

# spqk5nwps

March 29, 2024

## 0.0.1 Problem statement:-

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

Retaining high profitable customers is the main business goal here.

## 0.1 Steps:-

1. Reading, understanding and visualising the data
2. Preparing the data for modelling
3. Building the model
4. Evaluate the model

```
[2]: # Importing the libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

```
[3]: pd.set_option('display.max_columns', 500)
```

## 1 Reading and understanding the data

```
[4]: # Reading the dataset
df = pd.read_csv('telecom_churn_data.csv')
df.head()
```

```
[4]:  mobile_number  circle_id  loc_og_t2o_mou  std_og_t2o_mou  loc_ic_t2o_mou  \
0      7000842753         109             0.0             0.0             0.0
1      7001865778         109             0.0             0.0             0.0
2      7001625959         109             0.0             0.0             0.0
```

3	7001204172	109	0.0	0.0	0.0
4	7000142493	109	0.0	0.0	0.0

	last_date_of_month_6	last_date_of_month_7	last_date_of_month_8	\
0	6/30/2014	7/31/2014	8/31/2014	
1	6/30/2014	7/31/2014	8/31/2014	
2	6/30/2014	7/31/2014	8/31/2014	
3	6/30/2014	7/31/2014	8/31/2014	
4	6/30/2014	7/31/2014	8/31/2014	

	last_date_of_month_9	arpu_6	arpu_7	arpu_8	arpu_9	onnet_mou_6	\
0	9/30/2014	197.385	214.816	213.803	21.100	NaN	
1	9/30/2014	34.047	355.074	268.321	86.285	24.11	
2	9/30/2014	167.690	189.058	210.226	290.714	11.54	
3	9/30/2014	221.338	251.102	508.054	389.500	99.91	
4	9/30/2014	261.636	309.876	238.174	163.426	50.31	

	onnet_mou_7	onnet_mou_8	onnet_mou_9	offnet_mou_6	offnet_mou_7	\
0	NaN	0.00	NaN	NaN	NaN	
1	78.68	7.68	18.34	15.74	99.84	
2	55.24	37.26	74.81	143.33	220.59	
3	54.39	310.98	241.71	123.31	109.01	
4	149.44	83.89	58.78	76.96	91.88	

	offnet_mou_8	offnet_mou_9	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	\
0	0.00	NaN	NaN	NaN	0.00	
1	304.76	53.76	0.0	0.00	0.00	
2	208.36	118.91	0.0	0.00	0.00	
3	71.68	113.54	0.0	54.86	44.38	
4	124.26	45.81	0.0	0.00	0.00	

	roam_ic_mou_9	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	roam_og_mou_9	\
0	NaN	NaN	NaN	0.00	NaN	
1	0.00	0.0	0.00	0.00	0.00	
2	38.49	0.0	0.00	0.00	70.94	
3	0.00	0.0	28.09	39.04	0.00	
4	0.00	0.0	0.00	0.00	0.00	

	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2t_mou_9	\
0	NaN	NaN	0.00	NaN	
1	23.88	74.56	7.68	18.34	
2	7.19	28.74	13.58	14.39	
3	73.68	34.81	10.61	15.49	
4	50.31	149.44	83.89	58.78	

	loc_og_t2m_mou_6	loc_og_t2m_mou_7	loc_og_t2m_mou_8	loc_og_t2m_mou_9	\
0	NaN	NaN	0.00	NaN	

1	11.51	75.94	291.86	53.76
2	29.34	16.86	38.46	28.16
3	107.43	83.21	22.46	65.46
4	67.64	91.88	124.26	37.89

	loc_og_t2f_mou_6	loc_og_t2f_mou_7	loc_og_t2f_mou_8	loc_og_t2f_mou_9	\
0	NaN	NaN	0.00	NaN	
1	0.00	0.00	0.00	0.00	
2	24.11	21.79	15.61	22.24	
3	1.91	0.65	4.91	2.06	
4	0.00	0.00	0.00	1.93	

	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_t2c_mou_9	\
0	NaN	NaN	0.00	NaN	
1	0.0	2.91	0.00	0.00	
2	0.0	135.54	45.76	0.48	
3	0.0	0.00	0.00	0.00	
4	0.0	0.00	0.00	0.00	

	loc_og_mou_6	loc_og_mou_7	loc_og_mou_8	loc_og_mou_9	std_og_t2t_mou_6	\
0	NaN	NaN	0.00	NaN	NaN	
1	35.39	150.51	299.54	72.11	0.23	
2	60.66	67.41	67.66	64.81	4.34	
3	183.03	118.68	37.99	83.03	26.23	
4	117.96	241.33	208.16	98.61	0.00	

	std_og_t2t_mou_7	std_og_t2t_mou_8	std_og_t2t_mou_9	std_og_t2m_mou_6	\
0	NaN	0.00	NaN	NaN	
1	4.11	0.00	0.00	0.00	
2	26.49	22.58	8.76	41.81	
3	14.89	289.58	226.21	2.99	
4	0.00	0.00	0.00	9.31	

	std_og_t2m_mou_7	std_og_t2m_mou_8	std_og_t2m_mou_9	std_og_t2f_mou_6	\
0	NaN	0.00	NaN	NaN	
1	0.46	0.13	0.00	0.00	
2	67.41	75.53	9.28	1.48	
3	1.73	6.53	9.99	0.00	
4	0.00	0.00	0.00	0.00	

	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2f_mou_9	std_og_t2c_mou_6	\
0	NaN	0.00	NaN	NaN	
1	0.00	0.00	0.0	0.0	
2	14.76	22.83	0.0	0.0	
3	0.00	0.00	0.0	0.0	
4	0.00	0.00	0.0	0.0	

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_t2c_mou_9	std_og_mou_6	\
0	NaN	0.0	NaN	NaN	
1	0.0	0.0	0.0	0.23	
2	0.0	0.0	0.0	47.64	
3	0.0	0.0	0.0	29.23	
4	0.0	0.0	0.0	9.31	

	std_og_mou_7	std_og_mou_8	std_og_mou_9	isd_og_mou_6	isd_og_mou_7	\
0	NaN	0.00	NaN	NaN	NaN	
1	4.58	0.13	0.00	0.0	0.0	
2	108.68	120.94	18.04	0.0	0.0	
3	16.63	296.11	236.21	0.0	0.0	
4	0.00	0.00	0.00	0.0	0.0	

	isd_og_mou_8	isd_og_mou_9	spl_og_mou_6	spl_og_mou_7	spl_og_mou_8	\
0	0.0	NaN	NaN	NaN	0.00	
1	0.0	0.0	4.68	23.43	12.76	
2	0.0	0.0	46.56	236.84	96.84	
3	0.0	0.0	10.96	0.00	18.09	
4	0.0	0.0	0.00	0.00	0.00	

	spl_og_mou_9	og_others_6	og_others_7	og_others_8	og_others_9	\
0	NaN	NaN	NaN	0.0	NaN	
1	0.00	0.00	0.0	0.0	0.0	
2	42.08	0.45	0.0	0.0	0.0	
3	43.29	0.00	0.0	0.0	0.0	
4	5.98	0.00	0.0	0.0	0.0	

	total_og_mou_6	total_og_mou_7	total_og_mou_8	total_og_mou_9	\
0	0.00	0.00	0.00	0.00	
1	40.31	178.53	312.44	72.11	
2	155.33	412.94	285.46	124.94	
3	223.23	135.31	352.21	362.54	
4	127.28	241.33	208.16	104.59	

	loc_ic_t2t_mou_6	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2t_mou_9	\
0	NaN	NaN	0.16	NaN	
1	1.61	29.91	29.23	116.09	
2	115.69	71.11	67.46	148.23	
3	62.08	19.98	8.04	41.73	
4	105.68	88.49	233.81	154.56	

	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	loc_ic_t2m_mou_8	loc_ic_t2m_mou_9	\
0	NaN	NaN	4.13	NaN	
1	17.48	65.38	375.58	56.93	
2	14.38	15.44	38.89	38.98	
3	113.96	64.51	20.28	52.86	

4	106.84	109.54	104.13	48.24	
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	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	loc_ic_t2f_mou_9	\
0	NaN	NaN	1.15	NaN	
1	0.00	8.93	3.61	0.00	
2	99.48	122.29	49.63	158.19	
3	57.43	27.09	19.84	65.59	
4	1.50	0.00	0.00	0.00	

	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	loc_ic_mou_9	std_ic_t2t_mou_6	\
0	NaN	NaN	5.44	NaN	NaN	
1	19.09	104.23	408.43	173.03	0.00	
2	229.56	208.86	155.99	345.41	72.41	
3	233.48	111.59	48.18	160.19	43.48	
4	214.03	198.04	337.94	202.81	0.00	

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2t_mou_9	std_ic_t2m_mou_6	\
0	NaN	0.00	NaN	NaN	
1	0.00	2.35	0.00	5.90	
2	71.29	28.69	49.44	45.18	
3	66.44	0.00	129.84	1.33	
4	0.00	0.86	2.31	1.93	

	std_ic_t2m_mou_7	std_ic_t2m_mou_8	std_ic_t2m_mou_9	std_ic_t2f_mou_6	\
0	NaN	0.00	NaN	NaN	
1	0.00	12.49	15.01	0.00	
2	177.01	167.09	118.18	21.73	
3	38.56	4.94	13.98	1.18	
4	0.25	0.00	0.00	0.00	

	std_ic_t2f_mou_7	std_ic_t2f_mou_8	std_ic_t2f_mou_9	std_ic_t2o_mou_6	\
0	NaN	0.00	NaN	NaN	
1	0.00	0.00	0.00	0.0	
2	58.34	43.23	3.86	0.0	
3	0.00	0.00	0.00	0.0	
4	0.00	0.00	0.00	0.0	

	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_t2o_mou_9	std_ic_mou_6	\
0	NaN	0.0	NaN	NaN	
1	0.0	0.0	0.0	5.90	
2	0.0	0.0	0.0	139.33	
3	0.0	0.0	0.0	45.99	
4	0.0	0.0	0.0	1.93	

	std_ic_mou_7	std_ic_mou_8	std_ic_mou_9	total_ic_mou_6	total_ic_mou_7	\
0	NaN	0.00	NaN	0.00	0.00	
1	0.00	14.84	15.01	26.83	104.23	

2	306.66	239.03	171.49	370.04	519.53
3	105.01	4.94	143.83	280.08	216.61
4	0.25	0.86	2.31	216.44	198.29

	total_ic_mou_8	total_ic_mou_9	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	\
0	5.44	0.00	NaN	NaN	0.0	
1	423.28	188.04	0.00	0.0	0.0	
2	395.03	517.74	0.21	0.0	0.0	
3	53.13	305.38	0.59	0.0	0.0	
4	338.81	205.31	0.00	0.0	0.0	

	spl_ic_mou_9	isd_ic_mou_6	isd_ic_mou_7	isd_ic_mou_8	isd_ic_mou_9	\
0	NaN	NaN	NaN	0.0	NaN	
1	0.00	1.83	0.00	0.0	0.00	
2	0.45	0.00	0.85	0.0	0.01	
3	0.55	0.00	0.00	0.0	0.00	
4	0.18	0.00	0.00	0.0	0.00	

	ic_others_6	ic_others_7	ic_others_8	ic_others_9	total_rech_num_6	\
0	NaN	NaN	0.0	NaN	4	
1	0.00	0.00	0.0	0.00	4	
2	0.93	3.14	0.0	0.36	5	
3	0.00	0.00	0.0	0.80	10	
4	0.48	0.00	0.0	0.00	5	

	total_rech_num_7	total_rech_num_8	total_rech_num_9	total_rech_amt_6	\
0	3	2	6	362	
1	9	11	5	74	
2	4	2	7	168	
3	11	18	14	230	
4	6	3	4	196	

	total_rech_amt_7	total_rech_amt_8	total_rech_amt_9	max_rech_amt_6	\
0	252	252	0	252	
1	384	283	121	44	
2	315	116	358	86	
3	310	601	410	60	
4	350	287	200	56	

	max_rech_amt_7	max_rech_amt_8	max_rech_amt_9	date_of_last_rech_6	\
0	252	252	0	6/21/2014	
1	154	65	50	6/29/2014	
2	200	86	100	6/17/2014	
3	50	50	50	6/28/2014	
4	110	110	50	6/26/2014	

	date_of_last_rech_7	date_of_last_rech_8	date_of_last_rech_9	\
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0	7/16/2014	8/8/2014	9/28/2014
1	7/31/2014	8/28/2014	9/30/2014
2	7/24/2014	8/14/2014	9/29/2014
3	7/31/2014	8/31/2014	9/30/2014
4	7/28/2014	8/9/2014	9/28/2014

	last_day_rch_amt_6	last_day_rch_amt_7	last_day_rch_amt_8	\
0	252	252	252	
1	44	23	30	
2	0	200	86	
3	30	50	50	
4	50	110	110	

	last_day_rch_amt_9	date_of_last_rech_data_6	date_of_last_rech_data_7	\
0	0	6/21/2014	7/16/2014	
1	0	NaN	7/25/2014	
2	0	NaN	NaN	
3	30	NaN	NaN	
4	50	6/4/2014	NaN	

	date_of_last_rech_data_8	date_of_last_rech_data_9	total_rech_data_6	\
0	8/8/2014	NaN	1.0	
1	8/10/2014	NaN	NaN	
2	NaN	9/17/2014	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	1.0	

	total_rech_data_7	total_rech_data_8	total_rech_data_9	max_rech_data_6	\
0	1.0	1.0	NaN	252.0	
1	1.0	2.0	NaN	NaN	
2	NaN	NaN	1.0	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	56.0	

	max_rech_data_7	max_rech_data_8	max_rech_data_9	count_rech_2g_6	\
0	252.0	252.0	NaN	0.0	
1	154.0	25.0	NaN	NaN	
2	NaN	NaN	46.0	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	1.0	

	count_rech_2g_7	count_rech_2g_8	count_rech_2g_9	count_rech_3g_6	\
0	0.0	0.0	NaN	1.0	
1	1.0	2.0	NaN	NaN	
2	NaN	NaN	1.0	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	0.0	

	count_rech_3g_7	count_rech_3g_8	count_rech_3g_9	av_rech_amt_data_6	\
0	1.0	1.0	NaN	252.0	
1	0.0	0.0	NaN	NaN	
2	NaN	NaN	0.0	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	56.0	

	av_rech_amt_data_7	av_rech_amt_data_8	av_rech_amt_data_9	vol_2g_mb_6	\
0	252.0	252.0	NaN	30.13	
1	154.0	50.0	NaN	0.00	
2	NaN	NaN	46.0	0.00	
3	NaN	NaN	NaN	0.00	
4	NaN	NaN	NaN	0.00	

	vol_2g_mb_7	vol_2g_mb_8	vol_2g_mb_9	vol_3g_mb_6	vol_3g_mb_7	\
0	1.32	5.75	0.0	83.57	150.76	
1	108.07	365.47	0.0	0.00	0.00	
2	0.00	0.00	0.0	0.00	0.00	
3	0.00	0.00	0.0	0.00	0.00	
4	0.00	0.00	0.0	0.00	0.00	

	vol_3g_mb_8	vol_3g_mb_9	arpu_3g_6	arpu_3g_7	arpu_3g_8	arpu_3g_9	\
0	109.61	0.00	212.17	212.17	212.17	NaN	
1	0.00	0.00	NaN	0.00	0.00	NaN	
2	0.00	8.42	NaN	NaN	NaN	2.84	
3	0.00	0.00	NaN	NaN	NaN	NaN	
4	0.00	0.00	0.00	NaN	NaN	NaN	

	arpu_2g_6	arpu_2g_7	arpu_2g_8	arpu_2g_9	night_pck_user_6	\
0	212.17	212.17	212.17	NaN	0.0	
1	NaN	28.61	7.60	NaN	NaN	
2	NaN	NaN	NaN	0.0	NaN	
3	NaN	NaN	NaN	NaN	NaN	
4	0.00	NaN	NaN	NaN	0.0	

	night_pck_user_7	night_pck_user_8	night_pck_user_9	monthly_2g_6	\
0	0.0	0.0	NaN	0	
1	0.0	0.0	NaN	0	
2	NaN	NaN	0.0	0	
3	NaN	NaN	NaN	0	
4	NaN	NaN	NaN	0	

	monthly_2g_7	monthly_2g_8	monthly_2g_9	sachet_2g_6	sachet_2g_7	\
0	0	0	0	0	0	
1	1	0	0	0	0	
2	0	0	0	0	0	



3	0	0	0	0	0
4	0	0	0	1	0

	sachet_2g_8	sachet_2g_9	monthly_3g_6	monthly_3g_7	monthly_3g_8	\
0	0	0	1	1	1	
1	2	0	0	0	0	
2	0	1	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	monthly_3g_9	sachet_3g_6	sachet_3g_7	sachet_3g_8	sachet_3g_9	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	fb_user_6	fb_user_7	fb_user_8	fb_user_9	aon	aug_vbc_3g	jul_vbc_3g	\
0	1.0	1.0	1.0	NaN	968	30.4	0.0	
1	NaN	1.0	1.0	NaN	1006	0.0	0.0	
2	NaN	NaN	NaN	1.0	1103	0.0	0.0	
3	NaN	NaN	NaN	NaN	2491	0.0	0.0	
4	0.0	NaN	NaN	NaN	1526	0.0	0.0	

	jun_vbc_3g	sep_vbc_3g
0	101.20	3.58
1	0.00	0.00
2	4.17	0.00
3	0.00	0.00
4	0.00	0.00

```
[5]: df.shape
```

```
[5]: (99999, 226)
```

```
[6]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Columns: 226 entries, mobile_number to sep_vbc_3g
dtypes: float64(179), int64(35), object(12)
memory usage: 172.4+ MB
```

```
[7]: df.describe()
```

```
[7]:      mobile_number  circle_id  loc_og_t2o_mou  std_og_t2o_mou  \
count  9.999900e+04    99999.0        98981.0        98981.0
```

mean	7.001207e+09	109.0	0.0	0.0
std	6.956694e+05	0.0	0.0	0.0
min	7.000000e+09	109.0	0.0	0.0
25%	7.000606e+09	109.0	0.0	0.0
50%	7.001205e+09	109.0	0.0	0.0
75%	7.001812e+09	109.0	0.0	0.0
max	7.002411e+09	109.0	0.0	0.0

	loc_ic_t2o_mou	arpu_6	arpu_7	arpu_8	arpu_9 \
count	98981.0	99999.000000	99999.000000	99999.000000	99999.000000
mean	0.0	282.987358	278.536648	279.154731	261.645069
std	0.0	328.439770	338.156291	344.474791	341.998630
min	0.0	-2258.709000	-2014.045000	-945.808000	-1899.505000
25%	0.0	93.411500	86.980500	84.126000	62.685000
50%	0.0	197.704000	191.640000	192.080000	176.849000
75%	0.0	371.060000	365.344500	369.370500	353.466500
max	0.0	27731.088000	35145.834000	33543.624000	38805.617000

	onnet_mou_6	onnet_mou_7	onnet_mou_8	onnet_mou_9	offnet_mou_6 \
count	96062.000000	96140.000000	94621.000000	92254.000000	96062.000000
mean	132.395875	133.670805	133.018098	130.302327	197.935577
std	297.207406	308.794148	308.951589	308.477668	316.851613
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	7.380000	6.660000	6.460000	5.330000	34.730000
50%	34.310000	32.330000	32.360000	29.840000	96.310000
75%	118.740000	115.595000	115.860000	112.130000	231.860000
max	7376.710000	8157.780000	10752.560000	10427.460000	8362.360000

	offnet_mou_7	offnet_mou_8	offnet_mou_9	roam_ic_mou_6	roam_ic_mou_7 \
count	96140.000000	94621.000000	92254.000000	96062.000000	96140.000000
mean	197.045133	196.574803	190.337222	9.950013	7.149898
std	325.862803	327.170662	319.396092	72.825411	73.447948
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	32.190000	31.630000	27.130000	0.000000	0.000000
50%	91.735000	92.140000	87.290000	0.000000	0.000000
75%	226.815000	228.260000	220.505000	0.000000	0.000000
max	9667.130000	14007.340000	10310.760000	13724.380000	15371.040000

	roam_ic_mou_8	roam_ic_mou_9	roam_og_mou_6	roam_og_mou_7 \
count	94621.000000	92254.000000	96062.000000	96140.000000
mean	7.292981	6.343841	13.911337	9.818732
std	68.402466	57.137537	71.443196	58.455762
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	13095.360000	8464.030000	3775.110000	2812.040000

	roam_og_mou_8	roam_og_mou_9	loc_og_t2t_mou_6	loc_og_t2t_mou_7 \
count	94621.000000	92254.000000	96062.000000	96140.000000
mean	9.971890	8.555519	47.100763	46.473010
std	64.713221	58.438186	150.856393	155.318705
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	1.660000	1.630000
50%	0.000000	0.000000	11.910000	11.610000
75%	0.000000	0.000000	40.960000	39.910000
max	5337.040000	4428.460000	6431.330000	7400.660000

	loc_og_t2t_mou_8	loc_og_t2t_mou_9	loc_og_t2m_mou_6	loc_og_t2m_mou_7 \
count	94621.000000	92254.000000	96062.000000	96140.000000
mean	45.887806	44.584446	93.342088	91.397131
std	151.184830	147.995390	162.780544	157.492308
min	0.000000	0.000000	0.000000	0.000000
25%	1.600000	1.360000	9.880000	10.025000
50%	11.730000	11.260000	41.030000	40.430000
75%	40.110000	39.280000	110.390000	107.560000
max	10752.560000	10389.240000	4729.740000	4557.140000

	loc_og_t2m_mou_8	loc_og_t2m_mou_9	loc_og_t2f_mou_6	loc_og_t2f_mou_7 \
count	94621.000000	92254.000000	96062.000000	96140.000000
mean	91.755128	90.463192	3.751013	3.792985
std	156.537048	158.681454	14.230438	14.264986
min	0.000000	0.000000	0.000000	0.000000
25%	9.810000	8.810000	0.000000	0.000000
50%	40.360000	39.120000	0.000000	0.000000
75%	109.090000	106.810000	2.080000	2.090000
max	4961.330000	4429.880000	1466.030000	1196.430000

	loc_og_t2f_mou_8	loc_og_t2f_mou_9	loc_og_t2c_mou_6	loc_og_t2c_mou_7 \
count	94621.000000	92254.000000	96062.000000	96140.000000
mean	3.677991	3.655123	1.123056	1.368500
std	13.270996	13.457549	5.448946	7.533445
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	2.040000	1.940000	0.000000	0.000000
max	928.490000	927.410000	342.860000	916.240000

	loc_og_t2c_mou_8	loc_og_t2c_mou_9	loc_og_mou_6	loc_og_mou_7 \
count	94621.000000	92254.000000	96062.000000	96140.000000
mean	1.433821	1.232726	144.201175	141.670476
std	6.783335	5.619021	251.751489	248.731086
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	17.110000	17.480000

50%	0.000000	0.000000	65.110000	63.685000
75%	0.000000	0.000000	168.270000	164.382500
max	502.090000	339.840000	10643.380000	7674.780000

	loc_og_mou_8	loc_og_mou_9	std_og_t2t_mou_6	std_og_t2t_mou_7	\
count	94621.000000	92254.000000	96062.000000	96140.000000	
mean	141.328209	138.709970	79.829870	83.299598	
std	245.914311	245.934517	252.476533	263.631042	
min	0.000000	0.000000	0.000000	0.000000	
25%	17.110000	15.560000	0.000000	0.000000	
50%	63.730000	61.840000	0.000000	0.000000	
75%	166.110000	162.225000	30.807500	31.132500	
max	11039.910000	11099.260000	7366.580000	8133.660000	

	std_og_t2t_mou_8	std_og_t2t_mou_9	std_og_t2m_mou_6	std_og_t2m_mou_7	\
count	94621.000000	92254.000000	96062.000000	96140.000000	
mean	83.282673	82.342919	87.299624	90.804137	
std	265.486090	267.184991	255.617850	269.347911	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	3.950000	3.635000	
75%	30.580000	28.230000	53.290000	54.040000	
max	8014.430000	9382.580000	8314.760000	9284.740000	

	std_og_t2m_mou_8	std_og_t2m_mou_9	std_og_t2f_mou_6	std_og_t2f_mou_7	\
count	94621.000000	92254.000000	96062.000000	96140.000000	
mean	89.838390	86.276622	1.129011	1.115010	
std	271.757783	261.407396	7.984970	8.599406	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	3.310000	2.500000	0.000000	0.000000	
75%	52.490000	48.560000	0.000000	0.000000	
max	13950.040000	10223.430000	628.560000	544.630000	

	std_og_t2f_mou_8	std_og_t2f_mou_9	std_og_t2c_mou_6	std_og_t2c_mou_7	\
count	94621.000000	92254.000000	96062.0	96140.0	
mean	1.067792	1.042362	0.0	0.0	
std	7.905971	8.261770	0.0	0.0	
min	0.000000	0.000000	0.0	0.0	
25%	0.000000	0.000000	0.0	0.0	
50%	0.000000	0.000000	0.0	0.0	
75%	0.000000	0.000000	0.0	0.0	
max	516.910000	808.490000	0.0	0.0	

	std_og_t2c_mou_8	std_og_t2c_mou_9	std_og_mou_6	std_og_mou_7	\
count	94621.0	92254.0	96062.000000	96140.000000	
mean	0.0	0.0	168.261218	175.221436	

std	0.0	0.0	389.948499	408.922934
min	0.0	0.0	0.000000	0.000000
25%	0.0	0.0	0.000000	0.000000
50%	0.0	0.0	11.640000	11.090000
75%	0.0	0.0	144.837500	150.615000
max	0.0	0.0	8432.990000	10936.730000

	std_og_mou_8	std_og_mou_9	isd_og_mou_6	isd_og_mou_7	isd_og_mou_8	\
count	94621.000000	92254.000000	96062.000000	96140.000000	94621.000000	
mean	174.191498	169.664466	0.798277	0.776572	0.791247	
std	411.633049	405.138658	25.765248	25.603052	25.544471	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	10.410000	8.410000	0.000000	0.000000	0.000000	
75%	147.940000	142.105000	0.000000	0.000000	0.000000	
max	13980.060000	11495.310000	5900.660000	5490.280000	5681.540000	

	isd_og_mou_9	spl_og_mou_6	spl_og_mou_7	spl_og_mou_8	spl_og_mou_9	\
count	92254.000000	96062.000000	96140.000000	94621.000000	92254.000000	
mean	0.723892	3.916811	4.978279	5.053769	4.412767	
std	21.310751	14.936449	20.661570	17.855111	16.328227	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	2.430000	3.710000	3.990000	3.230000	
max	4244.530000	1023.210000	2372.510000	1390.880000	1635.710000	

	og_others_6	og_others_7	og_others_8	og_others_9	total_og_mou_6	\
count	96062.000000	96140.000000	94621.000000	92254.000000	99999.000000	
mean	0.454157	0.030235	0.033372	0.047456	305.133424	
std	4.125911	2.161717	2.323464	3.635466	463.419481	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	44.740000	
50%	0.000000	0.000000	0.000000	0.000000	145.140000	
75%	0.000000	0.000000	0.000000	0.000000	372.860000	
max	800.890000	370.130000	394.930000	787.790000	10674.030000	

	total_og_mou_7	total_og_mou_8	total_og_mou_9	loc_ic_t2t_mou_6	\
count	99999.000000	99999.000000	99999.000000	96062.000000	
mean	310.231175	304.119513	289.279198	47.922365	
std	480.031178	478.150031	468.980002	140.258485	
min	0.000000	0.000000	0.000000	0.000000	
25%	43.010000	38.580000	25.510000	2.990000	
50%	141.530000	138.610000	125.460000	15.690000	
75%	378.570000	369.900000	353.480000	46.840000	
max	11365.310000	14043.060000	11517.730000	6626.930000	

	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2t_mou_9	loc_ic_t2m_mou_6 \
count	96140.000000	94621.000000	92254.000000	96062.000000
mean	47.990520	47.211362	46.281794	107.475650
std	145.795055	137.239552	140.130610	171.713903
min	0.000000	0.000000	0.000000	0.000000
25%	3.230000	3.280000	3.290000	17.290000
50%	15.740000	16.030000	15.660000	56.490000
75%	45.810000	46.290000	45.180000	132.387500
max	9324.660000	10696.230000	10598.830000	4693.860000

	loc_ic_t2m_mou_7	loc_ic_t2m_mou_8	loc_ic_t2m_mou_9	loc_ic_t2f_mou_6 \
count	96140.000000	94621.000000	92254.000000	96062.000000
mean	107.120493	108.460515	106.155471	12.084305
std	169.423620	169.723759	165.492803	40.140895
min	0.000000	0.000000	0.000000	0.000000
25%	18.590000	18.930000	18.560000	0.000000
50%	57.080000	58.240000	56.610000	0.880000
75%	130.960000	133.930000	130.490000	8.140000
max	4455.830000	6274.190000	5463.780000	1872.340000

	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	loc_ic_t2f_mou_9	loc_ic_mou_6 \
count	96140.000000	94621.000000	92254.000000	96062.000000
mean	12.599697	11.751834	12.173105	167.491059
std	42.977442	39.125379	43.840776	254.124029
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	30.390000
50%	0.930000	0.930000	0.960000	92.160000
75%	8.282500	8.110000	8.140000	208.075000
max	1983.010000	2433.060000	4318.280000	7454.630000

	loc_ic_mou_7	loc_ic_mou_8	loc_ic_mou_9	std_ic_t2t_mou_6 \
count	96140.000000	94621.000000	92254.000000	96062.000000
mean	167.719540	167.432575	164.619293	9.575993
std	256.242707	250.025523	249.845070	54.330607
min	0.000000	0.000000	0.000000	0.000000
25%	32.460000	32.740000	32.290000	0.000000
50%	92.550000	93.830000	91.640000	0.000000
75%	205.837500	207.280000	202.737500	4.060000
max	9669.910000	10830.160000	10796.290000	5459.560000

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2t_mou_9	std_ic_t2m_mou_6 \
count	96140.000000	94621.000000	92254.000000	96062.000000
mean	10.011904	9.883921	9.432479	20.722240
std	57.411971	55.073186	53.376273	80.793414
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	2.030000

75%	4.230000	4.080000	3.510000	15.030000
max	5800.930000	4309.290000	3819.830000	5647.160000

	std_ic_t2m_mou_7	std_ic_t2m_mou_8	std_ic_t2m_mou_9	std_ic_t2f_mou_6 \
count	96140.000000	94621.000000	92254.000000	96062.000000
mean	21.656415	21.183211	19.620913	2.156397
std	86.521393	83.683565	74.913050	16.495594
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	2.040000	2.030000	1.740000	0.000000
75%	15.740000	15.360000	14.260000	0.000000
max	6141.880000	5645.860000	5689.760000	1351.110000

	std_ic_t2f_mou_7	std_ic_t2f_mou_8	std_ic_t2f_mou_9	std_ic_t2o_mou_6 \
count	96140.000000	94621.000000	92254.000000	96062.0
mean	2.216923	2.085004	2.173419	0.0
std	16.454061	15.812580	15.978601	0.0
min	0.000000	0.000000	0.000000	0.0
25%	0.000000	0.000000	0.000000	0.0
50%	0.000000	0.000000	0.000000	0.0
75%	0.000000	0.000000	0.000000	0.0
max	1136.080000	1394.890000	1431.960000	0.0

	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_t2o_mou_9	std_ic_mou_6 \
count	96140.0	94621.0	92254.0	96062.000000
mean	0.0	0.0	0.0	32.457179
std	0.0	0.0	0.0	106.283386
min	0.0	0.0	0.0	0.000000
25%	0.0	0.0	0.0	0.000000
50%	0.0	0.0	0.0	5.890000
75%	0.0	0.0	0.0	26.930000
max	0.0	0.0	0.0	5712.110000

	std_ic_mou_7	std_ic_mou_8	std_ic_mou_9	total_ic_mou_6 \
count	96140.000000	94621.000000	92254.000000	99999.000000
mean	33.887833	33.154735	31.229344	200.130037
std	113.720168	110.127008	101.982303	291.651671
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.010000	0.000000	38.530000
50%	5.960000	5.880000	5.380000	114.740000
75%	28.310000	27.710000	25.690000	251.670000
max	6745.760000	5957.140000	5956.660000	7716.140000

	total_ic_mou_7	total_ic_mou_8	total_ic_mou_9	spl_ic_mou_6 \
count	99999.000000	99999.000000	99999.000000	96062.000000
mean	202.853055	198.750783	189.214260	0.061557
std	298.124954	289.321094	284.823024	0.160920

min	0.000000	0.000000	0.000000	0.000000
25%	41.190000	38.290000	32.370000	0.000000
50%	116.340000	114.660000	105.890000	0.000000
75%	250.660000	248.990000	236.320000	0.000000
max	9699.010000	10830.380000	10796.590000	19.760000

	spl_ic_mou_7	spl_ic_mou_8	spl_ic_mou_9	isd_ic_mou_6	isd_ic_mou_7 \
count	96140.000000	94621.000000	92254.000000	96062.000000	96140.000000
mean	0.033585	0.040361	0.163137	7.460608	8.334936
std	0.155725	0.146147	0.527860	59.722948	65.219829
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.060000	0.000000	0.000000
max	21.330000	16.860000	62.380000	6789.410000	5289.540000

	isd_ic_mou_8	isd_ic_mou_9	ic_others_6	ic_others_7	ic_others_8 \
count	94621.000000	92254.000000	96062.000000	96140.000000	94621.000000
mean	8.442001	8.063003	0.854656	1.012960	0.970800
std	63.813098	63.505379	11.955164	12.673099	13.284348
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	4127.010000	5057.740000	1362.940000	1495.940000	2327.510000

	ic_others_9	total_rech_num_6	total_rech_num_7	total_rech_num_8 \
count	92254.000000	99999.000000	99999.000000	99999.000000
mean	1.017162	7.558806	7.700367	7.212912
std	12.381172	7.078405	7.070422	7.203753
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	3.000000	3.000000	3.000000
50%	0.000000	6.000000	6.000000	5.000000
75%	0.000000	9.000000	10.000000	9.000000
max	1005.230000	307.000000	138.000000	196.000000

	total_rech_num_9	total_rech_amt_6	total_rech_amt_7	total_rech_amt_8 \
count	99999.000000	99999.000000	99999.000000	99999.000000
mean	6.893019	327.514615	322.962970	324.157122
std	7.096261	398.019701	408.114237	416.540455
min	0.000000	0.000000	0.000000	0.000000
25%	3.000000	109.000000	100.000000	90.000000
50%	5.000000	230.000000	220.000000	225.000000
75%	9.000000	437.500000	428.000000	434.500000
max	131.000000	35190.000000	40335.000000	45320.000000

total_rech_amt_9	max_rech_amt_6	max_rech_amt_7	max_rech_amt_8 \
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count	99999.000000	99999.000000	99999.000000	99999.000000
mean	303.345673	104.637486	104.752398	107.728207
std	404.588583	120.614894	124.523970	126.902505
min	0.000000	0.000000	0.000000	0.000000
25%	52.000000	30.000000	30.000000	30.000000
50%	200.000000	110.000000	110.000000	98.000000
75%	415.000000	120.000000	128.000000	144.000000
max	37235.000000	4010.000000	4010.000000	4449.000000

	max_rech_amt_9	last_day_rch_amt_6	last_day_rch_amt_7	\
count	99999.000000	99999.000000	99999.000000	
mean	101.943889	63.156252	59.385804	
std	125.375109	97.356649	95.915385	
min	0.000000	0.000000	0.000000	
25%	28.000000	0.000000	0.000000	
50%	61.000000	30.000000	30.000000	
75%	144.000000	110.000000	110.000000	
max	3399.000000	4010.000000	4010.000000	

	last_day_rch_amt_8	last_day_rch_amt_9	total_rech_data_6	\
count	99999.000000	99999.000000	25153.000000	
mean	62.641716	43.901249	2.463802	
std	104.431816	90.809712	2.789128	
min	0.000000	0.000000	1.000000	
25%	0.000000	0.000000	1.000000	
50%	30.000000	0.000000	1.000000	
75%	130.000000	50.000000	3.000000	
max	4449.000000	3399.000000	61.000000	

	total_rech_data_7	total_rech_data_8	total_rech_data_9	\
count	25571.000000	26339.000000	25922.000000	
mean	2.666419	2.651999	2.441170	
std	3.031593	3.074987	2.516339	
min	1.000000	1.000000	1.000000	
25%	1.000000	1.000000	1.000000	
50%	1.000000	1.000000	2.000000	
75%	3.000000	3.000000	3.000000	
max	54.000000	60.000000	84.000000	

	max_rech_data_6	max_rech_data_7	max_rech_data_8	max_rech_data_9	\
count	25153.000000	25571.000000	26339.000000	25922.000000	
mean	126.393392	126.729459	125.717301	124.94144	
std	108.477235	109.765267	109.437851	111.36376	
min	1.000000	1.000000	1.000000	1.000000	
25%	25.000000	25.000000	25.000000	25.000000	
50%	145.000000	145.000000	145.000000	145.000000	
75%	177.000000	177.000000	179.000000	179.000000	

max	1555.000000	1555.000000	1555.000000	1555.000000
	count_rech_2g_6	count_rech_2g_7	count_rech_2g_8	count_rech_2g_9 \
count	25153.000000	25571.000000	26339.000000	25922.000000
mean	1.864668	2.044699	2.016288	1.781807
std	2.570254	2.768332	2.720132	2.214701
min	0.000000	0.000000	0.000000	0.000000
25%	1.000000	1.000000	1.000000	1.000000
50%	1.000000	1.000000	1.000000	1.000000
75%	2.000000	2.000000	2.000000	2.000000
max	42.000000	48.000000	44.000000	40.000000

	count_rech_3g_6	count_rech_3g_7	count_rech_3g_8	count_rech_3g_9 \
count	25153.000000	25571.000000	26339.000000	25922.000000
mean	0.599133	0.621720	0.635711	0.659363
std	1.274428	1.394524	1.422827	1.411513
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	1.000000	1.000000	1.000000	1.000000
max	29.000000	35.000000	45.000000	49.000000

	av_rech_amt_data_6	av_rech_amt_data_7	av_rech_amt_data_8 \
count	25153.000000	25571.000000	26339.000000
mean	192.600982	200.981292	197.526489
std	192.646318	196.791224	191.301305
min	1.000000	0.500000	0.500000
25%	82.000000	92.000000	87.000000
50%	154.000000	154.000000	154.000000
75%	252.000000	252.000000	252.000000
max	7546.000000	4365.000000	4076.000000

	av_rech_amt_data_9	vol_2g_mb_6	vol_2g_mb_7	vol_2g_mb_8 \
count	25922.000000	99999.000000	99999.000000	99999.000000
mean	192.734315	51.904956	51.229937	50.170154
std	188.400286	213.356445	212.302217	212.347892
min	1.000000	0.000000	0.000000	0.000000
25%	69.000000	0.000000	0.000000	0.000000
50%	164.000000	0.000000	0.000000	0.000000
75%	252.000000	0.000000	0.000000	0.000000
max	4061.000000	10285.900000	7873.550000	11117.610000

	vol_2g_mb_9	vol_3g_mb_6	vol_3g_mb_7	vol_3g_mb_8	vol_3g_mb_9 \
count	99999.000000	99999.000000	99999.000000	99999.000000	99999.000000
mean	44.719701	121.396219	128.995847	135.410689	136.056613
std	198.653570	544.247227	541.494013	558.775335	577.394194
min	0.000000	0.000000	0.000000	0.000000	0.000000

25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	8993.950000	45735.400000	28144.120000	30036.060000	39221.270000

	arpu_3g_6	arpu_3g_7	arpu_3g_8	arpu_3g_9	arpu_2g_6 \
count	25153.000000	25571.000000	26339.000000	25922.000000	25153.000000
mean	89.555057	89.384120	91.173849	100.264116	86.398003
std	193.124653	195.893924	188.180936	216.291992	172.767523
min	-30.820000	-26.040000	-24.490000	-71.090000	-35.830000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.480000	0.420000	0.880000	2.605000	10.830000
75%	122.070000	119.560000	122.070000	140.010000	122.070000
max	6362.280000	4980.900000	3716.900000	13884.310000	6433.760000

	arpu_2g_7	arpu_2g_8	arpu_2g_9	night_pck_user_6 \
count	25571.000000	26339.000000	25922.000000	25153.000000
mean	85.914450	86.599478	93.712026	0.025086
std	176.379871	168.247852	171.384224	0.156391
min	-15.480000	-55.830000	-45.740000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	8.810000	9.270000	14.800000	0.000000
75%	122.070000	122.070000	140.010000	0.000000
max	4809.360000	3483.170000	3467.170000	1.000000

	night_pck_user_7	night_pck_user_8	night_pck_user_9	monthly_2g_6 \
count	25571.000000	26339.000000	25922.000000	99999.000000
mean	0.023034	0.020844	0.015971	0.079641
std	0.150014	0.142863	0.125366	0.295058
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	4.000000

	monthly_2g_7	monthly_2g_8	monthly_2g_9	sachet_2g_6	sachet_2g_7 \
count	99999.000000	99999.000000	99999.000000	99999.000000	99999.000000
mean	0.083221	0.081001	0.068781	0.389384	0.439634
std	0.304395	0.299568	0.278120	1.497320	1.636230
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	5.000000	5.000000	4.000000	42.000000	48.000000

	sachet_2g_8	sachet_2g_9	monthly_3g_6	monthly_3g_7	monthly_3g_8 \
count	99999.000000	99999.000000	99999.000000	99999.000000	99999.000000

mean	0.450075	0.393104	0.075921	0.078581	0.082941
std	1.630263	1.347140	0.363371	0.387231	0.384947
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	44.000000	40.000000	14.000000	16.000000	16.000000

	monthly_3g_9	sachet_3g_6	sachet_3g_7	sachet_3g_8	sachet_3g_9 \
count	99999.000000	99999.000000	99999.000000	99999.000000	99999.000000
mean	0.086341	0.074781	0.080401	0.084501	0.084581
std	0.384978	0.568344	0.628334	0.660234	0.650457
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	11.000000	29.000000	35.000000	41.000000	49.000000

	fb_user_6	fb_user_7	fb_user_8	fb_user_9	aon \
count	25153.000000	25571.000000	26339.000000	25922.000000	99999.000000
mean	0.914404	0.908764	0.890808	0.860968	1219.854749
std	0.279772	0.287950	0.311885	0.345987	954.733842
min	0.000000	0.000000	0.000000	0.000000	180.000000
25%	1.000000	1.000000	1.000000	1.000000	467.000000
50%	1.000000	1.000000	1.000000	1.000000	863.000000
75%	1.000000	1.000000	1.000000	1.000000	1807.500000
max	1.000000	1.000000	1.000000	1.000000	4337.000000

	aug_vbc_3g	jul_vbc_3g	jun_vbc_3g	sep_vbc_3g
count	99999.000000	99999.000000	99999.000000	99999.000000
mean	68.170248	66.839062	60.021204	3.299373
std	267.580450	271.201856	253.938223	32.408353
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	12916.220000	9165.600000	11166.210000	2618.570000

## 1.1 Handling missing values

### Handling missing values in columns

