38
roam_ic_mou_8	5.38
std_og_t2f_mou_8	5.38
loc_og_t2f_mou_8	5.38
loc_ic_t2t_mou_8	5.38
date_of_last_rech_9	4.76
std_og_t2t_mou_6	3.94
onnet_mou_6	3.94
std_og_t2m_mou_6	3.94
spl_ic_mou_6	3.94
loc_ic_t2m_mou_6	3.94
isd_ic_mou_6	3.94
loc_og_t2m_mou_6	3.94
ic_others_6	3.94
loc_og_t2c_mou_6	3.94
loc_og_t2f_mou_6	3.94
loc_og_mou_6	3.94
std_ic_mou_6	3.94
std_og_t2f_mou_6	3.94
offnet_mou_6	3.94
loc_ic_t2f_mou_6	3.94
std_og_mou_6	3.94
loc_og_t2t_mou_6	3.94
std_ic_t2f_mou_6	3.94
isd_og_mou_6	3.94
std_ic_t2m_mou_6	3.94

og_others_6	3.94
std_ic_t2t_mou_6	3.94
roam_og_mou_6	3.94
loc_ic_mou_6	3.94
loc_ic_t2t_mou_6	3.94
roam_ic_mou_6	3.94
spl_og_mou_6	3.94
loc_ic_mou_7	3.86
std_ic_t2t_mou_7	3.86
isd_og_mou_7	3.86
og_others_7	3.86
std_og_mou_7	3.86
loc_ic_t2t_mou_7	3.86
loc_ic_t2m_mou_7	3.86
loc_ic_t2f_mou_7	3.86
std_og_t2f_mou_7	3.86
std_ic_t2m_mou_7	3.86
std_ic_t2f_mou_7	3.86
std_ic_mou_7	3.86
std_og_t2m_mou_7	3.86
std_og_t2t_mou_7	3.86
loc_og_mou_7	3.86
spl_ic_mou_7	3.86
isd_ic_mou_7	3.86
ic_others_7	3.86
loc_og_t2c_mou_7	3.86
loc_og_t2f_mou_7	3.86
loc_og_t2m_mou_7	3.86
loc_og_t2t_mou_7	3.86
roam_og_mou_7	3.86
roam_ic_mou_7	3.86
offnet_mou_7	3.86
onnet_mou_7	3.86
spl_og_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
aug_vbc_3g	0.00
jul_vbc_3g	0.00
jun_vbc_3g	0.00
monthly_3g_8	0.00
aon	0.00
monthly_2g_8	0.00
monthly_3g_6	0.00
sachet_2g_9	0.00
sachet_2g_8	0.00
sachet_2g_7	0.00
sachet_2g_6	0.00
monthly_2g_9	0.00
monthly_2g_7	0.00

```
monthly_3g_7             0.00
monthly_3g_9             0.00
monthly_2g_6             0.00
sachet_3g_6             0.00
sachet_3g_7             0.00
sachet_3g_8             0.00
sachet_3g_9             0.00
mobile_number            0.00
total_ic_mou_6           0.00
vol_3g_mb_9              0.00
vol_3g_mb_8              0.00
total_rech_num_9          0.00
total_rech_num_8          0.00
total_rech_num_7          0.00
total_rech_num_6          0.00
total_ic_mou_9           0.00
total_ic_mou_8           0.00
total_ic_mou_7           0.00
arpu_6                 0.00
total_og_mou_9           0.00
total_og_mou_8           0.00
total_og_mou_7           0.00
total_og_mou_6           0.00
arpu_9                 0.00
arpu_8                 0.00
arpu_7                 0.00
total_rech_amt_6          0.00
total_rech_amt_7          0.00
total_rech_amt_8          0.00
last_day_rch_amt_9         0.00
vol_3g_mb_7              0.00
vol_3g_mb_6              0.00
vol_2g_mb_9              0.00
vol_2g_mb_8              0.00
vol_2g_mb_7              0.00
vol_2g_mb_6              0.00
last_day_rch_amt_8         0.00
total_rech_amt_9          0.00
last_day_rch_amt_7         0.00
last_day_rch_amt_6         0.00
max_rech_amt_9            0.00
max_rech_amt_8            0.00
max_rech_amt_7            0.00
max_rech_amt_6            0.00
sep_vbc_3g              0.00
dtype: float64
```

As we can see that the columns with datetime values represented as object, they can be converted into datetime format

```
# selecting all the columns with datetime format
date_col= telecom_data.select_dtypes(include=['object'])
```

```
print("\nThese are the columns available with datetime format represented as
object\n",date_col.columns)

# Converting the selected columns to datetime format
for i in date_col.columns:
    telecom_data[i] = pd.to_datetime(telecom_data[i])

# Current dimension of the dataset
telecom_data.shape
```

```
These are the columns available with datetime format represented as
object
 Index(['date_of_last_rech_6', 'date_of_last_rech_7',
'date_of_last_rech_8',
       'date_of_last_rech_9', 'date_of_last_rech_data_6',
       'date_of_last_rech_data_7', 'date_of_last_rech_data_8',
       'date_of_last_rech_data_9'],
      dtype='object')
```

(99999, 210)

```
# confirming the conversion of dtype
telecom_data.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Data columns (total 210 columns):
 #    Column                     Dtype
---   ------                     -----
 0    mobile_number              int64
 1    arpu_6                     float64
 2    arpu_7                     float64
 3    arpu_8                     float64
 4    arpu_9                     float64
 5    onnet_mou_6                float64
 6    onnet_mou_7                float64
 7    onnet_mou_8                float64
 8    onnet_mou_9                float64
 9    offnet_mou_6               float64
 10   offnet_mou_7               float64
 11   offnet_mou_8               float64
 12   offnet_mou_9               float64
 13   roam_ic_mou_6              float64
 14   roam_ic_mou_7              float64
 15   roam_ic_mou_8              float64
 16   roam_ic_mou_9              float64
 17   roam_og_mou_6              float64
```

18	roam_og_mou_7	float64
19	roam_og_mou_8	float64
20	roam_og_mou_9	float64
21	loc_og_t2t_mou_6	float64
22	loc_og_t2t_mou_7	float64
23	loc_og_t2t_mou_8	float64
24	loc_og_t2t_mou_9	float64
25	loc_og_t2m_mou_6	float64
26	loc_og_t2m_mou_7	float64
27	loc_og_t2m_mou_8	float64
28	loc_og_t2m_mou_9	float64
29	loc_og_t2f_mou_6	float64
30	loc_og_t2f_mou_7	float64
31	loc_og_t2f_mou_8	float64
32	loc_og_t2f_mou_9	float64
33	loc_og_t2c_mou_6	float64
34	loc_og_t2c_mou_7	float64
35	loc_og_t2c_mou_8	float64
36	loc_og_t2c_mou_9	float64
37	loc_og_mou_6	float64
38	loc_og_mou_7	float64
39	loc_og_mou_8	float64
40	loc_og_mou_9	float64
41	std_og_t2t_mou_6	float64
42	std_og_t2t_mou_7	float64
43	std_og_t2t_mou_8	float64
44	std_og_t2t_mou_9	float64
45	std_og_t2m_mou_6	float64
46	std_og_t2m_mou_7	float64
47	std_og_t2m_mou_8	float64
48	std_og_t2m_mou_9	float64
49	std_og_t2f_mou_6	float64
50	std_og_t2f_mou_7	float64
51	std_og_t2f_mou_8	float64
52	std_og_t2f_mou_9	float64
53	std_og_mou_6	float64
54	std_og_mou_7	float64
55	std_og_mou_8	float64
56	std_og_mou_9	float64
57	isd_og_mou_6	float64
58	isd_og_mou_7	float64
59	isd_og_mou_8	float64
60	isd_og_mou_9	float64

61	spl_og_mou_6	float64
62	spl_og_mou_7	float64
63	spl_og_mou_8	float64
64	spl_og_mou_9	float64
65	og_others_6	float64
66	og_others_7	float64
67	og_others_8	float64
68	og_others_9	float64
69	total_og_mou_6	float64
70	total_og_mou_7	float64
71	total_og_mou_8	float64
72	total_og_mou_9	float64
73	loc_ic_t2t_mou_6	float64
74	loc_ic_t2t_mou_7	float64
75	loc_ic_t2t_mou_8	float64
76	loc_ic_t2t_mou_9	float64
77	loc_ic_t2m_mou_6	float64
78	loc_ic_t2m_mou_7	float64
79	loc_ic_t2m_mou_8	float64
80	loc_ic_t2m_mou_9	float64
81	loc_ic_t2f_mou_6	float64
82	loc_ic_t2f_mou_7	float64
83	loc_ic_t2f_mou_8	float64
84	loc_ic_t2f_mou_9	float64
85	loc_ic_mou_6	float64
86	loc_ic_mou_7	float64
87	loc_ic_mou_8	float64
88	loc_ic_mou_9	float64
89	std_ic_t2t_mou_6	float64
90	std_ic_t2t_mou_7	float64
91	std_ic_t2t_mou_8	float64
92	std_ic_t2t_mou_9	float64
93	std_ic_t2m_mou_6	float64
94	std_ic_t2m_mou_7	float64
95	std_ic_t2m_mou_8	float64
96	std_ic_t2m_mou_9	float64
97	std_ic_t2f_mou_6	float64
98	std_ic_t2f_mou_7	float64
99	std_ic_t2f_mou_8	float64
100	std_ic_t2f_mou_9	float64
101	std_ic_mou_6	float64
102	std_ic_mou_7	float64
103	std_ic_mou_8	float64

```
104  std_ic_mou_9               float64
105  total_ic_mou_6             float64
106  total_ic_mou_7             float64
107  total_ic_mou_8             float64
108  total_ic_mou_9             float64
109  spl_ic_mou_6               float64
110  spl_ic_mou_7               float64
111  spl_ic_mou_8               float64
112  spl_ic_mou_9               float64
113  isd_ic_mou_6               float64
114  isd_ic_mou_7               float64
115  isd_ic_mou_8               float64
116  isd_ic_mou_9               float64
117  ic_others_6                float64
118  ic_others_7                float64
119  ic_others_8                float64
120  ic_others_9                float64
121  total_rech_num_6           int64
122  total_rech_num_7           int64
123  total_rech_num_8           int64
124  total_rech_num_9           int64
125  total_rech_amt_6           int64
126  total_rech_amt_7           int64
127  total_rech_amt_8           int64
128  total_rech_amt_9           int64
129  max_rech_amt_6             int64
130  max_rech_amt_7             int64
131  max_rech_amt_8             int64
132  max_rech_amt_9             int64
133  date_of_last_rech_6        datetime64[ns]
134  date_of_last_rech_7        datetime64[ns]
135  date_of_last_rech_8        datetime64[ns]
136  date_of_last_rech_9        datetime64[ns]
137  last_day_rch_amt_6         int64
138  last_day_rch_amt_7         int64
139  last_day_rch_amt_8         int64
140  last_day_rch_amt_9         int64
141  date_of_last_rech_data_6   datetime64[ns]
142  date_of_last_rech_data_7   datetime64[ns]
143  date_of_last_rech_data_8   datetime64[ns]
144  date_of_last_rech_data_9   datetime64[ns]
145  total_rech_data_6          float64
146  total_rech_data_7          float64
```

147	total_rech_data_8	float64
148	total_rech_data_9	float64
149	max_rech_data_6	float64
150	max_rech_data_7	float64
151	max_rech_data_8	float64
152	max_rech_data_9	float64
153	count_rech_2g_6	float64
154	count_rech_2g_7	float64
155	count_rech_2g_8	float64
156	count_rech_2g_9	float64
157	count_rech_3g_6	float64
158	count_rech_3g_7	float64
159	count_rech_3g_8	float64
160	count_rech_3g_9	float64
161	av_rech_amt_data_6	float64
162	av_rech_amt_data_7	float64
163	av_rech_amt_data_8	float64
164	av_rech_amt_data_9	float64
165	vol_2g_mb_6	float64
166	vol_2g_mb_7	float64
167	vol_2g_mb_8	float64
168	vol_2g_mb_9	float64
169	vol_3g_mb_6	float64
170	vol_3g_mb_7	float64
171	vol_3g_mb_8	float64
172	vol_3g_mb_9	float64
173	arpu_3g_6	float64
174	arpu_3g_7	float64
175	arpu_3g_8	float64
176	arpu_3g_9	float64
177	arpu_2g_6	float64
178	arpu_2g_7	float64
179	arpu_2g_8	float64
180	arpu_2g_9	float64
181	night_pck_user_6	float64
182	night_pck_user_7	float64
183	night_pck_user_8	float64
184	night_pck_user_9	float64
185	monthly_2g_6	int64
186	monthly_2g_7	int64
187	monthly_2g_8	int64
188	monthly_2g_9	int64
189	sachet_2g_6	int64

```
 190   sachet_2g_7                  int64
 191   sachet_2g_8                  int64
 192   sachet_2g_9                  int64
 193   monthly_3g_6                 int64
 194   monthly_3g_7                 int64
 195   monthly_3g_8                 int64
 196   monthly_3g_9                 int64
 197   sachet_3g_6                  int64
 198   sachet_3g_7                  int64
 199   sachet_3g_8                  int64
 200   sachet_3g_9                  int64
 201   fb_user_6                    float64
 202   fb_user_7                    float64
 203   fb_user_8                    float64
 204   fb_user_9                    float64
 205   aon                          int64
 206   aug_vbc_3g                   float64
 207   jul_vbc_3g                   float64
 208   jun_vbc_3g                   float64
 209   sep_vbc_3g                   float64
dtypes: datetime64[ns](8), float64(168), int64(34)
memory usage: 160.2 MB
```

Handling missing values

Handling missing values of meaningful attribute column

```
# Handling missing values with respect to `data recharge` attributes
telecom_data[['date_of_last_rech_data_6','total_rech_data_6','max_rech_data_6']].head(10)
```

- Let us conside the column `date_of_last_rech_data` indicating the date of the last recharge made in any given month for mobile internet. Here it can deduced if the `total_rech_data` and the `max_rech_data` also has missing values, the missing values in all the columns mentioned can be considered as meaningful missing.
- Hence imputing 0 as their values.
- Meaningfull missing in this case represents the the customer has not done any recharge for mobile interenet.

Handling the missing values for the attributes `total_rech_data_*`, `max_rech_data_*` and for month 6,7,8 and 9

```
# Code for conditional imputation
start_time=time.time()
for i in range(len(telecom_data)):
  # Handling 'total_rech_data', 'max_rech_data' and for month 6
    if pd.isnull((telecom_data['total_rech_data_6'][i]) and (telecom_data['max_rech_data_6'][i])):
        if pd.isnull(telecom_data['date_of_last_rech_data_6'][i]):
            telecom_data['total_rech_data_6'][i]=0
            telecom_data['max_rech_data_6'][i]=0
```

```
 # Handling 'total_rech_data', 'max_rech_data' and for month 7
  if pd.isnull((telecom_data['total_rech_data_7'][i]) and (telecom_data['max_rech_data_7'][i])):
      if pd.isnull(telecom_data['date_of_last_rech_data_7'][i]):
          telecom_data['total_rech_data_7'][i]=0
          telecom_data['max_rech_data_7'][i]=0

 # Handling 'total_rech_data', 'max_rech_data' and for month 8
  if pd.isnull((telecom_data['total_rech_data_8'][i]) and (telecom_data['max_rech_data_8'][i])):
      if pd.isnull(telecom_data['date_of_last_rech_data_8'][i]):
          telecom_data['total_rech_data_8'][i]=0
          telecom_data['max_rech_data_8'][i]=0

 # Handling 'total_rech_data', 'max_rech_data' and for month 9
  if pd.isnull((telecom_data['total_rech_data_9'][i]) and (telecom_data['max_rech_data_9'][i])):
      if pd.isnull(telecom_data['date_of_last_rech_data_9'][i]):
          telecom_data['total_rech_data_9'][i]=0
          telecom_data['max_rech_data_9'][i]=0

end_time = time.time()
print("\nExecution Time = ", round(end_time-start_time,2),"seconds")
print("The columns
\n'total_rech_data_6','total_rech_data_7','total_rech_data_8','total_rech_data_9'\n'max_rech_dat
a_6','max_rech_data_7','max_rech_data_8','max_rech_data_9' are imputed with 0 based on the
condition explained above")
```

```
Execution Time =  382.04 seconds
The columns
'total_rech_data_6','total_rech_data_7','total_rech_data_8','total_rech
_data_9'
'max_rech_data_6','max_rech_data_7','max_rech_data_8','max_rech_data_9'
are imputed with 0 based on the condition explained above
```