```
[8]: # Cheking percent of missing values in columns
df_missing_columns = (round(((df.isnull().sum()/len(df.index))*100),2).
    .to_frame('null')).sort_values('null', ascending=False)
df_missing_columns
```

```

[8]:                                     null
arpu_3g_6                             74.85
night_pck_user_6                       74.85
total_rech_data_6                      74.85
arpu_2g_6                              74.85
max_rech_data_6                        74.85
fb_user_6                             74.85
av_rech_amt_data_6                     74.85
date_of_last_rech_data_6               74.85
count_rech_2g_6                        74.85
count_rech_3g_6                        74.85
date_of_last_rech_data_7               74.43
total_rech_data_7                      74.43
fb_user_7                             74.43
max_rech_data_7                        74.43
night_pck_user_7                       74.43
count_rech_2g_7                        74.43
av_rech_amt_data_7                     74.43
arpu_2g_7                              74.43
count_rech_3g_7                        74.43
arpu_3g_7                              74.43
total_rech_data_9                      74.08
count_rech_3g_9                        74.08
fb_user_9                             74.08
max_rech_data_9                        74.08
arpu_3g_9                              74.08
date_of_last_rech_data_9               74.08
night_pck_user_9                       74.08
arpu_2g_9                              74.08
count_rech_2g_9                        74.08
av_rech_amt_data_9                     74.08
...                                     ...
circle_id                             0.00
total_og_mou_8                         0.00
vol_3g_mb_7                           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
arpu_6                                0.00
last_date_of_month_6                   0.00
total_rech_num_8                       0.00
total_rech_num_9                       0.00
total_rech_amt_6                       0.00
total_rech_amt_7                       0.00
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_9   0.00
last_day_rch_amt_8   0.00
last_day_rch_amt_7   0.00
last_day_rch_amt_6   0.00
max_rech_amt_9       0.00
max_rech_amt_8       0.00
max_rech_amt_7       0.00
max_rech_amt_6       0.00
total_rech_amt_9     0.00
total_rech_amt_8     0.00
sep_vbc_3g           0.00

```

[226 rows x 1 columns]

```

[9]: # List the columns having more than 30% missing values
col_list_missing_30 = list(df_missing_columns.index[df_missing_columns['null']_
↪ > 30])

```

```

[10]: # Delete the columns having more than 30% missing values
df = df.drop(col_list_missing_30, axis=1)

```

```

[11]: df.shape

```

```

[11]: (99999, 186)

```

**Deleting the date columns as the date columns are not required in our analysis**

```

[12]: # List the date columns
date_cols = [k for k in df.columns.to_list() if 'date' in k]
print(date_cols)

```

```

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

```

```

[13]: # Dropping date columns
df = df.drop(date_cols, axis=1)

```

Dropping circle\_id column as this column has only one unique value. Hence there will be no impact of this column on the data analysis.

```

[14]: # Drop circle_id column
df = df.drop('circle_id', axis=1)

```

```
[15]: df.shape
```

```
[15]: (99999, 177)
```

### 1.1.1 Filter high-value customers

Creating column `avg_rech_amt_6_7` by summing up total recharge amount of month 6 and 7. Then taking the average of the sum.

```
[16]: df['avg_rech_amt_6_7'] = (df['total_rech_amt_6'] + df['total_rech_amt_7'])/2
```

Finding the 70th percentile of the `avg_rech_amt_6_7`

```
[17]: X = df['avg_rech_amt_6_7'].quantile(0.7)
X
```

```
[17]: 368.5
```

Filter the customers, who have recharged more than or equal to X.

```
[18]: df = df[df['avg_rech_amt_6_7'] >= X]
df.head()
```

```
[18]:
```

	mobile_number	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	arpu_6	\
7	7000701601	0.0	0.0	0.0	1069.180	
8	7001524846	0.0	0.0	0.0	378.721	
13	7002191713	0.0	0.0	0.0	492.846	
16	7000875565	0.0	0.0	0.0	430.975	
17	7000187447	0.0	0.0	0.0	690.008	

	arpu_7	arpu_8	arpu_9	onnet_mou_6	onnet_mou_7	onnet_mou_8	\
7	1349.850	3171.480	500.000	57.84	54.68	52.29	
8	492.223	137.362	166.787	413.69	351.03	35.08	
13	205.671	593.260	322.732	501.76	108.39	534.24	
16	299.869	187.894	206.490	50.51	74.01	70.61	
17	18.980	25.499	257.583	1185.91	9.28	7.79	

	onnet_mou_9	offnet_mou_6	offnet_mou_7	offnet_mou_8	offnet_mou_9	\
7	NaN	453.43	567.16	325.91	NaN	
8	33.46	94.66	80.63	136.48	108.71	
13	244.81	413.31	119.28	482.46	214.06	
16	31.34	296.29	229.74	162.76	224.39	
17	558.51	61.64	0.00	5.54	87.89	

	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_ic_mou_9	roam_og_mou_6	\
7	16.23	33.49	31.64	NaN	23.74	
8	0.00	0.00	0.00	0.00	0.00	
13	23.53	144.24	72.11	136.78	7.98	

16	0.00	2.83	0.00	0.00	0.00
17	0.00	4.76	4.81	0.00	0.00

	roam_og_mou_7	roam_og_mou_8	roam_og_mou_9	loc_og_t2t_mou_6	\
7	12.59	38.06	NaN	51.39	
8	0.00	0.00	0.00	297.13	
13	35.26	1.44	12.78	49.63	
16	17.74	0.00	0.00	42.61	
17	8.46	13.34	17.98	38.99	

	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2t_mou_9	loc_og_t2m_mou_6	\
7	31.38	40.28	NaN	308.63	
8	217.59	12.49	26.13	80.96	
13	6.19	36.01	6.14	151.13	
16	65.16	67.38	26.88	273.29	
17	0.00	0.00	36.41	58.54	

	loc_og_t2m_mou_7	loc_og_t2m_mou_8	loc_og_t2m_mou_9	loc_og_t2f_mou_6	\
7	447.38	162.28	NaN	62.13	
8	70.58	50.54	34.58	0.00	
13	47.28	294.46	108.24	4.54	
16	145.99	128.28	201.49	0.00	
17	0.00	0.00	9.38	0.00	

	loc_og_t2f_mou_7	loc_og_t2f_mou_8	loc_og_t2f_mou_9	loc_og_t2c_mou_6	\
7	55.14	53.23	NaN	0.0	
8	0.00	0.00	0.00	0.0	
13	0.00	23.51	5.29	0.0	
16	4.48	10.26	4.66	0.0	
17	0.00	0.00	0.00	0.0	

	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_t2c_mou_9	loc_og_mou_6	\
7	0.0	0.00	NaN	422.16	
8	0.0	7.15	0.0	378.09	
13	0.0	0.49	0.0	205.31	
16	0.0	0.00	0.0	315.91	
17	0.0	0.00	0.0	97.54	

	loc_og_mou_7	loc_og_mou_8	loc_og_mou_9	std_og_t2t_mou_6	\
7	533.91	255.79	NaN	4.30	
8	288.18	63.04	60.71	116.56	
13	53.48	353.99	119.69	446.41	
16	215.64	205.93	233.04	7.89	
17	0.00	0.00	45.79	1146.91	

	std_og_t2t_mou_7	std_og_t2t_mou_8	std_og_t2t_mou_9	std_og_t2m_mou_6	\
7	23.29	12.01	NaN	49.89	



8	133.43	22.58	7.33	13.69
13	85.98	498.23	230.38	255.36
16	2.58	3.23	4.46	22.99
17	0.81	0.00	504.11	1.55

	std_og_t2m_mou_7	std_og_t2m_mou_8	std_og_t2m_mou_9	std_og_t2f_mou_6	\
7	31.76	49.14	NaN	6.66	
8	10.04	75.69	74.13	0.00	
13	52.94	156.94	96.01	0.00	
16	64.51	18.29	13.79	0.00	
17	0.00	0.00	78.51	0.00	

	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2f_mou_9	std_og_t2c_mou_6	\
7	20.08	16.68	NaN	0.0	
8	0.00	0.00	0.00	0.0	
13	0.00	0.00	0.00	0.0	
16	0.00	0.00	4.43	0.0	
17	0.00	0.00	0.00	0.0	

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_t2c_mou_9	std_og_mou_6	\
7	0.0	0.0	NaN	60.86	
8	0.0	0.0	0.0	130.26	
13	0.0	0.0	0.0	701.78	
16	0.0	0.0	0.0	30.89	
17	0.0	0.0	0.0	1148.46	

	std_og_mou_7	std_og_mou_8	std_og_mou_9	isd_og_mou_6	isd_og_mou_7	\
7	75.14	77.84	NaN	0.0	0.18	
8	143.48	98.28	81.46	0.0	0.00	
13	138.93	655.18	326.39	0.0	0.00	
16	67.09	21.53	22.69	0.0	0.00	
17	0.81	0.00	582.63	0.0	0.00	

	isd_og_mou_8	isd_og_mou_9	spl_og_mou_6	spl_og_mou_7	spl_og_mou_8	\
7	10.01	NaN	4.50	0.00	6.50	
8	0.00	0.0	0.00	0.00	10.23	
13	1.29	0.0	0.00	0.00	4.78	
16	0.00	0.0	0.00	3.26	5.91	
17	0.00	0.0	2.58	0.00	0.00	

	spl_og_mou_9	og_others_6	og_others_7	og_others_8	og_others_9	\
7	NaN	0.00	0.0	0.0	NaN	
8	0.00	0.00	0.0	0.0	0.0	
13	0.00	0.00	0.0	0.0	0.0	
16	0.00	0.00	0.0	0.0	0.0	
17	2.64	0.93	0.0	0.0	0.0	

	total_og_mou_6	total_og_mou_7	total_og_mou_8	total_og_mou_9	\
7	487.53	609.24	350.16	0.00	
8	508.36	431.66	171.56	142.18	
13	907.09	192.41	1015.26	446.09	
16	346.81	286.01	233.38	255.74	
17	1249.53	0.81	0.00	631.08	

	loc_ic_t2t_mou_6	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2t_mou_9	\
7	58.14	32.26	27.31	NaN	
8	23.84	9.84	0.31	4.03	
13	67.88	7.58	52.58	24.98	
16	41.33	71.44	28.89	50.23	
17	34.54	0.00	0.00	40.91	

	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	loc_ic_t2m_mou_8	loc_ic_t2m_mou_9	\
7	217.56	221.49	121.19	NaN	
8	57.58	13.98	15.48	17.34	
13	142.88	18.53	195.18	104.79	
16	226.81	149.69	150.16	172.86	
17	47.41	2.31	0.00	43.86	

	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	loc_ic_t2f_mou_9	\
7	152.16	101.46	39.53	NaN	
8	0.00	0.00	0.00	0.00	
13	4.81	0.00	7.49	8.51	
16	8.71	8.68	32.71	65.21	
17	0.00	0.00	0.00	0.71	

	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	loc_ic_mou_9	std_ic_t2t_mou_6	\
7	427.88	355.23	188.04	NaN	36.89	
8	81.43	23.83	15.79	21.38	0.00	
13	215.58	26.11	255.26	138.29	115.68	
16	276.86	229.83	211.78	288.31	68.79	
17	81.96	2.31	0.00	85.49	8.63	

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2t_mou_9	std_ic_t2m_mou_6	\
7	11.83	30.39	NaN	91.44	
8	0.58	0.10	0.00	22.43	
13	38.29	154.58	62.39	308.13	
16	78.64	6.33	16.66	18.68	
17	0.00	0.00	0.00	1.28	

	std_ic_t2m_mou_7	std_ic_t2m_mou_8	std_ic_t2m_mou_9	std_ic_t2f_mou_6	\
7	126.99	141.33	NaN	52.19	
8	4.08	0.65	13.53	0.00	
13	29.79	317.91	151.51	0.00	
16	73.08	73.93	29.58	0.51	

17	0.00	0.00	1.63	0.00
----	------	------	------	------

	std_ic_t2f_mou_7	std_ic_t2f_mou_8	std_ic_t2f_mou_9	std_ic_t2o_mou_6	\
7	34.24	22.21	NaN	0.0	
8	0.00	0.00	0.0	0.0	
13	0.00	1.91	0.0	0.0	
16	0.00	2.18	0.0	0.0	
17	0.00	0.00	0.0	0.0	

	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_t2o_mou_9	std_ic_mou_6	\
7	0.0	0.0	NaN	180.54	
8	0.0	0.0	0.0	22.43	
13	0.0	0.0	0.0	423.81	
16	0.0	0.0	0.0	87.99	
17	0.0	0.0	0.0	9.91	

	std_ic_mou_7	std_ic_mou_8	std_ic_mou_9	total_ic_mou_6	total_ic_mou_7	\
7	173.08	193.94	NaN	626.46	558.04	
8	4.66	0.75	13.53	103.86	28.49	
13	68.09	474.41	213.91	968.61	172.58	
16	151.73	82.44	46.24	364.86	381.56	
17	0.00	0.00	1.63	91.88	2.31	

	total_ic_mou_8	total_ic_mou_9	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	\
7	428.74	0.00	0.21	0.0	0.0	
8	16.54	34.91	0.00	0.0	0.0	
13	1144.53	631.86	0.45	0.0	0.0	
16	294.46	334.56	0.00	0.0	0.0	
17	0.00	87.13	0.00	0.0	0.0	

	spl_ic_mou_9	isd_ic_mou_6	isd_ic_mou_7	isd_ic_mou_8	isd_ic_mou_9	\
7	NaN	2.06	14.53	31.59	NaN	
8	0.0	0.00	0.00	0.00	0.00	
13	0.0	245.28	62.11	393.39	259.33	
16	0.0	0.00	0.00	0.23	0.00	
17	0.0	0.00	0.00	0.00	0.00	

	ic_others_6	ic_others_7	ic_others_8	ic_others_9	total_rech_num_6	\
7	15.74	15.19	15.14	NaN	5	
8	0.00	0.00	0.00	0.00	19	
13	83.48	16.24	21.44	20.31	6	
16	0.00	0.00	0.00	0.00	10	
17	0.00	0.00	0.00	0.00	19	

	total_rech_num_7	total_rech_num_8	total_rech_num_9	total_rech_amt_6	\
7	5	7	3	1580	
8	21	14	15	437	

13	4	11	7	507
16	6	2	1	570
17	2	4	10	816

	total_rech_amt_7	total_rech_amt_8	total_rech_amt_9	max_rech_amt_6	\
7	790	3638	0	1580	
8	601	120	186	90	
13	253	717	353	110	
16	348	160	220	110	
17	0	30	335	110	

	max_rech_amt_7	max_rech_amt_8	max_rech_amt_9	last_day_rch_amt_6	\
7	790	1580	0	0	
8	154	30	36	50	
13	110	130	130	110	
16	110	130	220	100	
17	0	30	130	30	

	last_day_rch_amt_7	last_day_rch_amt_8	last_day_rch_amt_9	vol_2g_mb_6	\
7	0	779	0	0.0	
8	0	10	0	0.0	
13	50	0	0	0.0	
16	100	130	220	0.0	
17	0	0	0	0.0	

	vol_2g_mb_7	vol_2g_mb_8	vol_2g_mb_9	vol_3g_mb_6	vol_3g_mb_7	\
7	0.0	0.00	0.0	0.0	0.00	
8	356.0	0.03	0.0	0.0	750.95	
13	0.0	0.02	0.0	0.0	0.00	
16	0.0	0.00	0.0	0.0	0.00	
17	0.0	0.00	0.0	0.0	0.00	

	vol_3g_mb_8	vol_3g_mb_9	monthly_2g_6	monthly_2g_7	monthly_2g_8	\
7	0.00	0.0	0	0	0	
8	11.94	0.0	0	1	0	
13	0.00	0.0	0	0	0	
16	0.00	0.0	0	0	0	
17	0.00	0.0	0	0	0	

	monthly_2g_9	sachet_2g_6	sachet_2g_7	sachet_2g_8	sachet_2g_9	\
7	0	0	0	0	0	
8	0	0	1	3	0	
13	0	0	0	3	0	
16	0	0	0	0	0	
17	0	0	0	0	0	

monthly_3g_6	monthly_3g_7	monthly_3g_8	monthly_3g_9	sachet_3g_6	\
--------------	--------------	--------------	--------------	-------------	---

7	0	0	0	0	0
8	0	0	0	0	0
13	0	0	0	0	0
16	0	0	0	0	0
17	0	0	0	0	0

	sachet_3g_7	sachet_3g_8	sachet_3g_9	aon	aug_vbc_3g	jul_vbc_3g	\
7	0	0	0	802	57.74	19.38	
8	0	0	0	315	21.03	910.65	
13	0	0	0	2607	0.00	0.00	
16	0	0	0	511	0.00	2.45	
17	0	0	0	667	0.00	0.00	

	jun_vbc_3g	sep_vbc_3g	avg_rech_amt_6_7
7	18.74	0.0	1185.0
8	122.16	0.0	519.0
13	0.00	0.0	380.0
16	21.89	0.0	459.0
17	0.00	0.0	408.0

```
[19]: df.shape
```

```
[19]: (30011, 178)
```

We can see that we have around **~30K** rows after filtering

### Handling missing values in rows

```
[20]: # Count the rows having more than 50% missing values
df_missing_rows_50 = df[(df.isnull().sum(axis=1)) > (len(df.columns)//2)]
df_missing_rows_50.shape
```

```
[20]: (114, 178)
```

```
[21]: # Deleting the rows having more than 50% missing values
df = df.drop(df_missing_rows_50.index)
df.shape
```

```
[21]: (29897, 178)
```

```
[22]: # Checking the missing values in columns again
df_missing_columns = (round(((df.isnull().sum()/len(df.index))*100),2).
    ↳to_frame('null')).sort_values('null', ascending=False)
df_missing_columns
```

```
[22]:
loc_ic_mou_9      null
og_others_9      5.32
og_others_9      5.32
```

loc_og_t2t_mou_9	5.32
loc_ic_t2t_mou_9	5.32
loc_og_t2m_mou_9	5.32
loc_og_t2f_mou_9	5.32
loc_og_t2c_mou_9	5.32
std_ic_t2m_mou_9	5.32
loc_og_mou_9	5.32
std_og_t2t_mou_9	5.32
roam_og_mou_9	5.32
std_ic_t2o_mou_9	5.32
std_og_t2m_mou_9	5.32
std_og_t2f_mou_9	5.32
spl_og_mou_9	5.32
std_og_t2c_mou_9	5.32
std_og_mou_9	5.32
isd_og_mou_9	5.32
std_ic_t2t_mou_9	5.32
std_ic_mou_9	5.32
onnet_mou_9	5.32
spl_ic_mou_9	5.32
ic_others_9	5.32
isd_ic_mou_9	5.32
loc_ic_t2f_mou_9	5.32
offnet_mou_9	5.32
loc_ic_t2m_mou_9	5.32
std_ic_t2f_mou_9	5.32
roam_ic_mou_9	5.32
loc_og_t2t_mou_8	2.76
...	...
total_ic_mou_8	0.00
std_og_t2o_mou	0.00
loc_ic_t2o_mou	0.00
arpu_6	0.00
arpu_7	0.00
arpu_8	0.00
arpu_9	0.00
total_og_mou_6	0.00
total_og_mou_7	0.00
total_og_mou_8	0.00
total_og_mou_9	0.00
loc_og_t2o_mou	0.00
total_ic_mou_6	0.00
total_ic_mou_7	0.00
total_ic_mou_9	0.00
last_day_rch_amt_7	0.00
total_rech_num_6	0.00
total_rech_num_7	0.00

```
total_rech_num_8    0.00
total_rech_num_9    0.00
total_rech_amt_6    0.00
total_rech_amt_7    0.00
total_rech_amt_8    0.00
total_rech_amt_9    0.00
max_rech_amt_6      0.00
max_rech_amt_7      0.00
max_rech_amt_8      0.00
max_rech_amt_9      0.00
last_day_rch_amt_6  0.00
avg_rech_amt_6_7    0.00
```

```
[178 rows x 1 columns]
```

Looks like MOU for all the types of calls for the month of September (9) have missing values together for any particular record.

Lets check the records for the MOU for Sep(9), in which these coulums have missing values together.

```
[23]: # Listing the columns of MOU Sep(9)
print(((df_missing_columns[df_missing_columns['null'] == 5.32]).index).
      ↪to_list())
```

```
['loc_ic_mou_9', 'og_others_9', 'loc_og_t2t_mou_9', 'loc_ic_t2t_mou_9',
'loc_og_t2m_mou_9', 'loc_og_t2f_mou_9', 'loc_og_t2c_mou_9', 'std_ic_t2m_mou_9',
'loc_og_mou_9', 'std_og_t2t_mou_9', 'roam_og_mou_9', 'std_ic_t2o_mou_9',
'std_og_t2m_mou_9', 'std_og_t2f_mou_9', 'spl_og_mou_9', 'std_og_t2c_mou_9',
'std_og_mou_9', 'isd_og_mou_9', 'std_ic_t2t_mou_9', 'std_ic_mou_9',
'onnet_mou_9', 'spl_ic_mou_9', 'ic_others_9', 'isd_ic_mou_9',
'loc_ic_t2f_mou_9', 'offnet_mou_9', 'loc_ic_t2m_mou_9', 'std_ic_t2f_mou_9',
'roam_ic_mou_9']
```

```
[24]: # Creating a dataframe with the condition, in which MOU for Sep(9) are null
df_null_mou_9 = df[(df['loc_og_t2m_mou_9'].isnull()) & (df['loc_ic_t2f_mou_9'].
      ↪isnull()) & (df['roam_og_mou_9'].isnull()) & (df['std_ic_t2m_mou_9'].
      ↪isnull()) &
      (df['loc_og_t2t_mou_9'].isnull()) & (df['std_ic_t2t_mou_9'].isnull()) &
      ↪(df['loc_og_t2f_mou_9'].isnull()) & (df['loc_ic_mou_9'].isnull()) &
      (df['loc_og_t2c_mou_9'].isnull()) & (df['loc_og_mou_9'].isnull()) &
      ↪(df['std_og_t2t_mou_9'].isnull()) & (df['roam_ic_mou_9'].isnull()) &
      (df['loc_ic_t2m_mou_9'].isnull()) & (df['std_og_t2m_mou_9'].isnull()) &
      ↪(df['loc_ic_t2t_mou_9'].isnull()) & (df['std_og_t2f_mou_9'].isnull()) &
      (df['std_og_t2c_mou_9'].isnull()) & (df['og_others_9'].isnull()) &
      ↪(df['std_og_mou_9'].isnull()) & (df['spl_og_mou_9'].isnull()) &
      (df['std_ic_t2f_mou_9'].isnull()) & (df['isd_og_mou_9'].isnull()) &
      ↪(df['std_ic_mou_9'].isnull()) & (df['offnet_mou_9'].isnull()) &
```

```
(df['isd_ic_mou_9'].isnull()) & (df['ic_others_9'].isnull()) &
↳ (df['std_ic_t2o_mou_9'].isnull()) & (df['onnet_mou_9'].isnull()) &
(df['spl_ic_mou_9'].isnull())

df_null_mou_9.head()
```

```
[24]:
```

	mobile_number	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	arpu_6	\
7	7000701601	0.0	0.0	0.0	1069.180	
97	7000589828	0.0	0.0	0.0	374.863	
111	7001300706	0.0	0.0	0.0	596.301	
143	7000106299	0.0	0.0	0.0	695.609	
188	7000340381	0.0	0.0	0.0	734.641	

	arpu_7	arpu_8	arpu_9	onnet_mou_6	onnet_mou_7	onnet_mou_8	\
7	1349.850	3171.480	500.0	57.84	54.68	52.29	
97	294.023	183.043	0.0	433.59	415.66	221.06	
111	146.073	0.000	0.0	55.19	3.26	NaN	
143	39.981	0.000	0.0	1325.91	28.61	NaN	
188	183.668	0.000	0.0	4.38	0.98	NaN	

	onnet_mou_9	offnet_mou_6	offnet_mou_7	offnet_mou_8	offnet_mou_9	\
7	NaN	453.43	567.16	325.91	NaN	
97	NaN	74.54	43.66	31.86	NaN	
111	NaN	45.51	12.34	NaN	NaN	
143	NaN	13.91	1.89	NaN	NaN	
188	NaN	105.16	39.39	NaN	NaN	

	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_ic_mou_9	\
7	16.23	33.49	31.64	NaN	
97	0.00	0.00	6.16	NaN	
111	0.00	0.00	NaN	NaN	
143	0.00	8.94	NaN	NaN	
188	0.00	0.00	NaN	NaN	

	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	roam_og_mou_9	\
7	23.74	12.59	38.06	NaN	
97	0.00	0.00	23.91	NaN	
111	0.00	0.00	NaN	NaN	
143	0.00	8.53	NaN	NaN	
188	0.00	0.00	NaN	NaN	

	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2t_mou_9	\
7	51.39	31.38	40.28	NaN	
97	2.83	16.19	9.73	NaN	
111	55.19	3.26	NaN	NaN	
143	18.89	6.83	NaN	NaN	
188	4.38	0.98	NaN	NaN	



	loc_og_t2m_mou_6	loc_og_t2m_mou_7	loc_og_t2m_mou_8	loc_og_t2m_mou_9	\
7	308.63	447.38	162.28	NaN	
97	16.99	23.14	17.79	NaN	
111	43.83	12.34	NaN	NaN	
143	8.58	1.56	NaN	NaN	
188	99.81	38.98	NaN	NaN	

	loc_og_t2f_mou_6	loc_og_t2f_mou_7	loc_og_t2f_mou_8	loc_og_t2f_mou_9	\
7	62.13	55.14	53.23	NaN	
97	3.54	1.46	1.83	NaN	
111	0.00	0.00	NaN	NaN	
143	0.00	0.00	NaN	NaN	
188	5.34	0.41	NaN	NaN	

	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_t2c_mou_9	\
7	0.00	0.0	0.0	NaN	
97	0.40	0.0	0.0	NaN	
111	0.00	0.0	NaN	NaN	
143	2.09	0.0	NaN	NaN	
188	0.00	0.0	NaN	NaN	

	loc_og_mou_6	loc_og_mou_7	loc_og_mou_8	loc_og_mou_9	std_og_t2t_mou_6	\
7	422.16	533.91	255.79	NaN	4.30	
97	23.38	40.81	29.36	NaN	430.76	
111	99.03	15.61	NaN	NaN	0.00	
143	27.48	8.39	NaN	NaN	1307.01	
188	109.54	40.38	NaN	NaN	0.00	

	std_og_t2t_mou_7	std_og_t2t_mou_8	std_og_t2t_mou_9	std_og_t2m_mou_6	\
7	23.29	12.01	NaN	49.89	
97	399.46	191.31	NaN	53.59	
111	0.00	NaN	NaN	0.00	
143	13.58	NaN	NaN	1.95	
188	0.00	NaN	NaN	0.00	

	std_og_t2m_mou_7	std_og_t2m_mou_8	std_og_t2m_mou_9	std_og_t2f_mou_6	\
7	31.76	49.14	NaN	6.66	
97	13.81	8.33	NaN	0.00	
111	0.00	NaN	NaN	1.30	
143	0.00	NaN	NaN	0.00	
188	0.00	NaN	NaN	0.00	

	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2f_mou_9	std_og_t2c_mou_6	\
7	20.08	16.68	NaN	0.0	
97	0.00	0.00	NaN	0.0	
111	0.00	NaN	NaN	0.0	

143	0.00	NaN	NaN	0.0
188	0.00	NaN	NaN	0.0

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_t2c_mou_9	std_og_mou_6	\
7	0.0	0.0	NaN	60.86	
97	0.0	0.0	NaN	484.36	
111	0.0	NaN	NaN	1.30	
143	0.0	NaN	NaN	1308.96	
188	0.0	NaN	NaN	0.00	

	std_og_mou_7	std_og_mou_8	std_og_mou_9	isd_og_mou_6	isd_og_mou_7	\
7	75.14	77.84	NaN	0.0	0.18	
97	413.28	199.64	NaN	0.0	0.00	
111	0.00	NaN	NaN	0.0	0.00	
143	13.58	NaN	NaN	0.0	0.00	
188	0.00	NaN	NaN	0.0	0.00	

	isd_og_mou_8	isd_og_mou_9	spl_og_mou_6	spl_og_mou_7	spl_og_mou_8	\
7	10.01	NaN	4.50	0.00	6.50	
97	0.00	NaN	2.54	11.81	2.01	
111	NaN	NaN	0.38	2.71	NaN	
143	NaN	NaN	3.38	0.00	NaN	
188	NaN	NaN	0.00	0.00	NaN	

	spl_og_mou_9	og_others_6	og_others_7	og_others_8	og_others_9	\
7	NaN	0.00	0.0	0.0	NaN	
97	NaN	0.86	0.0	0.0	NaN	
111	NaN	1.29	0.0	NaN	NaN	
143	NaN	1.20	0.0	NaN	NaN	
188	NaN	0.00	0.0	NaN	NaN	

	total_og_mou_6	total_og_mou_7	total_og_mou_8	total_og_mou_9	\
7	487.53	609.24	350.16	0.0	
97	511.16	465.91	231.03	0.0	
111	102.01	18.33	0.00	0.0	
143	1341.03	21.98	0.00	0.0	
188	109.54	40.38	0.00	0.0	

	loc_ic_t2t_mou_6	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2t_mou_9	\
7	58.14	32.26	27.31	NaN	
97	11.61	32.89	4.46	NaN	
111	50.01	16.66	NaN	NaN	
143	30.19	7.06	NaN	NaN	
188	21.18	13.44	NaN	NaN	

	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	loc_ic_t2m_mou_8	loc_ic_t2m_mou_9	\
7	217.56	221.49	121.19	NaN	

97	16.94	26.94	26.63	NaN
111	160.68	58.53	NaN	NaN
143	27.98	1.35	NaN	NaN
188	217.03	56.63	NaN	NaN

	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	loc_ic_t2f_mou_9	\
7	152.16	101.46	39.53	NaN	
97	0.98	0.63	0.00	NaN	
111	5.06	0.40	NaN	NaN	
143	10.13	0.00	NaN	NaN	
188	18.28	2.94	NaN	NaN	

	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	loc_ic_mou_9	std_ic_t2t_mou_6	\
7	427.88	355.23	188.04	NaN	36.89	
97	29.54	60.48	31.09	NaN	0.49	
111	215.76	75.59	NaN	NaN	0.00	
143	68.31	8.41	NaN	NaN	25.56	
188	256.49	73.03	NaN	NaN	0.00	

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2t_mou_9	std_ic_t2m_mou_6	\
7	11.83	30.39	NaN	91.44	
97	1.36	1.06	NaN	0.00	
111	0.00	NaN	NaN	0.00	
143	0.00	NaN	NaN	0.00	
188	0.00	NaN	NaN	0.00	

	std_ic_t2m_mou_7	std_ic_t2m_mou_8	std_ic_t2m_mou_9	std_ic_t2f_mou_6	\
7	126.99	141.33	NaN	52.19	
97	4.16	0.00	NaN	0.00	
111	0.00	NaN	NaN	1.13	
143	0.00	NaN	NaN	0.00	
188	0.00	NaN	NaN	0.00	

	std_ic_t2f_mou_7	std_ic_t2f_mou_8	std_ic_t2f_mou_9	std_ic_t2o_mou_6	\
7	34.24	22.21	NaN	0.0	
97	0.00	0.00	NaN	0.0	
111	0.00	NaN	NaN	0.0	
143	0.00	NaN	NaN	0.0	
188	0.00	NaN	NaN	0.0	

	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_t2o_mou_9	std_ic_mou_6	\
7	0.0	0.0	NaN	180.54	
97	0.0	0.0	NaN	0.49	
111	0.0	NaN	NaN	1.13	
143	0.0	NaN	NaN	25.56	
188	0.0	NaN	NaN	0.00	

	std_ic_mou_7	std_ic_mou_8	std_ic_mou_9	total_ic_mou_6	total_ic_mou_7	\
7	173.08	193.94	NaN	626.46	558.04	
97	5.53	1.06	NaN	32.04	67.84	
111	0.00	NaN	NaN	217.04	75.59	
143	0.00	NaN	NaN	93.88	8.41	
188	0.00	NaN	NaN	256.49	73.03	

	total_ic_mou_8	total_ic_mou_9	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	\
7	428.74	0.0	0.21	0.0	0.0	
97	32.16	0.0	0.63	0.0	0.0	
111	0.00	0.0	0.00	0.0	NaN	
143	0.00	0.0	0.00	0.0	NaN	
188	0.00	0.0	0.00	0.0	NaN	

	spl_ic_mou_9	isd_ic_mou_6	isd_ic_mou_7	isd_ic_mou_8	isd_ic_mou_9	\
7	NaN	2.06	14.53	31.59	NaN	
97	NaN	0.00	0.00	0.00	NaN	
111	NaN	0.00	0.00	NaN	NaN	
143	NaN	0.00	0.00	NaN	NaN	
188	NaN	0.00	0.00	NaN	NaN	

	ic_others_6	ic_others_7	ic_others_8	ic_others_9	total_rech_num_6	\
7	15.74	15.19	15.14	NaN	5	
97	1.36	1.83	0.00	NaN	14	
111	0.15	0.00	NaN	NaN	12	
143	0.00	0.00	NaN	NaN	31	
188	0.00	0.00	NaN	NaN	6	

	total_rech_num_7	total_rech_num_8	total_rech_num_9	total_rech_amt_6	\
7	5	7	3	1580	
97	17	14	3	432	
111	8	5	2	704	
143	6	4	2	796	
188	1	0	0	864	

	total_rech_amt_7	total_rech_amt_8	total_rech_amt_9	max_rech_amt_6	\
7	790	3638	0	1580	
97	328	206	0	36	
111	178	0	0	154	
143	40	0	0	90	
188	120	0	0	252	

	max_rech_amt_7	max_rech_amt_8	max_rech_amt_9	last_day_rch_amt_6	\
7	790	1580	0	0	
97	44	36	0	30	
111	50	0	0	154	
143	30	0	0	10	

188	120	0	0	252
-----	-----	---	---	-----

	last_day_rch_amt_7	last_day_rch_amt_8	last_day_rch_amt_9	vol_2g_mb_6	\
7	0	779	0	0.00	
97	20	0	0	0.00	
111	30	0	0	284.50	
143	0	0	0	0.00	
188	120	0	0	58.44	

	vol_2g_mb_7	vol_2g_mb_8	vol_2g_mb_9	vol_3g_mb_6	vol_3g_mb_7	\
7	0.0	0.0	0.0	0.0	0.0	
97	0.0	0.0	0.0	0.0	0.0	
111	0.0	0.0	0.0	0.0	0.0	
143	0.0	0.0	0.0	0.0	0.0	
188	0.0	0.0	0.0	1522.4	0.0	

	vol_3g_mb_8	vol_3g_mb_9	monthly_2g_6	monthly_2g_7	monthly_2g_8	\
7	0.0	0.0	0	0	0	
97	0.0	0.0	0	0	0	
111	0.0	0.0	1	0	0	
143	0.0	0.0	0	0	0	
188	0.0	0.0	0	0	0	

	monthly_2g_9	sachet_2g_6	sachet_2g_7	sachet_2g_8	sachet_2g_9	\
7	0	0	0	0	0	
97	0	0	0	0	0	
111	0	0	0	0	0	
143	0	0	0	0	0	
188	0	0	0	0	0	

	monthly_3g_6	monthly_3g_7	monthly_3g_8	monthly_3g_9	sachet_3g_6	\
7	0	0	0	0	0	
97	0	0	0	0	0	
111	0	0	0	0	1	
143	0	0	0	0	0	
188	2	0	0	0	0	

	sachet_3g_7	sachet_3g_8	sachet_3g_9	aon	aug_vbc_3g	jul_vbc_3g	\
7	0	0	0	802	57.74	19.38	
97	0	0	0	502	0.00	0.00	
111	0	0	0	332	0.00	0.00	
143	0	0	0	264	0.00	0.00	
188	0	0	0	244	0.00	831.48	

	jun_vbc_3g	sep_vbc_3g	avg_rech_amt_6_7
7	18.74	0.0	1185.0
97	0.00	0.0	380.0

111	0.00	0.0	441.0
143	0.00	0.0	418.0
188	1223.04	0.0	492.0

```
[25]: df_null_mou_9.shape
```

```
[25]: (1590, 178)
```

```
[26]: # Deleting the records for which MDU for Sep(9) are null
df = df.drop(df_null_mou_9.index)
```

```
[27]: # Again Cheking percent of missing values in columns
df_missing_columns = (round(((df.isnull()).sum()/len(df.index))*100),2).
    to_frame('null').sort_values('null', ascending=False)
df_missing_columns
```

```
[27]:
```

	null
isd_og_mou_8	0.55
roam_ic_mou_8	0.55
loc_og_mou_8	0.55
std_ic_t2o_mou_8	0.55
roam_og_mou_8	0.55
loc_ic_t2f_mou_8	0.55
loc_og_t2t_mou_8	0.55
std_ic_t2f_mou_8	0.55
std_og_t2m_mou_8	0.55
loc_og_t2m_mou_8	0.55
std_og_t2t_mou_8	0.55
std_ic_t2m_mou_8	0.55
loc_og_t2f_mou_8	0.55
spl_og_mou_8	0.55
loc_ic_mou_8	0.55
loc_og_t2c_mou_8	0.55
std_ic_t2t_mou_8	0.55
loc_ic_t2m_mou_8	0.55
std_og_t2f_mou_8	0.55
spl_ic_mou_8	0.55
std_ic_mou_8	0.55
offnet_mou_8	0.55
ic_others_8	0.55
og_others_8	0.55
loc_ic_t2t_mou_8	0.55
onnet_mou_8	0.55
isd_ic_mou_8	0.55
std_og_t2c_mou_8	0.55
std_og_mou_8	0.55
isd_og_mou_6	0.50

```

...
arpu_9      0.00
arpu_8      0.00
arpu_7      0.00
arpu_6      0.00
loc_ic_t2o_mou 0.00
std_og_t2o_mou 0.00
std_og_mou_9 0.00
spl_og_mou_9 0.00
isd_ic_mou_9 0.00
og_others_9 0.00
spl_ic_mou_9 0.00
total_ic_mou_9 0.00
total_ic_mou_8 0.00
total_ic_mou_7 0.00
total_ic_mou_6 0.00
std_ic_mou_9 0.00
std_ic_t2o_mou_9 0.00
std_ic_t2f_mou_9 0.00
std_ic_t2m_mou_9 0.00
std_ic_t2t_mou_9 0.00
loc_ic_mou_9 0.00
loc_ic_t2f_mou_9 0.00
loc_og_t2o_mou 0.00
loc_ic_t2m_mou_9 0.00
loc_ic_t2t_mou_9 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
avg_rech_amt_6_7 0.00

```

```
[178 rows x 1 columns]
```

Looks like MOU for all the types of calls for the month of Aug (8) have missing values together for any particular record.

Lets check the records for the MOU for Aug(8), in which these coulums have missing values together.

```
[28]: # Listing the columns of MOU Aug(8)
print(((df_missing_columns[df_missing_columns['null'] == 0.55]).index).
      .to_list())
```

```

['isd_og_mou_8', 'roam_ic_mou_8', 'loc_og_mou_8', 'std_ic_t2o_mou_8',
'roam_og_mou_8', 'loc_ic_t2f_mou_8', 'loc_og_t2t_mou_8', 'std_ic_t2f_mou_8',
'std_og_t2m_mou_8', 'loc_og_t2m_mou_8', 'std_og_t2t_mou_8', 'std_ic_t2m_mou_8',
'loc_og_t2f_mou_8', 'spl_og_mou_8', 'loc_ic_mou_8', 'loc_og_t2c_mou_8',
'std_ic_t2t_mou_8', 'loc_ic_t2m_mou_8', 'std_og_t2f_mou_8', 'spl_ic_mou_8',

```

```
'std_ic_mou_8', 'offnet_mou_8', 'ic_others_8', 'og_others_8',
'loc_ic_t2t_mou_8', 'onnet_mou_8', 'isd_ic_mou_8', 'std_og_t2c_mou_8',
'std_og_mou_8']
```

```
[29]: # Creating a dataframe with the condition, in which MOU for Aug(8) are null
df_null_mou_8 = df[(df['loc_og_t2m_mou_8'].isnull()) & (df['loc_ic_t2f_mou_8'].
↳ isnull()) & (df['roam_og_mou_8'].isnull()) & (df['std_ic_t2m_mou_8'].
↳ isnull()) &
(df['loc_og_t2t_mou_8'].isnull()) & (df['std_ic_t2t_mou_8'].isnull()) &
↳ (df['loc_og_t2f_mou_8'].isnull()) & (df['loc_ic_mou_8'].isnull()) &
(df['loc_og_t2c_mou_8'].isnull()) & (df['loc_og_mou_8'].isnull()) &
↳ (df['std_og_t2t_mou_8'].isnull()) & (df['roam_ic_mou_8'].isnull()) &
(df['loc_ic_t2m_mou_8'].isnull()) & (df['std_og_t2m_mou_8'].isnull()) &
↳ (df['loc_ic_t2t_mou_8'].isnull()) & (df['std_og_t2f_mou_8'].isnull()) &
(df['std_og_t2c_mou_8'].isnull()) & (df['og_others_8'].isnull()) &
↳ (df['std_og_mou_8'].isnull()) & (df['spl_og_mou_8'].isnull()) &
(df['std_ic_t2f_mou_8'].isnull()) & (df['isd_og_mou_8'].isnull()) &
↳ (df['std_ic_mou_8'].isnull()) & (df['offnet_mou_8'].isnull()) &
(df['isd_ic_mou_8'].isnull()) & (df['ic_others_8'].isnull()) &
↳ (df['std_ic_t2o_mou_8'].isnull()) & (df['onnet_mou_8'].isnull()) &
(df['spl_ic_mou_8'].isnull())

df_null_mou_8.head()
```

```
[29]:      mobile_number  loc_og_t2o_mou  std_og_t2o_mou  loc_ic_t2o_mou  arpu_6  \
375      7002252754          0.0          0.0          0.0  580.477
578      7000248548          0.0          0.0          0.0  569.612
788      7000636808          0.0          0.0          0.0  532.742
1802     7000516213          0.0          0.0          0.0  810.455
4837     7002192662          0.0          0.0          0.0  649.150
```

```
      arpu_7  arpu_8  arpu_9  onnet_mou_6  onnet_mou_7  onnet_mou_8  \
375    111.878    0.0  378.881      249.43      39.64      NaN
578    237.289    0.0   4.440      718.01     212.73      NaN
788    546.756    0.0  269.274     1173.39     891.83      NaN
1802     0.000    0.0   0.000       91.33        NaN      NaN
4837   149.572    0.0   0.250     1354.24      85.13      NaN
```

```
      onnet_mou_9  offnet_mou_6  offnet_mou_7  offnet_mou_8  offnet_mou_9  \
375      245.06      62.24      37.24      NaN      144.53
578         0.00     487.06     139.71      NaN       1.26
788     149.34      61.59     137.14      NaN     428.36
1802         0.00    1371.04        NaN      NaN       0.00
4837        0.43      50.63      37.13      NaN       0.00
```

```
      roam_ic_mou_6  roam_ic_mou_7  roam_ic_mou_8  roam_ic_mou_9  \
375         25.49      19.43        NaN       0.00
```



578	0.00	2.01	NaN	6.43
788	0.00	1.48	NaN	0.00
1802	1.21	NaN	NaN	0.00
4837	0.00	12.84	NaN	1.25

	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	roam_og_mou_9	\
375	312.59	78.58	NaN	0.00	
578	0.00	6.30	NaN	1.26	
788	0.00	14.43	NaN	0.00	
1802	11.23	NaN	NaN	3.91	
4837	0.00	44.78	NaN	0.43	

	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2t_mou_9	\
375	0.00	0.00	NaN	11.54	
578	11.28	27.89	NaN	0.00	
788	31.06	27.49	NaN	7.39	
1802	17.86	NaN	NaN	0.00	
4837	6.71	1.35	NaN	0.00	

	loc_og_t2m_mou_6	loc_og_t2m_mou_7	loc_og_t2m_mou_8	loc_og_t2m_mou_9	\
375	0.00	0.00	NaN	25.31	
578	42.24	46.94	NaN	0.00	
788	34.66	60.86	NaN	34.23	
1802	84.51	NaN	NaN	0.00	
4837	15.18	15.76	NaN	0.00	

	loc_og_t2f_mou_6	loc_og_t2f_mou_7	loc_og_t2f_mou_8	loc_og_t2f_mou_9	\
375	0.0	0.0	NaN	0.0	
578	0.0	0.0	NaN	0.0	
788	0.0	0.0	NaN	0.0	
1802	0.0	NaN	NaN	0.0	
4837	0.0	0.0	NaN	0.0	

	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_t2c_mou_9	\
375	0.00	0.0	NaN	0.41	
578	2.33	0.0	NaN	0.00	
788	0.00	0.0	NaN	5.58	
1802	10.29	NaN	NaN	0.00	
4837	0.00	0.0	NaN	0.00	

	loc_og_mou_6	loc_og_mou_7	loc_og_mou_8	loc_og_mou_9	\
375	0.00	0.00	NaN	36.86	
578	53.53	74.84	NaN	0.00	
788	65.73	88.36	NaN	41.63	
1802	102.38	NaN	NaN	0.00	
4837	21.89	17.11	NaN	0.00	

	std_og_t2t_mou_6	std_og_t2t_mou_7	std_og_t2t_mou_8	std_og_t2t_mou_9	\
375	0.00	0.00	NaN	233.51	
578	706.73	178.53	NaN	0.00	
788	1142.33	854.08	NaN	141.94	
1802	73.46	NaN	NaN	0.00	
4837	1347.53	48.48	NaN	0.00	

	std_og_t2m_mou_6	std_og_t2m_mou_7	std_og_t2m_mou_8	std_og_t2m_mou_9	\
375	0.00	0.00	NaN	118.79	
578	442.48	92.76	NaN	0.00	
788	26.93	67.24	NaN	388.54	
1802	1207.86	NaN	NaN	0.00	
4837	35.44	11.88	NaN	0.00	

	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2f_mou_9	\
375	0.0	0.0	NaN	0.0	
578	0.0	0.0	NaN	0.0	
788	0.0	0.0	NaN	0.0	
1802	0.0	NaN	NaN	0.0	
4837	0.0	0.0	NaN	0.0	

	std_og_t2c_mou_6	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_t2c_mou_9	\
375	0.0	0.0	NaN	0.0	
578	0.0	0.0	NaN	0.0	
788	0.0	0.0	NaN	0.0	
1802	0.0	NaN	NaN	0.0	
4837	0.0	0.0	NaN	0.0	

	std_og_mou_6	std_og_mou_7	std_og_mou_8	std_og_mou_9	isd_og_mou_6	\
375	0.00	0.00	NaN	352.31	0.0	
578	1149.21	271.29	NaN	0.00	0.0	
788	1169.26	921.33	NaN	530.49	0.0	
1802	1281.33	NaN	NaN	0.00	0.0	
4837	1382.98	60.36	NaN	0.00	0.0	

	isd_og_mou_7	isd_og_mou_8	isd_og_mou_9	spl_og_mou_6	spl_og_mou_7	\
375	0.0	NaN	0.0	0.00	0.00	
578	0.0	NaN	0.0	2.58	1.21	
788	0.0	NaN	0.0	0.00	4.85	
1802	NaN	NaN	0.0	91.94	NaN	
4837	0.0	NaN	0.0	0.00	0.00	

	spl_og_mou_8	spl_og_mou_9	og_others_6	og_others_7	og_others_8	\
375	NaN	4.78	0.00	0.0	NaN	
578	NaN	0.00	1.55	0.0	NaN	
788	NaN	5.58	0.00	0.0	NaN	
1802	NaN	0.00	1.53	NaN	NaN	

4837	NaN	0.00	0.00	0.0	NaN
------	-----	------	------	-----	-----

	og_others_9	total_og_mou_6	total_og_mou_7	total_og_mou_8	\
375	0.0	0.00	0.00	0.0	
578	0.0	1206.88	347.36	0.0	
788	0.0	1234.99	1014.54	0.0	
1802	0.0	1477.19	0.00	0.0	
4837	0.0	1404.88	77.48	0.0	

	total_og_mou_9	loc_ic_t2t_mou_6	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	\
375	393.96	0.00	0.00	NaN	
578	0.00	48.01	63.39	NaN	
788	577.71	54.19	52.64	NaN	
1802	0.00	17.68	NaN	NaN	
4837	0.00	104.46	3.15	NaN	

	loc_ic_t2t_mou_9	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	loc_ic_t2m_mou_8	\
375	6.74	0.00	0.00	NaN	
578	0.00	83.09	64.31	NaN	
788	12.51	54.69	187.96	NaN	
1802	0.00	39.46	NaN	NaN	
4837	0.00	162.01	17.94	NaN	

	loc_ic_t2m_mou_9	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	\
375	38.53	0.00	0.00	NaN	
578	0.00	0.00	0.00	NaN	
788	81.83	1.16	2.01	NaN	
1802	0.00	0.70	NaN	NaN	
4837	0.00	0.00	0.00	NaN	

	loc_ic_t2f_mou_9	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	\
375	0.0	0.00	0.00	NaN	
578	0.0	131.11	127.71	NaN	
788	0.0	110.06	242.63	NaN	
1802	0.0	57.84	NaN	NaN	
4837	0.0	266.48	21.09	NaN	

	loc_ic_mou_9	std_ic_t2t_mou_6	std_ic_t2t_mou_7	std_ic_t2t_mou_8	\
375	45.28	0.00	0.00	NaN	
578	0.00	24.98	46.43	NaN	
788	94.34	14.55	5.48	NaN	
1802	0.00	1.88	NaN	NaN	
4837	0.00	35.11	31.96	NaN	

	std_ic_t2t_mou_9	std_ic_t2m_mou_6	std_ic_t2m_mou_7	std_ic_t2m_mou_8	\
375	8.31	0.00	0.00	NaN	
578	0.00	1.63	16.69	NaN	

788	25.61	11.49	62.19	NaN
1802	0.00	11.98	NaN	NaN
4837	0.00	48.48	0.00	NaN

	std_ic_t2m_mou_9	std_ic_t2f_mou_6	std_ic_t2f_mou_7	std_ic_t2f_mou_8	\
375	27.31	0.00	0.0	NaN	
578	0.00	0.00	0.0	NaN	
788	13.93	0.00	0.0	NaN	
1802	0.00	0.00	NaN	NaN	
4837	0.00	0.28	0.0	NaN	

	std_ic_t2f_mou_9	std_ic_t2o_mou_6	std_ic_t2o_mou_7	std_ic_t2o_mou_8	\
375	0.0	0.0	0.0	NaN	
578	0.0	0.0	0.0	NaN	
788	0.0	0.0	0.0	NaN	
1802	0.0	0.0	NaN	NaN	
4837	0.0	0.0	0.0	NaN	

	std_ic_t2o_mou_9	std_ic_mou_6	std_ic_mou_7	std_ic_mou_8	\
375	0.0	0.00	0.00	NaN	
578	0.0	26.61	63.13	NaN	
788	0.0	26.04	67.68	NaN	
1802	0.0	13.86	NaN	NaN	
4837	0.0	83.88	31.96	NaN	

	std_ic_mou_9	total_ic_mou_6	total_ic_mou_7	total_ic_mou_8	\
375	35.63	0.00	0.00	0.0	
578	0.00	157.73	190.84	0.0	
788	39.54	140.74	310.31	0.0	
1802	0.00	71.71	0.00	0.0	
4837	0.00	350.36	53.06	0.0	

	total_ic_mou_9	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	spl_ic_mou_9	\
375	80.91	0.00	0.0	NaN	0.00	
578	0.00	0.00	0.0	NaN	0.00	
788	134.14	0.73	0.0	NaN	0.25	
1802	0.00	0.00	NaN	NaN	0.00	
4837	0.00	0.00	0.0	NaN	0.00	

	isd_ic_mou_6	isd_ic_mou_7	isd_ic_mou_8	isd_ic_mou_9	ic_others_6	\
375	0.0	0.0	NaN	0.0	0.00	
578	0.0	0.0	NaN	0.0	0.00	
788	0.0	0.0	NaN	0.0	3.89	
1802	0.0	NaN	NaN	0.0	0.00	
4837	0.0	0.0	NaN	0.0	0.00	

ic_others_7	ic_others_8	ic_others_9	total_rech_num_6	\
-------------	-------------	-------------	------------------	---

375	0.0	NaN	0.0	17
578	0.0	NaN	0.0	19
788	0.0	NaN	0.0	10
1802	NaN	NaN	0.0	21
4837	0.0	NaN	0.0	11

	total_rech_num_7	total_rech_num_8	total_rech_num_9	total_rech_amt_6	\
375	6	3	11	700	
578	10	0	4	717	
788	7	4	5	714	
1802	3	0	0	955	
4837	6	3	4	666	

	total_rech_amt_7	total_rech_amt_8	total_rech_amt_9	max_rech_amt_6	\
375	130	0	440	80	
578	220	0	0	110	
788	494	0	336	128	
1802	0	0	0	110	
4837	176	0	0	110	

	max_rech_amt_7	max_rech_amt_8	max_rech_amt_9	last_day_rch_amt_6	\
375	50	0	50	30	
578	50	0	0	27	
788	128	0	130	128	
1802	0	0	0	30	
4837	110	0	0	20	

	last_day_rch_amt_7	last_day_rch_amt_8	last_day_rch_amt_9	vol_2g_mb_6	\
375	0	0	30	0.0	
578	30	0	0	0.0	
788	0	0	130	0.0	
1802	0	0	0	0.0	
4837	0	0	0	0.0	

	vol_2g_mb_7	vol_2g_mb_8	vol_2g_mb_9	vol_3g_mb_6	vol_3g_mb_7	\
375	0.0	0.0	0.0	0.0	0.0	
578	0.0	0.0	0.0	0.0	0.0	
788	0.0	0.0	0.0	0.0	0.0	
1802	0.0	0.0	0.0	0.0	0.0	
4837	0.0	0.0	0.0	0.0	0.0	

	vol_3g_mb_8	vol_3g_mb_9	monthly_2g_6	monthly_2g_7	monthly_2g_8	\
375	0.0	0.0	0	0	0	
578	0.0	0.0	0	0	0	
788	0.0	0.0	0	0	0	
1802	0.0	0.0	0	0	0	
4837	0.0	0.0	0	0	0	

	monthly_2g_9	sachet_2g_6	sachet_2g_7	sachet_2g_8	sachet_2g_9	\
375	0	0	0	0	0	
578	0	0	0	0	0	
788	0	0	0	0	0	
1802	0	0	0	0	0	
4837	0	0	0	0	0	

	monthly_3g_6	monthly_3g_7	monthly_3g_8	monthly_3g_9	sachet_3g_6	\
375	0	0	0	0	0	
578	0	0	0	0	0	
788	0	0	0	0	0	
1802	0	0	0	0	0	
4837	0	0	0	0	0	

	sachet_3g_7	sachet_3g_8	sachet_3g_9	aon	aug_vbc_3g	jul_vbc_3g	\
375	0	0	0	1102	0.0	0.0	
578	0	0	0	274	0.0	0.0	
788	0	0	0	936	0.0	0.0	
1802	0	0	0	755	0.0	0.0	
4837	0	0	0	520	0.0	0.0	

	jun_vbc_3g	sep_vbc_3g	avg_rech_amt_6_7
375	0.0	0.0	415.0
578	0.0	0.0	468.5
788	0.0	0.0	604.0
1802	0.0	0.0	477.5
4837	0.0	0.0	421.0

```
[30]: # Deleting the records for which MOU for Aug(8) are null
df = df.drop(df_null_mou_8.index)
```

```
[31]: # Again cheking percent of missing values in columns
df_missing_columns = (round(((df.isnull().sum())/len(df.index))*100),2).
    to_frame('null').sort_values('null', ascending=False)
df_missing_columns
```

```
[31]:
null
roam_ic_mou_6    0.44
spl_og_mou_6     0.44
og_others_6      0.44
loc_ic_t2t_mou_6 0.44
loc_og_t2m_mou_6 0.44
loc_og_t2c_mou_6 0.44
loc_ic_t2m_mou_6 0.44
isd_og_mou_6     0.44
loc_og_t2t_mou_6 0.44
```

std_og_t2m_mou_6	0.44
loc_ic_t2f_mou_6	0.44
ic_others_6	0.44
roam_og_mou_6	0.44
loc_ic_mou_6	0.44
std_og_mou_6	0.44
loc_og_t2f_mou_6	0.44
isd_ic_mou_6	0.44
std_ic_t2t_mou_6	0.44
std_ic_mou_6	0.44
std_og_t2t_mou_6	0.44
std_ic_t2o_mou_6	0.44
std_og_t2f_mou_6	0.44
std_ic_t2f_mou_6	0.44
spl_ic_mou_6	0.44
onnet_mou_6	0.44
std_og_t2c_mou_6	0.44
std_ic_t2m_mou_6	0.44
offnet_mou_6	0.44
loc_og_mou_6	0.44
std_og_t2f_mou_7	0.16
...	...
loc_ic_t2m_mou_8	0.00
std_ic_t2o_mou_8	0.00
std_ic_t2f_mou_9	0.00
std_ic_t2f_mou_8	0.00
std_ic_t2m_mou_9	0.00
std_ic_t2m_mou_8	0.00
std_ic_t2t_mou_9	0.00
std_ic_t2t_mou_8	0.00
loc_ic_mou_9	0.00
loc_ic_mou_8	0.00
loc_ic_t2f_mou_9	0.00
loc_ic_t2f_mou_8	0.00
loc_og_t2o_mou	0.00
loc_ic_t2m_mou_9	0.00
loc_ic_t2t_mou_9	0.00
std_og_t2c_mou_9	0.00
loc_ic_t2t_mou_8	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
og_others_9	0.00
og_others_8	0.00
spl_og_mou_9	0.00
spl_og_mou_8	0.00

```
isd_og_mou_9      0.00
isd_og_mou_8      0.00
std_og_mou_9      0.00
std_og_mou_8      0.00
avg_rech_amt_6_7  0.00
```

```
[178 rows x 1 columns]
```

Looks like MOU for all the types of calls for the month of Jun (6) have missing values together for any particular record.

Lets check the records for the MOU for Jun(6), in which these coulums have missing values together.

```
[32]: # Listing the columns of MOU Jun(6)
print(((df_missing_columns[df_missing_columns['null'] == 0.44]).index).
      ↪to_list())
```

```
['roam_ic_mou_6', 'spl_og_mou_6', 'og_others_6', 'loc_ic_t2t_mou_6',
'loc_og_t2m_mou_6', 'loc_og_t2c_mou_6', 'loc_ic_t2m_mou_6', 'isd_og_mou_6',
'loc_og_t2t_mou_6', 'std_og_t2m_mou_6', 'loc_ic_t2f_mou_6', 'ic_others_6',
'roam_og_mou_6', 'loc_ic_mou_6', 'std_og_mou_6', 'loc_og_t2f_mou_6',
'isd_ic_mou_6', 'std_ic_t2t_mou_6', 'std_ic_mou_6', 'std_og_t2t_mou_6',
'std_ic_t2o_mou_6', 'std_og_t2f_mou_6', 'std_ic_t2f_mou_6', 'spl_ic_mou_6',
'onnet_mou_6', 'std_og_t2c_mou_6', 'std_ic_t2m_mou_6', 'offnet_mou_6',
'loc_og_mou_6']
```

```
[33]: # Creating a dataframe with the condition, in which MOU for Jun(6) are null
df_null_mou_6 = df[(df['loc_og_t2m_mou_6'].isnull()) & (df['loc_ic_t2f_mou_6'].
      ↪isnull()) & (df['roam_og_mou_6'].isnull()) & (df['std_ic_t2m_mou_6'].
      ↪isnull()) &
      (df['loc_og_t2t_mou_6'].isnull()) & (df['std_ic_t2t_mou_6'].isnull()) &
      ↪(df['loc_og_t2f_mou_6'].isnull()) & (df['loc_ic_mou_6'].isnull()) &
      (df['loc_og_t2c_mou_6'].isnull()) & (df['loc_og_mou_6'].isnull()) &
      ↪(df['std_og_t2t_mou_6'].isnull()) & (df['roam_ic_mou_6'].isnull()) &
      (df['loc_ic_t2m_mou_6'].isnull()) & (df['std_og_t2m_mou_6'].isnull()) &
      ↪(df['loc_ic_t2t_mou_6'].isnull()) & (df['std_og_t2f_mou_6'].isnull()) &
      (df['std_og_t2c_mou_6'].isnull()) & (df['og_others_6'].isnull()) &
      ↪(df['std_og_mou_6'].isnull()) & (df['spl_og_mou_6'].isnull()) &
      (df['std_ic_t2f_mou_6'].isnull()) & (df['isd_og_mou_6'].isnull()) &
      ↪(df['std_ic_mou_6'].isnull()) & (df['offnet_mou_6'].isnull()) &
      (df['isd_ic_mou_6'].isnull()) & (df['ic_others_6'].isnull()) &
      ↪(df['std_ic_t2o_mou_6'].isnull()) & (df['onnet_mou_6'].isnull()) &
      (df['spl_ic_mou_6'].isnull()))

df_null_mou_6.head()
```



```

[33]: mobile_number loc_og_t2o_mou std_og_t2o_mou loc_ic_t2o_mou arpu_6 \
77      7001328263      0.0      0.0      0.0      30.000
364      7002168045      0.0      0.0      0.0      0.000
423      7000635248      0.0      0.0      0.0      213.802
934      7002152278      0.0      0.0      0.0      48.000
1187     7000486275      0.0      0.0      0.0      0.000

      arpu_7 arpu_8 arpu_9 onnet_mou_6 onnet_mou_7 onnet_mou_8 \
77      82.378 674.950 158.710      NaN      34.23      149.69
364     792.112 989.368 923.040      NaN      433.49      198.96
423     304.194 149.710 329.643      NaN      0.00      0.00
934     764.152 500.030 194.400      NaN      14.24      17.48
1187    757.170 995.719   0.000      NaN     1366.71     2268.91

      onnet_mou_9 offnet_mou_6 offnet_mou_7 offnet_mou_8 offnet_mou_9 \
77          6.31      NaN      39.44      179.18      57.68
364        571.99      NaN      845.11      923.58      828.29
423          0.00      NaN      10.03       1.45       0.34
934          7.69      NaN      16.99      76.86      43.64
1187         0.00      NaN       7.78      36.13       0.00

      roam_ic_mou_6 roam_ic_mou_7 roam_ic_mou_8 roam_ic_mou_9 \
77          NaN      0.0      0.00      0.0
364          NaN      0.0      0.00      0.0
423          NaN      0.0      0.00      0.0
934          NaN      0.0      8.81      0.0
1187         NaN      0.0      8.08      0.0

      roam_og_mou_6 roam_og_mou_7 roam_og_mou_8 roam_og_mou_9 \
77          NaN      0.0      0.00      0.00
364          NaN      0.0      0.00      0.00
423          NaN      0.0      0.00      0.00
934          NaN      0.0      1.56      0.00
1187         NaN      0.0     25.23      0.21

      loc_og_t2t_mou_6 loc_og_t2t_mou_7 loc_og_t2t_mou_8 loc_og_t2t_mou_9 \
77          NaN      34.23      149.69      6.31
364          NaN      28.78       7.46      64.73
423          NaN      0.00      0.00      0.00
934          NaN      0.08      17.48      7.69
1187         NaN      4.76      46.18      0.00

      loc_og_t2m_mou_6 loc_og_t2m_mou_7 loc_og_t2m_mou_8 loc_og_t2m_mou_9 \
77          NaN      32.18      101.63      29.41
364          NaN      78.78      584.76     490.71
423          NaN      0.00       0.58       0.33
934          NaN      16.99      63.23      39.99

```

1187	NaN	7.78	31.29	0.00
	loc_og_t2f_mou_6	loc_og_t2f_mou_7	loc_og_t2f_mou_8	loc_og_t2f_mou_9 \
77	NaN	0.91	29.86	28.26
364	NaN	21.58	9.43	0.00
423	NaN	0.00	0.00	0.00
934	NaN	0.00	12.08	3.65
1187	NaN	0.00	0.00	0.00
	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_t2c_mou_9 \
77	NaN	0.0	3.9	0.00
364	NaN	0.0	0.0	2.78
423	NaN	0.0	0.0	0.00
934	NaN	0.0	0.0	0.00
1187	NaN	0.0	0.0	0.00
	loc_og_mou_6	loc_og_mou_7	loc_og_mou_8	loc_og_mou_9 \
77	NaN	67.33	281.19	63.99
364	NaN	129.14	601.66	555.44
423	NaN	0.00	0.58	0.33
934	NaN	17.08	92.79	51.34
1187	NaN	12.54	77.48	0.00
	std_og_t2t_mou_6	std_og_t2t_mou_7	std_og_t2t_mou_8	std_og_t2t_mou_9 \
77	NaN	0.00	0.00	0.00
364	NaN	404.71	191.49	507.26
423	NaN	0.00	0.00	0.00
934	NaN	14.16	0.00	0.00
1187	NaN	1361.94	2202.03	0.00
	std_og_t2m_mou_6	std_og_t2m_mou_7	std_og_t2m_mou_8	std_og_t2m_mou_9 \
77	NaN	0.00	0.00	0.00
364	NaN	722.01	321.41	302.91
423	NaN	0.00	0.25	0.00
934	NaN	0.00	0.00	0.00
1187	NaN	0.00	1.13	0.00
	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2f_mou_9 \
77	NaN	6.35	40.09	0.0
364	NaN	0.00	0.00	0.0
423	NaN	0.00	0.61	0.0
934	NaN	0.00	0.00	0.0
1187	NaN	0.00	0.00	0.0
	std_og_t2c_mou_6	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_t2c_mou_9 \
77	NaN	0.0	0.0	0.0
364	NaN	0.0	0.0	0.0

423	NaN	0.0	0.0	0.0
934	NaN	0.0	0.0	0.0
1187	NaN	0.0	0.0	0.0

	std_og_mou_6	std_og_mou_7	std_og_mou_8	std_og_mou_9	isd_og_mou_6 \
77	NaN	6.35	40.09	0.00	NaN
364	NaN	1126.73	512.91	810.18	NaN
423	NaN	0.00	0.86	0.00	NaN
934	NaN	14.16	0.00	0.00	NaN
1187	NaN	1361.94	2203.16	0.00	NaN

	isd_og_mou_7	isd_og_mou_8	isd_og_mou_9	spl_og_mou_6	spl_og_mou_7 \
77	2.93	28.04	3.25	NaN	0.00
364	0.00	0.00	0.00	NaN	45.14
423	10.03	0.00	0.01	NaN	0.00
934	20.13	8.41	0.00	NaN	0.00
1187	0.00	0.00	0.00	NaN	3.34

	spl_og_mou_8	spl_og_mou_9	og_others_6	og_others_7	og_others_8 \
77	7.58	0.00	NaN	0.0	0.0
364	13.84	37.74	NaN	0.0	0.0
423	0.00	0.00	NaN	0.0	0.0
934	0.00	0.00	NaN	0.0	0.0
1187	1.78	0.00	NaN	0.0	0.0

	og_others_9	total_og_mou_6	total_og_mou_7	total_og_mou_8 \
77	0.0	0.0	76.61	356.93
364	0.0	0.0	1301.03	1128.43
423	0.0	0.0	10.03	1.45
934	0.0	0.0	51.38	101.21
1187	0.0	0.0	1377.84	2282.43

	total_og_mou_9	loc_ic_t2t_mou_6	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8 \
77	67.24	NaN	79.46	191.24
364	1403.38	NaN	7.41	10.23
423	0.34	NaN	0.00	0.00
934	51.34	NaN	0.39	20.09
1187	0.00	NaN	19.34	56.38

	loc_ic_t2t_mou_9	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	loc_ic_t2m_mou_8 \
77	5.26	NaN	43.31	94.18
364	17.46	NaN	69.39	93.48
423	0.00	NaN	0.00	0.00
934	12.19	NaN	4.53	51.16
1187	0.00	NaN	28.19	16.31

	loc_ic_t2m_mou_9	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8 \
--	------------------	------------------	------------------	--------------------

77	16.39	NaN	2.03	0.00
364	44.89	NaN	0.00	0.83
423	0.00	NaN	0.00	0.00
934	59.83	NaN	7.80	17.08
1187	0.00	NaN	0.00	0.00

	loc_ic_t2f_mou_9	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	\
77	15.78	NaN	124.81	285.43	
364	0.00	NaN	76.81	104.54	
423	0.00	NaN	0.00	0.00	
934	5.13	NaN	12.73	88.34	
1187	0.00	NaN	47.54	72.69	

	loc_ic_mou_9	std_ic_t2t_mou_6	std_ic_t2t_mou_7	std_ic_t2t_mou_8	\
77	37.44	NaN	8.00	0.00	
364	62.36	NaN	5.81	10.09	
423	0.00	NaN	0.00	0.00	
934	77.16	NaN	0.00	0.00	
1187	0.00	NaN	125.44	149.81	

	std_ic_t2t_mou_9	std_ic_t2m_mou_6	std_ic_t2m_mou_7	std_ic_t2m_mou_8	\
77	0.00	NaN	0.00	0.00	
364	22.36	NaN	37.94	86.63	
423	0.00	NaN	0.00	0.00	
934	0.00	NaN	0.00	0.00	
1187	0.00	NaN	9.84	17.06	

	std_ic_t2m_mou_9	std_ic_t2f_mou_6	std_ic_t2f_mou_7	std_ic_t2f_mou_8	\
77	0.00	NaN	0.0	0.00	
364	34.49	NaN	0.0	0.00	
423	0.00	NaN	0.0	0.36	
934	0.00	NaN	0.0	0.00	
1187	0.00	NaN	0.0	0.00	

	std_ic_t2f_mou_9	std_ic_t2o_mou_6	std_ic_t2o_mou_7	std_ic_t2o_mou_8	\
77	15.93	NaN	0.0	0.0	
364	0.00	NaN	0.0	0.0	
423	0.00	NaN	0.0	0.0	
934	0.00	NaN	0.0	0.0	
1187	0.00	NaN	0.0	0.0	

	std_ic_t2o_mou_9	std_ic_mou_6	std_ic_mou_7	std_ic_mou_8	\
77	0.0	NaN	8.00	0.00	
364	0.0	NaN	43.76	96.73	
423	0.0	NaN	0.00	0.36	
934	0.0	NaN	0.00	0.00	
1187	0.0	NaN	135.29	166.88	

	std_ic_mou_9	total_ic_mou_6	total_ic_mou_7	total_ic_mou_8	\
77	15.93	0.0	135.38	289.33	
364	56.86	0.0	185.14	219.59	
423	0.00	0.0	8.31	0.36	
934	0.00	0.0	14.69	100.94	
1187	0.00	0.0	182.84	239.58	

	total_ic_mou_9	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	spl_ic_mou_9	\
77	53.38	NaN	0.0	0.0	0.0	
364	129.19	NaN	0.0	0.0	0.0	
423	0.00	NaN	0.0	0.0	0.0	
934	78.99	NaN	0.0	0.0	0.0	
1187	0.00	NaN	0.0	0.0	0.0	

	isd_ic_mou_6	isd_ic_mou_7	isd_ic_mou_8	isd_ic_mou_9	ic_others_6	\
77	NaN	2.56	0.50	0.00	NaN	
364	NaN	64.56	18.31	9.96	NaN	
423	NaN	8.31	0.00	0.00	NaN	
934	NaN	1.96	12.59	1.83	NaN	
1187	NaN	0.00	0.00	0.00	NaN	

	ic_others_7	ic_others_8	ic_others_9	total_rech_num_6	\
77	0.0	3.39	0.0	4	
364	0.0	0.00	0.0	4	
423	0.0	0.00	0.0	4	
934	0.0	0.00	0.0	3	
1187	0.0	0.00	0.0	2	

	total_rech_num_7	total_rech_num_8	total_rech_num_9	total_rech_amt_6	\
77	5	3	3	0	
364	12	24	20	0	
423	4	3	3	252	
934	4	9	4	0	
1187	20	24	6	0	

	total_rech_amt_7	total_rech_amt_8	total_rech_amt_9	max_rech_amt_6	\
77	1154	750	0	0	
364	970	1104	1214	0	
423	591	0	382	252	
934	1302	150	108	0	
1187	883	1160	0	0	

	max_rech_amt_7	max_rech_amt_8	max_rech_amt_9	last_day_rch_amt_6	\
77	1000	750	0	0	
364	154	154	250	0	
423	339	0	252	252	

934	550	150	54	0
1187	150	250	0	0

	last_day_rch_amt_7	last_day_rch_amt_8	last_day_rch_amt_9	vol_2g_mb_6	\
77	0	750	0	0.0	
364	50	50	0	0.0	
423	0	0	0	3.3	
934	0	150	0	0.0	
1187	30	0	0	0.0	

	vol_2g_mb_7	vol_2g_mb_8	vol_2g_mb_9	vol_3g_mb_6	vol_3g_mb_7	\
77	96.48	0.00	0.00	0.00	0.00	
364	565.78	2108.66	0.00	0.00	0.00	
423	38.45	0.00	4.52	669.36	837.18	
934	0.31	38.77	78.66	0.00	1045.79	
1187	0.00	0.00	0.00	0.00	0.00	

	vol_3g_mb_8	vol_3g_mb_9	monthly_2g_6	monthly_2g_7	monthly_2g_8	\
77	0.00	0.00	0	1	0	
364	0.00	0.00	0	1	1	
423	0.00	423.59	0	0	0	
934	245.91	471.48	0	0	0	
1187	0.00	0.00	0	0	0	

	monthly_2g_9	sachet_2g_6	sachet_2g_7	sachet_2g_8	sachet_2g_9	\
77	0	0	0	0	0	
364	0	0	0	2	0	
423	0	0	0	0	0	
934	0	0	0	0	0	
1187	0	0	0	0	0	

	monthly_3g_6	monthly_3g_7	monthly_3g_8	monthly_3g_9	sachet_3g_6	\
77	0	0	0	0	0	
364	0	0	0	0	0	
423	1	1	0	1	0	
934	0	1	1	0	0	
1187	0	0	0	0	0	

	sachet_3g_7	sachet_3g_8	sachet_3g_9	aon	aug_vbc_3g	jul_vbc_3g	\
77	0	0	0	1894	0.00	0.00	
364	0	1	0	424	0.00	0.00	
423	0	0	0	945	73.55	266.94	
934	0	2	1	490	188.83	215.00	
1187	0	0	0	737	0.00	0.00	

	jun_vbc_3g	sep_vbc_3g	avg_rech_amt_6_7
77	0.00	0.00	577.0

364	0.00	0.00	485.0
423	63.04	0.00	421.5
934	0.00	24.18	651.0
1187	0.00	0.00	441.5