Handling the missing values for the attributes `count_rech_2g_*`,`count_rech_3g_*` for month 6,7,8 and 9

```
# Checking the related columns values
telecom_data[['count_rech_2g_6','count_rech_3g_6','total_rech_data_6']].head(10)
```

From the above tablular the column values of `total_rech_data` for each month from 6 to 9 respectively is the sum of the columns values of `count_rech_2g` for each month from 6 to 9 respectively and `count_rech_3g` for each month from 6 to 9 respectively, which derives to a multicollinearity issue. In order to reduce the multicollinearity, we can drop the columns `count_rech_2g` for each month from 6 to 9 respectively and `count_rech_3g` for each month from 6 to 9 respectively.

```
# Dropping the columns 'count_rech_2g_*' & 'count_rech_3g_*' for the months 6,7,8 and 9
telecom_data.drop(['count_rech_2g_6','count_rech_3g_6',
                   'count_rech_2g_7','count_rech_3g_7',
                   'count_rech_2g_8','count_rech_3g_8',
                   'count_rech_2g_9','count_rech_3g_9'],axis=1, inplace=True)
```

```
print("The 'count_rech_2g_6','count_rech_3g_6','count_rech_2g_7','count_rech_3g_7','count_rech_2g_8','count_rech_3g_8','count_rech_2g_9','count_rech_3g_9' columns are dropped as they can be explained from the 'total_rech_data'column")
```

```
The
'count_rech_2g_6','count_rech_3g_6','count_rech_2g_7','count_rech_3g_7'
,'count_rech_2g_8','count_rech_3g_8','count_rech_2g_9','count_rech_3g_9
' columns are dropped as they can be explained from the
'total_rech_data'column
```

```
# The curent dimensions of the dataset
telecom_data.shape
```

(99999, 202)

Handling the missing values for the attributes `arpu_3g_*`,`arpu_2g_*` for month 6,7,8 and 9

```
# Checking the related columns values
telecom_data[['arpu_3g_6','arpu_2g_6','av_rech_amt_data_6']].head(10)
# Checking the correlation between the above mentioned columns in tabular for months 6,7,8 and 9
print("Correlation table for month 6\n\n", telecom_data[['arpu_3g_6','arpu_2g_6','av_rech_amt_data_6']].corr())
print("\nCorrelation table for month 7\n\n", telecom_data[['arpu_3g_7','arpu_2g_7','av_rech_amt_data_7']].corr())
print("\nCorrelation table for month 8\n\n", telecom_data[['arpu_3g_8','arpu_2g_8','av_rech_amt_data_8']].corr())
print("\nCorrelation table for month 9\n\n", telecom_data[['arpu_3g_9','arpu_2g_9','av_rech_amt_data_9']].corr())
```

```
Correlation table for month 6

                    arpu_3g_6  arpu_2g_6  av_rech_amt_data_6
arpu_3g_6           1.000000   0.932232   0.809695
arpu_2g_6           0.932232   1.000000   0.834065
av_rech_amt_data_6  0.809695   0.834065   1.000000

Correlation table for month 7

                    arpu_3g_7  arpu_2g_7  av_rech_amt_data_7
arpu_3g_7           1.000000   0.930366   0.796131
arpu_2g_7           0.930366   1.000000   0.815933
av_rech_amt_data_7  0.796131   0.815933   1.000000

Correlation table for month 8

                    arpu_3g_8  arpu_2g_8  av_rech_amt_data_8
arpu_3g_8           1.000000   0.924925   0.787165
arpu_2g_8           0.924925   1.000000   0.805482
av_rech_amt_data_8  0.787165   0.805482   1.000000
```

```
Correlation table for month 9

                     arpu_3g_9  arpu_2g_9  av_rech_amt_data_9
arpu_3g_9             1.000000   0.852253   0.722932
arpu_2g_9             0.852253   1.000000   0.817815
av_rech_amt_data_9    0.722932   0.817815   1.000000
```

From the above correlation table between attributes `arpu_2g_*` and `arpu_3g_*` for each month from 6 to 9 respectively is highly correlated to the attribute `av_rech_amt_data_*` for each month from 6 to 9 respectively.
Considering the high correlation between them, it is safer to drop the attributes `arpu_2g_*` and `arpu_3g_*`.

```
# Dropping the columns 'arpu_3g_*'&'arpu_2g_*' in month 6,7,8 and 9 datafrom the dataset
telecom_data.drop(['arpu_3g_6','arpu_2g_6',
              'arpu_3g_7','arpu_2g_7',
              'arpu_3g_8','arpu_2g_8',
              'arpu_3g_9','arpu_2g_9'],axis=1, inplace=True)
print("\nThe columns'arpu_3g_6','arpu_2g_6','arpu_3g_7','arpu_2g_7','arpu_3g_8','arpu_2g_8','arpu_3g_9','arpu_2g_9' are dropped from the dataset due to high corellation between their respective arpu_* variable in the dataset\n")
```

```
The
columns'arpu_3g_6','arpu_2g_6','arpu_3g_7','arpu_2g_7','arpu_3g_8','arp
u_2g_8','arpu_3g_9','arpu_2g_9' are dropped from the dataset due to
high corellation between their respective arpu_* variable in the
dataset
```

```
# The curent dimensions of the dataset
telecom_data.shape
```

(99999, 194)

Handling the other attributes with higher missing value percentage

The column `fb_user_*` and `night_pck_user_*` for each month from 6 to 9 respectively has a missing values above 50% and does not seem to add any information to understand the data. Hence we can drop these columns for further analysis.

```
telecom_data.drop(['fb_user_6','fb_user_7','fb_user_8','fb_user_9',
              'night_pck_user_6','night_pck_user_7','night_pck_user_8','night_pck_user_9'],
              axis=1, inplace=True)
print("\nThe columns 'fb_user_6','fb_user_7','fb_user_8','fb_user_9','night_pck_user_6','night_pck_user_7','night_pck_user_8','night_pck_user_9' are dropped from the dataset as it has no meaning to the data snd has high missing values above 50%\n")
```

```
The columns
'fb_user_6','fb_user_7','fb_user_8','fb_user_9','night_pck_user_6','night_pck_user_7','night_pck_user_8','night_pck_user_9' are dropped from the dataset as it has no meaning to the data snd has high missing values above 50%
```

```
# The curent dimensions of the dataset
telecom_data.shape
```

```
(99999, 186)
```

Handling the missing values for the attributes `av_rech_amt_data_*` for month 6,7,8 and 9

```
# Checking the related columns values
telecom_data[['av_rech_amt_data_7','max_rech_data_7','total_rech_data_7']].head(10)
```

From the above tabular it is deduced that the missing values for the column `av_rech_amt_data_*` for each month from 6 to 9 can be replaced as 0 if the `total_rech_data_*` for each month from 6 to 9 respectively is 0. i.e. if the total recharge done is 0 then the average recharge amount shall also be 0.

```
# Code for conditional imputation
start_time = time.time()
for i in range(len(telecom_data)):
  # Handling `av_rech_amt_data`  for month 6
   if (pd.isnull(telecom_data['av_rech_amt_data_6'][i]) and
(telecom_data['total_rech_data_6'][i]==0)):
       telecom_data['av_rech_amt_data_6'][i] = 0

  # Handling `av_rech_amt_data`  for month 7
   if (pd.isnull(telecom_data['av_rech_amt_data_7'][i]) and
(telecom_data['total_rech_data_7'][i]==0)):
       telecom_data['av_rech_amt_data_7'][i] = 0

  # Handling `av_rech_amt_data`  for month 8
   if (pd.isnull(telecom_data['av_rech_amt_data_8'][i]) and
(telecom_data['total_rech_data_8'][i]==0)):
       telecom_data['av_rech_amt_data_8'][i] = 0

  # Handling `av_rech_amt_data`  for month 9
   if (pd.isnull(telecom_data['av_rech_amt_data_9'][i]) and
(telecom_data['total_rech_data_9'][i]==0)):
       telecom_data['av_rech_amt_data_9'][i] = 0


end_time=time.time()
print("\nExecution Time = ", round(end_time-start_time,2),"seconds")
print("\nThe columns 'av_rech_amt_data_6','av_rech_amt_data_7','av_rech_amt_data_8' and
'av_rech_amt_data_9' are imputed with 0 based on the condition explained above\n")
```

```
Execution Time =  189.69 seconds
```

```
The columns
'av_rech_amt_data_6','av_rech_amt_data_7','av_rech_amt_data_8' and
'av_rech_amt_data_9' are imputed with 0 based on the condition
explained above
```

```
# Checkng the overall missing values in the dataset
((telecom_data.isnull().sum()/telecom_data.shape[0])*100).round(2).sort_values(ascending=False)
date_of_last_rech_data_6    74.85
date_of_last_rech_data_7    74.43
date_of_last_rech_data_9    74.08
date_of_last_rech_data_8    73.66
og_others_9                 7.75
loc_og_t2f_mou_9            7.75
loc_og_t2t_mou_9            7.75
loc_ic_t2f_mou_9            7.75
std_ic_mou_9                7.75
std_og_t2f_mou_9            7.75
loc_og_t2m_mou_9            7.75
loc_ic_mou_9                7.75
std_og_t2m_mou_9            7.75
std_ic_t2f_mou_9            7.75
std_ic_t2t_mou_9            7.75
loc_og_t2c_mou_9            7.75
std_ic_t2m_mou_9            7.75
std_og_t2t_mou_9            7.75
loc_og_mou_9                7.75
std_og_mou_9                7.75
spl_ic_mou_9                7.75
roam_og_mou_9               7.75
spl_og_mou_9                7.75
loc_ic_t2t_mou_9            7.75
isd_og_mou_9                7.75
roam_ic_mou_9               7.75
loc_ic_t2m_mou_9            7.75
isd_ic_mou_9                7.75
onnet_mou_9                 7.75
ic_others_9                 7.75
offnet_mou_9                7.75
og_others_8                 5.38
std_ic_t2t_mou_8            5.38
std_og_t2m_mou_8            5.38
loc_ic_t2m_mou_8            5.38
spl_og_mou_8                5.38
loc_ic_t2f_mou_8            5.38
loc_ic_mou_8                5.38
std_og_t2f_mou_8            5.38
isd_og_mou_8                5.38
```

std_og_mou_8	5.38
std_og_t2t_mou_8	5.38
loc_ic_t2t_mou_8	5.38
std_ic_t2m_mou_8	5.38
loc_og_t2t_mou_8	5.38
onnet_mou_8	5.38
ic_others_8	5.38
offnet_mou_8	5.38
roam_ic_mou_8	5.38
isd_ic_mou_8	5.38
roam_og_mou_8	5.38
loc_og_mou_8	5.38
spl_ic_mou_8	5.38
loc_og_t2m_mou_8	5.38
std_ic_mou_8	5.38
loc_og_t2f_mou_8	5.38
loc_og_t2c_mou_8	5.38
std_ic_t2f_mou_8	5.38
date_of_last_rech_9	4.76
loc_ic_mou_6	3.94
spl_ic_mou_6	3.94
std_ic_mou_6	3.94
loc_ic_t2f_mou_6	3.94
isd_ic_mou_6	3.94
loc_ic_t2t_mou_6	3.94
ic_others_6	3.94
std_ic_t2t_mou_6	3.94
loc_ic_t2m_mou_6	3.94
std_ic_t2f_mou_6	3.94
std_ic_t2m_mou_6	3.94
loc_og_t2c_mou_6	3.94
spl_og_mou_6	3.94
std_og_t2t_mou_6	3.94
loc_og_t2f_mou_6	3.94
std_og_t2m_mou_6	3.94
onnet_mou_6	3.94
std_og_t2f_mou_6	3.94
loc_og_t2m_mou_6	3.94
std_og_mou_6	3.94
isd_og_mou_6	3.94
loc_og_t2t_mou_6	3.94
loc_og_mou_6	3.94
roam_og_mou_6	3.94
og_others_6	3.94
roam_ic_mou_6	3.94
offnet_mou_6	3.94
offnet_mou_7	3.86
loc_og_t2c_mou_7	3.86
onnet_mou_7	3.86
loc_og_t2f_mou_7	3.86

std_ic_mou_7	3.86
isd_ic_mou_7	3.86
loc_og_t2m_mou_7	3.86
roam_og_mou_7	3.86
loc_og_t2t_mou_7	3.86
roam_ic_mou_7	3.86
std_ic_t2f_mou_7	3.86
ic_others_7	3.86
spl_ic_mou_7	3.86
loc_og_mou_7	3.86
std_og_t2f_mou_7	3.86
loc_ic_t2t_mou_7	3.86
og_others_7	3.86
loc_ic_t2m_mou_7	3.86
spl_og_mou_7	3.86
loc_ic_t2f_mou_7	3.86
std_og_mou_7	3.86
loc_ic_mou_7	3.86
isd_og_mou_7	3.86
std_og_t2m_mou_7	3.86
std_ic_t2t_mou_7	3.86
std_og_t2t_mou_7	3.86
std_ic_t2m_mou_7	3.86
date_of_last_rech_8	3.62
date_of_last_rech_7	1.77
date_of_last_rech_6	1.61
jun_vbc_3g	0.00
vol_2g_mb_8	0.00
vol_3g_mb_6	0.00
av_rech_amt_data_6	0.00
vol_2g_mb_9	0.00
vol_2g_mb_7	0.00
vol_3g_mb_8	0.00
av_rech_amt_data_7	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_8	0.00
av_rech_amt_data_9	0.00
aug_vbc_3g	0.00
jul_vbc_3g	0.00
vol_3g_mb_7	0.00
sachet_3g_9	0.00
vol_3g_mb_9	0.00
monthly_3g_6	0.00
sachet_3g_7	0.00
aon	0.00
max_rech_data_8	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
monthly_3g_7	0.00

```
sachet_3g_8             0.00
monthly_2g_6            0.00
sachet_2g_9             0.00
sachet_2g_8             0.00
sachet_2g_7             0.00
sachet_2g_6             0.00
monthly_2g_9            0.00
monthly_2g_8            0.00
monthly_2g_7            0.00
max_rech_data_9         0.00
mobile_number           0.00
max_rech_data_7         0.00
arpu_6                  0.00
total_rech_num_7        0.00
total_rech_num_6        0.00
total_ic_mou_9          0.00
total_ic_mou_8          0.00
total_ic_mou_7          0.00
total_ic_mou_6          0.00
total_og_mou_9          0.00
total_rech_num_9        0.00
total_og_mou_8          0.00
total_og_mou_7          0.00
total_og_mou_6          0.00
arpu_9                  0.00
arpu_8                  0.00
arpu_7                  0.00
total_rech_num_8        0.00
total_rech_amt_6        0.00
max_rech_data_6         0.00
last_day_rch_amt_7      0.00
total_rech_data_9       0.00
total_rech_data_8       0.00
total_rech_data_7       0.00
total_rech_data_6       0.00
last_day_rch_amt_9      0.00
last_day_rch_amt_8      0.00
last_day_rch_amt_6      0.00
total_rech_amt_7        0.00
max_rech_amt_9          0.00
max_rech_amt_8          0.00
max_rech_amt_7          0.00
max_rech_amt_6          0.00
total_rech_amt_9        0.00
total_rech_amt_8        0.00
sep_vbc_3g              0.00
dtype: float64
```

```
telecom_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
```

```
Columns: 186 entries, mobile_number to sep_vbc_3g
dtypes: datetime64[ns](8), float64(144), int64(34)
memory usage: 141.9 MB
```

From the above results, we can conclude, the `date_of_last_rech_data_*` corresponding to months 6,7,8 and 9 are of no value after the conditional imputation of of columns `total_rech_data_*`, `max_rech_data_*`are completes.
Also the missing value percentage is high for these columns and can be dropped from the dataset.

```
# Dropping the columns related to datetime dtype from the dataset
telecom_data.drop(["date_of_last_rech_data_6","date_of_last_rech_data_7",
                   "date_of_last_rech_data_8","date_of_last_rech_data_9"], axis=1, inplace=True)
print("\nThe columns 'date_of_last_rech_data_6','date_of_last_rech_data_7','date_of_last_rech_data_8','date_of_last_rech_data_9' are dropped as it has no significance to the data\n")
```

```
The columns
'date_of_last_rech_data_6','date_of_last_rech_data_7','date_of_last_rech_data_8','date_of_last_rech_data_9' are dropped as it has no significance to the data
```

As we can no more utilise the datetime column, we can drop the `date_of_last_rech_data_*` column corresponding to months 6,7,8 and 9 respectively.

```
# Dropping the columns related to datetime dtype from the dataset
telecom_data.drop(["date_of_last_rech_6","date_of_last_rech_7",
                   "date_of_last_rech_8","date_of_last_rech_9"], axis=1, inplace=True)
print("\nThe columns 'date_of_last_rech_6','date_of_last_rech_7','date_of_last_rech_8','date_of_last_rech_9' are dropped as it has no significance to the data\n")
```

```
The columns
'date_of_last_rech_6','date_of_last_rech_7','date_of_last_rech_8','date_of_last_rech_9' are dropped as it has no significance to the data
```

```
# The curent dimensions of the dataset
telecom_data.shape
```

(99999, 178)

Since the columns used to determine the High Value Customer is clear of null values, we can filter the overall data and then handle the remaining missing values for each column

Filtering the High Value Customer from Good Phase

```
# Filtering the data
 # We are filtering the data in accordance to total revenue generated per customer.
```

```
# first we need the total amount recharge amount done for data alone, we have average rechage amount done.

# Calculating the total recharge amount done for data alone in months 6,7,8 and 9
telecom_data['total_rech_amt_data_6']=telecom_data['av_rech_amt_data_6'] * telecom_data['total_rech_data_6']
telecom_data['total_rech_amt_data_7']=telecom_data['av_rech_amt_data_7'] * telecom_data['total_rech_data_7']

# Calculating the overall recharge amount for the months 6,7,8 and 9
telecom_data['overall_rech_amt_6'] = telecom_data['total_rech_amt_data_6'] + telecom_data['total_rech_amt_6']
telecom_data['overall_rech_amt_7'] = telecom_data['total_rech_amt_data_7'] + telecom_data['total_rech_amt_7']

# Calculating the average recharge done by customer in months June and July(i.e. 6th and 7th month)
telecom_data['avg_rech_amt_6_7'] = (telecom_data['overall_rech_amt_6'] + telecom_data['overall_rech_amt_7'])/2

# Finding the value of 70th percentage in the overall revenues defining the high value customer creteria for the company
cut_off = telecom_data['avg_rech_amt_6_7'].quantile(0.70)
print("\nThe 70th quantile value to determine the High Value Customer is: ",cut_off,"\n")

# Filtering the data to the top 30% considered as High Value Customer
telecom_data = telecom_data[telecom_data['avg_rech_amt_6_7'] >= cut_off]
```

```
The 70th quantile value to determine the High Value Customer is:  478.0
```

```
# The curent dimension of the dataset
telecom_data.shape
```

(30001, 183)

The total number of customers is now limited to ~30k who lies under the High Value customer criteria basen upon which the model is built.

```
# Let us check the missing values percentages again for the HVC group
   # Checkng the overall missing values in the dataset
((telecom_data.isnull().sum()/telecom_data.shape[0])*100).round(2).sort_values(ascending=False)
```

```
loc_ic_t2f_mou_9       6.34
spl_og_mou_9           6.34
loc_og_t2m_mou_9       6.34
loc_og_t2f_mou_9       6.34
loc_ic_t2t_mou_9       6.34
isd_og_mou_9           6.34
loc_og_t2t_mou_9       6.34
loc_ic_t2m_mou_9       6.34
```

std_og_t2t_mou_9	6.34
roam_og_mou_9	6.34
std_og_mou_9	6.34
loc_ic_mou_9	6.34
std_ic_t2t_mou_9	6.34
roam_ic_mou_9	6.34
loc_og_t2c_mou_9	6.34
std_ic_t2m_mou_9	6.34
offnet_mou_9	6.34
std_ic_t2f_mou_9	6.34
std_og_t2f_mou_9	6.34
std_ic_mou_9	6.34
onnet_mou_9	6.34
spl_ic_mou_9	6.34
loc_og_mou_9	6.34
isd_ic_mou_9	6.34
std_og_t2m_mou_9	6.34
ic_others_9	6.34
og_others_9	6.34
std_og_mou_8	3.91
isd_og_mou_8	3.91
std_og_t2f_mou_8	3.91
std_ic_t2t_mou_8	3.91
og_others_8	3.91
loc_ic_t2t_mou_8	3.91
loc_ic_t2m_mou_8	3.91
loc_ic_t2f_mou_8	3.91
loc_ic_mou_8	3.91
std_ic_t2m_mou_8	3.91
std_ic_t2f_mou_8	3.91
std_ic_mou_8	3.91
spl_ic_mou_8	3.91
isd_ic_mou_8	3.91
ic_others_8	3.91
std_og_t2m_mou_8	3.91
spl_og_mou_8	3.91
std_og_t2t_mou_8	3.91
offnet_mou_8	3.91
loc_og_t2t_mou_8	3.91
loc_og_t2f_mou_8	3.91
roam_og_mou_8	3.91
roam_ic_mou_8	3.91
loc_og_t2c_mou_8	3.91
loc_og_t2m_mou_8	3.91
loc_og_mou_8	3.91
onnet_mou_8	3.91
offnet_mou_6	1.82
std_og_t2m_mou_6	1.82
loc_ic_t2m_mou_6	1.82
loc_og_t2m_mou_6	1.82

ic_others_6	1.82
loc_ic_t2f_mou_6	1.82
loc_og_t2t_mou_6	1.82
onnet_mou_6	1.82
std_ic_t2t_mou_6	1.82
isd_ic_mou_6	1.82
std_ic_mou_6	1.82
roam_og_mou_6	1.82
std_ic_t2m_mou_6	1.82
loc_ic_t2t_mou_6	1.82
spl_ic_mou_6	1.82
roam_ic_mou_6	1.82
std_ic_t2f_mou_6	1.82
loc_ic_mou_6	1.82
loc_og_mou_6	1.82
std_og_t2t_mou_6	1.82
loc_og_t2c_mou_6	1.82
std_og_t2f_mou_6	1.82
isd_og_mou_6	1.82
loc_og_t2f_mou_6	1.82
spl_og_mou_6	1.82
std_og_mou_6	1.82
og_others_6	1.82
std_ic_mou_7	1.79
roam_ic_mou_7	1.79
std_ic_t2f_mou_7	1.79
std_og_mou_7	1.79
offnet_mou_7	1.79
std_ic_t2m_mou_7	1.79
loc_og_mou_7	1.79
ic_others_7	1.79
std_og_t2m_mou_7	1.79
std_og_t2f_mou_7	1.79
spl_ic_mou_7	1.79
onnet_mou_7	1.79
isd_og_mou_7	1.79
loc_og_t2c_mou_7	1.79
std_og_t2t_mou_7	1.79
loc_og_t2t_mou_7	1.79
loc_ic_t2t_mou_7	1.79
loc_og_t2m_mou_7	1.79
loc_ic_t2m_mou_7	1.79
loc_og_t2f_mou_7	1.79
og_others_7	1.79
loc_ic_t2f_mou_7	1.79
isd_ic_mou_7	1.79
loc_ic_mou_7	1.79
spl_og_mou_7	1.79
roam_og_mou_7	1.79
std_ic_t2t_mou_7	1.79

monthly_2g_9	0.00
monthly_2g_8	0.00
vol_2g_mb_6	0.00
av_rech_amt_data_8	0.00
sachet_2g_6	0.00
sachet_2g_7	0.00
av_rech_amt_data_9	0.00
vol_3g_mb_6	0.00
monthly_2g_7	0.00
monthly_2g_6	0.00
vol_3g_mb_9	0.00
vol_3g_mb_8	0.00
vol_2g_mb_9	0.00
vol_3g_mb_7	0.00
sachet_2g_9	0.00
vol_2g_mb_7	0.00
vol_2g_mb_8	0.00
sachet_2g_8	0.00
jul_vbc_3g	0.00
monthly_3g_6	0.00
monthly_3g_7	0.00
overall_rech_amt_7	0.00
overall_rech_amt_6	0.00
total_rech_amt_data_7	0.00
total_rech_amt_data_6	0.00
sep_vbc_3g	0.00
jun_vbc_3g	0.00
av_rech_amt_data_6	0.00
aug_vbc_3g	0.00
aon	0.00
sachet_3g_9	0.00
sachet_3g_8	0.00
sachet_3g_7	0.00
sachet_3g_6	0.00
monthly_3g_9	0.00
monthly_3g_8	0.00
av_rech_amt_data_7	0.00
mobile_number	0.00
max_rech_data_9	0.00
total_rech_amt_6	0.00
total_rech_num_8	0.00
total_rech_num_7	0.00
total_rech_num_6	0.00
total_ic_mou_9	0.00
total_ic_mou_8	0.00
total_ic_mou_7	0.00
total_ic_mou_6	0.00
arpu_6	0.00
total_og_mou_9	0.00
total_og_mou_8	0.00

```
total_og_mou_7          0.00
total_og_mou_6          0.00
arpu_9                  0.00
arpu_8                  0.00
arpu_7                  0.00
total_rech_num_9        0.00
total_rech_amt_7        0.00
max_rech_data_8         0.00
total_rech_amt_8        0.00
max_rech_data_7         0.00
max_rech_data_6         0.00
total_rech_data_9       0.00
total_rech_data_8       0.00
total_rech_data_7       0.00
total_rech_data_6       0.00
last_day_rch_amt_9      0.00
last_day_rch_amt_8      0.00
last_day_rch_amt_7      0.00
last_day_rch_amt_6      0.00
max_rech_amt_9          0.00
max_rech_amt_8          0.00
max_rech_amt_7          0.00
max_rech_amt_6          0.00
total_rech_amt_9        0.00
avg_rech_amt_6_7        0.00
dtype: float64
```

*** The remaining attributes with missing value can be imputed using the advanced imputation technique like `KNNImputer`.***

```
# Numerical columns available
num_col = telecom_data.select_dtypes(include = ['int64','float64']).columns.tolist()
# Importing the libraries for Scaling and Imputation
from sklearn.impute import KNNImputer
from sklearn.preprocessing import MinMaxScaler

# Calling the Scaling function
scalar = MinMaxScaler()

# Scaling and transforming the data for the columns that are numerical
telecom_data[num_col]=scalar.fit_transform(telecom_data[num_col])

# Calling the KNN Imputer function
knn=KNNImputer(n_neighbors=3)

# Imputing the NaN values using KNN Imputer
start_time=time.time()

telecom_data_knn = pd.DataFrame(knn.fit_transform(telecom_data[num_col]))
telecom_data_knn.columns=telecom_data[num_col].columns

end_time=time.time()
```

```
print("\nExecution Time = ", round(end_time-start_time,2),"seconds\n")
```

```
Execution Time =  170.72 seconds
```

```
# check for any null values after imputation for numerical columns
telecom_data_knn.isnull().sum().sum()
```

0

The KNN Imputer has replaced all the null values in the numerical column usingK-means algorithm sucessfully

```
# Since we sclaed the numerical columns for the purpose of handling the null values,
   #we can restore the sclaed alues to its original form.

# Converting the scaled data back to the original data
telecom_data[num_col]=scalar.inverse_transform(telecom_data_knn)

# Checking the top 10 data
telecom_data.head(10)
# Checking the overall missing values in the dataset
((telecom_data.isnull().sum()/telecom_data.shape[0])*100).round(2).sort_values(ascending=Fals
e)
```

```
mobile_number         0.0
isd_ic_mou_8          0.0
ic_others_6           0.0
ic_others_7           0.0
ic_others_8           0.0
ic_others_9           0.0
total_rech_num_6      0.0
total_rech_num_7      0.0
total_rech_num_8      0.0
total_rech_num_9      0.0
total_rech_amt_6      0.0
total_rech_amt_7      0.0
total_rech_amt_8      0.0
total_rech_amt_9      0.0
max_rech_amt_6        0.0
max_rech_amt_7        0.0
max_rech_amt_8        0.0
max_rech_amt_9        0.0
last_day_rch_amt_6    0.0
last_day_rch_amt_7    0.0
last_day_rch_amt_8    0.0
isd_ic_mou_9          0.0
isd_ic_mou_7          0.0
total_rech_data_6     0.0
isd_ic_mou_6          0.0
std_ic_t2m_mou_7      0.0
std_ic_t2m_mou_8      0.0
std_ic_t2m_mou_9      0.0
```

std_ic_t2f_mou_6	0.0
std_ic_t2f_mou_7	0.0
std_ic_t2f_mou_8	0.0
std_ic_t2f_mou_9	0.0
std_ic_mou_6	0.0
std_ic_mou_7	0.0
std_ic_mou_8	0.0
std_ic_mou_9	0.0
total_ic_mou_6	0.0
total_ic_mou_7	0.0
total_ic_mou_8	0.0
total_ic_mou_9	0.0
spl_ic_mou_6	0.0
spl_ic_mou_7	0.0
spl_ic_mou_8	0.0
spl_ic_mou_9	0.0
last_day_rch_amt_9	0.0
total_rech_data_7	0.0
std_ic_t2t_mou_9	0.0
sachet_2g_6	0.0
sachet_2g_8	0.0
sachet_2g_9	0.0
monthly_3g_6	0.0
monthly_3g_7	0.0
monthly_3g_8	0.0
monthly_3g_9	0.0
sachet_3g_6	0.0
sachet_3g_7	0.0
sachet_3g_8	0.0
sachet_3g_9	0.0
aon	0.0
aug_vbc_3g	0.0
jul_vbc_3g	0.0
jun_vbc_3g	0.0
sep_vbc_3g	0.0
total_rech_amt_data_6	0.0
total_rech_amt_data_7	0.0
overall_rech_amt_6	0.0
overall_rech_amt_7	0.0
sachet_2g_7	0.0
monthly_2g_9	0.0
total_rech_data_8	0.0
monthly_2g_8	0.0
total_rech_data_9	0.0
max_rech_data_6	0.0
max_rech_data_7	0.0
max_rech_data_8	0.0
max_rech_data_9	0.0
av_rech_amt_data_6	0.0
av_rech_amt_data_7	0.0

av_rech_amt_data_8	0.0
av_rech_amt_data_9	0.0
vol_2g_mb_6	0.0
vol_2g_mb_7	0.0
vol_2g_mb_8	0.0
vol_2g_mb_9	0.0
vol_3g_mb_6	0.0
vol_3g_mb_7	0.0
vol_3g_mb_8	0.0
vol_3g_mb_9	0.0
monthly_2g_6	0.0
monthly_2g_7	0.0
std_ic_t2m_mou_6	0.0
std_ic_t2t_mou_8	0.0
arpu_6	0.0
loc_og_t2t_mou_8	0.0
loc_og_t2m_mou_6	0.0
loc_og_t2m_mou_7	0.0
loc_og_t2m_mou_8	0.0
loc_og_t2m_mou_9	0.0
loc_og_t2f_mou_6	0.0
loc_og_t2f_mou_7	0.0
loc_og_t2f_mou_8	0.0
loc_og_t2f_mou_9	0.0
loc_og_t2c_mou_6	0.0
loc_og_t2c_mou_7	0.0
loc_og_t2c_mou_8	0.0
loc_og_t2c_mou_9	0.0
loc_og_mou_6	0.0
loc_og_mou_7	0.0
loc_og_mou_8	0.0
loc_og_mou_9	0.0
std_og_t2t_mou_6	0.0
std_og_t2t_mou_7	0.0
std_og_t2t_mou_8	0.0
loc_og_t2t_mou_9	0.0
loc_og_t2t_mou_7	0.0
std_og_t2m_mou_6	0.0
loc_og_t2t_mou_6	0.0
arpu_7	0.0
arpu_8	0.0
arpu_9	0.0
onnet_mou_6	0.0
onnet_mou_7	0.0
onnet_mou_8	0.0
onnet_mou_9	0.0
offnet_mou_6	0.0
offnet_mou_7	0.0
offnet_mou_8	0.0
offnet_mou_9	0.0

roam_ic_mou_6	0.0
roam_ic_mou_7	0.0
roam_ic_mou_8	0.0
roam_ic_mou_9	0.0
roam_og_mou_6	0.0
roam_og_mou_7	0.0
roam_og_mou_8	0.0
roam_og_mou_9	0.0
std_og_t2t_mou_9	0.0
std_og_t2m_mou_7	0.0
std_ic_t2t_mou_7	0.0
total_og_mou_6	0.0
total_og_mou_8	0.0
total_og_mou_9	0.0
loc_ic_t2t_mou_6	0.0
loc_ic_t2t_mou_7	0.0
loc_ic_t2t_mou_8	0.0
loc_ic_t2t_mou_9	0.0
loc_ic_t2m_mou_6	0.0
loc_ic_t2m_mou_7	0.0
loc_ic_t2m_mou_8	0.0
loc_ic_t2m_mou_9	0.0
loc_ic_t2f_mou_6	0.0
loc_ic_t2f_mou_7	0.0
loc_ic_t2f_mou_8	0.0
loc_ic_t2f_mou_9	0.0
loc_ic_mou_6	0.0
loc_ic_mou_7	0.0
loc_ic_mou_8	0.0
loc_ic_mou_9	0.0
std_ic_t2t_mou_6	0.0
total_og_mou_7	0.0
og_others_9	0.0
std_og_t2m_mou_8	0.0
og_others_8	0.0
std_og_t2m_mou_9	0.0
std_og_t2f_mou_6	0.0
std_og_t2f_mou_7	0.0
std_og_t2f_mou_8	0.0
std_og_t2f_mou_9	0.0
std_og_mou_6	0.0
std_og_mou_7	0.0
std_og_mou_8	0.0
std_og_mou_9	0.0
isd_og_mou_6	0.0
isd_og_mou_7	0.0
isd_og_mou_8	0.0
isd_og_mou_9	0.0
spl_og_mou_6	0.0
spl_og_mou_7	0.0

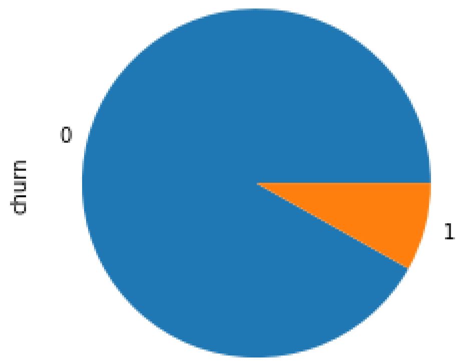
```
spl_og_mou_8          0.0
spl_og_mou_9          0.0
og_others_6           0.0
og_others_7           0.0
avg_rech_amt_6_7      0.0
dtype: float64
# Reconfirming for missing values if any
telecom_data.isnull().sum().sum()
0
```

Defining Churn variable

As explained above in the introduction, we are deriving based on usage based for this model.