```
[34]: # Deleting the records for which MOU for Jun(6) are null
df = df.drop(df_null_mou_6.index)
```

```
[35]: # Again cheking percent of missing values in columns
df_missing_columns = (round(((df.isnull()).sum()/len(df.index))*100),2).
↳to_frame('null').sort_values('null', ascending=False)
df_missing_columns
```

```
[35]:
null
loc_ic_t2f_mou_7 0.12
isd_ic_mou_7     0.12
loc_og_t2f_mou_7 0.12
loc_og_t2c_mou_7 0.12
loc_og_mou_7     0.12
std_og_t2t_mou_7 0.12
std_og_t2f_mou_7 0.12
std_og_t2c_mou_7 0.12
std_og_mou_7     0.12
ic_others_7     0.12
isd_og_mou_7    0.12
spl_og_mou_7    0.12
loc_og_t2t_mou_7 0.12
og_others_7     0.12
spl_ic_mou_7    0.12
loc_ic_t2t_mou_7 0.12
std_ic_mou_7    0.12
loc_ic_t2m_mou_7 0.12
std_ic_t2o_mou_7 0.12
std_ic_t2f_mou_7 0.12
loc_ic_mou_7    0.12
std_ic_t2t_mou_7 0.12
loc_og_t2m_mou_7 0.12
std_og_t2m_mou_7 0.12
std_ic_t2m_mou_7 0.12
roam_ic_mou_7   0.12
onnet_mou_7     0.12
roam_og_mou_7   0.12
offnet_mou_7    0.12
isd_ic_mou_8    0.00
...
loc_ic_t2m_mou_8 0.00
loc_ic_t2f_mou_6 0.00
```

```

std_og_t2f_mou_6 0.00
loc_og_t2o_mou 0.00
loc_ic_t2f_mou_8 0.00
loc_ic_t2f_mou_9 0.00
loc_ic_mou_6 0.00
loc_ic_mou_8 0.00
loc_ic_mou_9 0.00
std_ic_t2t_mou_6 0.00
total_og_mou_7 0.00
total_og_mou_6 0.00
og_others_9 0.00
og_others_8 0.00
std_og_t2f_mou_8 0.00
std_og_t2f_mou_9 0.00
std_og_t2c_mou_6 0.00
std_og_t2c_mou_8 0.00
std_og_t2c_mou_9 0.00
std_og_mou_6 0.00
std_og_mou_8 0.00
std_og_mou_9 0.00
isd_og_mou_6 0.00
isd_og_mou_8 0.00
isd_og_mou_9 0.00
spl_og_mou_6 0.00
spl_og_mou_8 0.00
spl_og_mou_9 0.00
og_others_6 0.00
avg_rech_amt_6_7 0.00

```

```
[178 rows x 1 columns]
```

Looks like MOU for all the types of calls for the month of July (7) have missing values together for any particular record.

Lets check the records for the MOU for Jul(7), in which these coulums have missing values together.

```
[36]: # Listing the columns of MOU Jul(7)
print(((df_missing_columns[df_missing_columns['null'] == 0.12]).index).
      to_list())
```

```

['loc_ic_t2f_mou_7', 'isd_ic_mou_7', 'loc_og_t2f_mou_7', 'loc_og_t2c_mou_7',
'loc_og_mou_7', 'std_og_t2t_mou_7', 'std_og_t2f_mou_7', 'std_og_t2c_mou_7',
'std_og_mou_7', 'ic_others_7', 'isd_og_mou_7', 'spl_og_mou_7',
'loc_og_t2t_mou_7', 'og_others_7', 'spl_ic_mou_7', 'loc_ic_t2t_mou_7',
'std_ic_mou_7', 'loc_ic_t2m_mou_7', 'std_ic_t2o_mou_7', 'std_ic_t2f_mou_7',
'loc_ic_mou_7', 'std_ic_t2t_mou_7', 'loc_og_t2m_mou_7', 'std_og_t2m_mou_7',
'std_ic_t2m_mou_7', 'roam_ic_mou_7', 'onnet_mou_7', 'roam_og_mou_7',
'offnet_mou_7']

```



```
[37]: # Creating a dataframe with the condition, in which MOU for Jul(7) are null
df_null_mou_7 = df[(df['loc_og_t2m_mou_7'].isnull()) & (df['loc_ic_t2f_mou_7'].
↳ isnull()) & (df['roam_og_mou_7'].isnull()) & (df['std_ic_t2m_mou_7'].
↳ isnull()) &
(df['loc_og_t2t_mou_7'].isnull()) & (df['std_ic_t2t_mou_7'].isnull()) &↳
↳ (df['loc_og_t2f_mou_7'].isnull()) & (df['loc_ic_mou_7'].isnull()) &
(df['loc_og_t2c_mou_7'].isnull()) & (df['loc_og_mou_7'].isnull()) &↳
↳ (df['std_og_t2t_mou_7'].isnull()) & (df['roam_ic_mou_7'].isnull()) &
(df['loc_ic_t2m_mou_7'].isnull()) & (df['std_og_t2m_mou_7'].isnull()) &↳
↳ (df['loc_ic_t2t_mou_7'].isnull()) & (df['std_og_t2f_mou_7'].isnull()) &
(df['std_og_t2c_mou_7'].isnull()) & (df['og_others_7'].isnull()) &↳
↳ (df['std_og_mou_7'].isnull()) & (df['spl_og_mou_7'].isnull()) &
(df['std_ic_t2f_mou_7'].isnull()) & (df['isd_og_mou_7'].isnull()) &↳
↳ (df['std_ic_mou_7'].isnull()) & (df['offnet_mou_7'].isnull()) &
(df['isd_ic_mou_7'].isnull()) & (df['ic_others_7'].isnull()) &↳
↳ (df['std_ic_t2o_mou_7'].isnull()) & (df['onnet_mou_7'].isnull()) &
(df['spl_ic_mou_7'].isnull())]

df_null_mou_7.head()
```

```
[37]:
```

	mobile_number	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	\
5616	7001238202	0.0	0.0	0.0	
9451	7001477649	0.0	0.0	0.0	
9955	7001658068	0.0	0.0	0.0	
10724	7001391499	0.0	0.0	0.0	
12107	7000131738	0.0	0.0	0.0	

	arpu_6	arpu_7	arpu_8	arpu_9	onnet_mou_6	onnet_mou_7	\
5616	760.815	531.088	992.818	1144.676	324.91	NaN	
9451	1129.566	0.000	128.252	802.648	11.89	NaN	
9955	925.028	189.000	789.761	445.707	46.39	NaN	
10724	894.818	85.000	207.040	363.314	117.21	NaN	
12107	1803.475	0.000	0.600	25.243	1742.61	NaN	

	onnet_mou_8	onnet_mou_9	offnet_mou_6	offnet_mou_7	offnet_mou_8	\
5616	386.13	1180.29	350.29	NaN	399.64	
9451	1.46	33.89	259.18	NaN	26.21	
9955	43.39	56.61	333.78	NaN	196.53	
10724	97.01	35.43	119.79	NaN	12.79	
12107	0.00	0.00	278.79	NaN	14.29	

	offnet_mou_9	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	\
5616	887.76	463.63	NaN	221.46	
9451	241.18	9.98	NaN	1.73	
9955	144.73	0.00	NaN	0.00	
10724	92.04	0.00	NaN	0.00	

12107	4.50	0.00	NaN	0.00	
	roam_ic_mou_9	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	\
5616	0.0	505.71	NaN	175.93	
9451	0.0	5.66	NaN	2.46	
9955	0.0	0.00	NaN	0.00	
10724	0.0	0.00	NaN	0.00	
12107	0.0	0.00	NaN	0.00	
	roam_og_mou_9	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	\
5616	0.0	145.91	NaN	243.43	
9451	0.0	6.73	NaN	1.46	
9955	0.0	46.39	NaN	43.39	
10724	0.0	115.08	NaN	97.01	
12107	0.0	96.08	NaN	0.00	
	loc_og_t2t_mou_9	loc_og_t2m_mou_6	loc_og_t2m_mou_7	loc_og_t2m_mou_8	\
5616	1108.38	0.85	NaN	184.78	
9451	20.84	171.46	NaN	20.54	
9955	56.61	227.91	NaN	163.68	
10724	34.98	86.39	NaN	6.59	
12107	0.00	64.98	NaN	0.86	
	loc_og_t2m_mou_9	loc_og_t2f_mou_6	loc_og_t2f_mou_7	loc_og_t2f_mou_8	\
5616	300.19	1.13	NaN	7.94	
9451	148.88	0.00	NaN	0.00	
9955	121.54	104.69	NaN	28.96	
10724	55.44	17.18	NaN	6.19	
12107	0.00	0.00	NaN	0.00	
	loc_og_t2f_mou_9	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	\
5616	67.11	0.00	NaN	12.51	
9451	0.00	0.00	NaN	0.00	
9955	21.04	0.00	NaN	0.00	
10724	28.08	0.00	NaN	0.00	
12107	0.00	50.03	NaN	13.43	
	loc_og_t2c_mou_9	loc_og_mou_6	loc_og_mou_7	loc_og_mou_8	\
5616	18.89	147.89	NaN	436.16	
9451	0.00	178.19	NaN	22.01	
9955	0.00	379.01	NaN	236.04	
10724	0.05	218.66	NaN	109.81	
12107	4.50	161.06	NaN	0.86	
	loc_og_mou_9	std_og_t2t_mou_6	std_og_t2t_mou_7	std_og_t2t_mou_8	\
5616	1475.69	0.96	NaN	17.06	
9451	169.73	5.16	NaN	0.00	

9955	199.21	0.00	NaN	0.00
10724	118.51	2.13	NaN	0.00
12107	0.00	1646.53	NaN	0.00

	std_og_t2t_mou_9	std_og_t2m_mou_6	std_og_t2m_mou_7	std_og_t2m_mou_8	\
5616	69.51	15.91	NaN	144.04	
9451	13.05	0.00	NaN	0.00	
9955	0.00	0.00	NaN	0.00	
10724	0.45	2.43	NaN	0.00	
12107	0.00	140.16	NaN	0.00	

	std_og_t2m_mou_9	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	\
5616	490.61	0.00	NaN	0.0	
9451	0.00	0.00	NaN	0.0	
9955	1.26	1.16	NaN	2.9	
10724	7.18	6.09	NaN	0.0	
12107	0.00	1.26	NaN	0.0	

	std_og_t2f_mou_9	std_og_t2c_mou_6	std_og_t2c_mou_7	std_og_t2c_mou_8	\
5616	13.33	0.0	NaN	0.0	
9451	0.00	0.0	NaN	0.0	
9955	0.00	0.0	NaN	0.0	
10724	1.28	0.0	NaN	0.0	
12107	0.00	0.0	NaN	0.0	

	std_og_t2c_mou_9	std_og_mou_6	std_og_mou_7	std_og_mou_8	\
5616	0.0	16.88	NaN	161.11	
9451	0.0	5.16	NaN	0.00	
9955	0.0	1.16	NaN	2.90	
10724	0.0	10.66	NaN	0.00	
12107	0.0	1787.96	NaN	0.00	

	std_og_mou_9	isd_og_mou_6	isd_og_mou_7	isd_og_mou_8	isd_og_mou_9	\
5616	573.46	0.00	NaN	0.00	0.00	
9451	13.05	74.91	NaN	4.74	92.29	
9955	1.26	53.14	NaN	31.06	33.69	
10724	8.91	16.86	NaN	6.21	2.18	
12107	0.00	0.00	NaN	0.00	0.00	

	spl_og_mou_6	spl_og_mou_7	spl_og_mou_8	spl_og_mou_9	og_others_6	\
5616	4.71	NaN	12.56	18.89	0.00	
9451	7.13	NaN	0.00	1.08	0.00	
9955	0.00	NaN	0.00	0.00	0.00	
10724	0.00	NaN	0.00	0.05	0.00	
12107	72.61	NaN	13.43	4.50	1.76	

og_others_7	og_others_8	og_others_9	total_og_mou_6	total_og_mou_7	\
-------------	-------------	-------------	----------------	----------------	---

5616	NaN	0.0	0.0	169.49	0.0
9451	NaN	0.0	0.0	265.41	0.0
9955	NaN	0.0	0.0	433.33	0.0
10724	NaN	0.0	0.0	246.19	0.0
12107	NaN	0.0	0.0	2023.41	0.0

	total_og_mou_8	total_og_mou_9	loc_ic_t2t_mou_6	loc_ic_t2t_mou_7	\
5616	609.84	2068.06	78.76	NaN	
9451	26.76	276.16	17.24	NaN	
9955	270.01	234.18	80.98	NaN	
10724	116.03	129.66	887.04	NaN	
12107	14.29	4.50	65.76	NaN	

	loc_ic_t2t_mou_8	loc_ic_t2t_mou_9	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	\
5616	233.66	558.84	1.36	NaN	
9451	0.60	36.69	130.09	NaN	
9955	32.69	112.14	201.38	NaN	
10724	200.51	408.66	104.18	NaN	
12107	1.73	5.88	92.18	NaN	

	loc_ic_t2m_mou_8	loc_ic_t2m_mou_9	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	\
5616	11.53	75.31	6.61	NaN	
9451	16.54	110.19	25.46	NaN	
9955	169.24	155.58	41.68	NaN	
10724	22.24	76.39	16.74	NaN	
12107	5.59	2.75	0.00	NaN	

	loc_ic_t2f_mou_8	loc_ic_t2f_mou_9	loc_ic_mou_6	loc_ic_mou_7	\
5616	0.00	31.81	86.74	NaN	
9451	8.76	40.24	172.81	NaN	
9955	25.68	12.33	324.04	NaN	
10724	1.61	28.18	1007.98	NaN	
12107	0.00	0.00	157.94	NaN	

	loc_ic_mou_8	loc_ic_mou_9	std_ic_t2t_mou_6	std_ic_t2t_mou_7	\
5616	245.19	665.98	0.00	NaN	
9451	25.91	187.14	1.50	NaN	
9955	227.63	280.06	0.00	NaN	
10724	224.38	513.24	0.00	NaN	
12107	7.33	8.63	103.66	NaN	

	std_ic_t2t_mou_8	std_ic_t2t_mou_9	std_ic_t2m_mou_6	std_ic_t2m_mou_7	\
5616	12.13	42.39	21.76	NaN	
9451	0.00	0.00	0.41	NaN	
9955	0.00	0.00	0.98	NaN	
10724	0.00	0.00	5.94	NaN	
12107	0.00	0.00	3.01	NaN	

	std_ic_t2m_mou_8	std_ic_t2m_mou_9	std_ic_t2f_mou_6	std_ic_t2f_mou_7	\
5616	110.99	263.98	0.0	NaN	
9451	0.00	12.29	0.0	NaN	
9955	2.13	2.58	0.0	NaN	
10724	0.00	4.88	0.0	NaN	
12107	0.00	0.00	0.0	NaN	

	std_ic_t2f_mou_8	std_ic_t2f_mou_9	std_ic_t2o_mou_6	std_ic_t2o_mou_7	\
5616	0.00	6.43	0.0	NaN	
9451	0.00	4.48	0.0	NaN	
9955	0.23	0.00	0.0	NaN	
10724	10.03	1.26	0.0	NaN	
12107	0.00	0.00	0.0	NaN	

	std_ic_t2o_mou_8	std_ic_t2o_mou_9	std_ic_mou_6	std_ic_mou_7	\
5616	0.0	0.0	21.76	NaN	
9451	0.0	0.0	1.91	NaN	
9955	0.0	0.0	0.98	NaN	
10724	0.0	0.0	5.94	NaN	
12107	0.0	0.0	106.68	NaN	

	std_ic_mou_8	std_ic_mou_9	total_ic_mou_6	total_ic_mou_7	\
5616	123.13	312.81	189.81	0.0	
9451	0.00	16.78	217.33	0.0	
9955	2.36	2.58	332.33	0.0	
10724	10.03	6.14	1140.54	0.0	
12107	0.00	0.00	265.03	0.0	

	total_ic_mou_8	total_ic_mou_9	spl_ic_mou_6	spl_ic_mou_7	\
5616	397.13	1020.16	0.00	NaN	
9451	43.44	307.43	0.00	NaN	
9955	506.94	526.54	0.00	NaN	
10724	342.78	642.33	0.14	NaN	
12107	7.33	8.63	0.00	NaN	

	spl_ic_mou_8	spl_ic_mou_9	isd_ic_mou_6	isd_ic_mou_7	isd_ic_mou_8	\
5616	0.00	0.13	81.29	NaN	28.79	
9451	0.00	0.00	42.59	NaN	17.53	
9955	0.00	0.00	7.29	NaN	173.61	
10724	0.08	0.09	126.13	NaN	106.53	
12107	0.00	0.00	0.00	NaN	0.00	

	isd_ic_mou_9	ic_others_6	ic_others_7	ic_others_8	ic_others_9	\
5616	41.23	0.00	NaN	0.00	0.00	
9451	103.49	0.00	NaN	0.00	0.00	
9955	229.44	0.00	NaN	103.33	14.45	

10724	116.83	0.33	NaN	1.74	5.99
12107	0.00	0.40	NaN	0.00	0.00

	total_rech_num_6	total_rech_num_7	total_rech_num_8	total_rech_num_9	\
5616	5	7	9	13	
9451	14	4	4	9	
9955	6	1	4	3	
10724	8	3	3	5	
12107	17	2	1	2	

	total_rech_amt_6	total_rech_amt_7	total_rech_amt_8	total_rech_amt_9	\
5616	776	780	904	1591	
9451	1206	0	223	991	
9955	1385	0	835	912	
10724	1020	0	360	480	
12107	1990	0	0	30	

	max_rech_amt_6	max_rech_amt_7	max_rech_amt_8	max_rech_amt_9	\
5616	250	330	200	289	
9451	250	0	130	130	
9955	350	0	300	479	
10724	500	0	130	150	
12107	250	0	0	30	

	last_day_rch_amt_6	last_day_rch_amt_7	last_day_rch_amt_8	\
5616	250	0	130	
9451	250	0	130	
9955	250	0	300	
10724	500	0	130	
12107	110	0	0	

	last_day_rch_amt_9	vol_2g_mb_6	vol_2g_mb_7	vol_2g_mb_8	vol_2g_mb_9	\
5616	250	0.00	0.0	11.26	83.32	
9451	130	321.86	0.0	0.00	431.85	
9955	479	0.00	0.0	0.00	0.00	
10724	0	0.00	0.0	0.00	0.00	
12107	30	0.00	0.0	0.00	0.00	

	vol_3g_mb_6	vol_3g_mb_7	vol_3g_mb_8	vol_3g_mb_9	monthly_2g_6	\
5616	0.0	0.0	79.94	668.4	0	
9451	0.0	0.0	0.00	0.0	1	
9955	0.0	0.0	0.00	0.0	0	
10724	0.0	0.0	0.00	0.0	0	
12107	0.0	0.0	0.00	0.0	0	

	monthly_2g_7	monthly_2g_8	monthly_2g_9	sachet_2g_6	sachet_2g_7	\
5616	0	1	1	0	0	

9451	0	0	1	1	0
9955	0	0	0	0	0
10724	0	0	0	0	0
12107	0	0	0	0	0

	sachet_2g_8	sachet_2g_9	monthly_3g_6	monthly_3g_7	monthly_3g_8	\
5616	0	0	0	0	0	
9451	0	2	0	0	0	
9955	0	0	0	0	0	
10724	0	0	0	0	0	
12107	0	0	0	0	0	

	monthly_3g_9	sachet_3g_6	sachet_3g_7	sachet_3g_8	sachet_3g_9	aon	\
5616	0	0	0	0	0	576	
9451	0	0	0	0	0	672	
9955	0	0	0	0	0	3107	
10724	0	0	0	0	0	2664	
12107	0	0	0	0	0	219	

	aug_vbc_3g	jul_vbc_3g	jun_vbc_3g	sep_vbc_3g	avg_rech_amt_6_7
5616	63.38	0.0	0.0	163.39	778.0
9451	0.00	0.0	0.0	0.00	603.0
9955	0.00	0.0	0.0	0.00	692.5
10724	0.00	0.0	0.0	0.00	510.0
12107	0.00	0.0	0.0	0.00	995.0

```
[38]: # Deleting the records for which MOU for Jul(7) are null
df = df.drop(df_null_mou_7.index)
```

```
[39]: # Again cheking percent of missing values in columns
df_missing_columns = (round(((df.isnull()).sum()/len(df.index))*100),2).
↳to_frame('null').sort_values('null', ascending=False)
df_missing_columns
```

```
[39]:
null
mobile_number      0.0
total_rech_num_7   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
isd_ic_mou_6	0.0
isd_ic_mou_7	0.0
isd_ic_mou_8	0.0
isd_ic_mou_9	0.0
ic_others_6	0.0
ic_others_7	0.0
ic_others_8	0.0
ic_others_9	0.0
std_ic_mou_6	0.0
std_ic_t2o_mou_9	0.0
std_ic_t2o_mou_8	0.0
std_ic_t2t_mou_9	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
...	...
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
spl_og_mou_6	0.0
isd_og_mou_8	0.0
std_og_t2t_mou_8	0.0
std_og_t2f_mou_9	0.0
std_og_t2t_mou_9	0.0
std_og_t2m_mou_6	0.0
std_og_t2m_mou_7	0.0
std_og_t2m_mou_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_t2c_mou_6	0.0
isd_og_mou_7	0.0
std_og_t2c_mou_7	0.0
std_og_t2c_mou_8	0.0
std_og_t2c_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
avg_rech_amt_6_7  0.0
```

```
[178 rows x 1 columns]
```

We can see there are no more missing values in any columns.

```
[40]: df.shape
```

```
[40]: (27991, 178)
```

```
[41]: # Checking percentage of rows we have lost while handling the missing values
round((1- (len(df.index)/30011)),2)
```

```
[41]: 0.07
```

We can see that we have lost almost 7% records. But we have enough number of records to do our analysis.

### 1.1.2 Tag churners

Now tag the churned customers (churn=1, else 0) based on the fourth month as follows: Those who have not made any calls (either incoming or outgoing) AND have not used mobile internet even once in the churn phase.

```
[42]: df['churn'] = np.where((df['total_ic_mou_9']==0) & (df['total_og_mou_9']==0) &
    ↪(df['vol_2g_mb_9']==0) & (df['vol_3g_mb_9']==0), 1, 0)
```

```
[43]: df.head()
```

```
[43]:
```

	mobile_number	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	arpu_6	\
8	7001524846	0.0	0.0	0.0	378.721	
13	7002191713	0.0	0.0	0.0	492.846	
16	7000875565	0.0	0.0	0.0	430.975	
17	7000187447	0.0	0.0	0.0	690.008	
21	7002124215	0.0	0.0	0.0	514.453	

	arpu_7	arpu_8	arpu_9	onnet_mou_6	onnet_mou_7	onnet_mou_8	\
8	492.223	137.362	166.787	413.69	351.03	35.08	
13	205.671	593.260	322.732	501.76	108.39	534.24	
16	299.869	187.894	206.490	50.51	74.01	70.61	
17	18.980	25.499	257.583	1185.91	9.28	7.79	
21	597.753	637.760	578.596	102.41	132.11	85.14	

	onnet_mou_9	offnet_mou_6	offnet_mou_7	offnet_mou_8	offnet_mou_9	\
8	33.46	94.66	80.63	136.48	108.71	
13	244.81	413.31	119.28	482.46	214.06	
16	31.34	296.29	229.74	162.76	224.39	

17	558.51	61.64	0.00	5.54	87.89
21	161.63	757.93	896.68	983.39	869.89

	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_ic_mou_9	roam_og_mou_6	\
8	0.00	0.00	0.00	0.00	0.00	
13	23.53	144.24	72.11	136.78	7.98	
16	0.00	2.83	0.00	0.00	0.00	
17	0.00	4.76	4.81	0.00	0.00	
21	0.00	0.00	0.00	0.00	0.00	

	roam_og_mou_7	roam_og_mou_8	roam_og_mou_9	loc_og_t2t_mou_6	\
8	0.00	0.00	0.00	297.13	
13	35.26	1.44	12.78	49.63	
16	17.74	0.00	0.00	42.61	
17	8.46	13.34	17.98	38.99	
21	0.00	0.00	0.00	4.48	

	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2t_mou_9	loc_og_t2m_mou_6	\
8	217.59	12.49	26.13	80.96	
13	6.19	36.01	6.14	151.13	
16	65.16	67.38	26.88	273.29	
17	0.00	0.00	36.41	58.54	
21	6.16	23.34	29.98	91.81	

	loc_og_t2m_mou_7	loc_og_t2m_mou_8	loc_og_t2m_mou_9	loc_og_t2f_mou_6	\
8	70.58	50.54	34.58	0.00	
13	47.28	294.46	108.24	4.54	
16	145.99	128.28	201.49	0.00	
17	0.00	0.00	9.38	0.00	
21	87.93	104.81	107.54	0.75	

	loc_og_t2f_mou_7	loc_og_t2f_mou_8	loc_og_t2f_mou_9	loc_og_t2c_mou_6	\
8	0.00	0.00	0.00	0.0	
13	0.00	23.51	5.29	0.0	
16	4.48	10.26	4.66	0.0	
17	0.00	0.00	0.00	0.0	
21	0.00	1.58	0.00	0.0	

	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_t2c_mou_9	loc_og_mou_6	\
8	0.0	7.15	0.0	378.09	
13	0.0	0.49	0.0	205.31	
16	0.0	0.00	0.0	315.91	
17	0.0	0.00	0.0	97.54	
21	0.0	0.00	0.0	97.04	

	loc_og_mou_7	loc_og_mou_8	loc_og_mou_9	std_og_t2t_mou_6	\
8	288.18	63.04	60.71	116.56	

13	53.48	353.99	119.69	446.41
16	215.64	205.93	233.04	7.89
17	0.00	0.00	45.79	1146.91
21	94.09	129.74	137.53	97.93

	std_og_t2t_mou_7	std_og_t2t_mou_8	std_og_t2t_mou_9	std_og_t2m_mou_6	\
8	133.43	22.58	7.33	13.69	
13	85.98	498.23	230.38	255.36	
16	2.58	3.23	4.46	22.99	
17	0.81	0.00	504.11	1.55	
21	125.94	61.79	131.64	665.36	

	std_og_t2m_mou_7	std_og_t2m_mou_8	std_og_t2m_mou_9	std_og_t2f_mou_6	\
8	10.04	75.69	74.13	0.0	
13	52.94	156.94	96.01	0.0	
16	64.51	18.29	13.79	0.0	
17	0.00	0.00	78.51	0.0	
21	808.74	876.99	762.34	0.0	

	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2f_mou_9	std_og_t2c_mou_6	\
8	0.0	0.0	0.00	0.0	
13	0.0	0.0	0.00	0.0	
16	0.0	0.0	4.43	0.0	
17	0.0	0.0	0.00	0.0	
21	0.0	0.0	0.00	0.0	

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_t2c_mou_9	std_og_mou_6	\
8	0.0	0.0	0.0	130.26	
13	0.0	0.0	0.0	701.78	
16	0.0	0.0	0.0	30.89	
17	0.0	0.0	0.0	1148.46	
21	0.0	0.0	0.0	763.29	

	std_og_mou_7	std_og_mou_8	std_og_mou_9	isd_og_mou_6	isd_og_mou_7	\
8	143.48	98.28	81.46	0.0	0.0	
13	138.93	655.18	326.39	0.0	0.0	
16	67.09	21.53	22.69	0.0	0.0	
17	0.81	0.00	582.63	0.0	0.0	
21	934.69	938.79	893.99	0.0	0.0	

	isd_og_mou_8	isd_og_mou_9	spl_og_mou_6	spl_og_mou_7	spl_og_mou_8	\
8	0.00	0.0	0.00	0.00	10.23	
13	1.29	0.0	0.00	0.00	4.78	
16	0.00	0.0	0.00	3.26	5.91	
17	0.00	0.0	2.58	0.00	0.00	
21	0.00	0.0	0.00	0.00	0.00	

	spl_og_mou_9	og_others_6	og_others_7	og_others_8	og_others_9	\
8	0.00	0.00	0.0	0.0	0.0	
13	0.00	0.00	0.0	0.0	0.0	
16	0.00	0.00	0.0	0.0	0.0	
17	2.64	0.93	0.0	0.0	0.0	
21	0.00	0.00	0.0	0.0	0.0	

	total_og_mou_6	total_og_mou_7	total_og_mou_8	total_og_mou_9	\
8	508.36	431.66	171.56	142.18	
13	907.09	192.41	1015.26	446.09	
16	346.81	286.01	233.38	255.74	
17	1249.53	0.81	0.00	631.08	
21	860.34	1028.79	1068.54	1031.53	

	loc_ic_t2t_mou_6	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2t_mou_9	\
8	23.84	9.84	0.31	4.03	
13	67.88	7.58	52.58	24.98	
16	41.33	71.44	28.89	50.23	
17	34.54	0.00	0.00	40.91	
21	2.48	10.19	19.54	17.99	

	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	loc_ic_t2m_mou_8	loc_ic_t2m_mou_9	\
8	57.58	13.98	15.48	17.34	
13	142.88	18.53	195.18	104.79	
16	226.81	149.69	150.16	172.86	
17	47.41	2.31	0.00	43.86	
21	118.23	74.63	129.16	113.46	

	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	loc_ic_t2f_mou_9	\
8	0.00	0.00	0.00	0.00	
13	4.81	0.00	7.49	8.51	
16	8.71	8.68	32.71	65.21	
17	0.00	0.00	0.00	0.71	
21	4.61	2.84	10.39	8.41	

	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	loc_ic_mou_9	std_ic_t2t_mou_6	\
8	81.43	23.83	15.79	21.38	0.00	
13	215.58	26.11	255.26	138.29	115.68	
16	276.86	229.83	211.78	288.31	68.79	
17	81.96	2.31	0.00	85.49	8.63	
21	125.33	87.68	159.11	139.88	14.06	

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2t_mou_9	std_ic_t2m_mou_6	\
8	0.58	0.10	0.00	22.43	
13	38.29	154.58	62.39	308.13	
16	78.64	6.33	16.66	18.68	
17	0.00	0.00	0.00	1.28	

21	5.98	0.18	16.74	67.69		
	std_ic_t2m_mou_7	std_ic_t2m_mou_8	std_ic_t2m_mou_9	std_ic_t2f_mou_6	\	
8	4.08	0.65	13.53	0.00		
13	29.79	317.91	151.51	0.00		
16	73.08	73.93	29.58	0.51		
17	0.00	0.00	1.63	0.00		
21	38.23	101.74	95.98	0.00		
	std_ic_t2f_mou_7	std_ic_t2f_mou_8	std_ic_t2f_mou_9	std_ic_t2o_mou_6	\	
8	0.0	0.00	0.0	0.0		
13	0.0	1.91	0.0	0.0		
16	0.0	2.18	0.0	0.0		
17	0.0	0.00	0.0	0.0		
21	0.0	0.00	0.0	0.0		
	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_t2o_mou_9	std_ic_mou_6	\	
8	0.0	0.0	0.0	22.43		
13	0.0	0.0	0.0	423.81		
16	0.0	0.0	0.0	87.99		
17	0.0	0.0	0.0	9.91		
21	0.0	0.0	0.0	81.76		
	std_ic_mou_7	std_ic_mou_8	std_ic_mou_9	total_ic_mou_6	total_ic_mou_7	\
8	4.66	0.75	13.53	103.86	28.49	
13	68.09	474.41	213.91	968.61	172.58	
16	151.73	82.44	46.24	364.86	381.56	
17	0.00	0.00	1.63	91.88	2.31	
21	44.21	101.93	112.73	207.09	131.89	
	total_ic_mou_8	total_ic_mou_9	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	\
8	16.54	34.91	0.00	0.0	0.0	
13	1144.53	631.86	0.45	0.0	0.0	
16	294.46	334.56	0.00	0.0	0.0	
17	0.00	87.13	0.00	0.0	0.0	
21	261.04	252.61	0.00	0.0	0.0	
	spl_ic_mou_9	isd_ic_mou_6	isd_ic_mou_7	isd_ic_mou_8	isd_ic_mou_9	\
8	0.0	0.00	0.00	0.00	0.00	
13	0.0	245.28	62.11	393.39	259.33	
16	0.0	0.00	0.00	0.23	0.00	
17	0.0	0.00	0.00	0.00	0.00	
21	0.0	0.00	0.00	0.00	0.00	
	ic_others_6	ic_others_7	ic_others_8	ic_others_9	total_rech_num_6	\
8	0.00	0.00	0.00	0.00	19	
13	83.48	16.24	21.44	20.31	6	

16	0.00	0.00	0.00	0.00	10
17	0.00	0.00	0.00	0.00	19
21	0.00	0.00	0.00	0.00	22

	total_rech_num_7	total_rech_num_8	total_rech_num_9	total_rech_amt_6	\
8	21	14	15	437	
13	4	11	7	507	
16	6	2	1	570	
17	2	4	10	816	
21	26	27	17	600	

	total_rech_amt_7	total_rech_amt_8	total_rech_amt_9	max_rech_amt_6	\
8	601	120	186	90	
13	253	717	353	110	
16	348	160	220	110	
17	0	30	335	110	
21	680	718	680	50	

	max_rech_amt_7	max_rech_amt_8	max_rech_amt_9	last_day_rch_amt_6	\
8	154	30	36	50	
13	110	130	130	110	
16	110	130	220	100	
17	0	30	130	30	
21	50	50	50	30	

	last_day_rch_amt_7	last_day_rch_amt_8	last_day_rch_amt_9	vol_2g_mb_6	\
8	0	10	0	0.0	
13	50	0	0	0.0	
16	100	130	220	0.0	
17	0	0	0	0.0	
21	20	50	30	0.0	

	vol_2g_mb_7	vol_2g_mb_8	vol_2g_mb_9	vol_3g_mb_6	vol_3g_mb_7	\
8	356.0	0.03	0.0	0.0	750.95	
13	0.0	0.02	0.0	0.0	0.00	
16	0.0	0.00	0.0	0.0	0.00	
17	0.0	0.00	0.0	0.0	0.00	
21	0.0	0.00	0.0	0.0	0.00	

	vol_3g_mb_8	vol_3g_mb_9	monthly_2g_6	monthly_2g_7	monthly_2g_8	\
8	11.94	0.0	0	1	0	
13	0.00	0.0	0	0	0	
16	0.00	0.0	0	0	0	
17	0.00	0.0	0	0	0	
21	0.00	0.0	0	0	0	

monthly_2g_9	sachet_2g_6	sachet_2g_7	sachet_2g_8	sachet_2g_9	\
--------------	-------------	-------------	-------------	-------------	---

8	0	0	1	3	0
13	0	0	0	3	0
16	0	0	0	0	0
17	0	0	0	0	0
21	0	0	0	0	0

	monthly_3g_6	monthly_3g_7	monthly_3g_8	monthly_3g_9	sachet_3g_6	\
8	0	0	0	0	0	
13	0	0	0	0	0	
16	0	0	0	0	0	
17	0	0	0	0	0	
21	0	0	0	0	0	

	sachet_3g_7	sachet_3g_8	sachet_3g_9	aon	aug_vbc_3g	jul_vbc_3g	\
8	0	0	0	315	21.03	910.65	
13	0	0	0	2607	0.00	0.00	
16	0	0	0	511	0.00	2.45	
17	0	0	0	667	0.00	0.00	
21	0	0	0	720	0.00	0.00	

	jun_vbc_3g	sep_vbc_3g	avg_rech_amt_6_7	churn
8	122.16	0.0	519.0	0
13	0.00	0.0	380.0	0
16	21.89	0.0	459.0	0
17	0.00	0.0	408.0	0
21	0.00	0.0	640.0	0

Deleting all the attributes corresponding to the churn phase

```
[44]: # List the columns for churn month(9)
col_9 = [col for col in df.columns.to_list() if '_9' in col]
print(col_9)

['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_t2c_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_t2o_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', 'vol_2g_mb_9',
'vol_3g_mb_9', 'monthly_2g_9', 'sachet_2g_9', 'monthly_3g_9', 'sachet_3g_9']

[45]: # Deleting the churn month columns
df = df.drop(col_9, axis=1)
```

```
[46]: # Dropping sep_vbc_3g column
df = df.drop('sep_vbc_3g', axis=1)
```

### Checking churn percentage

```
[47]: round(100*(df['churn'].mean()),2)
```

```
[47]: 3.39
```

There is very little percentage of churn rate. We will take care of the class imbalance later.

## 1.2 Outliers treatment

In the filtered dataset except mobile\_number and churn columns all the columns are numeric types. Hence, converting mobile\_number and churn datatype to object.