For that, we need to find the derive churn variable using `total_ic_mou_9`,`total_og_mou_9`,`vol_2g_mb_9` and `vol_3g_mb_9` attributes

```
# Selecting the columns to define churn variable (i.e. TARGET Variable)
churn_col=['total_ic_mou_9','total_og_mou_9','vol_2g_mb_9','vol_3g_mb_9']
telecom_data[churn_col].info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30001 entries, 0 to 99997
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   total_ic_mou_9  30001 non-null  float64
 1   total_og_mou_9  30001 non-null  float64
 2   vol_2g_mb_9     30001 non-null  float64
 3   vol_3g_mb_9     30001 non-null  float64
dtypes: float64(4)
memory usage: 1.1 MB

# Initializing the churn variable.
telecom_data['churn']=0

# Imputing the churn values based on the condition
telecom_data['churn'] = np.where(telecom_data[churn_col].sum(axis=1) == 0, 1, 0)
# Checking the top 10 data
telecom_data.head(10)
# lets find out churn/non churn percentage
print((telecom_data['churn'].value_counts()/len(telecom_data))*100)
((telecom_data['churn'].value_counts()/len(telecom_data))*100).plot(kind="pie")
plt.show()
0    91.863605
1     8.136395
Name: churn, dtype: float64
```



As we can see that 91% of the customers do not churn, there is a possibility of class imbalance

Since this variable `churn` is the target variable, all the columns relating to this variable(i.e. all columns with suffix _9) can be dropped forn the dataset.

```
# Selecting all the churn phase columns in order to drop then

churn_phase_cols = [col for col in telecom_data.columns if '_9' in col]
print("The columns from churn phase are:\n",churn_phase_cols)
```

```
The columns from churn phase are:
 ['arpu_9', 'onnet_mou_9', 'offnet_mou_9', 'roam_ic_mou_9',
'roam_og_mou_9', 'loc_og_t2t_mou_9', 'loc_og_t2m_mou_9',
'loc_og_t2f_mou_9', 'loc_og_t2c_mou_9', 'loc_og_mou_9',
'std_og_t2t_mou_9', 'std_og_t2m_mou_9', 'std_og_t2f_mou_9',
'std_og_mou_9', 'isd_og_mou_9', 'spl_og_mou_9', 'og_others_9',
'total_og_mou_9', 'loc_ic_t2t_mou_9', 'loc_ic_t2m_mou_9',
'loc_ic_t2f_mou_9', 'loc_ic_mou_9', 'std_ic_t2t_mou_9',
'std_ic_t2m_mou_9', 'std_ic_t2f_mou_9', 'std_ic_mou_9',
'total_ic_mou_9', 'spl_ic_mou_9', 'isd_ic_mou_9', 'ic_others_9',
'total_rech_num_9', 'total_rech_amt_9', 'max_rech_amt_9',
'last_day_rch_amt_9', 'total_rech_data_9', 'max_rech_data_9',
'av_rech_amt_data_9', 'vol_2g_mb_9', 'vol_3g_mb_9', 'monthly_2g_9',
'sachet_2g_9', 'monthly_3g_9', 'sachet_3g_9']
```

```
# Dropping the selected churn phase columns
telecom_data.drop(churn_phase_cols, axis=1, inplace=True)

# The curent dimension of the dataset after dropping the churn related columns
telecom_data.shape
```

(30001, 141)

We can still clean the data by few possible columns relating to the good phase.

As we derived few columns in the good phase earlier, we can drop those related columns during creation.

```
# telecom_data['total_rech_amt_data_6']=telecom_data['av_rech_amt_data_6'] * telecom_data['total_rech_data_6']
```

```
# telecom_data['total_rech_amt_data_7']=telecom_data['av_rech_amt_data_7'] *
telecom_data['total_rech_data_7']

# # Calculating the overall recharge amount for the months 6,7,8 and 9
# telecom_data['overall_rech_amt_6'] = telecom_data['total_rech_amt_data_6'] +
telecom_data['total_rech_amt_6']
# telecom_data['overall_rech_amt_7'] = telecom_data['total_rech_amt_data_7'] +
telecom_data['total_rech_amt_7']

telecom_data.drop(['total_rech_amt_data_6','av_rech_amt_data_6',
                 'total_rech_data_6','total_rech_amt_6',
                'total_rech_amt_data_7','av_rech_amt_data_7',
                 'total_rech_data_7','total_rech_amt_7'], axis=1, inplace=True)
```

We can also create new columns for the defining the good phase variables and drop the seperate 6th and 7 month variables.

Before proceding to check the remaining missing value handling, let us check the collineartity of the indepedent variables and try to understand their dependencies.

```
# creating a list of column names for each month
mon_6_cols = [col for col in telecom_data.columns if '_6' in col]
mon_7_cols = [col for col in telecom_data.columns if '_7' in col]
mon_8_cols = [col for col in telecom_data.columns if '_8' in col]
# lets check the correlation amongst the independent variables, drop the highly correlated ones
telecom_data_corr = telecom_data.corr()
telecom_data_corr.loc[:,:] = np.tril(telecom_data_corr, k=-1)
telecom_data_corr = telecom_data_corr.stack()
telecom_data_corr
telecom_data_corr[(telecom_data_corr > 0.80) | (telecom_data_corr <
-0.80)].sort_values(ascending=False)
```

```
total_rech_amt_8    arpu_8              0.955351
isd_og_mou_8        isd_og_mou_7        0.943433
                    isd_og_mou_6        0.919641
isd_og_mou_7        isd_og_mou_6        0.916237
sachet_2g_8         total_rech_data_8   0.900629
total_ic_mou_6      loc_ic_mou_6        0.895099
total_ic_mou_8      loc_ic_mou_8        0.893072
total_ic_mou_7      loc_ic_mou_7        0.883070
std_og_t2t_mou_8    onnet_mou_8         0.860483
std_og_t2t_mou_7    onnet_mou_7         0.860275
std_og_t2t_mou_6    onnet_mou_6         0.859593
avg_rech_amt_6_7    overall_rech_amt_7  0.856275
std_og_t2m_mou_7    offnet_mou_7        0.854685
std_og_t2m_mou_8    offnet_mou_8        0.851049
total_og_mou_8      std_og_mou_8        0.848858
total_og_mou_7      std_og_mou_7        0.848825
loc_ic_mou_8        loc_ic_t2m_mou_8    0.847512
std_ic_mou_8        std_ic_t2m_mou_8    0.845590
loc_ic_mou_6        loc_ic_t2m_mou_6    0.844418
loc_og_mou_8        loc_og_mou_7        0.844245
loc_ic_mou_8        loc_ic_mou_7        0.842908
```

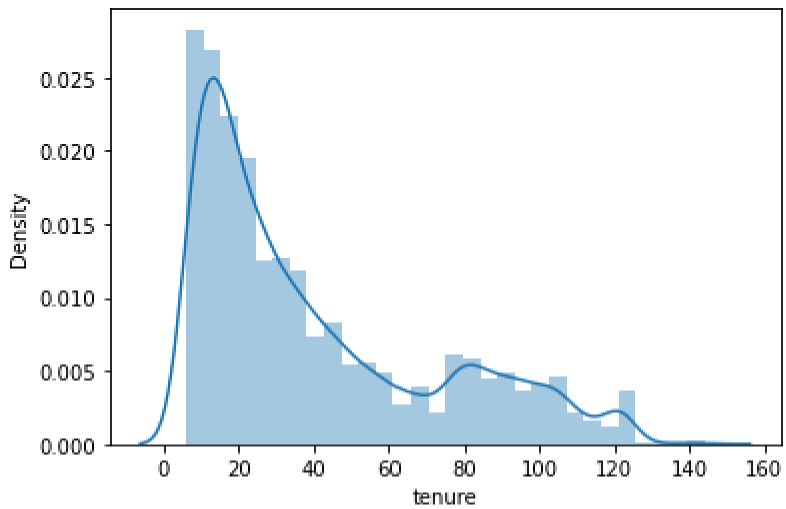
```
avg_rech_amt_6_7    overall_rech_amt_6    0.842748
loc_og_t2t_mou_8    loc_og_t2t_mou_7      0.834612
loc_ic_mou_7        loc_ic_t2m_mou_7      0.834557
total_og_mou_6      std_og_mou_6          0.831720
std_og_t2m_mou_6    offnet_mou_6          0.830433
loc_og_t2m_mou_8    loc_og_t2m_mou_7      0.826720
loc_ic_mou_7        loc_ic_mou_6          0.821979
total_ic_mou_8      total_ic_mou_7        0.820529
std_ic_mou_7        std_ic_t2m_mou_7      0.819316
loc_ic_t2m_mou_8    loc_ic_t2m_mou_7      0.814748
std_ic_mou_6        std_ic_t2m_mou_6      0.814081
loc_og_t2f_mou_7    loc_og_t2f_mou_6      0.809471
onnet_mou_8         onnet_mou_7           0.808507
loc_ic_t2t_mou_8    loc_ic_t2t_mou_7      0.808102
loc_og_mou_7        loc_og_mou_6          0.807980
std_og_t2t_mou_8    std_og_t2t_mou_7      0.804607
loc_og_mou_6        loc_og_t2m_mou_6      0.803954
loc_ic_t2t_mou_7    loc_ic_t2t_mou_6      0.803421
total_ic_mou_7      total_ic_mou_6        0.803042
av_rech_amt_data_8  max_rech_data_8       0.801613
dtype: float64
```

```
col_to_drop=['total_rech_amt_8','isd_og_mou_8','isd_og_mou_7','sachet_2g_8','total_ic_mou_6',

'total_ic_mou_8','total_ic_mou_7','std_og_t2t_mou_6','std_og_t2t_mou_8','std_og_t2t_mou_7',
            'std_og_t2m_mou_7','std_og_t2m_mou_8',]

# These columns can be dropped as they are highly collinered with other predictor variables.
# criteria set is for collinearity of 85%

#  dropping these column
telecom_data.drop(col_to_drop, axis=1, inplace=True)
# The curent dimension of the dataset after dropping few unwanted columns
telecom_data.shape
```

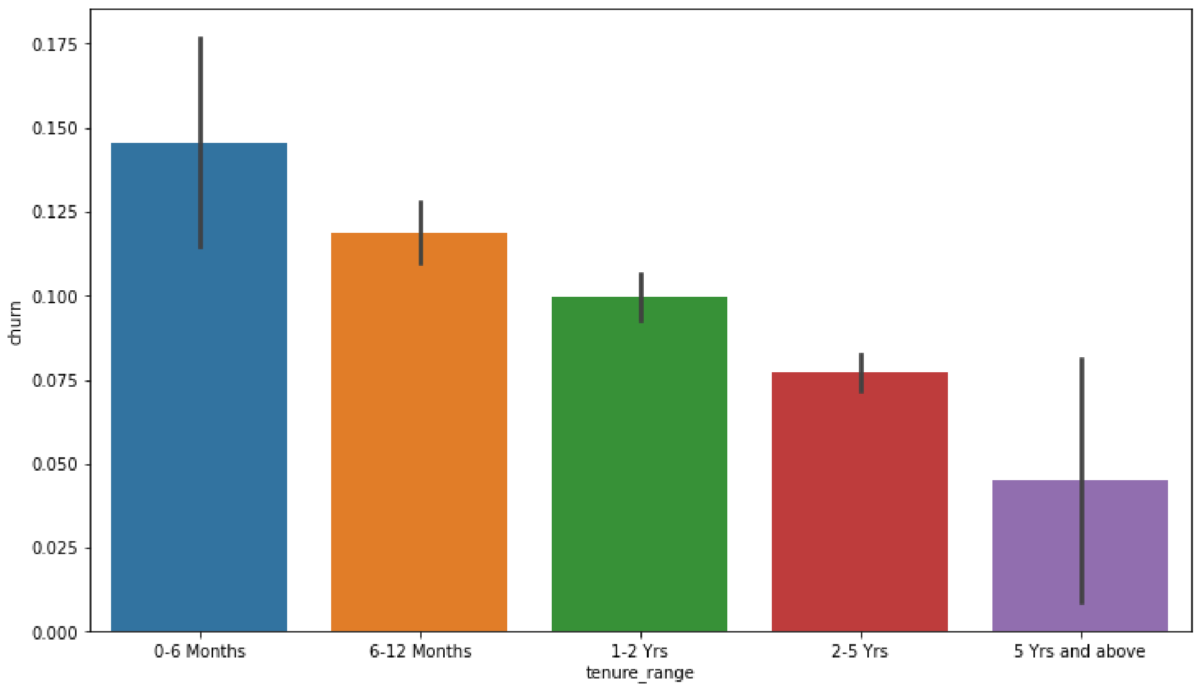
```
(30001, 121)
```

Deriving new variables to understand the data

```
# We have a column called 'aon'

# we can derive new variables from this to explain the data w.r.t churn.

# creating a new variable 'tenure'
telecom_data['tenure'] = (telecom_data['aon']/30).round(0)

# Since we derived a new column from 'aon', we can drop it
telecom_data.drop('aon',axis=1, inplace=True)
# Checking the distribution of he tenure variable

sns.distplot(telecom_data['tenure'],bins=30)
plt.show()
```



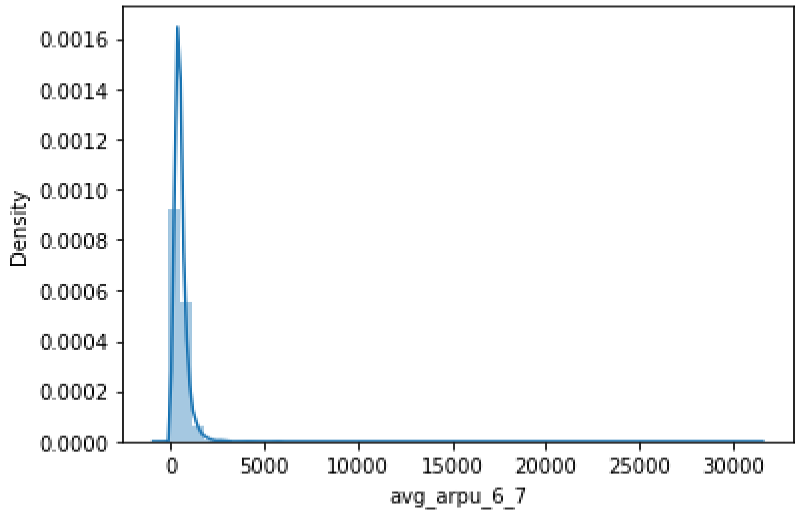

```
tn_range = [0, 6, 12, 24, 60, 61]
tn_label = [ '0-6 Months', '6-12 Months', '1-2 Yrs', '2-5 Yrs', '5 Yrs and above']
telecom_data['tenure_range'] = pd.cut(telecom_data['tenure'], tn_range, labels=tn_label)
telecom_data['tenure_range'].head()
0     2-5 Yrs
7     2-5 Yrs
8     6-12 Months
21     1-2 Yrs
23     1-2 Yrs
Name: tenure_range, dtype: category
Categories (5, object): ['0-6 Months' < '6-12 Months' < '1-2 Yrs' < '2-5 Yrs' < '5 Yrs and above']
# Plotting a bar plot for tenure range
plt.figure(figsize=[12,7])
sns.barplot(x='tenure_range',y='churn', data=telecom_data)
plt.show()
```



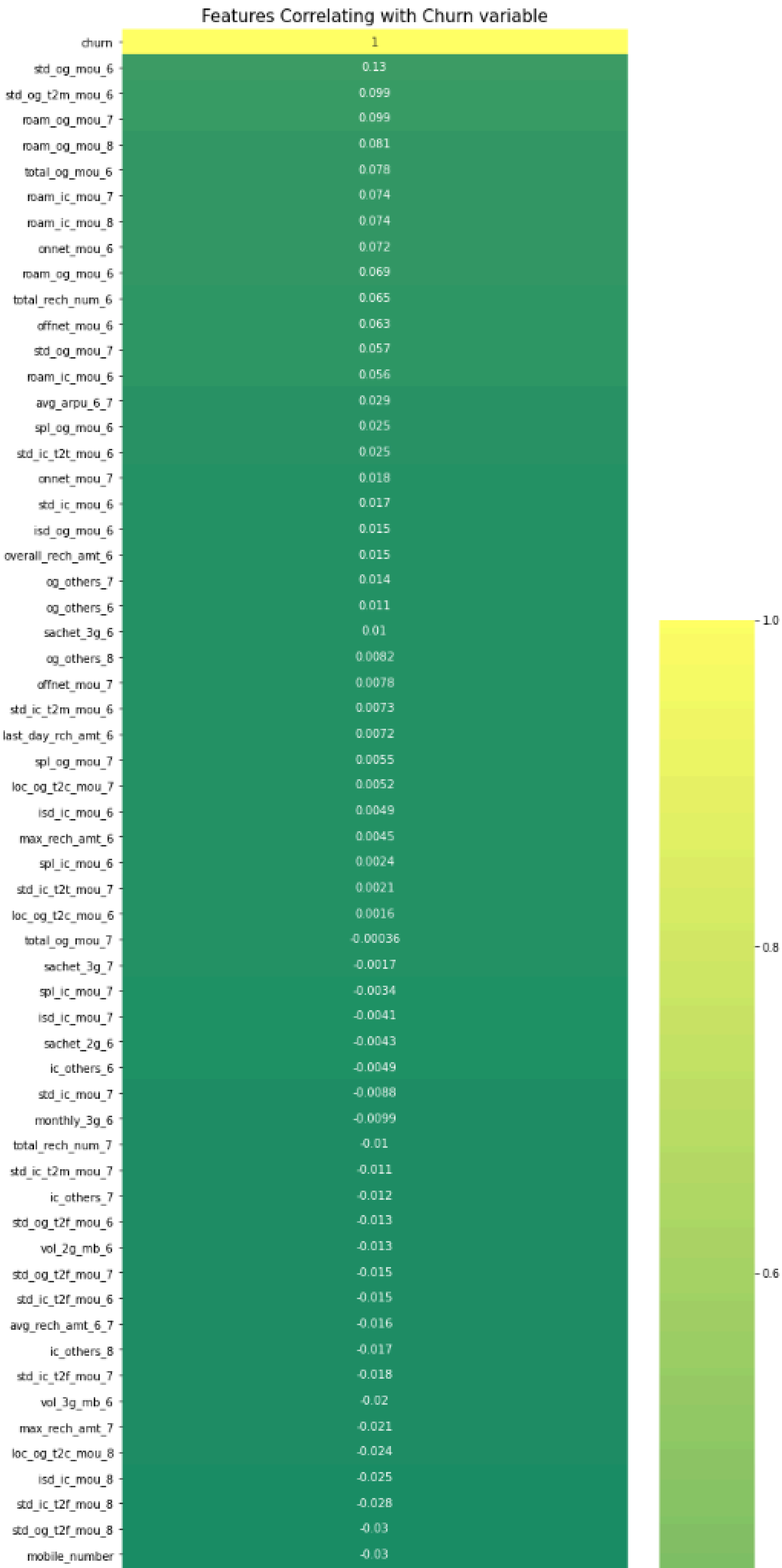
It can be seen that the maximum churn rate happens within 0-6 month, but it gradually decreases as the customer retains in the network.

The average revenue per user is good phase of customer is given by arpu_6 and arpu_7. since we have two seperate averages, lets take an average to these two and drop the other columns.

```
telecom_data["avg_arpu_6_7"]= (telecom_data['arpu_6']+telecom_data['arpu_7'])/2
telecom_data['avg_arpu_6_7'].head()
0     206.1005
7     1209.5150
8     435.4720
21     556.1030
23     134.1235
Name: avg_arpu_6_7, dtype: float64
# Lets drop the original columns as they are derived to a new column for better understanding of the data

telecom_data.drop(['arpu_6','arpu_7'], axis=1, inplace=True)


# The curent dimension of the dataset after dropping few unwanted columns
telecom_data.shape
(30001, 121)
# Visualizing the column created
sns.distplot(telecom_data['avg_arpu_6_7'])
plt.show()
```



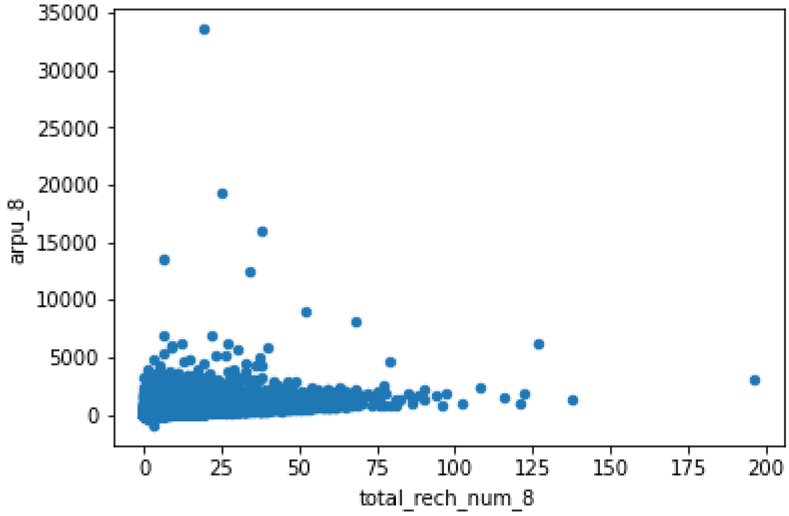

```
# Checking Correlation between target variable(SalePrice) with the other variable in the dataset
plt.figure(figsize=(10,50))
heatmap_churn = sns.heatmap(telecom_data.corr()[['churn']].sort_values(ascending=False,
by='churn'),annot=True,
                              cmap='summer')
heatmap_churn.set_title("Features Correlating with Churn variable", fontsize=15)

Text(0.5, 1.0, 'Features Correlating with Churn variable')
```



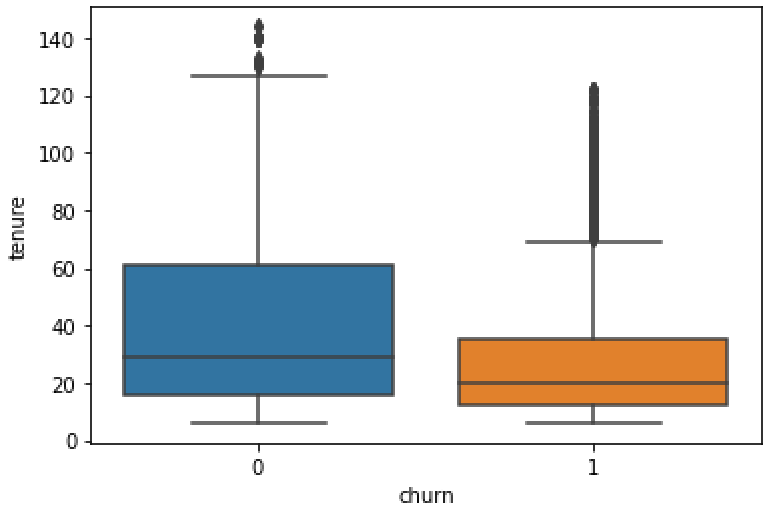
Features Correlating with Churn variable
churn 1
std_og_mou_6 0.13
std_og_t2m_mou_6 0.099
roam_og_mou_7 0.099
roam_og_mou_8 0.081
total_og_mou_6 0.078
roam_ic_mou_7 0.074
roam_ic_mou_8 0.074
onnet_mou_6 0.072
roam_og_mou_6 0.069
total_rech_num_6 0.065
offnet_mou_6 0.063
std_og_mou_7 0.057
roam_ic_mou_6 0.056
avg_arpu_6_7 0.029
spl_og_mou_6 0.025
std_ic_t2t_mou_6 0.025
onnet_mou_7 0.018
std_ic_mou_6 0.017
isd_og_mou_6 0.015
overall_rech_amt_6 0.015
og_others_7 0.014
og_others_6 0.011
sachet_3g_6 0.01
og_others_8 0.0082
offnet_mou_7 0.0078
std_ic_t2m_mou_6 0.0073
last_day_rch_amt_6 0.0072
spl_og_mou_7 0.0055
loc_og_t2c_mou_7 0.0052
isd_ic_mou_6 0.0049
max_rech_amt_6 0.0045
spl_ic_mou_6 0.0024
std_ic_t2t_mou_7 0.0021
loc_og_t2c_mou_6 0.0016
total_og_mou_7 -0.00036
sachet_3g_7 -0.0017
spl_ic_mou_7 -0.0034
isd_ic_mou_7 -0.0041
sachet_2g_6 -0.0043
ic_others_6 -0.0049
std_ic_mou_7 -0.0088
monthly_3g_6 -0.0099
total_rech_num_7 -0.01
std_ic_t2m_mou_7 -0.011
ic_others_7 -0.012
std_og_t2f_mou_6 -0.013
vol_2g_mb_6 -0.013
std_og_t2f_mou_7 -0.015
std_ic_t2f_mou_6 -0.015
avg_rech_amt_6_7 -0.016
ic_others_8 -0.017
std_ic_t2f_mou_7 -0.018
vol_3g_mb_6 -0.02
max_rech_amt_7 -0.021
loc_og_t2c_mou_8 -0.024
isd_ic_mou_8 -0.025
std_ic_t2f_mou_8 -0.028
std_og_t2f_mou_8 -0.03
mobile_number -0.03
1.0
0.8
0.6

- Avg Outgoing Calls & calls on romaning for 6 & 7th months are positively correlated with churn.
- Avg Revenue, No. Of Recharge for 8th month has negative correlation with churn.

```
# lets now draw a scatter plot between total recharge and avg revenue for the 8th month
telecom_data[['total_rech_num_8', 'arpu_8']].plot.scatter(x = 'total_rech_num_8',
                                        y='arpu_8')
plt.show()
```



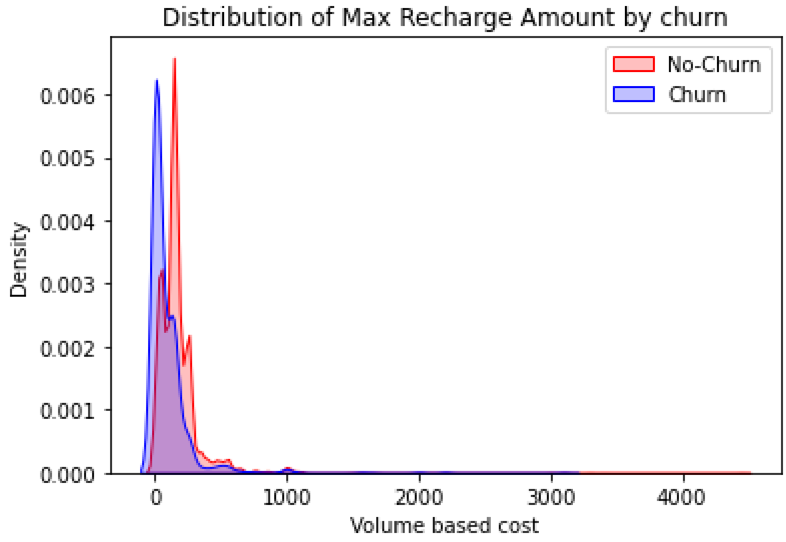

```
sns.boxplot(x = telecom_data.churn, y = telecom_data.tenure)

plt.show()
```



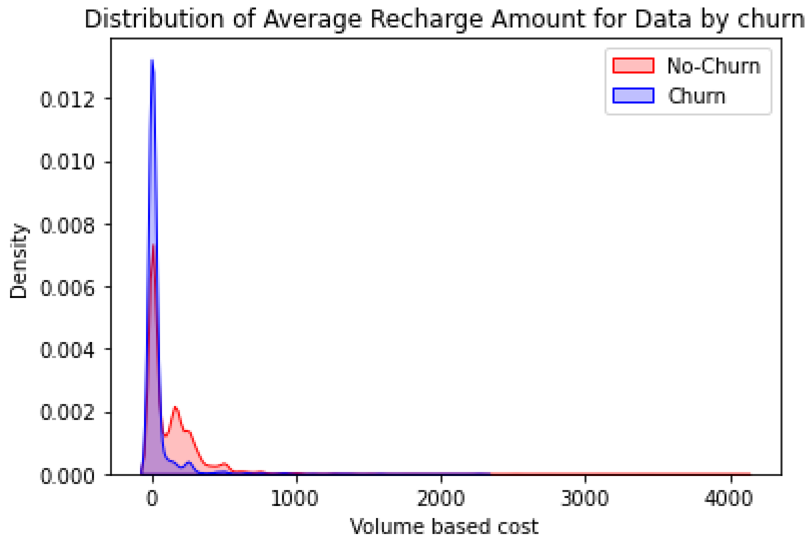
From the above plot , its clear tenured customers do no churn and they keep availing telecom services

```
# Plot between churn vs max rechare amount
ax = sns.kdeplot(telecom_data.max_rech_amt_8[(telecom_data["churn"] == 0)],
            color="Red", shade = True)
ax = sns.kdeplot(telecom_data.max_rech_amt_8[(telecom_data["churn"] == 1)],
            ax =ax, color="Blue", shade= True)
ax.legend(["No-Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Volume based cost')
```

```
ax.set_title('Distribution of Max Recharge Amount by churn')
plt.show()
```



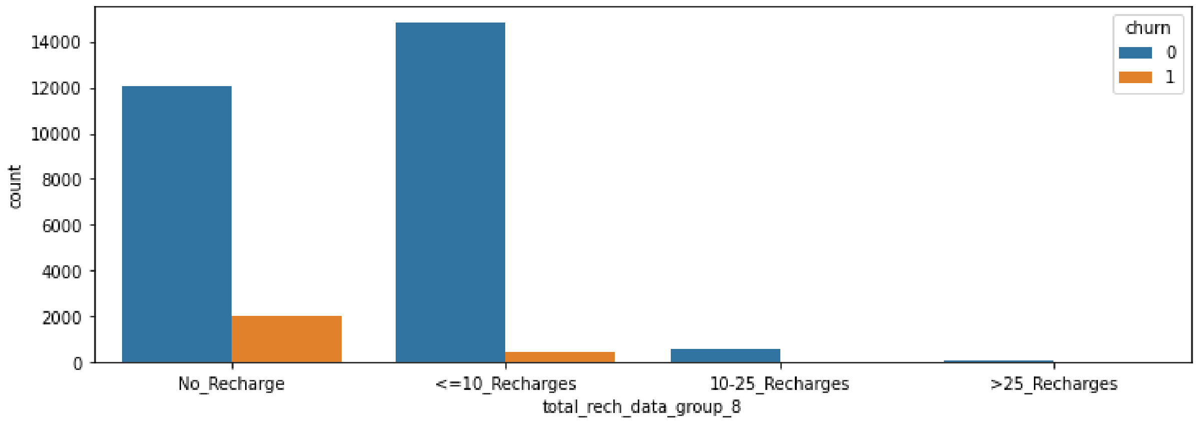

```
# churn vs max rechare amount
ax = sns.kdeplot(telecom_data.av_rech_amt_data_8[(telecom_data["churn"] == 0)],
            color="Red", shade = True)
ax = sns.kdeplot(telecom_data.av_rech_amt_data_8[(telecom_data["churn"] == 1)],
            ax =ax, color="Blue", shade= True)
ax.legend(["No-Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Volume based cost')
ax.set_title('Distribution of Average Recharge Amount for Data by churn')
plt.show()
```