```
[48]: df['mobile_number'] = df['mobile_number'].astype(object)
df['churn'] = df['churn'].astype(object)
```

```
[49]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 27991 entries, 8 to 99997
Columns: 136 entries, mobile_number to churn
dtypes: float64(109), int64(25), object(2)
memory usage: 29.3+ MB
```

```
[50]: # List only the numeric columns
numeric_cols = df.select_dtypes(exclude=['object']).columns
print(numeric_cols)
```

```
Index(['loc_og_t2o_mou', 'std_og_t2o_mou', 'loc_ic_t2o_mou', 'arpu_6',
      'arpu_7', 'arpu_8', 'onnet_mou_6', 'onnet_mou_7', 'onnet_mou_8',
      'offnet_mou_6',
      ...
      'monthly_3g_7', 'monthly_3g_8', 'sachet_3g_6', 'sachet_3g_7',
      'sachet_3g_8', 'aon', 'aug_vbc_3g', 'jul_vbc_3g', 'jun_vbc_3g',
      'avg_rech_amt_6_7'],
      dtype='object', length=134)
```

```
[51]: # Removing outliers below 10th and above 90th percentile
for col in numeric_cols:
    q1 = df[col].quantile(0.10)
    q3 = df[col].quantile(0.90)
    iqr = q3-q1
    range_low = q1-1.5*iqr
    range_high = q3+1.5*iqr
    # Assigning the filtered dataset into data
```



```
data = df.loc[(df[col] > range_low) & (df[col] < range_high)]

data.shape
```

```
[51]: (27705, 136)
```

### 1.2.1 Derive new features

```
[52]: # List the columns of total mou, rech_num and rech_amt
[total for total in data.columns.to_list() if 'total' in total]
```

```
[52]: ['total_og_mou_6',
      'total_og_mou_7',
      'total_og_mou_8',
      'total_ic_mou_6',
      'total_ic_mou_7',
      'total_ic_mou_8',
      'total_rech_num_6',
      'total_rech_num_7',
      'total_rech_num_8',
      'total_rech_amt_6',
      'total_rech_amt_7',
      'total_rech_amt_8']
```

**Deriving new column decrease\_mou\_action** This column indicates whether the minutes of usage of the customer has decreased in the action phase than the good phase.

```
[53]: # Total mou at good phase incoming and outgoing
data['total_mou_good'] = (data['total_og_mou_6'] + data['total_ic_mou_6'])
```

```
[54]: # Avg. mou at action phase
# We are taking average because there are two months(7 and 8) in action phase
data['avg_mou_action'] = (data['total_og_mou_7'] + data['total_og_mou_8'] +
    ↪ data['total_ic_mou_7'] + data['total_ic_mou_8'])/2
```

```
[55]: # Difference avg_mou_good and avg_mou_action
data['diff_mou'] = data['avg_mou_action'] - data['total_mou_good']
```

```
[56]: # Checking whether the mou has decreased in action phase
data['decrease_mou_action'] = np.where((data['diff_mou'] < 0), 1, 0)
```

```
[57]: data.head()
```

```
[57]:  mobile_number  loc_og_t2o_mou  std_og_t2o_mou  loc_ic_t2o_mou  arpu_6  \
8      7001524846             0.0             0.0             0.0  378.721
13     7002191713             0.0             0.0             0.0  492.846
16     7000875565             0.0             0.0             0.0  430.975
```

17	7000187447	0.0	0.0	0.0	690.008
21	7002124215	0.0	0.0	0.0	514.453

	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	\
8	492.223	137.362	413.69	351.03	35.08	94.66	
13	205.671	593.260	501.76	108.39	534.24	413.31	
16	299.869	187.894	50.51	74.01	70.61	296.29	
17	18.980	25.499	1185.91	9.28	7.79	61.64	
21	597.753	637.760	102.41	132.11	85.14	757.93	

	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	\
8	80.63	136.48	0.00	0.00	0.00	
13	119.28	482.46	23.53	144.24	72.11	
16	229.74	162.76	0.00	2.83	0.00	
17	0.00	5.54	0.00	4.76	4.81	
21	896.68	983.39	0.00	0.00	0.00	

	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	\
8	0.00	0.00	0.00	297.13	
13	7.98	35.26	1.44	49.63	
16	0.00	17.74	0.00	42.61	
17	0.00	8.46	13.34	38.99	
21	0.00	0.00	0.00	4.48	

	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2m_mou_6	loc_og_t2m_mou_7	\
8	217.59	12.49	80.96	70.58	
13	6.19	36.01	151.13	47.28	
16	65.16	67.38	273.29	145.99	
17	0.00	0.00	58.54	0.00	
21	6.16	23.34	91.81	87.93	

	loc_og_t2m_mou_8	loc_og_t2f_mou_6	loc_og_t2f_mou_7	loc_og_t2f_mou_8	\
8	50.54	0.00	0.00	0.00	
13	294.46	4.54	0.00	23.51	
16	128.28	0.00	4.48	10.26	
17	0.00	0.00	0.00	0.00	
21	104.81	0.75	0.00	1.58	

	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_mou_6	\
8	0.0	0.0	7.15	378.09	
13	0.0	0.0	0.49	205.31	
16	0.0	0.0	0.00	315.91	
17	0.0	0.0	0.00	97.54	
21	0.0	0.0	0.00	97.04	

	loc_og_mou_7	loc_og_mou_8	std_og_t2t_mou_6	std_og_t2t_mou_7	\
8	288.18	63.04	116.56	133.43	

13	53.48	353.99	446.41	85.98
16	215.64	205.93	7.89	2.58
17	0.00	0.00	1146.91	0.81
21	94.09	129.74	97.93	125.94

	std_og_t2t_mou_8	std_og_t2m_mou_6	std_og_t2m_mou_7	std_og_t2m_mou_8	\
8	22.58	13.69	10.04	75.69	
13	498.23	255.36	52.94	156.94	
16	3.23	22.99	64.51	18.29	
17	0.00	1.55	0.00	0.00	
21	61.79	665.36	808.74	876.99	

	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2c_mou_6	\
8	0.0	0.0	0.0	0.0	
13	0.0	0.0	0.0	0.0	
16	0.0	0.0	0.0	0.0	
17	0.0	0.0	0.0	0.0	
21	0.0	0.0	0.0	0.0	

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_mou_6	std_og_mou_7	\
8	0.0	0.0	130.26	143.48	
13	0.0	0.0	701.78	138.93	
16	0.0	0.0	30.89	67.09	
17	0.0	0.0	1148.46	0.81	
21	0.0	0.0	763.29	934.69	

	std_og_mou_8	isd_og_mou_6	isd_og_mou_7	isd_og_mou_8	spl_og_mou_6	\
8	98.28	0.0	0.0	0.00	0.00	
13	655.18	0.0	0.0	1.29	0.00	
16	21.53	0.0	0.0	0.00	0.00	
17	0.00	0.0	0.0	0.00	2.58	
21	938.79	0.0	0.0	0.00	0.00	

	spl_og_mou_7	spl_og_mou_8	og_others_6	og_others_7	og_others_8	\
8	0.00	10.23	0.00	0.0	0.0	
13	0.00	4.78	0.00	0.0	0.0	
16	3.26	5.91	0.00	0.0	0.0	
17	0.00	0.00	0.93	0.0	0.0	
21	0.00	0.00	0.00	0.0	0.0	

	total_og_mou_6	total_og_mou_7	total_og_mou_8	loc_ic_t2t_mou_6	\
8	508.36	431.66	171.56	23.84	
13	907.09	192.41	1015.26	67.88	
16	346.81	286.01	233.38	41.33	
17	1249.53	0.81	0.00	34.54	
21	860.34	1028.79	1068.54	2.48	

	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	\
8	9.84	0.31	57.58	13.98	
13	7.58	52.58	142.88	18.53	
16	71.44	28.89	226.81	149.69	
17	0.00	0.00	47.41	2.31	
21	10.19	19.54	118.23	74.63	

	loc_ic_t2m_mou_8	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	\
8	15.48	0.00	0.00	0.00	
13	195.18	4.81	0.00	7.49	
16	150.16	8.71	8.68	32.71	
17	0.00	0.00	0.00	0.00	
21	129.16	4.61	2.84	10.39	

	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	std_ic_t2t_mou_6	\
8	81.43	23.83	15.79	0.00	
13	215.58	26.11	255.26	115.68	
16	276.86	229.83	211.78	68.79	
17	81.96	2.31	0.00	8.63	
21	125.33	87.68	159.11	14.06	

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2m_mou_6	std_ic_t2m_mou_7	\
8	0.58	0.10	22.43	4.08	
13	38.29	154.58	308.13	29.79	
16	78.64	6.33	18.68	73.08	
17	0.00	0.00	1.28	0.00	
21	5.98	0.18	67.69	38.23	

	std_ic_t2m_mou_8	std_ic_t2f_mou_6	std_ic_t2f_mou_7	std_ic_t2f_mou_8	\
8	0.65	0.00	0.0	0.00	
13	317.91	0.00	0.0	1.91	
16	73.93	0.51	0.0	2.18	
17	0.00	0.00	0.0	0.00	
21	101.74	0.00	0.0	0.00	

	std_ic_t2o_mou_6	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_mou_6	\
8	0.0	0.0	0.0	22.43	
13	0.0	0.0	0.0	423.81	
16	0.0	0.0	0.0	87.99	
17	0.0	0.0	0.0	9.91	
21	0.0	0.0	0.0	81.76	

	std_ic_mou_7	std_ic_mou_8	total_ic_mou_6	total_ic_mou_7	\
8	4.66	0.75	103.86	28.49	
13	68.09	474.41	968.61	172.58	
16	151.73	82.44	364.86	381.56	
17	0.00	0.00	91.88	2.31	

21	44.21	101.93	207.09	131.89	
----	-------	--------	--------	--------	--

	total_ic_mou_8	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	isd_ic_mou_6 \
8	16.54	0.00	0.0	0.0	0.00
13	1144.53	0.45	0.0	0.0	245.28
16	294.46	0.00	0.0	0.0	0.00
17	0.00	0.00	0.0	0.0	0.00
21	261.04	0.00	0.0	0.0	0.00

	isd_ic_mou_7	isd_ic_mou_8	ic_others_6	ic_others_7	ic_others_8 \
8	0.00	0.00	0.00	0.00	0.00
13	62.11	393.39	83.48	16.24	21.44
16	0.00	0.23	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	0.00
21	0.00	0.00	0.00	0.00	0.00

	total_rech_num_6	total_rech_num_7	total_rech_num_8	total_rech_amt_6 \
8	19	21	14	437
13	6	4	11	507
16	10	6	2	570
17	19	2	4	816
21	22	26	27	600

	total_rech_amt_7	total_rech_amt_8	max_rech_amt_6	max_rech_amt_7 \
8	601	120	90	154
13	253	717	110	110
16	348	160	110	110
17	0	30	110	0
21	680	718	50	50

	max_rech_amt_8	last_day_rch_amt_6	last_day_rch_amt_7 \
8	30	50	0
13	130	110	50
16	130	100	100
17	30	30	0
21	50	30	20

	last_day_rch_amt_8	vol_2g_mb_6	vol_2g_mb_7	vol_2g_mb_8	vol_3g_mb_6 \
8	10	0.0	356.0	0.03	0.0
13	0	0.0	0.0	0.02	0.0
16	130	0.0	0.0	0.00	0.0
17	0	0.0	0.0	0.00	0.0
21	50	0.0	0.0	0.00	0.0

	vol_3g_mb_7	vol_3g_mb_8	monthly_2g_6	monthly_2g_7	monthly_2g_8 \
8	750.95	11.94	0	1	0
13	0.00	0.00	0	0	0

16	0.00	0.00	0	0	0
17	0.00	0.00	0	0	0
21	0.00	0.00	0	0	0

	sachet_2g_6	sachet_2g_7	sachet_2g_8	monthly_3g_6	monthly_3g_7	\
8	0	1	3	0	0	
13	0	0	3	0	0	
16	0	0	0	0	0	
17	0	0	0	0	0	
21	0	0	0	0	0	

	monthly_3g_8	sachet_3g_6	sachet_3g_7	sachet_3g_8	aon	aug_vbc_3g	\
8	0	0	0	0	315	21.03	
13	0	0	0	0	2607	0.00	
16	0	0	0	0	511	0.00	
17	0	0	0	0	667	0.00	
21	0	0	0	0	720	0.00	

	jul_vbc_3g	jun_vbc_3g	avg_rech_amt_6_7	churn	total_mou_good	\
8	910.65	122.16	519.0	0	612.22	
13	0.00	0.00	380.0	0	1875.70	
16	2.45	21.89	459.0	0	711.67	
17	0.00	0.00	408.0	0	1341.41	
21	0.00	0.00	640.0	0	1067.43	

	avg_mou_action	diff_mou	decrease_mou_action
8	324.125	-288.095	1
13	1262.390	-613.310	1
16	597.705	-113.965	1
17	1.560	-1339.850	1
21	1245.130	177.700	0

**Deriving new column decrease\_rech\_num\_action** This column indicates whether the number of recharge of the customer has decreased in the action phase than the good phase.

```
[58]: # Avg rech number at action phase
data['avg_rech_num_action'] = (data['total_rech_num_7'] +
↪data['total_rech_num_8'])/2

[59]: # Difference total_rech_num_6 and avg_rech_action
data['diff_rech_num'] = data['avg_rech_num_action'] - data['total_rech_num_6']

[60]: # Checking if rech_num has decreased in action phase
data['decrease_rech_num_action'] = np.where((data['diff_rech_num'] < 0), 1, 0)

[61]: data.head()
```

```

[61]:  mobile_number  loc_og_t2o_mou  std_og_t2o_mou  loc_ic_t2o_mou  arpu_6  \
8      7001524846      0.0      0.0      0.0  378.721
13     7002191713      0.0      0.0      0.0  492.846
16     7000875565      0.0      0.0      0.0  430.975
17     7000187447      0.0      0.0      0.0  690.008
21     7002124215      0.0      0.0      0.0  514.453

      arpu_7  arpu_8  onnet_mou_6  onnet_mou_7  onnet_mou_8  offnet_mou_6  \
8  492.223  137.362      413.69      351.03      35.08      94.66
13 205.671  593.260      501.76      108.39     534.24     413.31
16 299.869  187.894      50.51      74.01      70.61     296.29
17  18.980   25.499     1185.91       9.28       7.79      61.64
21 597.753  637.760      102.41     132.11      85.14     757.93

      offnet_mou_7  offnet_mou_8  roam_ic_mou_6  roam_ic_mou_7  roam_ic_mou_8  \
8      80.63      136.48      0.00      0.00      0.00
13     119.28     482.46     23.53     144.24     72.11
16     229.74     162.76      0.00      2.83      0.00
17       0.00       5.54      0.00      4.76      4.81
21     896.68     983.39      0.00      0.00      0.00

      roam_og_mou_6  roam_og_mou_7  roam_og_mou_8  loc_og_t2t_mou_6  \
8      0.00      0.00      0.00      297.13
13     7.98     35.26      1.44      49.63
16     0.00     17.74      0.00     42.61
17     0.00      8.46     13.34     38.99
21     0.00      0.00      0.00      4.48

      loc_og_t2t_mou_7  loc_og_t2t_mou_8  loc_og_t2m_mou_6  loc_og_t2m_mou_7  \
8      217.59      12.49      80.96      70.58
13       6.19     36.01     151.13     47.28
16     65.16     67.38     273.29    145.99
17       0.00      0.00     58.54      0.00
21      6.16     23.34     91.81     87.93

      loc_og_t2m_mou_8  loc_og_t2f_mou_6  loc_og_t2f_mou_7  loc_og_t2f_mou_8  \
8      50.54      0.00      0.00      0.00
13     294.46      4.54      0.00     23.51
16     128.28      0.00      4.48     10.26
17       0.00      0.00      0.00      0.00
21     104.81      0.75      0.00      1.58

      loc_og_t2c_mou_6  loc_og_t2c_mou_7  loc_og_t2c_mou_8  loc_og_mou_6  \
8      0.0      0.0      7.15     378.09
13      0.0      0.0      0.49     205.31
16      0.0      0.0      0.00     315.91
17      0.0      0.0      0.00      97.54

```

21	0.0	0.0	0.00	97.04
----	-----	-----	------	-------

	loc_og_mou_7	loc_og_mou_8	std_og_t2t_mou_6	std_og_t2t_mou_7	\
8	288.18	63.04	116.56	133.43	
13	53.48	353.99	446.41	85.98	
16	215.64	205.93	7.89	2.58	
17	0.00	0.00	1146.91	0.81	
21	94.09	129.74	97.93	125.94	

	std_og_t2t_mou_8	std_og_t2m_mou_6	std_og_t2m_mou_7	std_og_t2m_mou_8	\
8	22.58	13.69	10.04	75.69	
13	498.23	255.36	52.94	156.94	
16	3.23	22.99	64.51	18.29	
17	0.00	1.55	0.00	0.00	
21	61.79	665.36	808.74	876.99	

	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2c_mou_6	\
8	0.0	0.0	0.0	0.0	
13	0.0	0.0	0.0	0.0	
16	0.0	0.0	0.0	0.0	
17	0.0	0.0	0.0	0.0	
21	0.0	0.0	0.0	0.0	

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_mou_6	std_og_mou_7	\
8	0.0	0.0	130.26	143.48	
13	0.0	0.0	701.78	138.93	
16	0.0	0.0	30.89	67.09	
17	0.0	0.0	1148.46	0.81	
21	0.0	0.0	763.29	934.69	

	std_og_mou_8	isd_og_mou_6	isd_og_mou_7	isd_og_mou_8	spl_og_mou_6	\
8	98.28	0.0	0.0	0.00	0.00	
13	655.18	0.0	0.0	1.29	0.00	
16	21.53	0.0	0.0	0.00	0.00	
17	0.00	0.0	0.0	0.00	2.58	
21	938.79	0.0	0.0	0.00	0.00	

	spl_og_mou_7	spl_og_mou_8	og_others_6	og_others_7	og_others_8	\
8	0.00	10.23	0.00	0.0	0.0	
13	0.00	4.78	0.00	0.0	0.0	
16	3.26	5.91	0.00	0.0	0.0	
17	0.00	0.00	0.93	0.0	0.0	
21	0.00	0.00	0.00	0.0	0.0	

	total_og_mou_6	total_og_mou_7	total_og_mou_8	loc_ic_t2t_mou_6	\
8	508.36	431.66	171.56	23.84	
13	907.09	192.41	1015.26	67.88	



16	346.81	286.01	233.38	41.33
17	1249.53	0.81	0.00	34.54
21	860.34	1028.79	1068.54	2.48
	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7 \
8	9.84	0.31	57.58	13.98
13	7.58	52.58	142.88	18.53
16	71.44	28.89	226.81	149.69
17	0.00	0.00	47.41	2.31
21	10.19	19.54	118.23	74.63
	loc_ic_t2m_mou_8	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8 \
8	15.48	0.00	0.00	0.00
13	195.18	4.81	0.00	7.49
16	150.16	8.71	8.68	32.71
17	0.00	0.00	0.00	0.00
21	129.16	4.61	2.84	10.39
	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	std_ic_t2t_mou_6 \
8	81.43	23.83	15.79	0.00
13	215.58	26.11	255.26	115.68
16	276.86	229.83	211.78	68.79
17	81.96	2.31	0.00	8.63
21	125.33	87.68	159.11	14.06
	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2m_mou_6	std_ic_t2m_mou_7 \
8	0.58	0.10	22.43	4.08
13	38.29	154.58	308.13	29.79
16	78.64	6.33	18.68	73.08
17	0.00	0.00	1.28	0.00
21	5.98	0.18	67.69	38.23
	std_ic_t2m_mou_8	std_ic_t2f_mou_6	std_ic_t2f_mou_7	std_ic_t2f_mou_8 \
8	0.65	0.00	0.0	0.00
13	317.91	0.00	0.0	1.91
16	73.93	0.51	0.0	2.18
17	0.00	0.00	0.0	0.00
21	101.74	0.00	0.0	0.00
	std_ic_t2o_mou_6	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_mou_6 \
8	0.0	0.0	0.0	22.43
13	0.0	0.0	0.0	423.81
16	0.0	0.0	0.0	87.99
17	0.0	0.0	0.0	9.91
21	0.0	0.0	0.0	81.76
	std_ic_mou_7	std_ic_mou_8	total_ic_mou_6	total_ic_mou_7 \

8	4.66	0.75	103.86	28.49
13	68.09	474.41	968.61	172.58
16	151.73	82.44	364.86	381.56
17	0.00	0.00	91.88	2.31
21	44.21	101.93	207.09	131.89

	total_ic_mou_8	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	isd_ic_mou_6	\
8	16.54	0.00	0.0	0.0	0.00	
13	1144.53	0.45	0.0	0.0	245.28	
16	294.46	0.00	0.0	0.0	0.00	
17	0.00	0.00	0.0	0.0	0.00	
21	261.04	0.00	0.0	0.0	0.00	

	isd_ic_mou_7	isd_ic_mou_8	ic_others_6	ic_others_7	ic_others_8	\
8	0.00	0.00	0.00	0.00	0.00	
13	62.11	393.39	83.48	16.24	21.44	
16	0.00	0.23	0.00	0.00	0.00	
17	0.00	0.00	0.00	0.00	0.00	
21	0.00	0.00	0.00	0.00	0.00	

	total_rech_num_6	total_rech_num_7	total_rech_num_8	total_rech_amt_6	\
8	19	21	14	437	
13	6	4	11	507	
16	10	6	2	570	
17	19	2	4	816	
21	22	26	27	600	

	total_rech_amt_7	total_rech_amt_8	max_rech_amt_6	max_rech_amt_7	\
8	601	120	90	154	
13	253	717	110	110	
16	348	160	110	110	
17	0	30	110	0	
21	680	718	50	50	

	max_rech_amt_8	last_day_rch_amt_6	last_day_rch_amt_7	\
8	30	50	0	
13	130	110	50	
16	130	100	100	
17	30	30	0	
21	50	30	20	

	last_day_rch_amt_8	vol_2g_mb_6	vol_2g_mb_7	vol_2g_mb_8	vol_3g_mb_6	\
8	10	0.0	356.0	0.03	0.0	
13	0	0.0	0.0	0.02	0.0	
16	130	0.0	0.0	0.00	0.0	
17	0	0.0	0.0	0.00	0.0	
21	50	0.0	0.0	0.00	0.0	

	vol_3g_mb_7	vol_3g_mb_8	monthly_2g_6	monthly_2g_7	monthly_2g_8	\
8	750.95	11.94	0	1	0	
13	0.00	0.00	0	0	0	
16	0.00	0.00	0	0	0	
17	0.00	0.00	0	0	0	
21	0.00	0.00	0	0	0	

	sachet_2g_6	sachet_2g_7	sachet_2g_8	monthly_3g_6	monthly_3g_7	\
8	0	1	3	0	0	
13	0	0	3	0	0	
16	0	0	0	0	0	
17	0	0	0	0	0	
21	0	0	0	0	0	

	monthly_3g_8	sachet_3g_6	sachet_3g_7	sachet_3g_8	aon	aug_vbc_3g	\
8	0	0	0	0	315	21.03	
13	0	0	0	0	2607	0.00	
16	0	0	0	0	511	0.00	
17	0	0	0	0	667	0.00	
21	0	0	0	0	720	0.00	

	jul_vbc_3g	jun_vbc_3g	avg_rech_amt_6_7	churn	total_mou_good	\
8	910.65	122.16	519.0	0	612.22	
13	0.00	0.00	380.0	0	1875.70	
16	2.45	21.89	459.0	0	711.67	
17	0.00	0.00	408.0	0	1341.41	
21	0.00	0.00	640.0	0	1067.43	

	avg_mou_action	diff_mou	decrease_mou_action	avg_rech_num_action	\
8	324.125	-288.095		1	17.5
13	1262.390	-613.310		1	7.5
16	597.705	-113.965		1	4.0
17	1.560	-1339.850		1	3.0
21	1245.130	177.700		0	26.5

	diff_rech_num	decrease_rech_num_action
8	-1.5	1
13	1.5	0
16	-6.0	1
17	-16.0	1
21	4.5	0

**Deriving new column decrease\_rech\_amt\_action** This column indicates whether the amount of recharge of the customer has decreased in the action phase than the good phase.

```
[62]: # Avg rech_amt in action phase
data['avg_rech_amt_action'] = (data['total_rech_amt_7'] +
↪data['total_rech_amt_8'])/2

[63]: # Difference of action phase rech amt and good phase rech amt
data['diff_rech_amt'] = data['avg_rech_amt_action'] - data['total_rech_amt_6']

[64]: # Checking if rech_amt has decreased in action phase
data['decrease_rech_amt_action'] = np.where((data['diff_rech_amt'] < 0), 1, 0)

[66]: data.head()
```

```
[66]:  mobile_number  loc_og_t2o_mou  std_og_t2o_mou  loc_ic_t2o_mou  arpu_6  \
8      7001524846           0.0           0.0           0.0  378.721
13     7002191713           0.0           0.0           0.0  492.846
16     7000875565           0.0           0.0           0.0  430.975
17     7000187447           0.0           0.0           0.0  690.008
21     7002124215           0.0           0.0           0.0  514.453

      arpu_7  arpu_8  onnet_mou_6  onnet_mou_7  onnet_mou_8  offnet_mou_6  \
8    492.223  137.362    413.69    351.03    35.08    94.66
13   205.671  593.260    501.76    108.39    534.24    413.31
16   299.869  187.894    50.51    74.01    70.61    296.29
17    18.980   25.499   1185.91     9.28     7.79    61.64
21   597.753  637.760    102.41    132.11    85.14    757.93

      offnet_mou_7  offnet_mou_8  roam_ic_mou_6  roam_ic_mou_7  roam_ic_mou_8  \
8         80.63    136.48         0.00         0.00         0.00
13        119.28    482.46        23.53        144.24        72.11
16        229.74    162.76         0.00         2.83         0.00
17         0.00     5.54         0.00         4.76         4.81
21        896.68    983.39         0.00         0.00         0.00

      roam_og_mou_6  roam_og_mou_7  roam_og_mou_8  loc_og_t2t_mou_6  \
8         0.00         0.00         0.00        297.13
13         7.98        35.26         1.44        49.63
16         0.00        17.74         0.00        42.61
17         0.00         8.46        13.34        38.99
21         0.00         0.00         0.00         4.48

      loc_og_t2t_mou_7  loc_og_t2t_mou_8  loc_og_t2m_mou_6  loc_og_t2m_mou_7  \
8         217.59        12.49        80.96        70.58
13          6.19        36.01       151.13        47.28
16        65.16        67.38       273.29       145.99
17          0.00         0.00        58.54         0.00
21         6.16        23.34        91.81        87.93
```

	loc_og_t2m_mou_8	loc_og_t2f_mou_6	loc_og_t2f_mou_7	loc_og_t2f_mou_8	\
8	50.54	0.00	0.00	0.00	
13	294.46	4.54	0.00	23.51	
16	128.28	0.00	4.48	10.26	
17	0.00	0.00	0.00	0.00	
21	104.81	0.75	0.00	1.58	

	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_mou_6	\
8	0.0	0.0	7.15	378.09	
13	0.0	0.0	0.49	205.31	
16	0.0	0.0	0.00	315.91	
17	0.0	0.0	0.00	97.54	
21	0.0	0.0	0.00	97.04	

	loc_og_mou_7	loc_og_mou_8	std_og_t2t_mou_6	std_og_t2t_mou_7	\
8	288.18	63.04	116.56	133.43	
13	53.48	353.99	446.41	85.98	
16	215.64	205.93	7.89	2.58	
17	0.00	0.00	1146.91	0.81	
21	94.09	129.74	97.93	125.94	

	std_og_t2t_mou_8	std_og_t2m_mou_6	std_og_t2m_mou_7	std_og_t2m_mou_8	\
8	22.58	13.69	10.04	75.69	
13	498.23	255.36	52.94	156.94	
16	3.23	22.99	64.51	18.29	
17	0.00	1.55	0.00	0.00	
21	61.79	665.36	808.74	876.99	

	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2c_mou_6	\
8	0.0	0.0	0.0	0.0	
13	0.0	0.0	0.0	0.0	
16	0.0	0.0	0.0	0.0	
17	0.0	0.0	0.0	0.0	
21	0.0	0.0	0.0	0.0	

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_mou_6	std_og_mou_7	\
8	0.0	0.0	130.26	143.48	
13	0.0	0.0	701.78	138.93	
16	0.0	0.0	30.89	67.09	
17	0.0	0.0	1148.46	0.81	
21	0.0	0.0	763.29	934.69	

	std_og_mou_8	isd_og_mou_6	isd_og_mou_7	isd_og_mou_8	spl_og_mou_6	\
8	98.28	0.0	0.0	0.00	0.00	
13	655.18	0.0	0.0	1.29	0.00	
16	21.53	0.0	0.0	0.00	0.00	
17	0.00	0.0	0.0	0.00	2.58	

21	938.79	0.0	0.0	0.00	0.00
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	spl_og_mou_7	spl_og_mou_8	og_others_6	og_others_7	og_others_8	\
8	0.00	10.23	0.00	0.0	0.0	
13	0.00	4.78	0.00	0.0	0.0	
16	3.26	5.91	0.00	0.0	0.0	
17	0.00	0.00	0.93	0.0	0.0	
21	0.00	0.00	0.00	0.0	0.0	

	total_og_mou_6	total_og_mou_7	total_og_mou_8	loc_ic_t2t_mou_6	\
8	508.36	431.66	171.56	23.84	
13	907.09	192.41	1015.26	67.88	
16	346.81	286.01	233.38	41.33	
17	1249.53	0.81	0.00	34.54	
21	860.34	1028.79	1068.54	2.48	

	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	\
8	9.84	0.31	57.58	13.98	
13	7.58	52.58	142.88	18.53	
16	71.44	28.89	226.81	149.69	
17	0.00	0.00	47.41	2.31	
21	10.19	19.54	118.23	74.63	

	loc_ic_t2m_mou_8	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	\
8	15.48	0.00	0.00	0.00	
13	195.18	4.81	0.00	7.49	
16	150.16	8.71	8.68	32.71	
17	0.00	0.00	0.00	0.00	
21	129.16	4.61	2.84	10.39	

	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	std_ic_t2t_mou_6	\
8	81.43	23.83	15.79	0.00	
13	215.58	26.11	255.26	115.68	
16	276.86	229.83	211.78	68.79	
17	81.96	2.31	0.00	8.63	
21	125.33	87.68	159.11	14.06	

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2m_mou_6	std_ic_t2m_mou_7	\
8	0.58	0.10	22.43	4.08	
13	38.29	154.58	308.13	29.79	
16	78.64	6.33	18.68	73.08	
17	0.00	0.00	1.28	0.00	
21	5.98	0.18	67.69	38.23	

	std_ic_t2m_mou_8	std_ic_t2f_mou_6	std_ic_t2f_mou_7	std_ic_t2f_mou_8	\
8	0.65	0.00	0.0	0.00	
13	317.91	0.00	0.0	1.91	

16	73.93	0.51	0.0	2.18
17	0.00	0.00	0.0	0.00
21	101.74	0.00	0.0	0.00

	std_ic_t2o_mou_6	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_mou_6 \
8	0.0	0.0	0.0	22.43
13	0.0	0.0	0.0	423.81
16	0.0	0.0	0.0	87.99
17	0.0	0.0	0.0	9.91
21	0.0	0.0	0.0	81.76

	std_ic_mou_7	std_ic_mou_8	total_ic_mou_6	total_ic_mou_7 \
8	4.66	0.75	103.86	28.49
13	68.09	474.41	968.61	172.58
16	151.73	82.44	364.86	381.56
17	0.00	0.00	91.88	2.31
21	44.21	101.93	207.09	131.89

	total_ic_mou_8	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	isd_ic_mou_6 \
8	16.54	0.00	0.0	0.0	0.00
13	1144.53	0.45	0.0	0.0	245.28
16	294.46	0.00	0.0	0.0	0.00
17	0.00	0.00	0.0	0.0	0.00
21	261.04	0.00	0.0	0.0	0.00

	isd_ic_mou_7	isd_ic_mou_8	ic_others_6	ic_others_7	ic_others_8 \
8	0.00	0.00	0.00	0.00	0.00
13	62.11	393.39	83.48	16.24	21.44
16	0.00	0.23	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	0.00
21	0.00	0.00	0.00	0.00	0.00

	total_rech_num_6	total_rech_num_7	total_rech_num_8	total_rech_amt_6 \
8	19	21	14	437
13	6	4	11	507
16	10	6	2	570
17	19	2	4	816
21	22	26	27	600

	total_rech_amt_7	total_rech_amt_8	max_rech_amt_6	max_rech_amt_7 \
8	601	120	90	154
13	253	717	110	110
16	348	160	110	110
17	0	30	110	0
21	680	718	50	50

max_rech_amt_8	last_day_rch_amt_6	last_day_rch_amt_7 \
----------------	--------------------	----------------------

8	30	50	0
13	130	110	50
16	130	100	100
17	30	30	0
21	50	30	20

	last_day_rch_amt_8	vol_2g_mb_6	vol_2g_mb_7	vol_2g_mb_8	vol_3g_mb_6	\
8	10	0.0	356.0	0.03	0.0	
13	0	0.0	0.0	0.02	0.0	
16	130	0.0	0.0	0.00	0.0	
17	0	0.0	0.0	0.00	0.0	
21	50	0.0	0.0	0.00	0.0	

	vol_3g_mb_7	vol_3g_mb_8	monthly_2g_6	monthly_2g_7	monthly_2g_8	\
8	750.95	11.94	0	1	0	
13	0.00	0.00	0	0	0	
16	0.00	0.00	0	0	0	
17	0.00	0.00	0	0	0	
21	0.00	0.00	0	0	0	

	sachet_2g_6	sachet_2g_7	sachet_2g_8	monthly_3g_6	monthly_3g_7	\
8	0	1	3	0	0	
13	0	0	3	0	0	
16	0	0	0	0	0	
17	0	0	0	0	0	
21	0	0	0	0	0	

	monthly_3g_8	sachet_3g_6	sachet_3g_7	sachet_3g_8	aon	aug_vbc_3g	\
8	0	0	0	0	315	21.03	
13	0	0	0	0	2607	0.00	
16	0	0	0	0	511	0.00	
17	0	0	0	0	667	0.00	
21	0	0	0	0	720	0.00	

	jul_vbc_3g	jun_vbc_3g	avg_rech_amt_6_7	churn	total_mou_good	\
8	910.65	122.16	519.0	0	612.22	
13	0.00	0.00	380.0	0	1875.70	
16	2.45	21.89	459.0	0	711.67	
17	0.00	0.00	408.0	0	1341.41	
21	0.00	0.00	640.0	0	1067.43	

	avg_mou_action	diff_mou	decrease_mou_action	avg_rech_num_action	\
8	324.125	-288.095	1	17.5	
13	1262.390	-613.310	1	7.5	
16	597.705	-113.965	1	4.0	
17	1.560	-1339.850	1	3.0	
21	1245.130	177.700	0	26.5	



	diff_rech_num	decrease_rech_num_action	avg_rech_amt_action \
8	-1.5	1	360.5
13	1.5	0	485.0
16	-6.0	1	254.0
17	-16.0	1	15.0
21	4.5	0	699.0

	diff_rech_amt	decrease_rech_amt_action
8	-76.5	1
13	-22.0	1
16	-316.0	1
17	-801.0	1
21	99.0	0

**Deriving new column decrease\_arpu\_action** This column indicates whether the average revenue per customer has decreased in the action phase than the good phase.