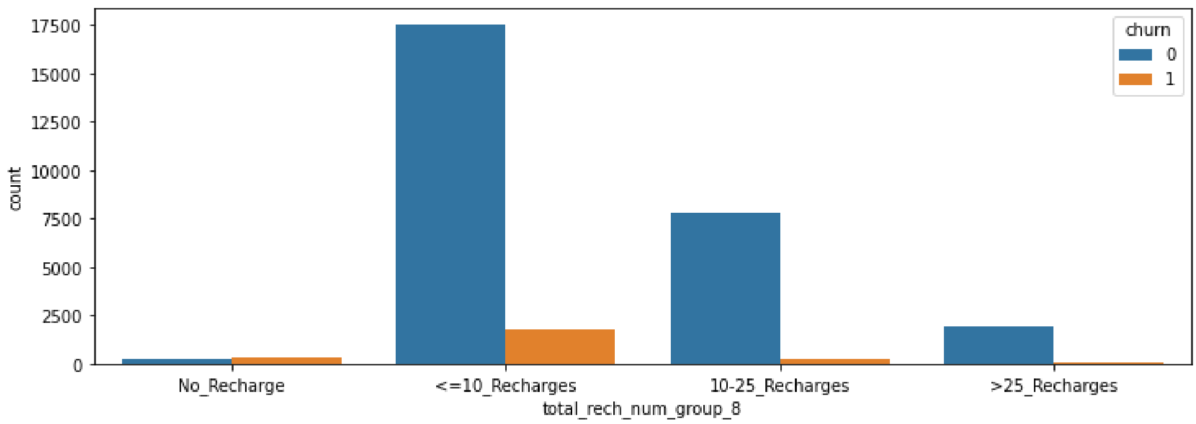

```
# Creating categories for month 8 column totalrecharge and their count
telecom_data['total_rech_data_group_8']=pd.cut(telecom_data['total_rech_data_8'],[-1,0,10,25,1
00],labels=["No_Recharge","<=10_Recharges","10-25_Recharges",">25_Recharges"])
telecom_data['total_rech_num_group_8']=pd.cut(telecom_data['total_rech_num_8'],[-1,0,10,25,1
000],labels=["No_Recharge","<=10_Recharges","10-25_Recharges",">25_Recharges"])
# Plotting the results
```

```
plt.figure(figsize=[12,4])
sns.countplot(data=telecom_data,x="total_rech_data_group_8",hue="churn")
print("\t\t\t\t\tDistribution of total_rech_data_8
variable\n",telecom_data['total_rech_data_group_8'].value_counts())
plt.show()
plt.figure(figsize=[12,4])
sns.countplot(data=telecom_data,x="total_rech_num_group_8",hue="churn")
print("\t\t\t\t\tDistribution of total_rech_num_8
variable\n",telecom_data['total_rech_num_group_8'].value_counts())
plt.show()
```

```
                                        Distribution of total_rech_data_8 variable
 <=10_Recharges      15307
No_Recharge         14048
10-25_Recharges     608
>25_Recharges       38
Name: total_rech_data_group_8, dtype: int64
```




```
                                        Distribution of total_rech_num_8 variable
 <=10_Recharges      19349
10-25_Recharges     8073
>25_Recharges       1996
No_Recharge         583
Name: total_rech_num_group_8, dtype: int64
```



As the number of recharge rate increases, the churn rate decreases clearly.

```
# Creating a dummy variable for some of the categorical variables and dropping the first one.
dummy =
pd.get_dummies(telecom_data[['total_rech_data_group_8','total_rech_num_group_8','tenure_ran
ge']], drop_first=True)
dummy.head()
```

	total_rech_data_group_8_<=10_Recharges	total_rech_data_group_8_10-25_Recharges	total_rech_data_group_8_>25_Recharges	total_rech_num_group_8_<=10_Recharges	total_rech_num_group_8_10-25_Recharges	total_rech_num_group_8_>25_Recharges	tenure_range_6-12 Months	tenure_range_1-2 Yrs	tenure_range_2-5 Yrs	tenure_range_5 Yrs and above
0	1	0	0	1	0	0	0	0	1	0
7	0	0	0	1	0	0	0	0	1	0
8	1	0	0	0	1	0	1	0	0	0
21	0	0	0	0	0	1	0	1	0	0
23	1	0	0	1	0	0	0	1	0	0

```
# Adding the results to the master dataframe
telecom_data = pd.concat([telecom_data, dummy], axis=1)
telecom_data.head()


# Creating a copy of the filtered dataframe

df=telecom_data[:].copy()

# Dropping unwanted columns
df.drop(['tenure_range','mobile_number','total_rech_data_group_8','total_rech_num_group_8','se
p_vbc_3g','tenure'], axis=1, inplace=True)
# Cheking the dataset
df.head()
# lets create X dataset for model building.
X = df.drop(['churn'],axis=1)
X.head()
```

```
# lets create y dataset for model building.
y=df['churn']
y.head()
```

```
0    1
7    1
8    0
21    0
23    0
Name: churn, dtype: int32
```

```
# split the dateset into train and test datasets
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, train_size=0.7, random_state=1)
print("Dimension of X_train:", X_train.shape)
print("Dimension of X_test:", X_test.shape)
```

```
Dimension of X_train: (21000, 126)
Dimension of X_test: (9001, 126)
```

```
X_train.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21000 entries, 15709 to 99093
Data columns (total 126 columns):
 #     Column                                     Dtype
---    ------                                     -----
 0     arpu_8                                     float64
 1     onnet_mou_6                                float64
 2     onnet_mou_7                                float64
 3     onnet_mou_8                                float64
 4     offnet_mou_6                               float64
 5     offnet_mou_7                               float64
 6     offnet_mou_8                               float64
 7     roam_ic_mou_6                              float64
 8     roam_ic_mou_7                              float64
 9     roam_ic_mou_8                              float64
 10    roam_og_mou_6                              float64
 11    roam_og_mou_7                              float64
 12    roam_og_mou_8                              float64
 13    loc_og_t2t_mou_6                           float64
 14    loc_og_t2t_mou_7                           float64
 15    loc_og_t2t_mou_8                           float64
 16    loc_og_t2m_mou_6                           float64
 17    loc_og_t2m_mou_7                           float64
 18    loc_og_t2m_mou_8                           float64
 19    loc_og_t2f_mou_6                           float64
 20    loc_og_t2f_mou_7                           float64
```

21	loc_og_t2f_mou_8	float64
22	loc_og_t2c_mou_6	float64
23	loc_og_t2c_mou_7	float64
24	loc_og_t2c_mou_8	float64
25	loc_og_mou_6	float64
26	loc_og_mou_7	float64
27	loc_og_mou_8	float64
28	std_og_t2m_mou_6	float64
29	std_og_t2f_mou_6	float64
30	std_og_t2f_mou_7	float64
31	std_og_t2f_mou_8	float64
32	std_og_mou_6	float64
33	std_og_mou_7	float64
34	std_og_mou_8	float64
35	isd_og_mou_6	float64
36	spl_og_mou_6	float64
37	spl_og_mou_7	float64
38	spl_og_mou_8	float64
39	og_others_6	float64
40	og_others_7	float64
41	og_others_8	float64
42	total_og_mou_6	float64
43	total_og_mou_7	float64
44	total_og_mou_8	float64
45	loc_ic_t2t_mou_6	float64
46	loc_ic_t2t_mou_7	float64
47	loc_ic_t2t_mou_8	float64
48	loc_ic_t2m_mou_6	float64
49	loc_ic_t2m_mou_7	float64
50	loc_ic_t2m_mou_8	float64
51	loc_ic_t2f_mou_6	float64
52	loc_ic_t2f_mou_7	float64
53	loc_ic_t2f_mou_8	float64
54	loc_ic_mou_6	float64
55	loc_ic_mou_7	float64
56	loc_ic_mou_8	float64
57	std_ic_t2t_mou_6	float64
58	std_ic_t2t_mou_7	float64
59	std_ic_t2t_mou_8	float64
60	std_ic_t2m_mou_6	float64
61	std_ic_t2m_mou_7	float64
62	std_ic_t2m_mou_8	float64
63	std_ic_t2f_mou_6	float64

64	std_ic_t2f_mou_7	float64
65	std_ic_t2f_mou_8	float64
66	std_ic_mou_6	float64
67	std_ic_mou_7	float64
68	std_ic_mou_8	float64
69	spl_ic_mou_6	float64
70	spl_ic_mou_7	float64
71	spl_ic_mou_8	float64
72	isd_ic_mou_6	float64
73	isd_ic_mou_7	float64
74	isd_ic_mou_8	float64
75	ic_others_6	float64
76	ic_others_7	float64
77	ic_others_8	float64
78	total_rech_num_6	float64
79	total_rech_num_7	float64
80	total_rech_num_8	float64
81	max_rech_amt_6	float64
82	max_rech_amt_7	float64
83	max_rech_amt_8	float64
84	last_day_rch_amt_6	float64
85	last_day_rch_amt_7	float64
86	last_day_rch_amt_8	float64
87	total_rech_data_8	float64
88	max_rech_data_6	float64
89	max_rech_data_7	float64
90	max_rech_data_8	float64
91	av_rech_amt_data_8	float64
92	vol_2g_mb_6	float64
93	vol_2g_mb_7	float64
94	vol_2g_mb_8	float64
95	vol_3g_mb_6	float64
96	vol_3g_mb_7	float64
97	vol_3g_mb_8	float64
98	monthly_2g_6	float64
99	monthly_2g_7	float64
100	monthly_2g_8	float64
101	sachet_2g_6	float64
102	sachet_2g_7	float64
103	monthly_3g_6	float64
104	monthly_3g_7	float64
105	monthly_3g_8	float64
106	sachet_3g_6	float64

```
 107   sachet_3g_7                              float64
 108   sachet_3g_8                              float64
 109   aug_vbc_3g                               float64
 110   jul_vbc_3g                               float64
 111   jun_vbc_3g                               float64
 112   overall_rech_amt_6                       float64
 113   overall_rech_amt_7                       float64
 114   avg_rech_amt_6_7                         float64
 115   avg_arpu_6_7                             float64
 116   total_rech_data_group_8_<=10_Recharges   uint8
 117   total_rech_data_group_8_10-25_Recharges  uint8
 118   total_rech_data_group_8_>25_Recharges    uint8
 119   total_rech_num_group_8_<=10_Recharges    uint8
 120   total_rech_num_group_8_10-25_Recharges   uint8
 121   total_rech_num_group_8_>25_Recharges     uint8
 122   tenure_range_6-12 Months                 uint8
 123   tenure_range_1-2 Yrs                     uint8
 124   tenure_range_2-5 Yrs                     uint8
 125   tenure_range_5 Yrs and above             uint8
dtypes: float64(116), uint8(10)
memory usage: 18.9 MB
```

```
num_col = X_train.select_dtypes(include = ['int64','float64']).columns.tolist()
# apply scaling on the dataset
from sklearn import preprocessing
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X_train[num_col] = scaler.fit_transform(X_train[num_col])
X_train.head()
```

Data Imbalance Handling

Using SMOTE method, we can balance the data w.r.t. churn variable and proceed further

```
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=42)
X_train_sm,y_train_sm = sm.fit_resample(X_train,y_train)
print("Dimension of X_train_sm Shape:", X_train_sm.shape)
print("Dimension of y_train_sm Shape:", y_train_sm.shape)
```

```
Dimension of X_train_sm Shape: (38576, 126)
Dimension of y_train_sm Shape: (38576,)
```

Logistic Regression

```
# Importing necessary libraries for Model creation
import statsmodels.api as sm
# Logistic regression model
logm1 = sm.GLM(y_train_sm,(sm.add_constant(X_train_sm)), family = sm.families.Binomial())
logm1.fit().summary()
```

Logistic Regression using Feature Selection (RFE method)

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()

from sklearn.feature_selection import RFE

# running RFE with 20 variables as output
rfe = RFE(logreg, 20)
rfe = rfe.fit(X_train_sm, y_train_sm)
rfe.support_
array([ True, False, False, False, False, False, False, False,  True,
       False, False, False,  True, False, False, False, False, False,
        True, 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,
       False, False,  True, False, False,  True, False, False, False,
        True, False,  True, False, False, False, False, False, False,
       False, False, False, False, False,  True, False, False,  True,
       False, False, False, False, False, False, False, False,  True,
       False, False, False, False, False,  True,  True, False, False,
       False,  True, False, False,  True, False, False, False, False,
       False,  True, False, False, False, False, False, False, False,
       False,  True, False, False, False, False, False,  True, False,
       False, False, False, False, False, False, False, False, False])
rfe_columns=X_train_sm.columns[rfe.support_]
print("The selected columns by RFE for modelling are: \n\n",rfe_columns)
The selected columns by RFE for modelling are:

 Index(['arpu_8', 'roam_ic_mou_7', 'roam_og_mou_8', 'loc_og_t2m_mou_8',
       'std_og_mou_7', 'total_og_mou_8', 'loc_ic_t2t_mou_8',
       'loc_ic_t2m_mou_8', 'loc_ic_mou_6', 'loc_ic_mou_8',
'std_ic_mou_8',
       'spl_ic_mou_8', 'total_rech_num_8', 'last_day_rch_amt_8',
       'total_rech_data_8', 'av_rech_amt_data_8', 'vol_2g_mb_8',
       'monthly_2g_8', 'aug_vbc_3g', 'avg_arpu_6_7'],
      dtype='object')

list(zip(X_train_sm.columns, rfe.support_, rfe.ranking_))
[('arpu_8', True, 1),
 ('onnet_mou_6', False, 22),
 ('onnet_mou_7', False, 37),
 ('onnet_mou_8', False, 42),
 ('offnet_mou_6', False, 35),
 ('offnet_mou_7', False, 21),
 ('offnet_mou_8', False, 26),
 ('roam_ic_mou_6', False, 13),
 ('roam_ic_mou_7', True, 1),
 ('roam_ic_mou_8', False, 60),
```

```
('roam_og_mou_6', False, 69),
('roam_og_mou_7', False, 33),
('roam_og_mou_8', True, 1),
('loc_og_t2t_mou_6', False, 65),
('loc_og_t2t_mou_7', False, 99),
('loc_og_t2t_mou_8', False, 19),
('loc_og_t2m_mou_6', False, 67),
('loc_og_t2m_mou_7', False, 74),
('loc_og_t2m_mou_8', True, 1),
('loc_og_t2f_mou_6', False, 107),
('loc_og_t2f_mou_7', False, 5),
('loc_og_t2f_mou_8', False, 25),
('loc_og_t2c_mou_6', False, 7),
('loc_og_t2c_mou_7', False, 66),
('loc_og_t2c_mou_8', False, 104),
('loc_og_mou_6', False, 48),
('loc_og_mou_7', False, 105),
('loc_og_mou_8', False, 2),
('std_og_t2m_mou_6', False, 93),
('std_og_t2f_mou_6', False, 79),
('std_og_t2f_mou_7', False, 27),
('std_og_t2f_mou_8', False, 4),
('std_og_mou_6', False, 46),
('std_og_mou_7', True, 1),
('std_og_mou_8', False, 64),
('isd_og_mou_6', False, 14),
('spl_og_mou_6', False, 87),
('spl_og_mou_7', False, 51),
('spl_og_mou_8', False, 36),
('og_others_6', False, 23),
('og_others_7', False, 82),
('og_others_8', False, 98),
('total_og_mou_6', False, 47),
('total_og_mou_7', False, 90),
('total_og_mou_8', True, 1),
('loc_ic_t2t_mou_6', False, 45),
('loc_ic_t2t_mou_7', False, 77),
('loc_ic_t2t_mou_8', True, 1),
('loc_ic_t2m_mou_6', False, 6),
('loc_ic_t2m_mou_7', False, 28),
('loc_ic_t2m_mou_8', True, 1),
('loc_ic_t2f_mou_6', False, 52),
('loc_ic_t2f_mou_7', False, 83),
('loc_ic_t2f_mou_8', False, 11),
('loc_ic_mou_6', True, 1),
('loc_ic_mou_7', False, 57),
('loc_ic_mou_8', True, 1),
('std_ic_t2t_mou_6', False, 59),
('std_ic_t2t_mou_7', False, 32),
('std_ic_t2t_mou_8', False, 12),
```

```
('std_ic_t2m_mou_6', False, 38),
('std_ic_t2m_mou_7', False, 39),
('std_ic_t2m_mou_8', False, 8),
('std_ic_t2f_mou_6', False, 95),
('std_ic_t2f_mou_7', False, 50),
('std_ic_t2f_mou_8', False, 34),
('std_ic_mou_6', False, 9),
('std_ic_mou_7', False, 73),
('std_ic_mou_8', True, 1),
('spl_ic_mou_6', False, 102),
('spl_ic_mou_7', False, 92),
('spl_ic_mou_8', True, 1),
('isd_ic_mou_6', False, 54),
('isd_ic_mou_7', False, 40),
('isd_ic_mou_8', False, 55),
('ic_others_6', False, 53),
('ic_others_7', False, 70),
('ic_others_8', False, 78),
('total_rech_num_6', False, 103),
('total_rech_num_7', False, 3),
('total_rech_num_8', True, 1),
('max_rech_amt_6', False, 81),
('max_rech_amt_7', False, 16),
('max_rech_amt_8', False, 72),
('last_day_rch_amt_6', False, 89),
('last_day_rch_amt_7', False, 15),
('last_day_rch_amt_8', True, 1),
('total_rech_data_8', True, 1),
('max_rech_data_6', False, 41),
('max_rech_data_7', False, 61),
('max_rech_data_8', False, 100),
('av_rech_amt_data_8', True, 1),
('vol_2g_mb_6', False, 43),
('vol_2g_mb_7', False, 17),
('vol_2g_mb_8', True, 1),
('vol_3g_mb_6', False, 97),
('vol_3g_mb_7', False, 62),
('vol_3g_mb_8', False, 71),
('monthly_2g_6', False, 44),
('monthly_2g_7', False, 18),
('monthly_2g_8', True, 1),
('sachet_2g_6', False, 63),
('sachet_2g_7', False, 106),
('monthly_3g_6', False, 84),
('monthly_3g_7', False, 49),
('monthly_3g_8', False, 75),
('sachet_3g_6', False, 10),
('sachet_3g_7', False, 24),
('sachet_3g_8', False, 76),
('aug_vbc_3g', True, 1),
```

('jul_vbc_3g', False, 58),
('jun_vbc_3g', False, 88),
('overall_rech_amt_6', False, 85),
('overall_rech_amt_7', False, 86),
('avg_rech_amt_6_7', False, 101),
('avg_arpu_6_7', True, 1),
('total_rech_data_group_8_<=10_Recharges', False, 68),
('total_rech_data_group_8_10-25_Recharges', False, 20),
('total_rech_data_group_8_>25_Recharges', False, 80),
('total_rech_num_group_8_<=10_Recharges', False, 31),
('total_rech_num_group_8_10-25_Recharges', False, 30),
('total_rech_num_group_8_>25_Recharges', False, 29),
('tenure_range_6-12 Months', False, 91),
('tenure_range_1-2 Yrs', False, 94),
('tenure_range_2-5 Yrs', False, 96),
('tenure_range_5 Yrs and above', False, 56)]

Assessing the model with StatsModels

```
X_train_SM = sm.add_constant(X_train_sm[rfe_columns])
logm2 = sm.GLM(y_train_sm,X_train_SM, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
# From the p-value of the individual columns,
  # we can drop the column 'loc_ic_t2t_mou_8' as it has high p-value of 0.80
rfe_columns_1=rfe_columns.drop('loc_ic_t2t_mou_8',1)
print("\nThe new set of edited featured are:\n",rfe_columns_1)
```

```
The new set of columns are:
 Index(['arpu_8', 'roam_ic_mou_7', 'roam_og_mou_8', 'loc_og_t2m_mou_8',
       'std_og_mou_7', 'total_og_mou_8', 'loc_ic_t2m_mou_8',
'loc_ic_mou_6',
       'loc_ic_mou_8', 'std_ic_mou_8', 'spl_ic_mou_8',
'total_rech_num_8',
       'last_day_rch_amt_8', 'total_rech_data_8', 'av_rech_amt_data_8',
       'vol_2g_mb_8', 'monthly_2g_8', 'aug_vbc_3g', 'avg_arpu_6_7'],
      dtype='object')
```

```
# Training the model with the edited feature list
X_train_SM = sm.add_constant(X_train_sm[rfe_columns_1])
logm2 = sm.GLM(y_train_sm,X_train_SM, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
# From the p-value of the individual columns,
  # we can drop the column 'loc_ic_t2m_mou_8' as it has high p-value of 0.80
rfe_columns_2=rfe_columns_1.drop('loc_ic_t2m_mou_8',1)
print("\nThe new set of edited featured are:\n",rfe_columns_2)
```

```
The new set of edited featured are:
 Index(['arpu_8', 'roam_ic_mou_7', 'roam_og_mou_8', 'loc_og_t2m_mou_8',
```

```
       'std_og_mou_7', 'total_og_mou_8', 'loc_ic_mou_6',
'loc_ic_mou_8',
       'std_ic_mou_8', 'spl_ic_mou_8', 'total_rech_num_8',
       'last_day_rch_amt_8', 'total_rech_data_8', 'av_rech_amt_data_8',
       'vol_2g_mb_8', 'monthly_2g_8', 'aug_vbc_3g', 'avg_arpu_6_7'],
      dtype='object')
```

```
# Training the model with the edited feature list
X_train_SM = sm.add_constant(X_train_sm[rfe_columns_2])
logm2 = sm.GLM(y_train_sm,X_train_SM, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
# Getting the predicted values on the train set
y_train_sm_pred = res.predict(X_train_SM)
y_train_sm_pred = y_train_sm_pred.values.reshape(-1)
y_train_sm_pred[:10]
array([1.38574250e-01, 4.01121753e-01, 3.24275768e-01, 4.14619020e-01,
       5.08729618e-01, 4.31066021e-01, 2.12010834e-05, 2.27844968e-01,
       5.14992869e-02, 7.08374581e-01])
```

Creating a dataframe with the actual churn flag and the predicted probabilities

```
y_train_sm_pred_final = pd.DataFrame({'Converted':y_train_sm.values,
'Converted_prob':y_train_sm_pred})
y_train_sm_pred_final.head()
```

Creating new column 'churn_pred' with 1 if Churn_Prob > 0.5 else 0

```
y_train_sm_pred_final['churn_pred'] = y_train_sm_pred_final.Converted_prob.map(lambda x: 1 if
x > 0.5 else 0)

# Viewing the prediction results
y_train_sm_pred_final.head()
from sklearn import metrics

# Confusion matrix
confusion = metrics.confusion_matrix(y_train_sm_pred_final.Converted,
y_train_sm_pred_final.churn_pred )
print(confusion)
[[15661  3627]
 [ 2775 16513]]

# Predicted     not_churn    churn
# Actual
# not_churn        15661      3627
# churn            2775       16513
# Checking the overall accuracy.
print("The overall accuracy of the model
is:",metrics.accuracy_score(y_train_sm_pred_final.Converted,
y_train_sm_pred_final.churn_pred))
The overall accuracy of the model is: 0.8340418913313977
```

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor
# Create a dataframe that will contain the names of all the feature variables and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train_sm[rfe_columns_2].columns
vif['VIF'] = [variance_inflation_factor(X_train_sm[rfe_columns].values, i) for i in range(X_train_sm[rfe_columns_2].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Metrics beyond simply accuracy

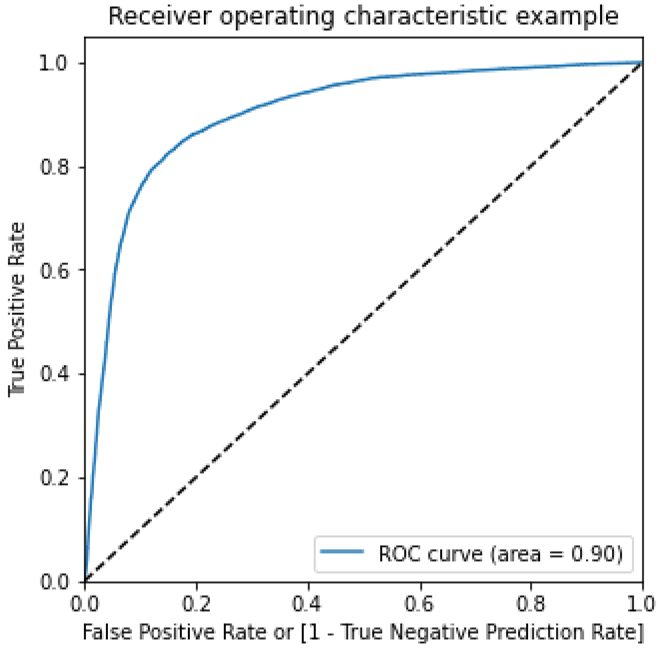
```
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives
# Let's see the sensitivity of our logistic regression model
print("Sensitivity = ",TP / float(TP+FN))

# Let us calculate specificity
print("Specificity = ",TN / float(TN+FP))

# Calculate false postive rate - predicting churn when customer does not have churned
print("False Positive Rate = ",FP/ float(TN+FP))

# positive predictive value
print ("Precision = ",TP / float(TP+FP))

# Negative predictive value
print ("True Negative Prediction Rate = ",TN / float(TN+ FN))
```

```
Sensitivity =  0.8561281625881377
Specificity =  0.8119556200746578
False Positive Rate =  0.18804437992534218
Precision =  0.8199106256206554
True Negative Prediction Rate =  0.8494792796702104
```

Plotting the ROC Curve

```
# Defining a function to plot the roc curve
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Prediction Rate]')
    plt.ylabel('True Positive Rate')
```

```
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return None
# Defining the variables to plot the curve
fpr, tpr, thresholds = metrics.roc_curve( y_train_sm_pred_final.Converted,
y_train_sm_pred_final.Converted_prob, drop_intermediate = False )
# Plotting the curve for the obtained metrics
draw_roc(y_train_sm_pred_final.Converted, y_train_sm_pred_final.Converted_prob)
```



Finding Optimal Cutoff Point

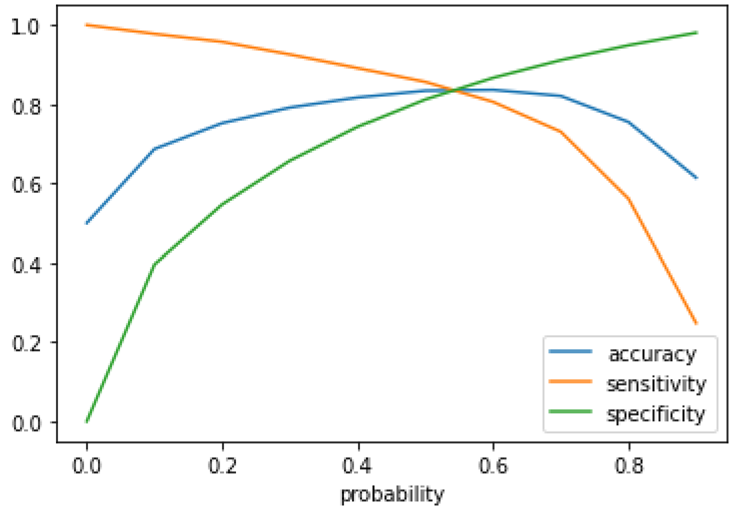
```
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_train_sm_pred_final[i]= y_train_sm_pred_final.Converted_prob.map(lambda x: 1 if x > i else
0)
y_train_sm_pred_final.head()
# Now let's calculate accuracy sensitivity and specificity for various probability cutoffs.
cutoff_df = pd.DataFrame( columns = ['probability','accuracy','sensitivity','specificity'])
from sklearn.metrics import confusion_matrix

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

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

```
    specificity = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensitivity = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensitivity,specificity]
print(cutoff_df)
```

```
     probability  accuracy  sensitivity  specificity
0.0  0.0          0.500000  1.000000     0.000000
0.1  0.1          0.686696  0.977603     0.395790
0.2  0.2          0.751996  0.957538     0.546454
0.3  0.3          0.791321  0.925653     0.656989
0.4  0.4          0.816881  0.891176     0.742586
0.5  0.5          0.834042  0.856128     0.811956
0.6  0.6          0.836116  0.805682     0.866549
0.7  0.7          0.820795  0.730350     0.911240
0.8  0.8          0.755003  0.561230     0.948776
0.9  0.9          0.614294  0.248185     0.980402
```

```
# plotting accuracy sensitivity and specificity for various probabilities calculated above.
cutoff_df.plot.line(x='probability', y=['accuracy','sensitivity','specificity'])
plt.show()
```

<Figure size 1080x1080 with 0 Axes>



Initially we selected the optimm point of classification as 0.5.

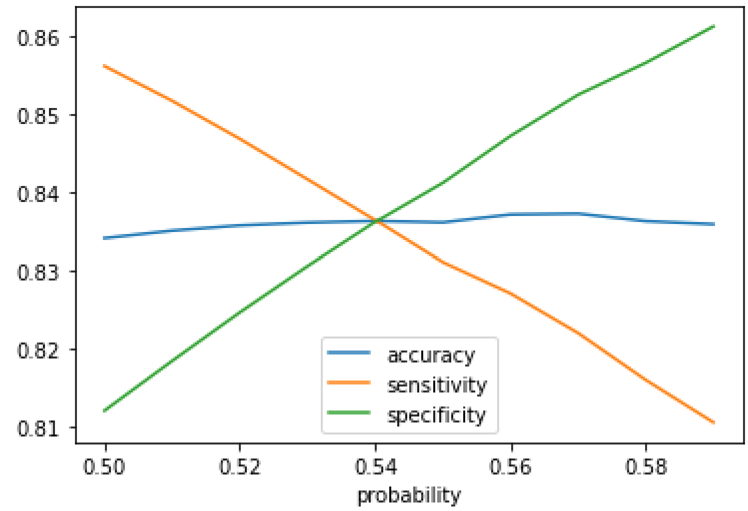
From the above graph, we can see the optimum cutoff is slightly higher than 0.5 but lies lower than 0.6. So lets tweek a little more within this range.

```
# Let's create columns with refined probability cutoffs
numbers = [0.50,0.51,0.52,0.53,0.54,0.55,0.56,0.57,0.58,0.59]
for i in numbers:
    y_train_sm_pred_final[i]= y_train_sm_pred_final.Converted_prob.map(lambda x: 1 if x > i else
0)
y_train_sm_pred_final.head()
# Now let's calculate accuracy sensitivity and specificity for various probability cutoffs.
cutoff_df = pd.DataFrame( columns = ['probability','accuracy','sensitivity','specificity'])
from sklearn.metrics import confusion_matrix
```

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

num = [0.50,0.51,0.52,0.53,0.54,0.55,0.56,0.57,0.58,0.59]
for i in num:
    cm1 = metrics.confusion_matrix(y_train_sm_pred_final.Converted, y_train_sm_pred_final[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1

    specificity = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensitivity = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensitivity,specificity]
print(cutoff_df)
```

	probability	accuracy	sensitivity	specificity
0.50	0.50	0.834042	0.856128	0.811956
0.51	0.51	0.835001	0.851669	0.818333
0.52	0.52	0.835675	0.846796	0.824554
0.53	0.53	0.836038	0.841611	0.830465
0.54	0.54	0.836245	0.836375	0.836116
0.55	0.55	0.836064	0.830983	0.841145
0.56	0.56	0.837075	0.826991	0.847159
0.57	0.57	0.837179	0.821910	0.852447
0.58	0.58	0.836219	0.815896	0.856543
0.59	0.59	0.835831	0.810452	0.861209

```
# plotting accuracy sensitivity and specificity for various probabilities calculated above.
cutoff_df.plot.line(x='probability', y=['accuracy','sensitivity','specificity'])
plt.show()
```



From the above graph we can conclude, the optimal cutoff point in the probability to define the predicted churn variabe converges at `0.54`

From the curve above, 0.2 is the optimum point to take it as a cutoff probability.