```
[67]: # ARUP in action phase
data['avg_arpu_action'] = (data['arpu_7'] + data['arpu_8'])/2
```

```
[68]: # Difference of good and action phase ARPU
data['diff_arpu'] = data['avg_arpu_action'] - data['arpu_6']
```

```
[69]: # Checking whether the arpu has decreased on the action month
data['decrease_arpu_action'] = np.where(data['diff_arpu'] < 0, 1, 0)
```

```
[70]: data.head()
```

```
[70]:  mobile_number  loc_og_t2o_mou  std_og_t2o_mou  loc_ic_t2o_mou  arpu_6 \
8      7001524846           0.0           0.0           0.0  378.721
13     7002191713           0.0           0.0           0.0  492.846
16     7000875565           0.0           0.0           0.0  430.975
17     7000187447           0.0           0.0           0.0  690.008
21     7002124215           0.0           0.0           0.0  514.453
```

	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6 \
8	492.223	137.362	413.69	351.03	35.08	94.66
13	205.671	593.260	501.76	108.39	534.24	413.31
16	299.869	187.894	50.51	74.01	70.61	296.29
17	18.980	25.499	1185.91	9.28	7.79	61.64
21	597.753	637.760	102.41	132.11	85.14	757.93

	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8 \
8	80.63	136.48	0.00	0.00	0.00
13	119.28	482.46	23.53	144.24	72.11
16	229.74	162.76	0.00	2.83	0.00

17	0.00	5.54	0.00	4.76	4.81
21	896.68	983.39	0.00	0.00	0.00

	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	\
8	0.00	0.00	0.00	297.13	
13	7.98	35.26	1.44	49.63	
16	0.00	17.74	0.00	42.61	
17	0.00	8.46	13.34	38.99	
21	0.00	0.00	0.00	4.48	

	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2m_mou_6	loc_og_t2m_mou_7	\
8	217.59	12.49	80.96	70.58	
13	6.19	36.01	151.13	47.28	
16	65.16	67.38	273.29	145.99	
17	0.00	0.00	58.54	0.00	
21	6.16	23.34	91.81	87.93	

	loc_og_t2m_mou_8	loc_og_t2f_mou_6	loc_og_t2f_mou_7	loc_og_t2f_mou_8	\
8	50.54	0.00	0.00	0.00	
13	294.46	4.54	0.00	23.51	
16	128.28	0.00	4.48	10.26	
17	0.00	0.00	0.00	0.00	
21	104.81	0.75	0.00	1.58	

	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_mou_6	\
8	0.0	0.0	7.15	378.09	
13	0.0	0.0	0.49	205.31	
16	0.0	0.0	0.00	315.91	
17	0.0	0.0	0.00	97.54	
21	0.0	0.0	0.00	97.04	

	loc_og_mou_7	loc_og_mou_8	std_og_t2t_mou_6	std_og_t2t_mou_7	\
8	288.18	63.04	116.56	133.43	
13	53.48	353.99	446.41	85.98	
16	215.64	205.93	7.89	2.58	
17	0.00	0.00	1146.91	0.81	
21	94.09	129.74	97.93	125.94	

	std_og_t2t_mou_8	std_og_t2m_mou_6	std_og_t2m_mou_7	std_og_t2m_mou_8	\
8	22.58	13.69	10.04	75.69	
13	498.23	255.36	52.94	156.94	
16	3.23	22.99	64.51	18.29	
17	0.00	1.55	0.00	0.00	
21	61.79	665.36	808.74	876.99	

	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2c_mou_6	\
8	0.0	0.0	0.0	0.0	

13	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0
21	0.0	0.0	0.0	0.0

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_mou_6	std_og_mou_7	\
8	0.0	0.0	130.26	143.48	
13	0.0	0.0	701.78	138.93	
16	0.0	0.0	30.89	67.09	
17	0.0	0.0	1148.46	0.81	
21	0.0	0.0	763.29	934.69	

	std_og_mou_8	isd_og_mou_6	isd_og_mou_7	isd_og_mou_8	spl_og_mou_6	\
8	98.28	0.0	0.0	0.00	0.00	
13	655.18	0.0	0.0	1.29	0.00	
16	21.53	0.0	0.0	0.00	0.00	
17	0.00	0.0	0.0	0.00	2.58	
21	938.79	0.0	0.0	0.00	0.00	

	spl_og_mou_7	spl_og_mou_8	og_others_6	og_others_7	og_others_8	\
8	0.00	10.23	0.00	0.0	0.0	
13	0.00	4.78	0.00	0.0	0.0	
16	3.26	5.91	0.00	0.0	0.0	
17	0.00	0.00	0.93	0.0	0.0	
21	0.00	0.00	0.00	0.0	0.0	

	total_og_mou_6	total_og_mou_7	total_og_mou_8	loc_ic_t2t_mou_6	\
8	508.36	431.66	171.56	23.84	
13	907.09	192.41	1015.26	67.88	
16	346.81	286.01	233.38	41.33	
17	1249.53	0.81	0.00	34.54	
21	860.34	1028.79	1068.54	2.48	

	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	\
8	9.84	0.31	57.58	13.98	
13	7.58	52.58	142.88	18.53	
16	71.44	28.89	226.81	149.69	
17	0.00	0.00	47.41	2.31	
21	10.19	19.54	118.23	74.63	

	loc_ic_t2m_mou_8	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	\
8	15.48	0.00	0.00	0.00	
13	195.18	4.81	0.00	7.49	
16	150.16	8.71	8.68	32.71	
17	0.00	0.00	0.00	0.00	
21	129.16	4.61	2.84	10.39	

	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	std_ic_t2t_mou_6	\
8	81.43	23.83	15.79	0.00	
13	215.58	26.11	255.26	115.68	
16	276.86	229.83	211.78	68.79	
17	81.96	2.31	0.00	8.63	
21	125.33	87.68	159.11	14.06	

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2m_mou_6	std_ic_t2m_mou_7	\
8	0.58	0.10	22.43	4.08	
13	38.29	154.58	308.13	29.79	
16	78.64	6.33	18.68	73.08	
17	0.00	0.00	1.28	0.00	
21	5.98	0.18	67.69	38.23	

	std_ic_t2m_mou_8	std_ic_t2f_mou_6	std_ic_t2f_mou_7	std_ic_t2f_mou_8	\
8	0.65	0.00	0.0	0.00	
13	317.91	0.00	0.0	1.91	
16	73.93	0.51	0.0	2.18	
17	0.00	0.00	0.0	0.00	
21	101.74	0.00	0.0	0.00	

	std_ic_t2o_mou_6	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_mou_6	\
8	0.0	0.0	0.0	22.43	
13	0.0	0.0	0.0	423.81	
16	0.0	0.0	0.0	87.99	
17	0.0	0.0	0.0	9.91	
21	0.0	0.0	0.0	81.76	

	std_ic_mou_7	std_ic_mou_8	total_ic_mou_6	total_ic_mou_7	\
8	4.66	0.75	103.86	28.49	
13	68.09	474.41	968.61	172.58	
16	151.73	82.44	364.86	381.56	
17	0.00	0.00	91.88	2.31	
21	44.21	101.93	207.09	131.89	

	total_ic_mou_8	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	isd_ic_mou_6	\
8	16.54	0.00	0.0	0.0	0.00	
13	1144.53	0.45	0.0	0.0	245.28	
16	294.46	0.00	0.0	0.0	0.00	
17	0.00	0.00	0.0	0.0	0.00	
21	261.04	0.00	0.0	0.0	0.00	

	isd_ic_mou_7	isd_ic_mou_8	ic_others_6	ic_others_7	ic_others_8	\
8	0.00	0.00	0.00	0.00	0.00	
13	62.11	393.39	83.48	16.24	21.44	
16	0.00	0.23	0.00	0.00	0.00	
17	0.00	0.00	0.00	0.00	0.00	

21	0.00	0.00	0.00	0.00	0.00
----	------	------	------	------	------

	total_rech_num_6	total_rech_num_7	total_rech_num_8	total_rech_amt_6	\
8	19	21	14	437	
13	6	4	11	507	
16	10	6	2	570	
17	19	2	4	816	
21	22	26	27	600	

	total_rech_amt_7	total_rech_amt_8	max_rech_amt_6	max_rech_amt_7	\
8	601	120	90	154	
13	253	717	110	110	
16	348	160	110	110	
17	0	30	110	0	
21	680	718	50	50	

	max_rech_amt_8	last_day_rch_amt_6	last_day_rch_amt_7	\
8	30	50	0	
13	130	110	50	
16	130	100	100	
17	30	30	0	
21	50	30	20	

	last_day_rch_amt_8	vol_2g_mb_6	vol_2g_mb_7	vol_2g_mb_8	vol_3g_mb_6	\
8	10	0.0	356.0	0.03	0.0	
13	0	0.0	0.0	0.02	0.0	
16	130	0.0	0.0	0.00	0.0	
17	0	0.0	0.0	0.00	0.0	
21	50	0.0	0.0	0.00	0.0	

	vol_3g_mb_7	vol_3g_mb_8	monthly_2g_6	monthly_2g_7	monthly_2g_8	\
8	750.95	11.94	0	1	0	
13	0.00	0.00	0	0	0	
16	0.00	0.00	0	0	0	
17	0.00	0.00	0	0	0	
21	0.00	0.00	0	0	0	

	sachet_2g_6	sachet_2g_7	sachet_2g_8	monthly_3g_6	monthly_3g_7	\
8	0	1	3	0	0	
13	0	0	3	0	0	
16	0	0	0	0	0	
17	0	0	0	0	0	
21	0	0	0	0	0	

	monthly_3g_8	sachet_3g_6	sachet_3g_7	sachet_3g_8	aon	aug_vbc_3g	\
8	0	0	0	0	315	21.03	
13	0	0	0	0	2607	0.00	

16	0	0	0	0	511	0.00
17	0	0	0	0	667	0.00
21	0	0	0	0	720	0.00

	jul_vbc_3g	jun_vbc_3g	avg_rech_amt_6_7	churn	total_mou_good	\
8	910.65	122.16	519.0	0	612.22	
13	0.00	0.00	380.0	0	1875.70	
16	2.45	21.89	459.0	0	711.67	
17	0.00	0.00	408.0	0	1341.41	
21	0.00	0.00	640.0	0	1067.43	

	avg_mou_action	diff_mou	decrease_mou_action	avg_rech_num_action	\
8	324.125	-288.095	1	17.5	
13	1262.390	-613.310	1	7.5	
16	597.705	-113.965	1	4.0	
17	1.560	-1339.850	1	3.0	
21	1245.130	177.700	0	26.5	

	diff_rech_num	decrease_rech_num_action	avg_rech_amt_action	\
8	-1.5	1	360.5	
13	1.5	0	485.0	
16	-6.0	1	254.0	
17	-16.0	1	15.0	
21	4.5	0	699.0	

	diff_rech_amt	decrease_rech_amt_action	avg_arpu_action	diff_arpu	\
8	-76.5	1	314.7925	-63.9285	
13	-22.0	1	399.4655	-93.3805	
16	-316.0	1	243.8815	-187.0935	
17	-801.0	1	22.2395	-667.7685	
21	99.0	0	617.7565	103.3035	

	decrease_arpu_action
8	1
13	1
16	1
17	1
21	0

**Deriving new column decrease\_vbc\_action** This column indicates whether the volume based cost of the customer has decreased in the action phase than the good phase.

```
[71]: # VBC in action phase
data['avg_vbc_3g_action'] = (data['jul_vbc_3g'] + data['aug_vbc_3g'])/2
```

```
[72]: # Difference of good and action phase VBC
data['diff_vbc'] = data['avg_vbc_3g_action'] - data['jun_vbc_3g']
```

```
[73]: # Checking whether the VBC has decreased on the action month
data['decrease_vbc_action'] = np.where(data['diff_vbc'] < 0 , 1, 0)
```

```
[74]: data.head()
```

```
[74]:  mobile_number  loc_og_t2o_mou  std_og_t2o_mou  loc_ic_t2o_mou  arpu_6  \
8      7001524846             0.0             0.0             0.0  378.721
13     7002191713             0.0             0.0             0.0  492.846
16     7000875565             0.0             0.0             0.0  430.975
17     7000187447             0.0             0.0             0.0  690.008
21     7002124215             0.0             0.0             0.0  514.453

      arpu_7  arpu_8  onnet_mou_6  onnet_mou_7  onnet_mou_8  offnet_mou_6  \
8  492.223  137.362      413.69      351.03       35.08       94.66
13  205.671  593.260      501.76      108.39      534.24      413.31
16  299.869  187.894       50.51       74.01       70.61      296.29
17   18.980   25.499     1185.91        9.28        7.79       61.64
21  597.753  637.760      102.41      132.11      85.14      757.93

      offnet_mou_7  offnet_mou_8  roam_ic_mou_6  roam_ic_mou_7  roam_ic_mou_8  \
8          80.63      136.48          0.00          0.00          0.00
13         119.28      482.46          23.53         144.24          72.11
16         229.74      162.76          0.00          2.83          0.00
17          0.00        5.54          0.00          4.76          4.81
21         896.68      983.39          0.00          0.00          0.00

      roam_og_mou_6  roam_og_mou_7  roam_og_mou_8  loc_og_t2t_mou_6  \
8          0.00          0.00          0.00          297.13
13          7.98          35.26          1.44          49.63
16          0.00          17.74          0.00          42.61
17          0.00          8.46          13.34          38.99
21          0.00          0.00          0.00          4.48

      loc_og_t2t_mou_7  loc_og_t2t_mou_8  loc_og_t2m_mou_6  loc_og_t2m_mou_7  \
8          217.59          12.49          80.96          70.58
13           6.19          36.01          151.13          47.28
16          65.16          67.38          273.29          145.99
17           0.00           0.00          58.54           0.00
21           6.16          23.34          91.81          87.93

      loc_og_t2m_mou_8  loc_og_t2f_mou_6  loc_og_t2f_mou_7  loc_og_t2f_mou_8  \
8          50.54          0.00          0.00          0.00
13         294.46          4.54          0.00          23.51
16         128.28          0.00          4.48          10.26
17           0.00          0.00          0.00          0.00
21         104.81          0.75          0.00          1.58
```

	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_mou_6	\
8	0.0	0.0	7.15	378.09	
13	0.0	0.0	0.49	205.31	
16	0.0	0.0	0.00	315.91	
17	0.0	0.0	0.00	97.54	
21	0.0	0.0	0.00	97.04	

	loc_og_mou_7	loc_og_mou_8	std_og_t2t_mou_6	std_og_t2t_mou_7	\
8	288.18	63.04	116.56	133.43	
13	53.48	353.99	446.41	85.98	
16	215.64	205.93	7.89	2.58	
17	0.00	0.00	1146.91	0.81	
21	94.09	129.74	97.93	125.94	

	std_og_t2t_mou_8	std_og_t2m_mou_6	std_og_t2m_mou_7	std_og_t2m_mou_8	\
8	22.58	13.69	10.04	75.69	
13	498.23	255.36	52.94	156.94	
16	3.23	22.99	64.51	18.29	
17	0.00	1.55	0.00	0.00	
21	61.79	665.36	808.74	876.99	

	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2c_mou_6	\
8	0.0	0.0	0.0	0.0	
13	0.0	0.0	0.0	0.0	
16	0.0	0.0	0.0	0.0	
17	0.0	0.0	0.0	0.0	
21	0.0	0.0	0.0	0.0	

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_mou_6	std_og_mou_7	\
8	0.0	0.0	130.26	143.48	
13	0.0	0.0	701.78	138.93	
16	0.0	0.0	30.89	67.09	
17	0.0	0.0	1148.46	0.81	
21	0.0	0.0	763.29	934.69	

	std_og_mou_8	isd_og_mou_6	isd_og_mou_7	isd_og_mou_8	spl_og_mou_6	\
8	98.28	0.0	0.0	0.00	0.00	
13	655.18	0.0	0.0	1.29	0.00	
16	21.53	0.0	0.0	0.00	0.00	
17	0.00	0.0	0.0	0.00	2.58	
21	938.79	0.0	0.0	0.00	0.00	

	spl_og_mou_7	spl_og_mou_8	og_others_6	og_others_7	og_others_8	\
8	0.00	10.23	0.00	0.0	0.0	
13	0.00	4.78	0.00	0.0	0.0	
16	3.26	5.91	0.00	0.0	0.0	
17	0.00	0.00	0.93	0.0	0.0	



21	0.00	0.00	0.00	0.0	0.0
----	------	------	------	-----	-----

	total_og_mou_6	total_og_mou_7	total_og_mou_8	loc_ic_t2t_mou_6	\
8	508.36	431.66	171.56	23.84	
13	907.09	192.41	1015.26	67.88	
16	346.81	286.01	233.38	41.33	
17	1249.53	0.81	0.00	34.54	
21	860.34	1028.79	1068.54	2.48	

	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	\
8	9.84	0.31	57.58	13.98	
13	7.58	52.58	142.88	18.53	
16	71.44	28.89	226.81	149.69	
17	0.00	0.00	47.41	2.31	
21	10.19	19.54	118.23	74.63	

	loc_ic_t2m_mou_8	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	\
8	15.48	0.00	0.00	0.00	
13	195.18	4.81	0.00	7.49	
16	150.16	8.71	8.68	32.71	
17	0.00	0.00	0.00	0.00	
21	129.16	4.61	2.84	10.39	

	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	std_ic_t2t_mou_6	\
8	81.43	23.83	15.79	0.00	
13	215.58	26.11	255.26	115.68	
16	276.86	229.83	211.78	68.79	
17	81.96	2.31	0.00	8.63	
21	125.33	87.68	159.11	14.06	

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2m_mou_6	std_ic_t2m_mou_7	\
8	0.58	0.10	22.43	4.08	
13	38.29	154.58	308.13	29.79	
16	78.64	6.33	18.68	73.08	
17	0.00	0.00	1.28	0.00	
21	5.98	0.18	67.69	38.23	

	std_ic_t2m_mou_8	std_ic_t2f_mou_6	std_ic_t2f_mou_7	std_ic_t2f_mou_8	\
8	0.65	0.00	0.0	0.00	
13	317.91	0.00	0.0	1.91	
16	73.93	0.51	0.0	2.18	
17	0.00	0.00	0.0	0.00	
21	101.74	0.00	0.0	0.00	

	std_ic_t2o_mou_6	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_mou_6	\
8	0.0	0.0	0.0	22.43	
13	0.0	0.0	0.0	423.81	

16	0.0	0.0	0.0	87.99
17	0.0	0.0	0.0	9.91
21	0.0	0.0	0.0	81.76

	std_ic_mou_7	std_ic_mou_8	total_ic_mou_6	total_ic_mou_7	\
8	4.66	0.75	103.86	28.49	
13	68.09	474.41	968.61	172.58	
16	151.73	82.44	364.86	381.56	
17	0.00	0.00	91.88	2.31	
21	44.21	101.93	207.09	131.89	

	total_ic_mou_8	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	isd_ic_mou_6	\
8	16.54	0.00	0.0	0.0	0.00	
13	1144.53	0.45	0.0	0.0	245.28	
16	294.46	0.00	0.0	0.0	0.00	
17	0.00	0.00	0.0	0.0	0.00	
21	261.04	0.00	0.0	0.0	0.00	

	isd_ic_mou_7	isd_ic_mou_8	ic_others_6	ic_others_7	ic_others_8	\
8	0.00	0.00	0.00	0.00	0.00	
13	62.11	393.39	83.48	16.24	21.44	
16	0.00	0.23	0.00	0.00	0.00	
17	0.00	0.00	0.00	0.00	0.00	
21	0.00	0.00	0.00	0.00	0.00	

	total_rech_num_6	total_rech_num_7	total_rech_num_8	total_rech_amt_6	\
8	19	21	14	437	
13	6	4	11	507	
16	10	6	2	570	
17	19	2	4	816	
21	22	26	27	600	

	total_rech_amt_7	total_rech_amt_8	max_rech_amt_6	max_rech_amt_7	\
8	601	120	90	154	
13	253	717	110	110	
16	348	160	110	110	
17	0	30	110	0	
21	680	718	50	50	

	max_rech_amt_8	last_day_rch_amt_6	last_day_rch_amt_7	\
8	30	50	0	
13	130	110	50	
16	130	100	100	
17	30	30	0	
21	50	30	20	

last_day_rch_amt_8	vol_2g_mb_6	vol_2g_mb_7	vol_2g_mb_8	vol_3g_mb_6	\
--------------------	-------------	-------------	-------------	-------------	---

8	10	0.0	356.0	0.03	0.0
13	0	0.0	0.0	0.02	0.0
16	130	0.0	0.0	0.00	0.0
17	0	0.0	0.0	0.00	0.0
21	50	0.0	0.0	0.00	0.0

	vol_3g_mb_7	vol_3g_mb_8	monthly_2g_6	monthly_2g_7	monthly_2g_8	\
8	750.95	11.94	0	1	0	
13	0.00	0.00	0	0	0	
16	0.00	0.00	0	0	0	
17	0.00	0.00	0	0	0	
21	0.00	0.00	0	0	0	

	sachet_2g_6	sachet_2g_7	sachet_2g_8	monthly_3g_6	monthly_3g_7	\
8	0	1	3	0	0	
13	0	0	3	0	0	
16	0	0	0	0	0	
17	0	0	0	0	0	
21	0	0	0	0	0	

	monthly_3g_8	sachet_3g_6	sachet_3g_7	sachet_3g_8	aon	aug_vbc_3g	\
8	0	0	0	0	315	21.03	
13	0	0	0	0	2607	0.00	
16	0	0	0	0	511	0.00	
17	0	0	0	0	667	0.00	
21	0	0	0	0	720	0.00	

	jul_vbc_3g	jun_vbc_3g	avg_rech_amt_6_7	churn	total_mou_good	\
8	910.65	122.16	519.0	0	612.22	
13	0.00	0.00	380.0	0	1875.70	
16	2.45	21.89	459.0	0	711.67	
17	0.00	0.00	408.0	0	1341.41	
21	0.00	0.00	640.0	0	1067.43	

	avg_mou_action	diff_mou	decrease_mou_action	avg_rech_num_action	\
8	324.125	-288.095		1	17.5
13	1262.390	-613.310		1	7.5
16	597.705	-113.965		1	4.0
17	1.560	-1339.850		1	3.0
21	1245.130	177.700		0	26.5

	diff_rech_num	decrease_rech_num_action	avg_rech_amt_action	\
8	-1.5		1	360.5
13	1.5		0	485.0
16	-6.0		1	254.0
17	-16.0		1	15.0
21	4.5		0	699.0

	diff_rech_amt	decrease_rech_amt_action	avg_arpu_action	diff_arpu	\
8	-76.5	1	314.7925	-63.9285	
13	-22.0	1	399.4655	-93.3805	
16	-316.0	1	243.8815	-187.0935	
17	-801.0	1	22.2395	-667.7685	
21	99.0	0	617.7565	103.3035	

	decrease_arpu_action	avg_vbc_3g_action	diff_vbc	decrease_vbc_action
8	1	465.840	343.680	0
13	1	0.000	0.000	0
16	1	1.225	-20.665	1
17	1	0.000	0.000	0
21	0	0.000	0.000	0

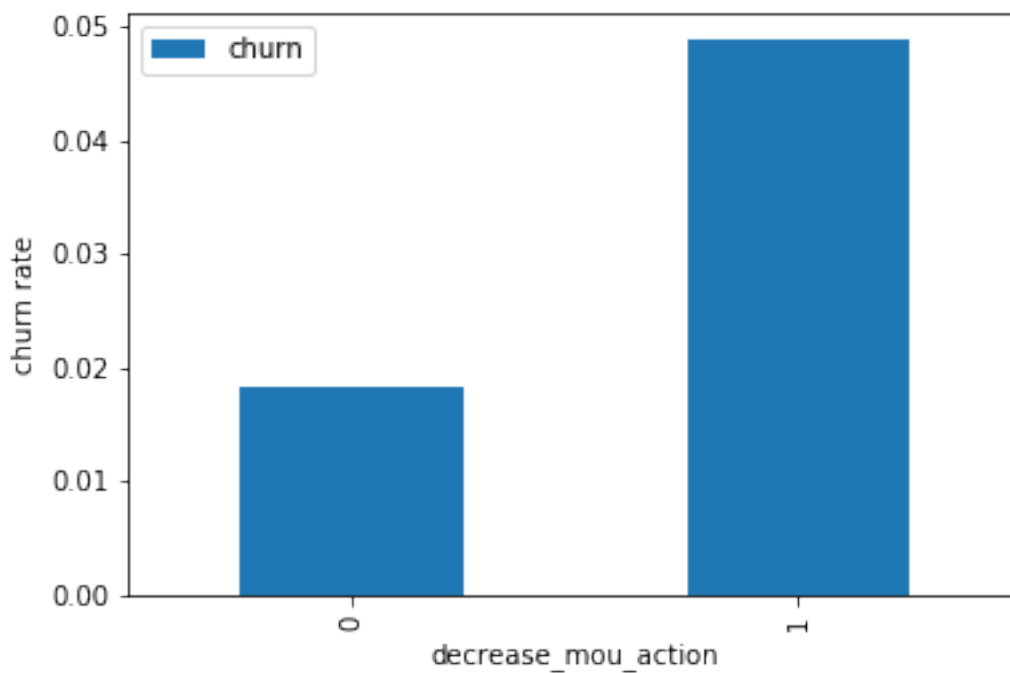
### 1.3 EDA

#### 1.3.1 Univariate analysis

Churn rate on the basis whether the customer decreased her/his MOU in action month

```
[75]: # Converting churn column to int in order to do aggfunc in the pivot table
data['churn'] = data['churn'].astype('int64')
```

```
[76]: data.pivot_table(values='churn', index='decrease_mou_action', aggfunc='mean').
      ↪ plot.bar()
plt.ylabel('churn rate')
plt.show()
```

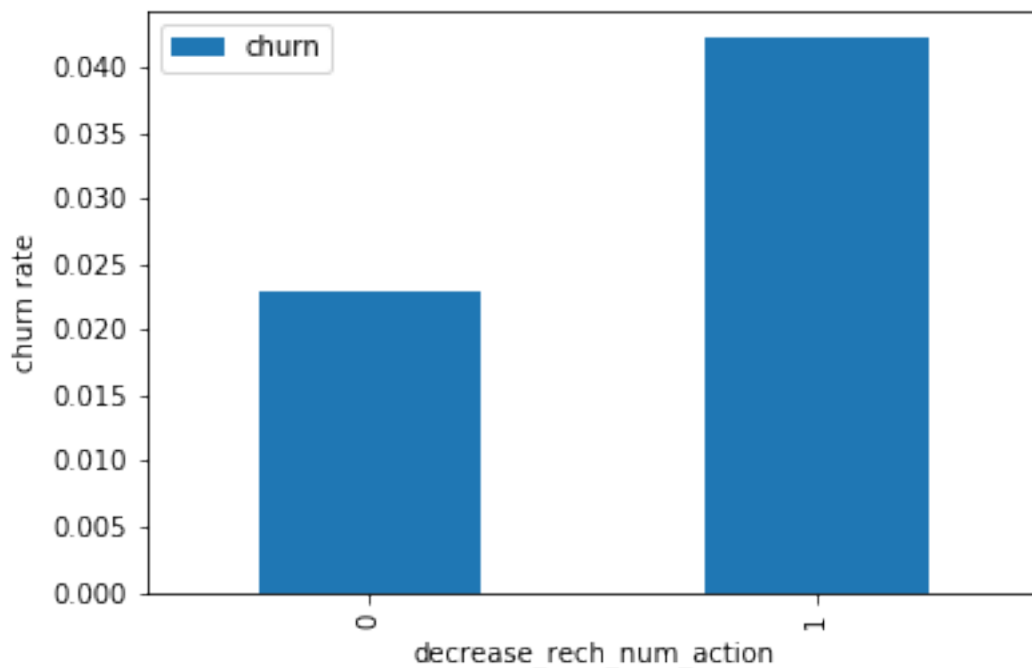


### *Analysis*

We can see that the churn rate is more for the customers, whose minutes of usage(mou) decreased in the action phase than the good phase.

**Churn rate on the basis whether the customer decreased her/his number of recharge in action month**

```
[77]: data.pivot_table(values='churn', index='decrease_rech_num_action',  
      ↪aggfunc='mean').plot.bar()  
plt.ylabel('churn rate')  
plt.show()
```

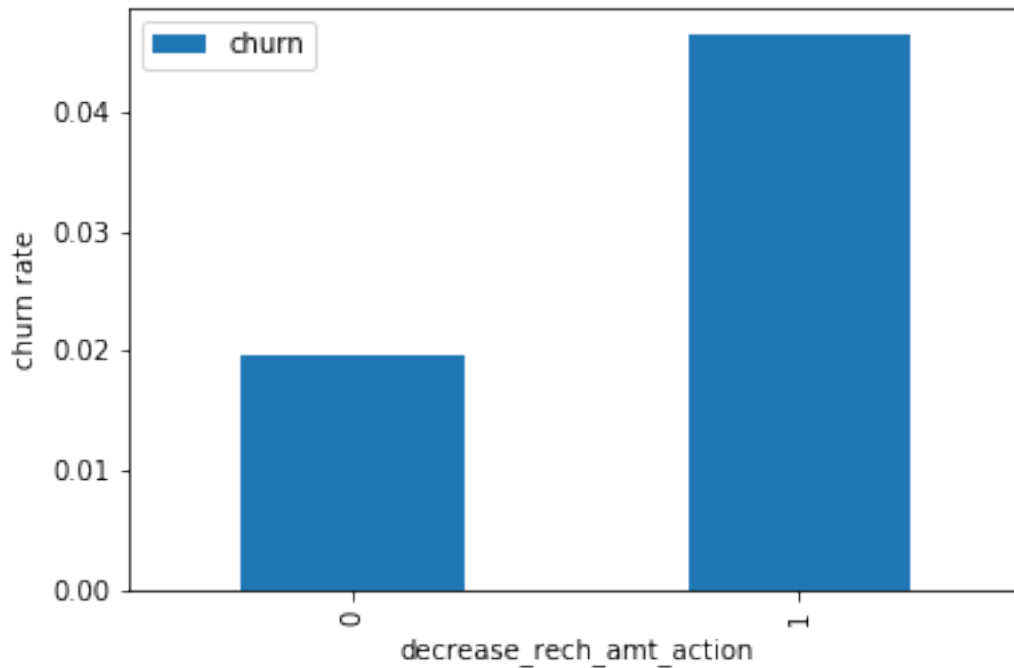


### *Analysis*

As expected, the churn rate is more for the customers, whose number of recharge in the action phase is lesser than the number in good phase.

**Churn rate on the basis whether the customer decreased her/his amount of recharge in action month**

```
[78]: data.pivot_table(values='churn', index='decrease_rech_amt_action',  
      ↪aggfunc='mean').plot.bar()  
plt.ylabel('churn rate')  
plt.show()
```

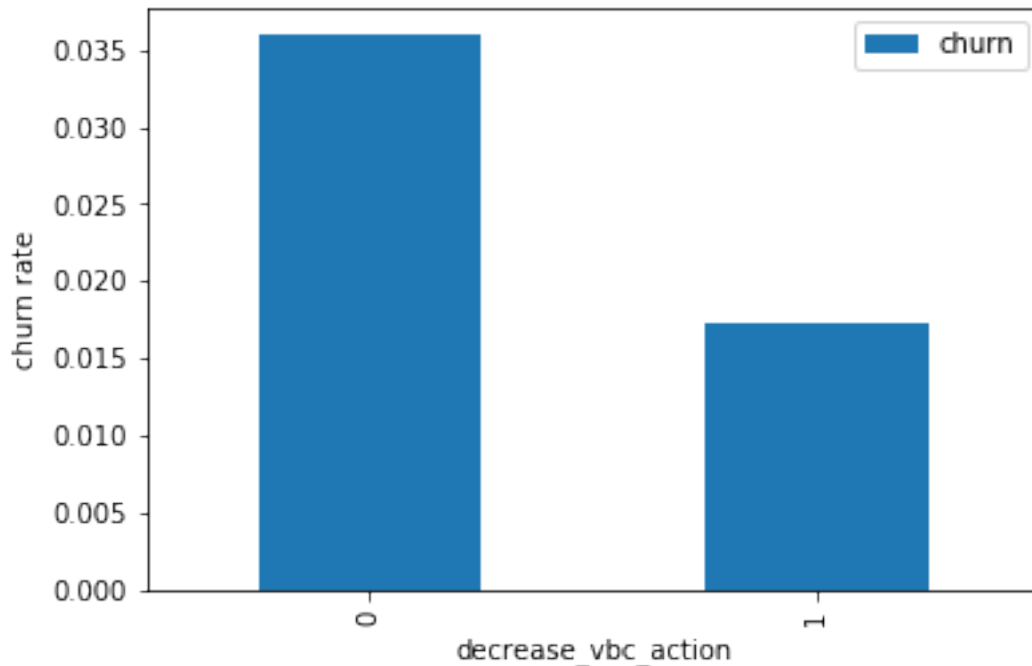


### *Analysis*

Here also we see the same behaviour. The churn rate is more for the customers, whose amount of recharge in the action phase is lesser than the amount in good phase.

**Churn rate on the basis whether the customer decreased her/his volume based cost in action month**

```
[79]: data.pivot_table(values='churn', index='decrease_vbc_action', aggfunc='mean').  
      ↪ plot.bar()  
      plt.ylabel('churn rate')  
      plt.show()
```



### Analysis

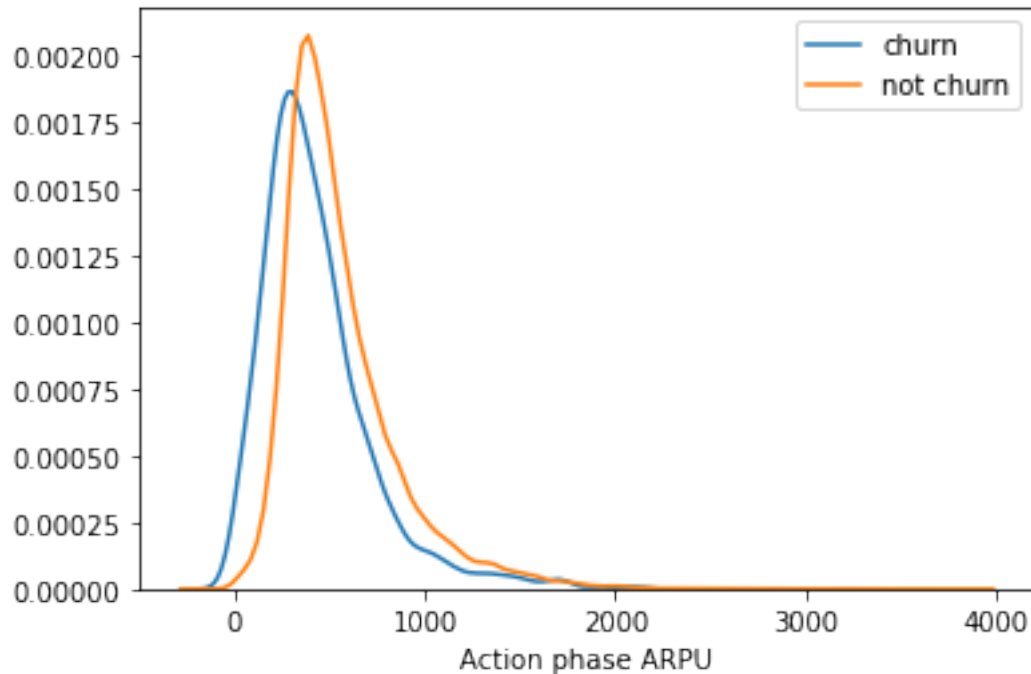
Here we see the expected result. The churn rate is more for the customers, whose volume based cost in action month is increased. That means the customers do not do the monthly recharge more when they are in the action phase.

**Analysis of the average revenue per customer (churn and not churn) in the action phase**

```
[80]: # Creating churn dataframe
data_churn = data[data['churn'] == 1]
# Creating not churn dataframe
data_non_churn = data[data['churn'] == 0]

[81]: # Distribution plot
ax = sns.distplot(data_churn['avg_arpu_action'], label='churn', hist=False)
ax = sns.distplot(data_non_churn['avg_arpu_action'], label='not_
      ↪churn', hist=False)
ax.set(xlabel='Action phase ARPU')
```

```
[81]: [Text(0.5, 0, 'Action phase ARPU')]
```



Average revenue per user (ARPU) for the churned customers is mostly densed on the 0 to 900. The higher ARPU customers are less likely to be churned.

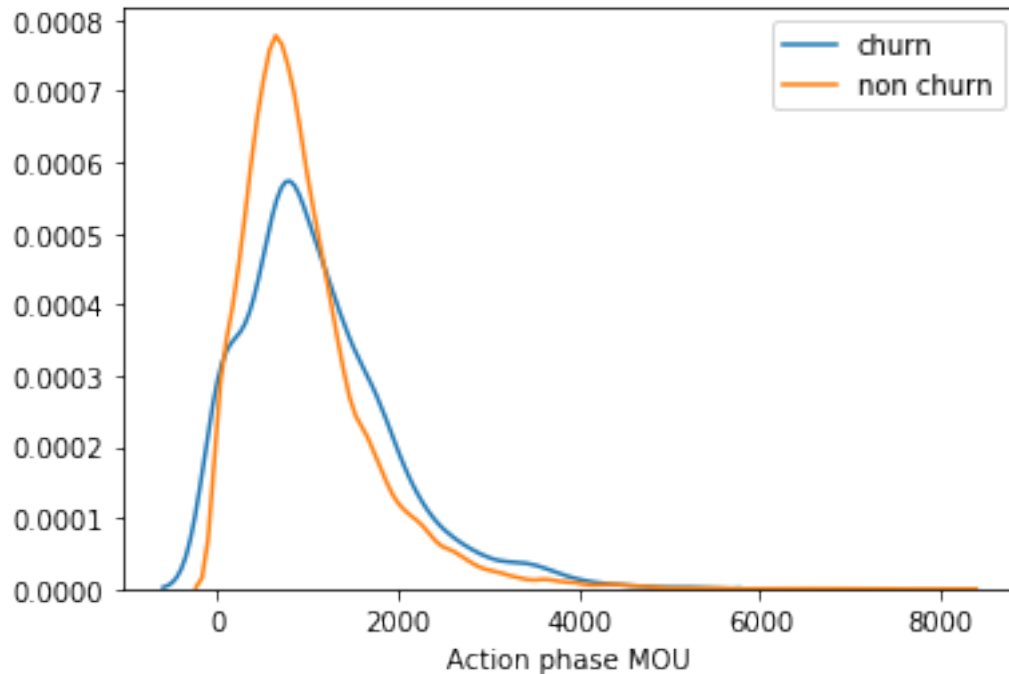
ARPU for the not churned customers is mostly densed on the 0 to 1000.

#### Analysis of the minutes of usage MOU (churn and not churn) in the action phase

```
[82]: # Distribution plot
ax = sns.distplot(data_churn['total_mou_good'],label='churn',hist=False)
ax = sns.distplot(data_non_churn['total_mou_good'],label='non churn',hist=False)
ax.set(xlabel='Action phase MOU')
```

```
[82]: [Text(0.5, 0, 'Action phase MOU')]
```



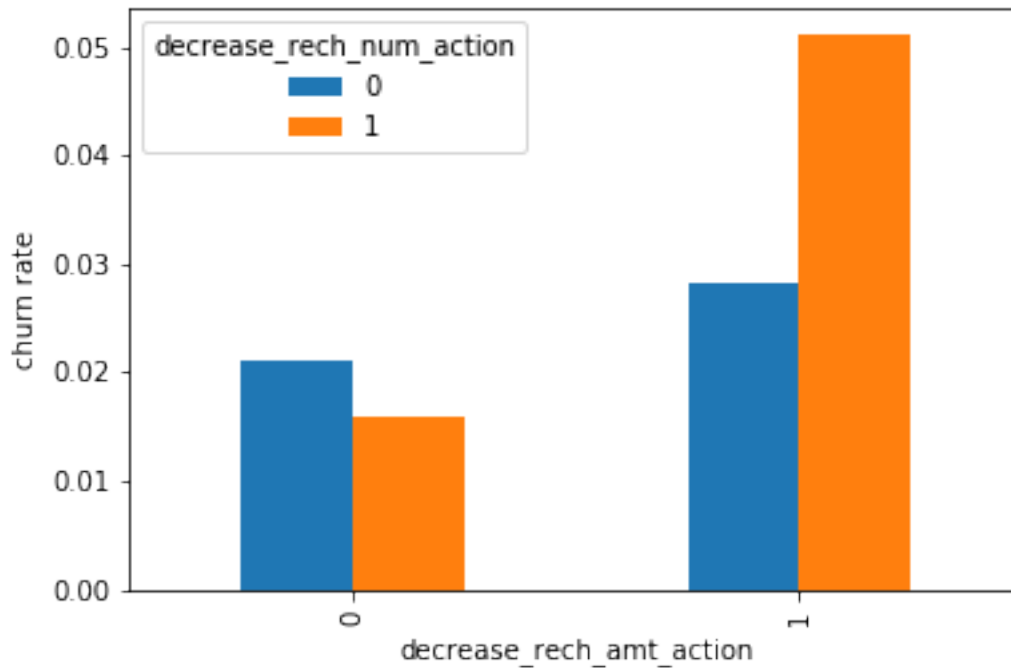


Minutes of usage(MOU) of the churn customers is mostly populated on the 0 to 2500 range. Higher the MOU, lesser the churn probability.

### 1.3.2 Bivariate analysis

Analysis of churn rate by the decreasing recharge amount and number of recharge in the action phase

```
[83]: data.pivot_table(values='churn', index='decrease_rech_amt_action',
    ↪columns='decrease_rech_num_action', aggfunc='mean').plot.bar()
plt.ylabel('churn rate')
plt.show()
```

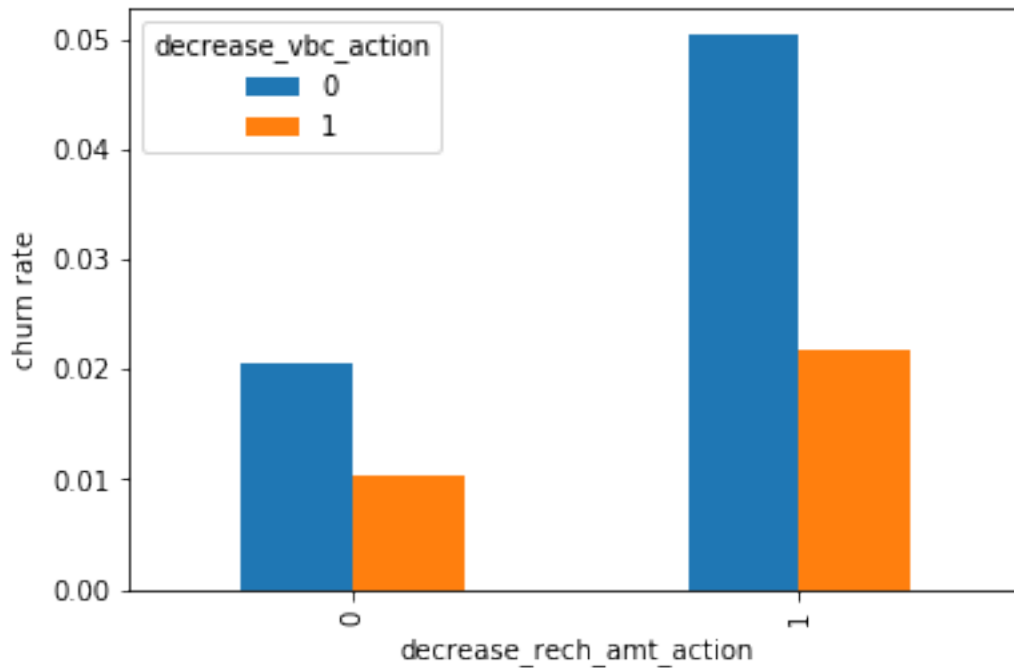


### *Analysis*

We can see from the above plot, that the churn rate is more for the customers, whose recharge amount as well as number of recharge have decreased in the action phase than the good phase.

**Analysis of churn rate by the decreasing recharge amount and volume based cost in the action phase**

```
[84]: data.pivot_table(values='churn', index='decrease_rech_amt_action',  
    ↪columns='decrease_vbc_action', aggfunc='mean').plot.bar()  
plt.ylabel('churn rate')  
plt.show()
```

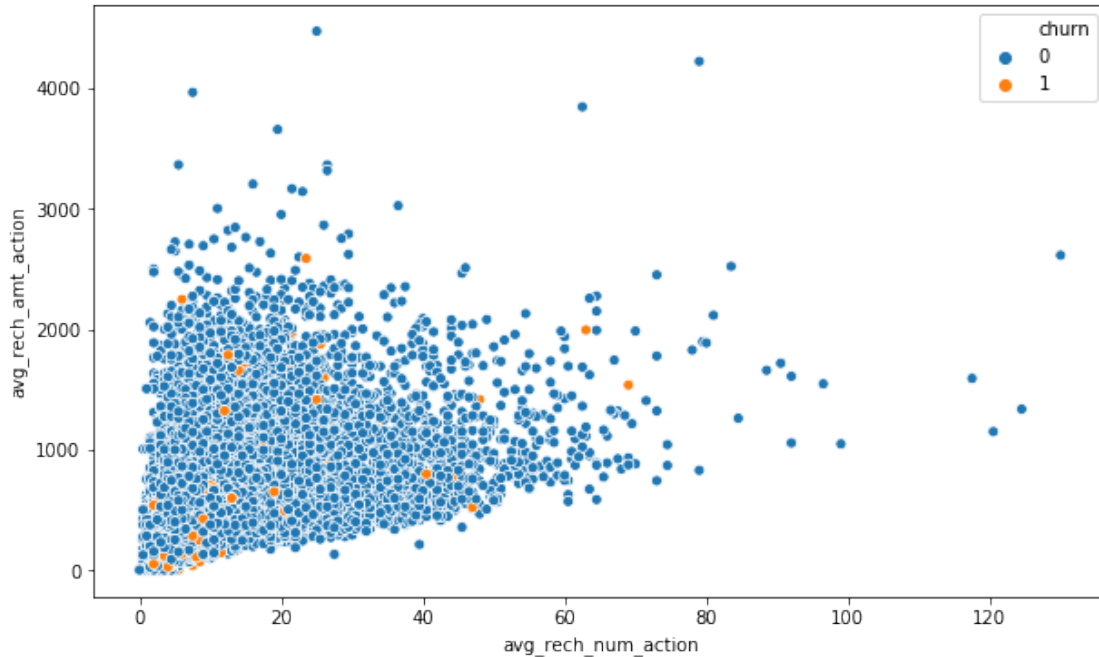


### *Analysis*

Here, also we can see that the churn rate is more for the customers, whose recharge amount is decreased along with the volume based cost is increased in the action month.

### **Analysis of recharge amount and number of recharge in action month**

```
[85]: plt.figure(figsize=(10,6))
      ax = sns.scatterplot('avg_rech_num_action', 'avg_rech_amt_action', hue='churn', data=data)
```



### Analysis

We can see from the above pattern that the recharge number and the recharge amount are mostly propotional. More the number of recharge, more the amount of the recharge.

### Dropping few derived columns, which are not required in further analysis

```
[86]: data = data.  
      ↪ drop(['total_mou_good', 'avg_mou_action', 'diff_mou', 'avg_rech_num_action', 'diff_rech_num', 'a  
      ↪  
      ↪ 'diff_rech_amt', 'avg_arpu_action', 'diff_arpu', 'avg_vbc_3g_action', 'diff_vbc', 'avg_rech_amt_  
      ↪ axis=1)
```

## 1.4 Train-Test Split

```
[87]: # Import library  
      from sklearn.model_selection import train_test_split
```

```
[88]: # Putting feature variables into X  
      X = data.drop(['mobile_number', 'churn'], axis=1)
```

```
[89]: # Putting target variable to y  
      y = data['churn']
```

```
[90]: # Splitting data into train and test set 80:20
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.8,
↪test_size=0.2, random_state=100)
```

### 1.4.1 Dealing with data imbalance

We are creating synthetic samples by doing upsampling using SMOTE(Synthetic Minority Over-sampling Technique).

```
[91]: # Importing SMOTE
from imblearn.over_sampling import SMOTE
```

```
[92]: # Instantiate SMOTE
sm = SMOTE(random_state=27)
```

```
[93]: # Fitting SMOTE to the train set
X_train, y_train = sm.fit_sample(X_train, y_train)
```

### 1.4.2 Feature Scaling

```
[94]: # Standardization method
from sklearn.preprocessing import StandardScaler
```

```
[95]: # Instantiate the Scaler
scaler = StandardScaler()
```

```
[97]: # List of the numeric columns
cols_scale = X_train.columns.to_list()
# Removing the derived binary columns
cols_scale.remove('decrease_mou_action')
cols_scale.remove('decrease_rech_num_action')
cols_scale.remove('decrease_rech_amt_action')
cols_scale.remove('decrease_arpu_action')
cols_scale.remove('decrease_vbc_action')
```

```
[98]: # Fit the data into scaler and transform
X_train[cols_scale] = scaler.fit_transform(X_train[cols_scale])
```

```
[99]: X_train.head()
```

```
[99]:   loc Og_t2o_mou  std Og_t2o_mou  loc Ic_t2o_mou   arpu_6   arpu_7 \
0          0.0          0.0          0.0  0.140777 -0.522792
1          0.0          0.0          0.0 -1.427243  4.428047
2          0.0          0.0          0.0 -0.222751  0.543206
3          0.0          0.0          0.0 -0.911173  0.842273
4          0.0          0.0          0.0  0.271356  0.247684

   arpu_8  onnet_mou_6  onnet_mou_7  onnet_mou_8  offnet_mou_6 \
```

0	-0.276289	0.106540	-0.662084	-0.465777	-0.211202
1	3.254270	-0.658491	-0.236590	-0.004450	-0.776075
2	0.809117	-0.601239	-0.599206	-0.331043	-0.363395
3	0.731302	-0.702232	-0.650471	-0.458464	-0.789784
4	1.256421	-0.356392	-0.180394	0.114727	0.899204

	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8 \
0	-0.636415	0.317224	-0.254996	-0.001208	-0.235211
1	2.523985	2.732154	-0.254996	-0.253231	-0.304660
2	-0.495976	-0.028236	-0.254996	-0.253231	-0.304660
3	-0.654483	-0.519047	-0.254996	-0.253231	-0.304660
4	0.904465	1.255807	-0.231882	-0.253231	-0.304660

	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6 \
0	-0.300833	-0.374857	-0.412810	-0.263308
1	-0.300833	-0.374857	-0.431026	-0.201396
2	-0.300833	-0.374857	-0.431026	0.077694
3	-0.300833	-0.374857	-0.431026	-0.192289
4	-0.202644	-0.374857	-0.431026	0.128384

	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2m_mou_6	loc_og_t2m_mou_7 \
0	-0.311548	-0.251411	0.485770	-0.190660
1	0.270791	0.198344	-0.529474	1.106670
2	-0.095916	0.228431	0.605362	0.258376
3	-0.181513	-0.064925	-0.371787	-0.205099
4	0.784682	1.062326	1.423002	0.996094

	loc_og_t2m_mou_8	loc_og_t2f_mou_6	loc_og_t2f_mou_7	loc_og_t2f_mou_8 \
0	-0.399182	-0.256866	-0.267401	-0.244832
1	0.288951	-0.276320	-0.267401	-0.244832
2	0.908270	1.475098	0.451689	-0.131562
3	-0.251524	-0.157090	0.216496	-0.244832
4	1.845573	0.780430	1.055332	0.519904

	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	loc_og_mou_6 \
0	-0.191587	-0.267368	-0.244432	0.129144
1	-0.191587	-0.267368	-0.244432	-0.477059
2	-0.191587	-0.267368	-0.244432	0.512549
3	1.002136	2.438345	2.557369	-0.364845
4	1.811266	-0.267368	0.843143	1.025297

	loc_og_mou_7	loc_og_mou_8	std_og_t2t_mou_6	std_og_t2t_mou_7 \
0	-0.335468	-0.418749	0.254982	-0.528622
1	0.843930	0.290569	-0.570615	-0.320253
2	0.121104	0.710496	-0.618738	-0.551860
3	-0.233086	-0.212616	-0.619956	-0.570510
4	1.183543	1.843624	-0.414192	-0.474892

	std_og_t2t_mou_8	std_og_t2m_mou_6	std_og_t2m_mou_7	std_og_t2m_mou_8	\
0	-0.338018	-0.342394	-0.504282	0.650664	
1	-0.041333	-0.512504	2.294191	3.087483	
2	-0.420186	-0.617043	-0.571393	-0.416795	
3	-0.420186	-0.621707	-0.578677	-0.406309	
4	-0.327001	0.357250	0.585026	0.555984	

	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	std_og_t2c_mou_6	\
0	-0.143576	-0.139257	-0.119299	0.0	
1	-0.143576	-0.139257	-0.119299	0.0	
2	-0.143576	-0.139257	-0.067469	0.0	
3	-0.143576	-0.139257	-0.119299	0.0	
4	-0.143576	-0.139257	-0.119299	0.0	

	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_mou_6	std_og_mou_7	\
0	0.0	0.0	-0.048161	-0.731560	
1	0.0	0.0	-0.771902	1.368343	
2	0.0	0.0	-0.878705	-0.794939	
3	0.0	0.0	-0.882786	-0.813361	
4	0.0	0.0	-0.062970	0.066271	

	std_og_mou_8	isd_og_mou_6	isd_og_mou_7	isd_og_mou_8	spl_og_mou_6	\
0	0.214243	-0.080803	-0.092449	-0.061631	-0.347585	
1	2.063999	-0.080803	-0.092449	-0.061631	-0.347585	
2	-0.563412	-0.080803	-0.031701	-0.061631	-0.347585	
3	-0.557142	-0.080803	-0.092449	-0.061631	0.299948	
4	0.157380	-0.080803	-0.092449	0.132387	0.906003	

	spl_og_mou_7	spl_og_mou_8	og_others_6	og_others_7	og_others_8	\
0	-0.363159	-0.017165	-0.346191	-0.015583	-0.013735	
1	-0.363159	-0.290355	-0.346191	-0.015583	-0.013735	
2	-0.203140	0.151727	-0.346191	-0.015583	-0.013735	
3	0.639325	0.743145	-0.244436	-0.015583	-0.013735	
4	-0.251495	0.107282	-0.346191	-0.015583	-0.013735	

	total_og_mou_6	total_og_mou_7	total_og_mou_8	loc_ic_t2t_mou_6	\
0	-0.000389	-0.860412	-0.011382	-0.203981	
1	-0.970285	1.670188	1.938953	-0.410762	
2	-0.637091	-0.716013	-0.155609	-0.073331	
3	-1.012362	-0.864684	-0.569774	-0.262725	
4	0.411184	0.572929	1.014123	-0.238919	

	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2m_mou_6	loc_ic_t2m_mou_7	\
0	-0.266718	-0.242771	-0.380593	-0.272733	
1	0.193158	0.156537	-0.481723	0.744741	
2	-0.082299	0.189717	0.211940	0.166326	

3	-0.287643	-0.150724	0.157353	0.540086
4	0.483606	0.750395	-0.281606	0.384609

	loc_ic_t2m_mou_8	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	loc_ic_t2f_mou_8	\
0	-0.437571	-0.290528	-0.270877	-0.150060	
1	0.256589	-0.290528	-0.270877	-0.257696	
2	0.542595	0.223523	-0.117519	0.167136	
3	-0.095861	-0.290528	-0.268736	-0.250781	
4	0.578588	0.220005	0.304016	0.113318	

	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	std_ic_t2t_mou_6	\
0	-0.409101	-0.363983	-0.440411	-0.175106	
1	-0.583307	0.570197	0.219470	-0.215496	
2	0.142990	0.054813	0.490068	-0.215496	
3	-0.061177	0.184367	-0.172152	-0.215496	
4	-0.286414	0.556564	0.777995	-0.215496	

	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2m_mou_6	std_ic_t2m_mou_7	\
0	-0.159825	0.078711	-0.164347	0.367474	
1	-0.200464	-0.112725	-0.355157	0.100763	
2	-0.200464	-0.187265	-0.361304	-0.256979	
3	-0.200464	-0.187265	-0.361304	-0.343715	
4	-0.200464	0.108490	-0.066471	1.099027	

	std_ic_t2m_mou_8	std_ic_t2f_mou_6	std_ic_t2f_mou_7	std_ic_t2f_mou_8	\
0	-0.117454	-0.135479	-0.137327	-0.110642	
1	-0.034777	-0.135479	-0.137327	-0.110642	
2	-0.217027	-0.135479	-0.137327	-0.109904	
3	-0.229338	-0.135479	-0.137327	-0.110642	
4	0.087246	0.078665	-0.072592	0.078362	

	std_ic_t2o_mou_6	std_ic_t2o_mou_7	std_ic_t2o_mou_8	std_ic_mou_6	\
0	0.0	0.0	0.0	-0.234904	
1	0.0	0.0	0.0	-0.386264	
2	0.0	0.0	0.0	-0.390310	
3	0.0	0.0	0.0	-0.390310	
4	0.0	0.0	0.0	-0.171917	

	std_ic_mou_7	std_ic_mou_8	total_ic_mou_6	total_ic_mou_7	total_ic_mou_8	\
0	0.121332	-0.064154	-0.475564	-0.287010	-0.420829	
1	-0.078694	-0.096335	-0.688082	0.417278	0.125859	
2	-0.312284	-0.272135	-0.073424	-0.106086	0.290685	
3	-0.368919	-0.281605	-0.248992	-0.029566	-0.273184	
4	0.581141	0.130311	-0.108798	2.215081	2.220000	

	spl_ic_mou_6	spl_ic_mou_7	spl_ic_mou_8	isd_ic_mou_6	isd_ic_mou_7	\
0	-0.366516	-0.089786	-0.192624	-0.151655	-0.153778	



1	-0.366516	-0.089786	-0.192624	-0.151655	-0.153778
2	-0.366516	-0.089786	-0.192624	-0.132791	-0.099984
3	-0.366516	0.968997	-0.192624	-0.151655	-0.153778
4	-0.366516	-0.089786	-0.192624	1.103151	4.262216

	isd_ic_mou_8	ic_others_6	ic_others_7	ic_others_8	total_rech_num_6 \
0	-0.126576	-0.099745	-0.121704	-0.081491	0.192736
1	-0.126576	-0.099745	-0.121704	-0.081491	-0.738325
2	-0.126576	-0.099745	-0.121704	-0.081491	-0.738325
3	-0.126576	-0.099745	-0.121704	-0.081491	-0.272794
4	4.608310	0.746998	26.877658	25.149134	-0.738325

	total_rech_num_7	total_rech_num_8	total_rech_amt_6	total_rech_amt_7 \
0	-0.444988	0.305289	0.044172	-0.726027
1	4.142873	2.933529	-1.364090	4.102682
2	-0.327351	-0.195328	-0.110493	0.728436
3	0.378474	0.555597	-0.946224	0.693869
4	-0.209713	0.555597	-0.368267	0.175368

	total_rech_amt_8	max_rech_amt_6	max_rech_amt_7	max_rech_amt_8 \
0	-0.235478	0.054992	0.023937	0.029739
1	3.350107	-0.748908	-0.386255	-0.054702
2	0.772451	0.039532	0.023937	0.198621
3	0.803137	0.054992	0.768359	0.966264
4	1.225665	-0.207821	-0.158371	0.029739

	last_day_rch_amt_6	last_day_rch_amt_7	last_day_rch_amt_8	vol_2g_mb_6 \
0	0.601511	-0.811577	-0.626096	-0.094017
1	-0.405085	-0.350629	-0.066907	-0.245535
2	0.272431	0.386888	0.565618	-0.077862
3	-0.598662	-0.535008	-0.351085	-0.059437
4	0.272431	0.386888	0.565618	-0.245535

	vol_2g_mb_7	vol_2g_mb_8	vol_3g_mb_6	vol_3g_mb_7	vol_3g_mb_8 \
0	0.696113	1.750783	0.510634	1.202971	-0.241652
1	-0.235847	-0.207939	-0.262491	-0.274601	-0.249913
2	-0.034247	0.104903	0.950720	1.994409	1.671342
3	-0.040569	-0.027155	2.610032	5.767468	4.000137
4	-0.235847	-0.207939	-0.262491	-0.274601	-0.249913

	monthly_2g_6	monthly_2g_7	monthly_2g_8	sachet_2g_6	sachet_2g_7 \
0	3.236849	3.104207	-0.232664	4.023237	2.358097
1	-0.246650	-0.251375	-0.232664	-0.255793	-0.269796
2	-0.246650	3.104207	-0.232664	0.457379	1.044151
3	3.236849	-0.251375	-0.232664	-0.255793	-0.269796
4	-0.246650	-0.251375	-0.232664	-0.255793	-0.269796

	sachet_2g_8	monthly_3g_6	monthly_3g_7	monthly_3g_8	sachet_3g_6	\
0	2.447476	-0.224183	-0.221779	-0.216364	-0.141182	
1	-0.268245	-0.224183	-0.221779	-0.216364	-0.141182	
2	1.089616	-0.224183	-0.221779	-0.216364	1.315163	
3	-0.268245	2.171393	9.083717	4.618685	-0.141182	
4	-0.268245	-0.224183	-0.221779	-0.216364	-0.141182	

	sachet_3g_7	sachet_3g_8	aon	aug_vbc_3g	jul_vbc_3g	jun_vbc_3g	\
0	-0.136208	-0.113882	-0.361238	-0.236209	-0.265392	0.110582	
1	-0.136208	-0.113882	-0.790173	-0.255884	-0.265392	-0.259366	
2	2.575301	2.526725	1.571302	3.307334	2.691063	1.700218	
3	-0.136208	-0.113882	-0.951024	-0.255884	-0.265392	-0.259366	
4	-0.136208	-0.113882	-0.519757	-0.255884	-0.265392	-0.259366	

	decrease_mou_action	decrease_rech_num_action	decrease_rech_amt_action	\
0	1	1	1	
1	0	0	0	
2	1	0	0	
3	0	0	0	
4	0	0	0	

	decrease_arpu_action	decrease_vbc_action
0	1	1
1	0	0
2	0	0
3	0	0
4	0	0

**Scaling the test set** We don't fit scaler on the test set. We only transform the test set.

```
[100]: # Transform the test set
X_test[cols_scale] = scaler.transform(X_test[cols_scale])
X_test.head()
```

```
[100]:      loc_og_t2o_mou  std_og_t2o_mou  loc_ic_t2o_mou  arpu_6  arpu_7  \
5704              0.0              0.0              0.0  0.244310 -0.268832
64892             0.0              0.0              0.0  0.048359 -0.779609
39613             0.0              0.0              0.0  0.545470  0.184388
93118             0.0              0.0              0.0  0.641508  0.816632
81235             0.0              0.0              0.0  3.878627  0.911619

      arpu_8  onnet_mou_6  onnet_mou_7  onnet_mou_8  offnet_mou_6  \
5704  1.005890   -0.725286   -0.690223   -0.476634    0.483540
64892 -0.157969   -0.734066   -0.698072   -0.502219   -0.358555
39613  1.403349   -0.537110   -0.521615   -0.206890    0.694901
93118 -0.211023   -0.058843    0.029897   -0.155872   -0.148197
81235  2.745295    4.117829    1.452446    2.809582   -0.002634
```

	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	\
5704	0.307300	2.323745	-0.077655	-0.253231	
64892	-0.577717	-0.256061	0.022864	-0.253231	
39613	0.435043	1.465067	-0.254996	-0.253231	
93118	-0.143451	-0.410827	-0.254996	-0.253231	
81235	-0.290323	0.029332	-0.254996	-0.253231	

	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	\
5704	-0.304660	0.215992	-0.374857	-0.431026	
64892	-0.304660	-0.120122	-0.374857	-0.431026	
39613	-0.304660	-0.300833	-0.374857	-0.431026	
93118	-0.304660	-0.300833	-0.374857	-0.431026	
81235	-0.003778	-0.300833	-0.374857	1.456232	

	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2m_mou_6	\
5704	-0.278217	-0.282623	-0.106758	0.028192	
64892	-0.278380	-0.302589	-0.174571	-0.300150	
39613	0.254268	0.146234	0.514266	2.795255	
93118	0.871759	1.002772	0.222587	0.871444	
81235	2.888120	0.289221	1.362336	0.767176	

	loc_og_t2m_mou_7	loc_og_t2m_mou_8	loc_og_t2f_mou_6	loc_og_t2f_mou_7	\
5704	0.006336	0.034141	-0.087435	-0.267401	
64892	-0.204014	-0.295881	-0.261886	-0.267401	
39613	2.186811	3.743713	0.011714	-0.076422	
93118	0.713384	-0.116066	1.669630	1.311405	
81235	0.540001	0.742988	0.005438	-0.267401	

	loc_og_t2f_mou_8	loc_og_t2c_mou_6	loc_og_t2c_mou_7	loc_og_t2c_mou_8	\
5704	-0.244832	0.037799	-0.267368	-0.244432	
64892	-0.244832	-0.191587	-0.267368	-0.244432	
39613	1.174644	-0.191587	-0.267368	-0.244432	
93118	0.642996	-0.191587	-0.267368	-0.244432	
81235	-0.244832	-0.191587	-0.267368	-0.244432	

	loc_og_mou_6	loc_og_mou_7	loc_og_mou_8	std_og_t2t_mou_6	\
5704	-0.161248	-0.195270	-0.055078	-0.610819	
64892	-0.379084	-0.337876	-0.306653	-0.619956	
39613	1.932970	1.438327	2.763270	-0.619956	
93118	1.189608	1.165755	0.093205	-0.358067	
81235	2.297311	0.506959	1.278083	3.237049	

	std_og_t2t_mou_7	std_og_t2t_mou_8	std_og_t2m_mou_6	std_og_t2m_mou_7	\
5704	-0.570510	-0.420186	0.346789	0.369671	
64892	-0.570510	-0.415897	-0.231854	-0.437192	
39613	-0.570510	-0.420186	-0.394991	-0.343132	

93118	-0.342850	-0.221957	-0.507976	-0.406765
81235	1.462701	2.078469	-0.263825	-0.435005

	std_og_t2m_mou_8	std_og_t2f_mou_6	std_og_t2f_mou_7	std_og_t2f_mou_8	\
5704	2.702104	-0.143576	-0.139257	-0.119299	
64892	-0.040526	-0.143576	-0.139257	-0.104326	
39613	-0.177784	1.244575	-0.139257	-0.119299	
93118	-0.346116	-0.143576	-0.139257	-0.119299	
81235	-0.400887	-0.143576	-0.139257	-0.119299	

	std_og_t2c_mou_6	std_og_t2c_mou_7	std_og_t2c_mou_8	std_og_mou_6	\
5704	0.0	0.0	0.0	-0.214836	
64892	0.0	0.0	0.0	-0.616620	
39613	0.0	0.0	0.0	-0.708089	
93118	0.0	0.0	0.0	-0.612400	
81235	0.0	0.0	0.0	2.200139	

	std_og_mou_7	std_og_mou_8	isd_og_mou_6	isd_og_mou_7	isd_og_mou_8	\
5704	-0.152215	1.550482	-0.080803	-0.092449	-0.061631	
64892	-0.714724	-0.306010	-0.080803	-0.092449	-0.061631	
39613	-0.649149	-0.402193	-0.080803	-0.092449	-0.061631	
93118	-0.530795	-0.384371	-0.080803	-0.092449	-0.061631	
81235	0.739892	1.109859	-0.080803	-0.092449	-0.061631	

	spl_og_mou_6	spl_og_mou_7	spl_og_mou_8	og_others_6	og_others_7	\
5704	1.055196	0.774917	0.757960	0.315218	-0.015583	
64892	-0.327156	-0.363159	-0.290355	-0.346191	-0.015583	
39613	-0.347585	-0.363159	-0.290355	-0.346191	-0.015583	
93118	-0.278869	-0.293867	-0.231687	-0.025662	-0.015583	
81235	0.049230	-0.363159	-0.290355	-0.346191	-0.015583	

	og_others_8	total_og_mou_6	total_og_mou_7	total_og_mou_8	\
5704	-0.013735	-0.254350	-0.209855	1.354152	
64892	-0.013735	-0.775847	-0.845314	-0.422452	
39613	-0.013735	0.155438	-0.005238	0.943279	
93118	-0.013735	-0.077192	-0.008896	-0.300672	
81235	-0.013735	3.147976	0.919824	1.568307	

	loc_ic_t2t_mou_6	loc_ic_t2t_mou_7	loc_ic_t2t_mou_8	loc_ic_t2m_mou_6	\
5704	-0.356975	-0.095026	0.281846	0.089162	
64892	-0.107944	-0.347607	-0.187444	0.377903	
39613	0.075275	-0.307553	-0.130965	-0.113096	
93118	2.234897	1.680142	1.178931	0.874402	
81235	0.238993	0.429108	0.113725	1.182362	

	loc_ic_t2m_mou_7	loc_ic_t2m_mou_8	loc_ic_t2f_mou_6	loc_ic_t2f_mou_7	\
5704	-0.112790	0.515971	-0.290528	-0.270877	

64892	0.199498	0.240935	-0.275866	-0.257495
39613	-0.328115	0.017490	-0.104613	-0.247057
93118	0.796818	0.524427	-0.043033	0.080535
81235	0.691388	0.502602	-0.182615	-0.060511

	loc_ic_t2f_mou_8	loc_ic_mou_6	loc_ic_mou_7	loc_ic_mou_8	\
5704	-0.194257	-0.156095	-0.166424	0.468259	
64892	-0.235146	0.172870	-0.078726	0.045944	
39613	-0.125105	-0.056143	-0.419352	-0.067426	
93118	0.274772	1.723994	1.417516	0.968096	
81235	-0.257696	0.923322	0.685320	0.369639	

	std_ic_t2t_mou_6	std_ic_t2t_mou_7	std_ic_t2t_mou_8	std_ic_t2m_mou_6	\
5704	-0.215496	-0.200464	-0.187265	0.113370	
64892	-0.215496	-0.152024	0.151031	2.985768	
39613	-0.215496	-0.200464	-0.187265	-0.190865	
93118	-0.141573	-0.121450	-0.104402	-0.219794	
81235	3.676291	2.238646	4.587345	-0.261982	

	std_ic_t2m_mou_7	std_ic_t2m_mou_8	std_ic_t2f_mou_6	std_ic_t2f_mou_7	\
5704	-0.185210	-0.166335	-0.135479	-0.137327	
64892	2.167834	2.203886	0.947838	2.883004	
39613	-0.281392	-0.252874	0.271115	-0.137327	
93118	-0.280534	-0.238753	-0.135479	-0.137327	
81235	-0.280902	-0.232114	-0.135479	-0.137327	

	std_ic_t2f_mou_8	std_ic_t2o_mou_6	std_ic_t2o_mou_7	std_ic_t2o_mou_8	\
5704	-0.110642	0.0	0.0	0.0	
64892	1.082447	0.0	0.0	0.0	
39613	-0.110642	0.0	0.0	0.0	
93118	-0.110642	0.0	0.0	0.0	
81235	-0.110642	0.0	0.0	0.0	

	std_ic_mou_6	std_ic_mou_7	std_ic_mou_8	total_ic_mou_6	\
5704	-0.077912	-0.265421	-0.233610	-0.194148	
64892	1.935296	1.671948	1.888954	1.033317	
39613	-0.231969	-0.328225	-0.299535	-0.176324	
93118	-0.250056	-0.277357	-0.247586	1.336498	
81235	2.151705	1.225035	2.089855	1.680641	

	total_ic_mou_7	total_ic_mou_8	spl_ic_mou_6	spl_ic_mou_7	\
5704	-0.204469	0.286255	-0.366516	-0.089786	
64892	0.758037	0.716003	-0.366516	-0.089786	
39613	-0.522456	-0.189128	-0.366516	-0.089786	
93118	1.048813	0.704124	-0.366516	-0.089786	
81235	1.061830	1.050754	-0.366516	-0.089786	

	spl_ic_mou_8	isd_ic_mou_6	isd_ic_mou_7	isd_ic_mou_8	ic_others_6	\
5704	-0.192624	-0.151655	0.285066	-0.126576	-0.099745	
64892	-0.192624	0.312051	-0.021464	-0.126576	-0.050008	
39613	-0.192624	-0.151655	-0.153778	-0.126576	-0.099745	
93118	-0.192624	-0.047189	-0.153778	-0.126576	-0.099745	
81235	-0.192624	-0.151655	-0.153778	-0.126576	-0.099745	

	ic_others_7	ic_others_8	total_rech_num_6	total_rech_num_7	\
5704	-0.121704	-0.081491	-0.156412	0.260837	
64892	4.574367	0.366640	-0.040029	-0.680263	
39613	-0.121704	-0.011433	-0.738325	-1.033175	
93118	-0.121704	-0.081491	-0.738325	0.025562	
81235	-0.121704	-0.081491	1.472945	0.025562	

	total_rech_num_8	total_rech_amt_6	total_rech_amt_7	total_rech_amt_8	\
5704	1.306523	0.087587	-0.236774	0.817300	
64892	0.054980	0.060452	-0.688801	-0.051360	
39613	-0.695945	0.421336	-0.518626	1.256352	
93118	-0.445637	1.126824	0.638030	-0.511656	
81235	0.555597	3.764262	0.688551	3.201396	

	max_rech_amt_6	max_rech_amt_7	max_rech_amt_8	last_day_rch_amt_6	\
5704	0.054992	-0.173563	0.029739	0.175643	
64892	0.054992	0.358167	0.551737	-0.598662	
39613	2.412584	2.340760	2.555285	3.553548	
93118	1.183544	0.753166	0.950911	1.530677	
81235	0.812513	0.008745	1.718554	0.175643	

	last_day_rch_amt_7	last_day_rch_amt_8	vol_2g_mb_6	vol_2g_mb_7	\
5704	0.368450	-0.351085	3.313695	2.175444	
64892	-0.350629	-0.626096	3.855666	6.784445	
39613	3.419926	3.040717	-0.245535	-0.235847	
93118	1.493164	-0.626096	-0.245535	-0.235847	
81235	-0.350629	1.207310	5.471850	2.782323	

	vol_2g_mb_8	vol_3g_mb_6	vol_3g_mb_7	vol_3g_mb_8	monthly_2g_6	\
5704	-0.098306	-0.262491	-0.063995	0.506232	3.236849	
64892	4.402555	1.716008	0.276844	0.288491	6.720348	
39613	-0.207939	-0.262491	-0.274601	-0.249913	-0.246650	
93118	-0.207939	-0.262491	-0.274601	-0.249913	-0.246650	
81235	1.989567	-0.262491	-0.274601	-0.249913	-0.246650	

	monthly_2g_7	monthly_2g_8	sachet_2g_6	sachet_2g_7	sachet_2g_8	\
5704	-0.251375	-0.232664	0.457379	2.358097	2.447476	
64892	3.104207	3.421905	-0.255793	-0.269796	2.447476	
39613	-0.251375	-0.232664	-0.255793	-0.269796	-0.268245	
93118	-0.251375	-0.232664	-0.255793	-0.269796	-0.268245	

81235	-0.251375	-0.232664	1.883722	1.044151	0.410685
-------	-----------	-----------	----------	----------	----------

	monthly_3g_6	monthly_3g_7	monthly_3g_8	sachet_3g_6	sachet_3g_7 \
5704	-0.224183	-0.221779	-0.216364	1.315163	1.219546
64892	-0.224183	-0.221779	-0.216364	-0.141182	-0.136208
39613	-0.224183	-0.221779	-0.216364	-0.141182	-0.136208
93118	-0.224183	-0.221779	-0.216364	-0.141182	-0.136208
81235	2.171393	-0.221779	2.201160	2.771508	2.575301

	sachet_3g_8	aon	aug_vbc_3g	jul_vbc_3g	jun_vbc_3g \
5704	2.526725	0.225051	0.018023	0.194794	-0.259366
64892	-0.113882	0.622516	2.423668	2.357564	5.861151
39613	-0.113882	2.966507	-0.255884	-0.265392	-0.259366
93118	-0.113882	1.742643	-0.255884	-0.265392	-0.259366
81235	1.206422	-0.244679	-0.255884	-0.265392	-0.259366

	decrease_mou_action	decrease_rech_num_action \
5704	0	0
64892	1	1
39613	1	1
93118	1	0
81235	1	1

	decrease_rech_amt_action	decrease_arpu_action	decrease_vbc_action
5704	1	1	0
64892	1	1	1
39613	1	0	0
93118	1	1	0
81235	1	1	0

## 2 Model with PCA

```
[101]: #Import PCA
from sklearn.decomposition import PCA
```

```
[102]: # Instantiate PCA
pca = PCA(random_state=42)
```

```
[103]: # Fit train set on PCA
pca.fit(X_train)
```

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