```
y_train_sm_pred_final['final_churn_pred'] = y_train_sm_pred_final.Converted_prob.map( lambda x: 1 if x > 0.54 else 0)

y_train_sm_pred_final.head()
# Calculating the ovearall accuracy again
print("The overall accuracy of the model now is:",metrics.accuracy_score(y_train_sm_pred_final.Converted, y_train_sm_pred_final.final_churn_pred))
```

```
The overall accuracy of the model now is: 0.8362453338863542
```

```
confusion2 = metrics.confusion_matrix(y_train_sm_pred_final.Converted, y_train_sm_pred_final.final_churn_pred )
print(confusion2)
```

```
[[16127  3161]
 [ 3156 16132]]
```

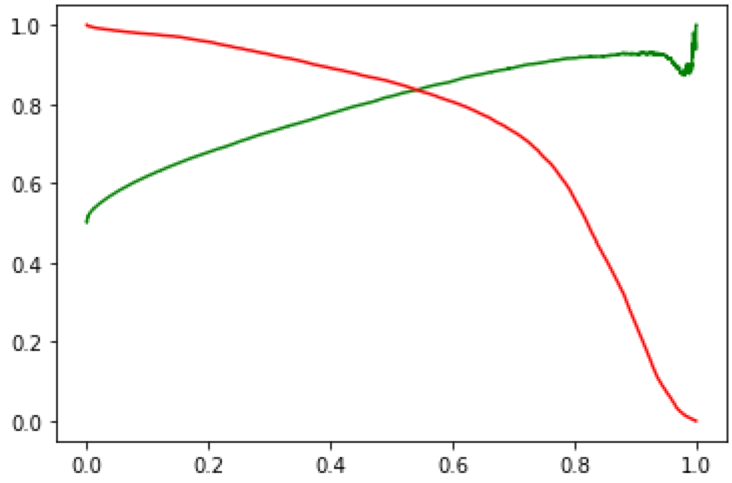
```
TP2 = confusion2[1,1] # true positive
TN2 = confusion2[0,0] # true negatives
FP2 = confusion2[0,1] # false positives
FN2 = confusion2[1,0] # false negatives

# Let's see the sensitivity of our logistic regression model
print("Sensitivity = ",TP2 / float(TP2+FN2))

# Let us calculate specificity
print("Specificity = ",TN2 / float(TN2+FP2))

# Calculate false postive rate - predicting churn when customer does not have churned
print("False Positive Rate = ",FP2/ float(TN2+FP2))

# positive predictive value
print ("Precision = ",TP2 / float(TP2+FP2))

# Negative predictive value
print ("True Negative Prediction Rate = ",TN2 / float(TN2 + FN2))
```

```
Sensitivity =  0.8363749481542928
Specificity =  0.8361157196184156
False Positive Rate =  0.1638842803815844
Precision =  0.8361581920903954
True Negative Prediction Rate =  0.8363325208733081
```

Precision and recall tradeoff

```
from sklearn.metrics import precision_recall_curve
p, r, thresholds = precision_recall_curve(y_train_sm_pred_final.Converted, y_train_sm_pred_final.Converted_prob)
```

```
# Plotting the curve
plt.plot(thresholds, p[:-1], "g-")
plt.plot(thresholds, r[:-1], "r-")
plt.show()
```



Making predictions on the test set

Transforming and feature selection for test data

```
# Scaling the test data
X_test[num_col] = scaler.transform(X_test[num_col])
X_test.head()
# Feature selection
X_test=X_test[rfe_columns_2]
X_test.head()
# Adding constant to the test model.
X_test_SM = sm.add_constant(X_test)
```

Predicting the target variable

```
y_test_pred = res.predict(X_test_SM)
print("\n The first ten probability value of the prediction are:\n",y_test_pred[:10])
35865    0.772260
41952    0.516558
98938    0.000325
29459    0.128443
70682    0.007754
58317    0.237200
4860    0.007990
16890    0.702931
61329    0.652452
94332    0.491091
dtype: float64
y_pred = pd.DataFrame(y_test_pred)
y_pred.head()
y_pred=y_pred.rename(columns = {0:"Conv_prob"})
y_test_df = pd.DataFrame(y_test)
y_test_df.head()
y_pred_final = pd.concat([y_test_df,y_pred],axis=1)
y_pred_final.head()
y_pred_final['test_churn_pred'] = y_pred_final.Conv_prob.map(lambda x: 1 if x>0.54 else 0)
```

```
y_pred_final.head()
# Checking the overall accuracy of the predicted set.
metrics.accuracy_score(y_pred_final.churn, y_pred_final.test_churn_pred)
```
0.8270192200866571

Metrics Evaluation

```
# Confusion Matrix
confusion2_test = metrics.confusion_matrix(y_pred_final.churn, y_pred_final.test_churn_pred)
print("Confusion Matrix\n",confusion2_test)
```
```
Confusion Matrix
 [[6860 1412]
 [ 145  584]]
```

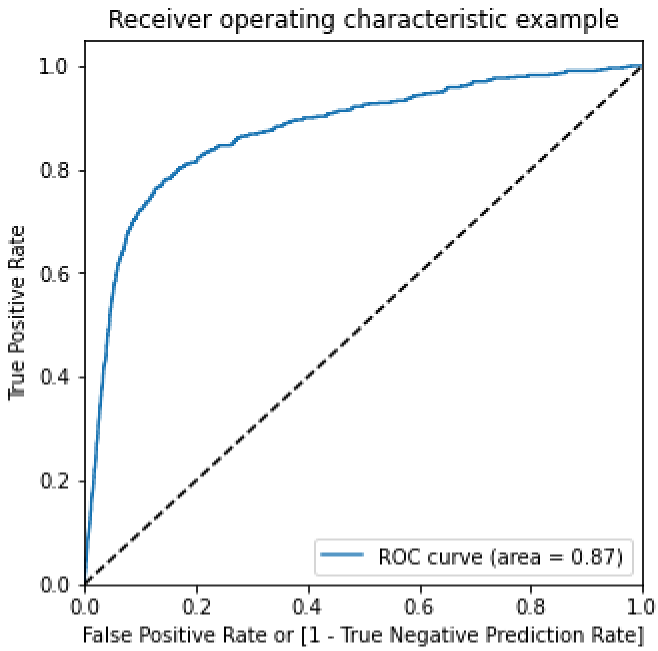
```
# Calculating model validation parameters
TP3 = confusion2_test[1,1] # true positive
TN3 = confusion2_test[0,0] # true negatives
FP3 = confusion2_test[0,1] # false positives
FN3 = confusion2_test[1,0] # false negatives
# Let's see the sensitivity of our logistic regression model
print("Sensitivity = ",TP3 / float(TP3+FN3))

# Let us calculate specificity
print("Specificity = ",TN3 / float(TN3+FP3))

# Calculate false postive rate - predicting churn when customer does not have churned
print("False Positive Rate = ",FP3/ float(TN3+FP3))

# positive predictive value
print ("Precision = ",TP3 / float(TP3+FP3))

# Negative predictive value
print ("True Negative Prediction Rate = ",TN3 / float(TN3+FN3))
```
```
Sensitivity =  0.8010973936899863
Specificity =  0.8293036750483559
False Positive Rate =  0.1706963249516441
Precision =  0.2925851703406814
True Negative Prediction Rate =  0.979300499643112
```

Explaining the results

```
print("The accuracy of the predicted model is: ",round(metrics.accuracy_score(y_pred_final.churn, y_pred_final.test_churn_pred),2)*100,"%")
print("The sensitivity of the predicted model is: ",round(TP3 / float(TP3+FN3),2)*100,"%")

print("\nAs the model created is based on a sentivity model, i.e. the True positive rate is given more importance as the actual and prediction of churn by a customer\n")
```
```
The accuracy of the predicted model is:  83.0 %
The sensitivity of the predicted model is:  80.0 %
```

```
As the model created is based on a sentivity model, i.e. the True
positive rate is given more importance as the actual and prediction of
churn by a customer
```

```
# ROC curve for the test dataset

# Defining the variables to plot the curve
fpr, tpr, thresholds = metrics.roc_curve(y_pred_final.churn,y_pred_final.Conv_prob,
drop_intermediate = False )
# Plotting the curve for the obtained metrics
draw_roc(y_pred_final.churn,y_pred_final.Conv_prob)
```



The AUC score for train dataset is 0.90 and the test dataset is 0.87.
This model can be considered as a good model.

Logistic Regression using PCA

```
# split the dateset into train and test datasets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, train_size=0.7,
random_state=1)
print("Dimension of X_train:", X_train.shape)
print("Dimension of X_test:", X_test.shape)

# apply scaling on the dataset

scaler = MinMaxScaler()
X_train[num_col] = scaler.fit_transform(X_train[num_col])
X_test[num_col] = scaler.transform(X_test[num_col])

# Applying SMOTE technique for data imbalance correction
```

```
sm = SMOTE(random_state=42)
X_train_sm,y_train_sm = sm.fit_resample(X_train,y_train)
print("Dimension of X_train_sm Shape:", X_train_sm.shape)
print("Dimension of y_train_sm Shape:", y_train_sm.shape)

X_train_sm.head()
```

```
Dimension of X_train: (21000, 126)
Dimension of X_test: (9001, 126)
Dimension of X_train_sm Shape: (38576, 126)
Dimension of y_train_sm Shape: (38576,)
```

```
# importing PCA
from sklearn.decomposition import PCA
pca = PCA(random_state=42)

# applying PCA on train data
pca.fit(X_train_sm)
PCA(random_state=42)
X_train_sm_pca=pca.fit_transform(X_train_sm)
print("Dimension of X_train_sm_pca: ",X_train_sm_pca.shape)

X_test_pca=pca.transform(X_test)
print("Dimension of X_test_pca: ",X_test_pca.shape)
```

```
Dimension of X_train_sm_pca:  (38576, 126)
Dimension of X_test_pca:  (9001, 126)
```

```
#Viewing the PCA components
pca.components_
array([[ 1.77080250e-02,  5.62945551e-03,  1.28071557e-02, ...,
        -8.33377373e-02,  2.03169293e-01, -2.25884463e-04],
       [ 1.17884332e-03,  1.36226801e-04,  2.66567649e-03, ...,
         6.62002105e-01, -7.17541378e-01,  1.93966990e-04],
       [ 8.31908962e-03, -2.32698646e-02, -1.53378013e-02, ...,
         7.54642802e-02,  5.50287343e-02,  1.26734621e-03],
       ...,
       [-3.94307290e-07,  1.32661563e-06, -2.21287988e-06, ...,
        -3.76725866e-08, -1.42403279e-08,  2.74517957e-08],
       [ 2.29473384e-07, -1.88640723e-06,  1.53383133e-06, ...,
        -3.64244933e-08, -2.71775061e-08, -3.24942343e-08],
       [-0.00000000e+00, -1.20429354e-16, -2.26455538e-17, ...,
         3.32681843e-18, -2.16312073e-18, -2.01305223e-17]])
```

Performing Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
logreg_pca = LogisticRegression()
logreg_pca.fit(X_train_sm_pca, y_train_sm)

# making the predictions
y_pred = logreg_pca.predict(X_test_pca)
```

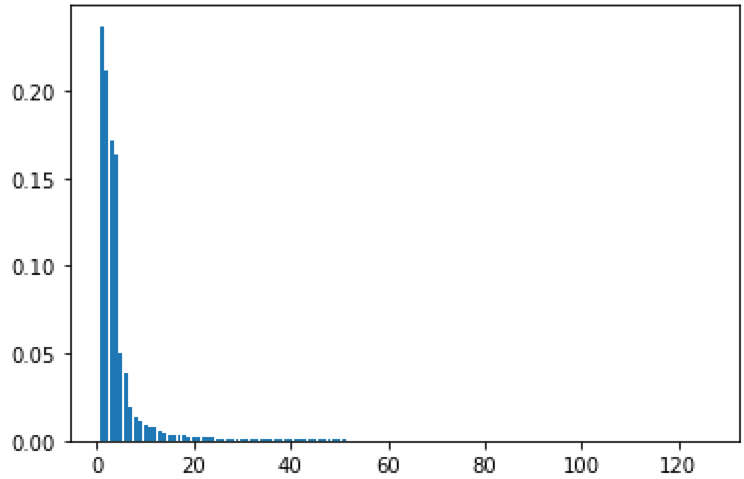
```
# converting the prediction into a dataframe
y_pred_df = pd.DataFrame(y_pred)
print("Dimension of y_pred_df:", y_pred_df.shape)
```

```
Dimension of y_pred_df: (9001, 1)
```

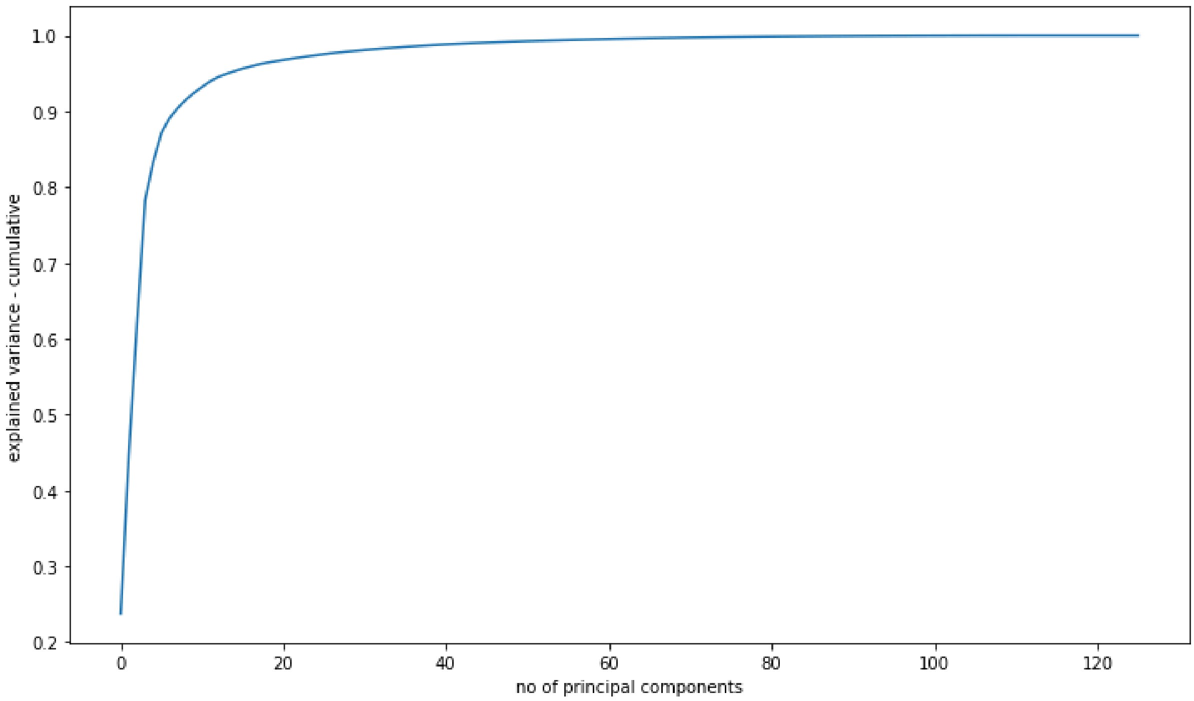
```
from sklearn.metrics import confusion_matrix, accuracy_score

# Checking the Confusion matrix
print("Confusion Matirx for y_test & y_pred\n",confusion_matrix(y_test,y_pred),"\n")

# Checking the Accuracy of the Predicted model.
print("Accuracy of the logistic regression model with PCA: ",accuracy_score(y_test,y_pred))
```

```
Confusion Matirx for y_test & y_pred
 [[6761 1511]
 [ 126  603]]

Accuracy of the logistic regression model with PCA:  0.818131318742362
```

```
plt.bar(range(1,len(pca.explained_variance_ratio_)+1),pca.explained_variance_ratio_)
plt.show()
```




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

# Making a scree plot
fig = plt.figure(figsize=[12,7])
plt.plot(var_cumu)
plt.xlabel('no of principal components')
plt.ylabel('explained variance - cumulative')
plt.show()
```




```
np.cumsum(np.round(pca.explained_variance_ratio_, decimals=3)*100)
array([23.7, 44.8, 62. , 78.3, 83.3, 87.1, 89. , 90.4, 91.5, 92.4, 93.2,
       93.9, 94.5, 94.9, 95.3, 95.6, 95.9, 96.2, 96.4, 96.6, 96.8, 97. ,
       97.2, 97.4, 97.5, 97.6, 97.7, 97.8, 97.9, 98. , 98.1, 98.2, 98.3,
       98.4, 98.5, 98.6, 98.7, 98.8, 98.9, 99. , 99.1, 99.2, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3, 99.3,
       99.3, 99.3, 99.3, 99.3, 99.3])
```

**90% of the data can be explained with 8 PCA components*

Fitting the dataset with the 8 explainable components

```
pca_8 = PCA(n_components=15)

train_pca_8 = pca_8.fit_transform(X_train_sm)
print("Dimension for Train dataset using PCA: ", train_pca_8.shape)

test_pca_8 = pca_8.transform(X_test)
print("Dimension for Test dataset using PCA: ", test_pca_8.shape)
```

```
Dimension for Train dataset using PCA:  (38576, 15)
Dimension for Test dataset using PCA:  (9001, 15)
```

```
logreg_pca_8 = LogisticRegression()
logreg_pca_8.fit(train_pca_8, y_train_sm)

# making the predictions
y_pred_8 = logreg_pca_8.predict(test_pca_8)
```

```python
# converting the prediction into a dataframe
y_pred_df_8 = pd.DataFrame(y_pred_8)
print("Dimension of y_pred_df_8: ", y_pred_df_8.shape)
```

```
Dimension of y_pred_df_8:  (9001, 1)
```

```python
# Checking the Confusion matrix
print("Confusion Matirx for y_test & y_pred\n",confusion_matrix(y_test,y_pred_8),"\n")

# Checking the Accuracy of the Predicted model.
print("Accuracy of the logistic regression model with PCA: ",accuracy_score(y_test,y_pred_8))
```

```
Confusion Matirx for y_test & y_pred
 [[6250 2022]
 [ 185  544]]

Accuracy of the logistic regression model with PCA:  0.7548050216642596
```

```python
# df_pca = pd.DataFrame(newdata, columns=["PC1", "PC2"])
# df.head()
```