```
[104]: # Principal components
pca.components_
```

```
[104]: array([[ -7.50315936e-20,  4.16333634e-17,  1.11022302e-16, ...,
        -2.59799614e-02, -2.57740516e-02,  1.40032998e-02],
        [-1.61507486e-19, -5.55111512e-17,  0.00000000e+00, ...,
        -1.16737642e-02, -9.94022864e-03, -1.42598315e-02],
        [ 1.91332162e-19, -2.77555756e-17,  0.00000000e+00, ...,
        -4.18532955e-02, -4.28357226e-02,  2.46812846e-02],
        ...,
        [-0.00000000e+00, -3.78694731e-02, -3.56427844e-02, ...,
         1.23056947e-16, -4.06575815e-17, -0.00000000e+00],
        [ 0.00000000e+00,  2.32804774e-01,  3.95374959e-02, ...,
         6.41847686e-17,  3.12250226e-17,  8.32667268e-17],
        [ 9.99999199e-01, -3.85782335e-04,  1.19512948e-03, ...,
         1.35525272e-20,  3.11708125e-19, -1.99086624e-17]])
```

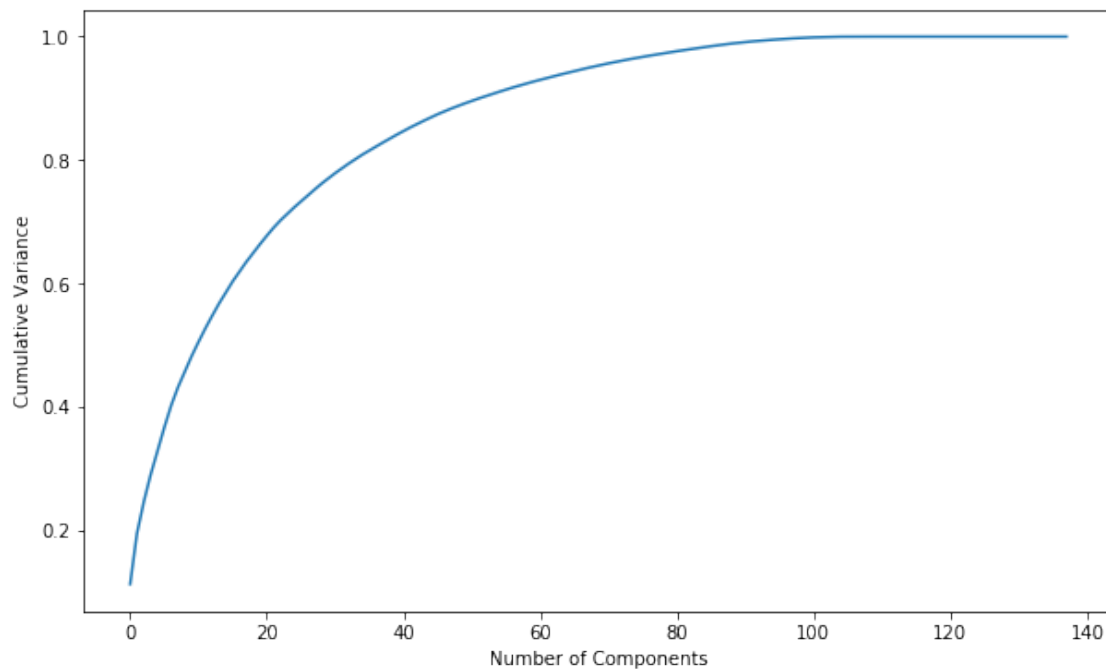
```
[105]: # Cumulative varinace of the PCs
variance_cumu = np.cumsum(pca.explained_variance_ratio_)
print(variance_cumu)
```

```
[0.11213256 0.19426234 0.24575583 0.28953571 0.32841891 0.36623473
0.40173361 0.43144425 0.45702167 0.48194328 0.50480575 0.52673812
0.54724457 0.5670202  0.58530008 0.60304258 0.6190213  0.63473458
0.64927873 0.66341423 0.67712828 0.69025011 0.7020618  0.71278516
0.72309435 0.73290234 0.74255604 0.75209676 0.76151565 0.77010093
0.77861315 0.7866115  0.79429496 0.80173555 0.80878909 0.81538157
0.82193734 0.8283476  0.83472622 0.84089758 0.84687761 0.85280024
0.85840083 0.86374029 0.86901646 0.87418749 0.87891437 0.88341796
0.887723   0.89186057 0.89588256 0.89966074 0.90339384 0.90704071
0.91060084 0.91411689 0.91752343 0.92076319 0.92395413 0.92705111
0.93001239 0.93296077 0.93580029 0.93862291 0.94138851 0.9441162
0.94678675 0.94937767 0.95188405 0.95433786 0.95665036 0.95893735
0.96116409 0.96323063 0.96526039 0.967203   0.96912626 0.97100138
0.97284931 0.9746657  0.97639261 0.97806622 0.97972617 0.98133794
0.98290963 0.98446566 0.98601222 0.98753485 0.98877905 0.98998795
0.99114751 0.99224606 0.99321228 0.99407803 0.9949224  0.99573799
0.99652652 0.99717502 0.99776401 0.99831985 0.99880793 0.99912289
0.99942656 0.99969174 0.99985313 0.99994737 0.99998103 0.99999839
0.99999963 0.99999989 1.         1.         1.         1.
1.         1.         1.         1.         1.         1.
1.         1.         1.         1.         1.         1.
1.         1.         1.         1.         1.         1.
1.         1.         1.         1.         1.         1.
1.         1.         1.         1.         1.         1.         ]
```

```
[106]: # Plotting scree plot
fig = plt.figure(figsize = (10,6))
plt.plot(variance_cumu)
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Variance')
```



```
[106]: Text(0, 0.5, 'Cumulative Variance')
```



We can see that 60 components explain almost more than 90% variance of the data. So, we will perform PCA with 60 components.

#### Performing PCA with 60 components

```
[107]: # Importing incremental PCA
from sklearn.decomposition import IncrementalPCA
```

```
[108]: # Instantiate PCA with 60 components
pca_final = IncrementalPCA(n_components=60)
```

```
[109]: # Fit and transform the X_train
X_train_pca = pca_final.fit_transform(X_train)
```

**Applying transformation on the test set** We are only doing Transform in the test set not the Fit-Transform. Because the Fitting is already done on the train set. So, we just have to do the transformation with the already fitted data on the train set.

```
[110]: X_test_pca = pca_final.transform(X_test)
```

**Emphasize Sensitivity/Recall than Accuracy** We are more focused on higher Sensitivity/Recall score than the accuracy.

Beacuse we need to care more about churn cases than the not churn cases. The main goal is to reatin the customers, who have the possiblity to churn. There should not be a problem, if we consider few not churn customers as churn customers and provide them some incentives for retaining them. Hence, the sensitivity score is more important here.

## 2.1 Logistic regression with PCA

```
[111]: # Importing scikit logistic regression module
from sklearn.linear_model import LogisticRegression
```

```
[112]: # Impoting metrics
from sklearn import metrics
from sklearn.metrics import confusion_matrix
```

**Tuning hyperparameter C** C is the the inverse of regularization strength in Logistic Regression. Higher values of C correspond to less regularization.

```
[113]: # Importing libraries for cross validation
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
```

```
[114]: # Creating KFold object with 5 splits
folds = KFold(n_splits=5, shuffle=True, random_state=4)

# Specify params
params = {"C": [0.01, 0.1, 1, 10, 100, 1000]}

# Specifing score as recall as we are more focused on acheiving the higher
↪ sensitivity than the accuracy
model_cv = GridSearchCV(estimator = LogisticRegression(),
                        param_grid = params,
                        scoring= 'recall',
                        cv = folds,
                        verbose = 1,
                        return_train_score=True)

# Fit the model
model_cv.fit(X_train_pca, y_train)
```

Fitting 5 folds for each of 6 candidates, totalling 30 fits

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
```

```
[Parallel(n_jobs=1)]: Done 30 out of 30 | elapsed: 21.6s finished
```

```
[114]: GridSearchCV(cv=KFold(n_splits=5, random_state=4, shuffle=True),
                  error_score=nan,
                  estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
```

```

fit_intercept=True,
intercept_scaling=1, l1_ratio=None,
max_iter=100, multi_class='auto',
n_jobs=None, penalty='l2',
random_state=None, solver='lbfgs',
tol=0.0001, verbose=0,
warm_start=False),

iid='deprecated', n_jobs=None,
param_grid={'C': [0.01, 0.1, 1, 10, 100, 1000]},
pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
scoring='recall', verbose=1)

```

```

[115]: # results of grid search CV
cv_results = pd.DataFrame(model_cv.cv_results_)
cv_results

```

```

[115]:  mean_fit_time  std_fit_time  mean_score_time  std_score_time  param_C  \
0      0.478627    0.060932      0.007600    1.200167e-03    0.01
1      0.731842    0.021868      0.006801    3.999949e-04    0.1
2      0.743043    0.008100      0.007000    6.325605e-04    1
3      0.754643    0.024106      0.007200    1.469782e-03    10
4      0.720841    0.015716      0.007000    1.784161e-07    100
5      0.719441    0.008778      0.006600    4.899208e-04   1000

      params  split0_test_score  split1_test_score  split2_test_score  \
0  {'C': 0.01}          0.900071          0.897759          0.895814
1  {'C': 0.1}           0.898177          0.896359          0.894651
2   {'C': 1}           0.898650          0.898693          0.895581
3   {'C': 10}          0.898887          0.898459          0.896744
4   {'C': 100}         0.899597          0.898226          0.896977
5   {'C': 1000}        0.899597          0.898226          0.896977

      split3_test_score  split4_test_score  mean_test_score  std_test_score  \
0          0.906425          0.887552          0.897524          0.006134
1          0.905959          0.889403          0.896910          0.005390
2          0.905028          0.890329          0.897656          0.004783
3          0.904562          0.889866          0.897704          0.004719
4          0.904330          0.890329          0.897892          0.004528
5          0.904330          0.890329          0.897892          0.004528

      rank_test_score  split0_train_score  split1_train_score  \
0                   5          0.901116          0.898256
1                   6          0.901174          0.898431
2                   4          0.901988          0.898606
3                   3          0.902511          0.898956
4                   1          0.902628          0.898722
5                   1          0.902628          0.898839

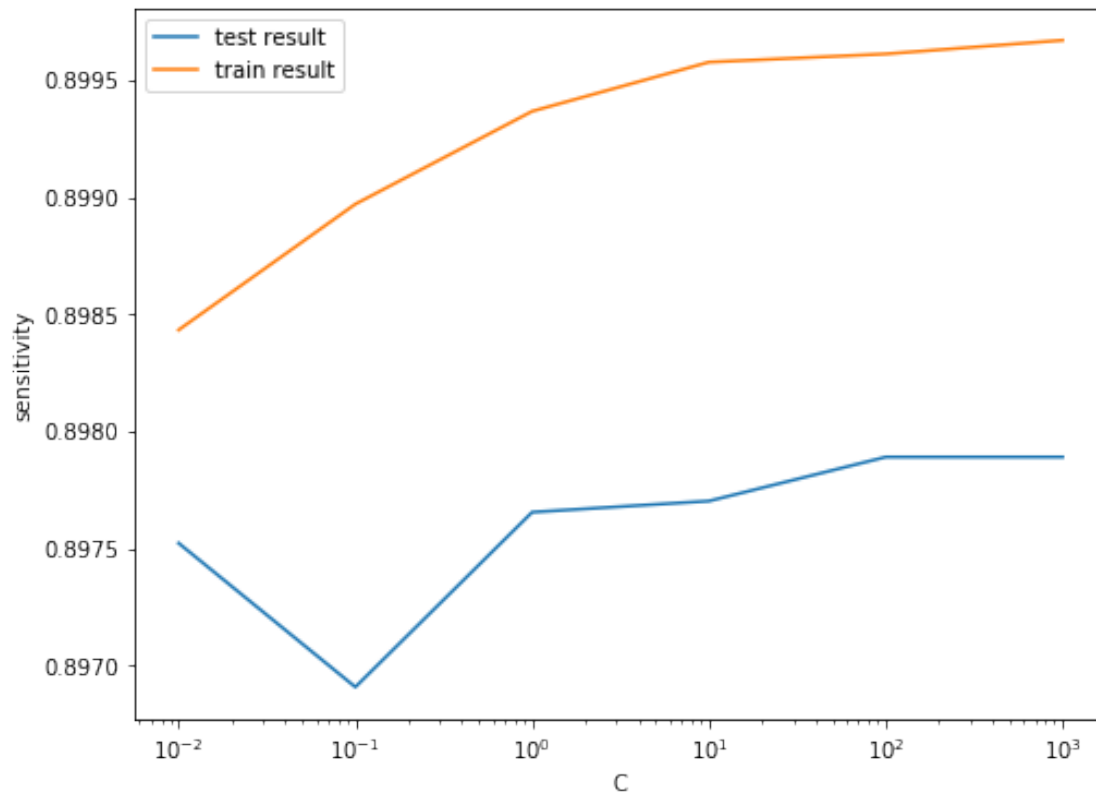
```

	split2_train_score	split3_train_score	split4_train_score \
0	0.899387	0.895440	0.897971
1	0.899270	0.896725	0.899257
2	0.898861	0.898184	0.899199
3	0.898394	0.898476	0.899550
4	0.898569	0.898593	0.899550
5	0.898686	0.898593	0.899608

	mean_train_score	std_train_score
0	0.898434	0.001861
1	0.898971	0.001440
2	0.899368	0.001351
3	0.899577	0.001524
4	0.899612	0.001550
5	0.899671	0.001521

```
[117]: # plot of C versus train and validation scores
```

```
plt.figure(figsize=(8, 6))
plt.plot(cv_results['param_C'], cv_results['mean_test_score'])
plt.plot(cv_results['param_C'], cv_results['mean_train_score'])
plt.xlabel('C')
plt.ylabel('sensitivity')
plt.legend(['test result', 'train result'], loc='upper left')
plt.xscale('log')
```



```
[119]: # Best score with best C
best_score = model_cv.best_score_
best_C = model_cv.best_params_['C']

print(" The highest test sensitivity is {0} at C = {1}".format(best_score,
↪best_C))
```

The highest test sensitivity is 0.8978916608693863 at C = 100

### Logistic regression with optimal C

```
[120]: # Instantiate the model with best C
logistic_pca = LogisticRegression(C=best_C)
```

```
[121]: # Fit the model on the train set
log_pca_model = logistic_pca.fit(X_train_pca, y_train)
```

### Prediction on the train set

```
[122]: # Predictions on the train set
y_train_pred = log_pca_model.predict(X_train_pca)
```

```
[123]: # Confusion matrix
confusion = metrics.confusion_matrix(y_train, y_train_pred)
print(confusion)
```

```
[[17908  3517]
 [ 2154 19271]]
```

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

```
[125]: # Accuracy
print("Accuracy:-",metrics.accuracy_score(y_train, y_train_pred))

# Sensitivity
print("Sensitivity:-",TP / float(TP+FN))

# Specificity
print("Specificity:-", TN / float(TN+FP))
```

```
Accuracy:- 0.8676546091015169
Sensitivity:- 0.899463243873979
Specificity:- 0.8358459743290548
```

#### **Prediction on the test set**

```
[126]: # Prediction on the test set
y_test_pred = log_pca_model.predict(X_test_pca)
```

```
[127]: # Confusion matrix
confusion = metrics.confusion_matrix(y_test, y_test_pred)
print(confusion)
```

```
[[4452  896]
 [  36  157]]
```

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

```
[129]: # Accuracy
print("Accuracy:-",metrics.accuracy_score(y_test, y_test_pred))

# Sensitivity
print("Sensitivity:-",TP / float(TP+FN))
```

```
# Specificity
print("Specificity:-", TN / float(TN+FP))
```

Accuracy:- 0.8317993142032124  
 Sensitivity:- 0.8134715025906736  
 Specificity:- 0.8324607329842932

### *Model summary*

- Train set
  - Accuracy = 0.86
  - Sensitivity = 0.89
  - Specificity = 0.83
- Test set
  - Accuracy = 0.83
  - Sensitivity = 0.81
  - Specificity = 0.83

Overall, the model is performing well in the test set, what it had learnt from the train set.

## 2.2 Support Vector Machine(SVM) with PCA

```
[130]: # Importing SVC
from sklearn.svm import SVC
```

**Hyperparameter tuning** C:- Regularization parameter.

gamma:- Handles non linear classifications.

```
[131]: # specify range of hyperparameters

hyper_params = [ {'gamma': [1e-2, 1e-3, 1e-4],
                  'C': [1, 10, 100, 1000]}]

# specify model with RBF kernel
model = SVC(kernel="rbf")

# set up GridSearchCV()
model_cv = GridSearchCV(estimator = model,
                        param_grid = hyper_params,
                        scoring= 'accuracy',
                        cv = 3,
                        verbose = 1,
                        return_train_score=True)

# fit the model
model_cv.fit(X_train_pca, y_train)
```

Fitting 3 folds for each of 12 candidates, totalling 36 fits

[Parallel(n\_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

[Parallel(n\_jobs=1)]: Done 36 out of 36 | elapsed: 95.4min finished

```
[131]: GridSearchCV(cv=3, error_score=nan,
                  estimator=SVC(C=1.0, break_ties=False, cache_size=200,
                                class_weight=None, coef0=0.0,
                                decision_function_shape='ovr', degree=3,
                                gamma='scale', kernel='rbf', max_iter=-1,
                                probability=False, random_state=None, shrinking=True,
                                tol=0.001, verbose=False),
                  iid='deprecated', n_jobs=None,
                  param_grid=[{'C': [1, 10, 100, 1000],
                               'gamma': [0.01, 0.001, 0.0001]}],
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
                  scoring='accuracy', verbose=1)
```

```
[132]: # cv results
cv_results = pd.DataFrame(model_cv.cv_results_)
cv_results
```

```
[132]:
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C \
0	42.032071	0.126973	12.777397	0.027355	1
1	53.846413	0.407173	17.470999	0.045588	1
2	67.914884	0.491901	22.857974	0.176785	1
3	39.426255	0.483549	8.479152	0.292587	10
4	47.964410	0.411481	14.921520	0.169904	10
5	57.650298	0.850001	19.027755	0.122431	10
6	57.674299	6.235520	670.884914	941.456985	100
7	56.490898	0.578504	11.192307	0.035219	100
8	54.180099	0.697826	16.342601	0.187994	100
9	93.312670	2.057615	3.813552	0.053278	1000
10	127.868314	3.560431	8.287141	0.121411	1000
11	79.973241	1.123954	14.635170	0.255735	1000

	param_gamma	params	split0_test_score \
0	0.01	{'C': 1, 'gamma': 0.01}	0.944903
1	0.001	{'C': 1, 'gamma': 0.001}	0.883366
2	0.0001	{'C': 1, 'gamma': 0.0001}	0.858513
3	0.01	{'C': 10, 'gamma': 0.01}	0.967096
4	0.001	{'C': 10, 'gamma': 0.001}	0.910459
5	0.0001	{'C': 10, 'gamma': 0.0001}	0.870414
6	0.01	{'C': 100, 'gamma': 0.01}	0.973397
7	0.001	{'C': 100, 'gamma': 0.001}	0.935662
8	0.0001	{'C': 100, 'gamma': 0.0001}	0.884906
9	0.01	{'C': 1000, 'gamma': 0.01}	0.972277
10	0.001	{'C': 1000, 'gamma': 0.001}	0.955965



```
11      0.0001  {'C': 1000, 'gamma': 0.0001}      0.908499
```

	split1_test_score	split2_test_score	mean_test_score	std_test_score \
0	0.941679	0.940699	0.942427	0.001796
1	0.884268	0.884058	0.883897	0.000385
2	0.858433	0.859133	0.858693	0.000313
3	0.965413	0.965063	0.965858	0.000887
4	0.911433	0.908073	0.909988	0.001412
5	0.869355	0.872786	0.870852	0.001434
6	0.976686	0.975775	0.975286	0.001387
7	0.935518	0.934608	0.935263	0.000467
8	0.886438	0.886718	0.886021	0.000797
9	0.977876	0.976336	0.975496	0.002362
10	0.955121	0.955472	0.955519	0.000346
11	0.910943	0.907302	0.908915	0.001515

	rank_test_score	split0_train_score	split1_train_score \
0	5	0.947210	0.947247
1	10	0.883813	0.886757
2	12	0.858993	0.859908
3	3	0.975040	0.973536
4	7	0.913709	0.911891
5	11	0.871421	0.873875
6	2	0.991318	0.990444
7	6	0.941819	0.942066
8	9	0.886368	0.888893
9	1	0.998425	0.998495
10	4	0.965623	0.965345
11	8	0.912868	0.910806

	split2_train_score	mean_train_score	std_train_score
0	0.947702	0.947386	0.000224
1	0.885707	0.885426	0.001218
2	0.859173	0.859358	0.000396
3	0.974306	0.974294	0.000614
4	0.912381	0.912660	0.000768
5	0.870690	0.871995	0.001362
6	0.990198	0.990653	0.000481
7	0.941681	0.941855	0.000159
8	0.888543	0.887935	0.001117
9	0.998495	0.998471	0.000033
10	0.966465	0.965811	0.000476
11	0.911996	0.911890	0.000845

Plotting the accuracy with various C and gamma values

```

[133]: # converting C to numeric type for plotting on x-axis
cv_results['param_C'] = cv_results['param_C'].astype('int')

# # plotting
plt.figure(figsize=(16,6))

# subplot 1/3
plt.subplot(131)
gamma_01 = cv_results[cv_results['param_gamma']==0.01]

plt.plot(gamma_01["param_C"], gamma_01["mean_test_score"])
plt.plot(gamma_01["param_C"], gamma_01["mean_train_score"])
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title("Gamma=0.01")
plt.ylim([0.80, 1])
plt.legend(['test accuracy', 'train accuracy'], loc='upper left')
plt.xscale('log')

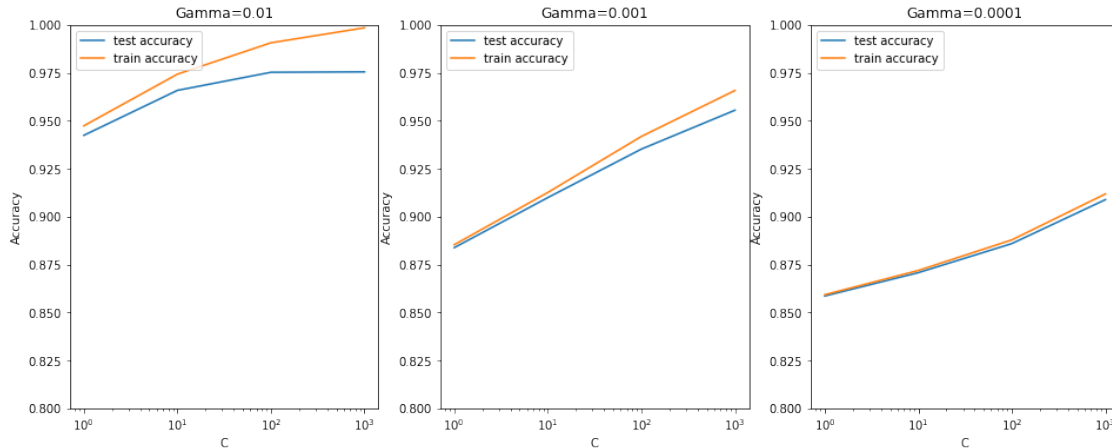
# subplot 2/3
plt.subplot(132)
gamma_001 = cv_results[cv_results['param_gamma']==0.001]

plt.plot(gamma_001["param_C"], gamma_001["mean_test_score"])
plt.plot(gamma_001["param_C"], gamma_001["mean_train_score"])
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title("Gamma=0.001")
plt.ylim([0.80, 1])
plt.legend(['test accuracy', 'train accuracy'], loc='upper left')
plt.xscale('log')

# subplot 3/3
plt.subplot(133)
gamma_0001 = cv_results[cv_results['param_gamma']==0.0001]

plt.plot(gamma_0001["param_C"], gamma_0001["mean_test_score"])
plt.plot(gamma_0001["param_C"], gamma_0001["mean_train_score"])
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title("Gamma=0.0001")
plt.ylim([0.80, 1])
plt.legend(['test accuracy', 'train accuracy'], loc='upper left')
plt.xscale('log')

```



```
[201]: # Printing the best score
best_score = model_cv.best_score_
best_hyperparams = model_cv.best_params_

print("The best test score is {0} corresponding to hyperparameters {1}".
      ↪format(best_score, best_hyperparams))
```

The best test score is 0.9754959911159373 corresponding to hyperparameters {'C': 1000, 'gamma': 0.01}

From the above plot, we can see that higher value of gamma leads to overfitting the model. With the lowest value of gamma (0.0001) we have train and test accuracy almost same.

Also, at C=100 we have a good accuracy and the train and test scores are comparable.

Though sklearn suggests the optimal scores mentioned above (gamma=0.01, C=1000), one could argue that it is better to choose a simpler, more non-linear model with gamma=0.0001. This is because the optimal values mentioned here are calculated based on the average test accuracy (but not considering subjective parameters such as model complexity).

We can achieve comparable average test accuracy (~90%) with gamma=0.0001 as well, though we'll have to increase the cost C for that. So to achieve high accuracy, there's a tradeoff between: - High gamma (i.e. high non-linearity) and average value of C - Low gamma (i.e. less non-linearity) and high value of C

We argue that the model will be simpler if it has as less non-linearity as possible, so we choose gamma=0.0001 and a high C=100.

### Build the model with optimal hyperparameters

```
[134]: # Building the model with optimal hyperparameters
svm_pca_model = SVC(C=100, gamma=0.0001, kernel="rbf")

svm_pca_model.fit(X_train_pca, y_train)
```

```
[134]: SVC(C=100, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
        decision_function_shape='ovr', degree=3, gamma=0.0001, kernel='rbf',
        max_iter=-1, probability=False, random_state=None, shrinking=True,
        tol=0.001, verbose=False)
```

#### Prediction on the train set

```
[135]: # Predictions on the train set
y_train_pred = svm_pca_model.predict(X_train_pca)
```

```
[136]: # Confusion matrix
confusion = metrics.confusion_matrix(y_train, y_train_pred)
print(confusion)
```

```
[[18376  3049]
 [ 1585 19840]]
```

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

```
[138]: # Accuracy
print("Accuracy:-", metrics.accuracy_score(y_train, y_train_pred))

# Sensitivity
print("Sensitivity:-", TP / float(TP+FN))

# Specificity
print("Specificity:-", TN / float(TN+FP))
```

```
Accuracy:- 0.891855309218203
Sensitivity:- 0.9260210035005835
Specificity:- 0.8576896149358226
```

#### Prediction on the test set

```
[139]: # Prediction on the test set
y_test_pred = svm_pca_model.predict(X_test_pca)
```

```
[140]: # Confusion matrix
confusion = metrics.confusion_matrix(y_test, y_test_pred)
print(confusion)
```

```
[[4557  791]
 [  36  157]]
```

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

```
[142]: # Accuracy
print("Accuracy:-", metrics.accuracy_score(y_test, y_test_pred))

# Sensitivity
print("Sensitivity:-", TP / float(TP+FN))

# Specificity
print("Specificity:-", TN / float(TN+FP))
```

Accuracy:- 0.8507489622811767  
Sensitivity:- 0.8134715025906736  
Specificity:- 0.8520942408376964

### *Model summary*

- Train set
  - Accuracy = 0.89
  - Sensitivity = 0.92
  - Specificity = 0.85
- Test set
  - Accuracy = 0.85
  - Sensitivity = 0.81
  - Specificity = 0.85

## 2.3 Decision tree with PCA

```
[143]: # Importing decision tree classifier
from sklearn.tree import DecisionTreeClassifier
```

### Hyperparameter tuning

```
[144]: # Create the parameter grid
param_grid = {
    'max_depth': range(5, 15, 5),
    'min_samples_leaf': range(50, 150, 50),
    'min_samples_split': range(50, 150, 50),
}

# Instantiate the grid search model
dtree = DecisionTreeClassifier()

grid_search = GridSearchCV(estimator = dtree,
```

```

        param_grid = param_grid,
        scoring= 'recall',
        cv = 5,
        verbose = 1)

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

```

Fitting 5 folds for each of 8 candidates, totalling 40 fits

[Parallel(n\_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

[Parallel(n\_jobs=1)]: Done 40 out of 40 | elapsed: 1.7min finished

```

[144]: GridSearchCV(cv=5, error_score=nan,
                  estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
                                                    criterion='gini', max_depth=None,
                                                    max_features=None,
                                                    max_leaf_nodes=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=0.0,
                                                    presort='deprecated',
                                                    random_state=None,
                                                    splitter='best'),
                  iid='deprecated', n_jobs=None,
                  param_grid={'max_depth': range(5, 15, 5),
                              'min_samples_leaf': range(50, 150, 50),
                              'min_samples_split': range(50, 150, 50)},
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring='recall', verbose=1)

```

```

[145]: # cv results
cv_results = pd.DataFrame(grid_search.cv_results_)
cv_results

```

```

[145]:
   mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
0      1.948911      0.023829      0.008601      0.00049
1      1.941111      0.010277      0.008400      0.00049
2      1.925310      0.003188      0.008400      0.00049
3      1.925510      0.002871      0.008600      0.00049
4      3.343991      0.015459      0.008601      0.00049
5      3.370193      0.083993      0.008601      0.00049
6      3.199783      0.044874      0.008801      0.00040
7      3.186582      0.025967      0.008801      0.00040

```

```

   param_max_depth  param_min_samples_leaf  param_min_samples_split  \

```

0	5	50	50
1	5	50	100
2	5	100	50
3	5	100	100
4	10	50	50
5	10	50	100
6	10	100	50
7	10	100	100

	params	split0_test_score	\
0	{'max_depth': 5, 'min_samples_leaf': 50, 'min_...	0.862310	
1	{'max_depth': 5, 'min_samples_leaf': 50, 'min_...	0.862310	
2	{'max_depth': 5, 'min_samples_leaf': 100, 'min_...	0.858110	
3	{'max_depth': 5, 'min_samples_leaf': 100, 'min_...	0.858110	
4	{'max_depth': 10, 'min_samples_leaf': 50, 'min_...	0.886114	
5	{'max_depth': 10, 'min_samples_leaf': 50, 'min_...	0.886114	
6	{'max_depth': 10, 'min_samples_leaf': 100, 'mi...	0.889615	
7	{'max_depth': 10, 'min_samples_leaf': 100, 'mi...	0.889615	

	split1_test_score	split2_test_score	split3_test_score	split4_test_score	\
0	0.855776	0.878413	0.875379	0.855309	
1	0.855776	0.878413	0.875379	0.855309	
2	0.855309	0.875846	0.869078	0.849008	
3	0.855309	0.875846	0.869078	0.849008	
4	0.894516	0.903851	0.905484	0.913652	
5	0.894516	0.903851	0.905484	0.912485	
6	0.869778	0.875613	0.891949	0.884247	
7	0.871179	0.875613	0.891949	0.883781	

	mean_test_score	std_test_score	rank_test_score
0	0.865438	0.009725	5
1	0.865438	0.009725	5
2	0.861470	0.009686	7
3	0.861470	0.009686	7
4	0.900723	0.009503	1
5	0.900490	0.009192	2
6	0.882240	0.008389	4
7	0.882427	0.007964	3

```
[146]: # Printing the optimal sensitivity score and hyperparameters
print("Best sensitivity:-", grid_search.best_score_)
print(grid_search.best_estimator_)
```

```
Best sensitivity:- 0.9007234539089849
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                        max_depth=10, max_features=None, max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
```

```
min_samples_leaf=50, min_samples_split=50,
min_weight_fraction_leaf=0.0, presort='deprecated',
random_state=None, splitter='best')
```

### Model with optimal hyperparameters

```
[147]: # Model with optimal hyperparameters
dt_pca_model = DecisionTreeClassifier(criterion = "gini",
                                     random_state = 100,
                                     max_depth=10,
                                     min_samples_leaf=50,
                                     min_samples_split=50)

dt_pca_model.fit(X_train_pca, y_train)
```

```
[147]: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                             max_depth=10, max_features=None, max_leaf_nodes=None,
                             min_impurity_decrease=0.0, min_impurity_split=None,
                             min_samples_leaf=50, min_samples_split=50,
                             min_weight_fraction_leaf=0.0, presort='deprecated',
                             random_state=100, splitter='best')
```

### Prediction on the train set

```
[148]: # Predictions on the train set
y_train_pred = dt_pca_model.predict(X_train_pca)
```

```
[149]: # Confusion matrix
confusion = metrics.confusion_matrix(y_train, y_train_pred)
print(confusion)
```

```
[[18913  2512]
 [ 1763 19662]]
```

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

```
[151]: # Accuracy
print("Accuracy:-", metrics.accuracy_score(y_train, y_train_pred))

# Sensitivity
print("Sensitivity:-", TP / float(TP+FN))

# Specificity
print("Specificity:-", TN / float(TN+FP))
```



Accuracy:- 0.9002333722287048  
Sensitivity:- 0.9177129521586931  
Specificity:- 0.8827537922987164

#### Prediction on the test set

```
[152]: # Prediction on the test set
y_test_pred = dt_pca_model.predict(X_test_pca)
```

```
[153]: # Confusion matrix
confusion = metrics.confusion_matrix(y_test, y_test_pred)
print(confusion)
```

```
[[4632  716]
 [  58 135]]
```

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

```
[155]: # Accuracy
print("Accuracy:-", metrics.accuracy_score(y_test, y_test_pred))

# Sensitivity
print("Sensitivity:-", TP / float(TP+FN))

# Specificity
print("Specificity:-", TN / float(TN+FP))
```

Accuracy:- 0.8603140227395777  
Sensitivity:- 0.6994818652849741  
Specificity:- 0.8661181750186986

#### Model summary

- Train set
  - Accuracy = 0.90
  - Sensitivity = 0.91
  - Specificity = 0.88
- Test set
  - Accuracy = 0.86
  - Sensitivity = 0.70
  - Specificity = 0.87

We can see from the model performance that the Sensitivity has been decreased while evaluating the model on the test set. However, the accuracy and specificity is quite good in the test set.

## 2.4 Random forest with PCA

```
[156]: # Importing random forest classifier
from sklearn.ensemble import RandomForestClassifier
```

### Hyperparameter tuning

```
[157]: param_grid = {
        'max_depth': range(5,10,5),
        'min_samples_leaf': range(50, 150, 50),
        'min_samples_split': range(50, 150, 50),
        'n_estimators': [100,200,300],
        'max_features': [10, 20]
    }
    # Create a based model
    rf = RandomForestClassifier()
    # Instantiate the grid search model
    grid_search = GridSearchCV(estimator = rf,
                               param_grid = param_grid,
                               cv = 3,
                               n_jobs = -1,
                               verbose = 1,
                               return_train_score=True)

    # Fit the model
    grid_search.fit(X_train_pca, y_train)
```

Fitting 3 folds for each of 24 candidates, totalling 72 fits

[Parallel(n\_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.

[Parallel(n\_jobs=-1)]: Done 42 tasks | elapsed: 13.6min

[Parallel(n\_jobs=-1)]: Done 72 out of 72 | elapsed: 132.9min finished

```
[157]: GridSearchCV(cv=3, error_score=nan,
                  estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                                    class_weight=None,
                                                    criterion='gini', max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=0.0,
                                                    n_estimators=100, n_jobs=None,
                                                    oob_score=False,
                                                    random_state=None, verbose=0,
```

```

warm_start=False),
iid='deprecated', n_jobs=-1,
param_grid={'max_depth': range(5, 10, 5), 'max_features': [10, 20],
            'min_samples_leaf': range(50, 150, 50),
            'min_samples_split': range(50, 150, 50),
            'n_estimators': [100, 200, 300]},
pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
scoring=None, verbose=1)

```

```

[158]: # printing the optimal accuracy score and hyperparameters
print('We can get accuracy of', grid_search.best_score_, 'using', grid_search.
      ↪ best_params_)

```

We can get accuracy of 0.8449241538567582 using {'max\_depth': 5, 'max\_features': 20, 'min\_samples\_leaf': 50, 'min\_samples\_split': 100, 'n\_estimators': 300}

### Model with optimal hyperparameters

```

[159]: # model with the best hyperparameters

rfc_model = RandomForestClassifier(bootstrap=True,
                                max_depth=5,
                                min_samples_leaf=50,
                                min_samples_split=100,
                                max_features=20,
                                n_estimators=300)

```

```

[160]: # Fit the model
rfc_model.fit(X_train_pca, y_train)

```

```

[160]: RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                             criterion='gini', max_depth=5, max_features=20,
                             max_leaf_nodes=None, max_samples=None,
                             min_impurity_decrease=0.0, min_impurity_split=None,
                             min_samples_leaf=50, min_samples_split=100,
                             min_weight_fraction_leaf=0.0, n_estimators=300,
                             n_jobs=None, oob_score=False, random_state=None,
                             verbose=0, warm_start=False)

```

### Prediction on the train set

```

[161]: # Predictions on the train set
y_train_pred = rfc_model.predict(X_train_pca)

```

```

[162]: # Confusion matrix
confusion = metrics.confusion_matrix(y_train, y_train_pred)
print(confusion)

```

```
[[17363 4062]
 [ 2419 19006]]
```

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

```
[164]: # Accuracy
      print("Accuracy:-",metrics.accuracy_score(y_train, y_train_pred))

      # Sensitivity
      print("Sensitivity:-",TP / float(TP+FN))

      # Specificity
      print("Specificity:-", TN / float(TN+FP))
```

```
Accuracy:- 0.8487514585764294
Sensitivity:- 0.8870945157526254
Specificity:- 0.8104084014002334
```

#### Prediction on the test set

```
[165]: # Prediction on the test set
      y_test_pred = rfc_model.predict(X_test_pca)
```

```
[166]: # Confusion matrix
      confusion = metrics.confusion_matrix(y_test, y_test_pred)
      print(confusion)
```

```
[[4294 1054]
 [  47  146]]
```

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

```
[168]: # Accuracy
      print("Accuracy:-",metrics.accuracy_score(y_test, y_test_pred))

      # Sensitivity
      print("Sensitivity:-",TP / float(TP+FN))

      # Specificity
      print("Specificity:-", TN / float(TN+FP))
```

```
Accuracy:- 0.8012994044396319
Sensitivity:- 0.7564766839378239
```

Specificity:- 0.8029169783096485

### ***Model summary***

- Train set
  - Accuracy = 0.84
  - Sensitivity = 0.88
  - Specificity = 0.80
- Test set
  - Accuracy = 0.80
  - Sensitivity = 0.75
  - Specificity = 0.80

We can see from the model performance that the Sensitivity has been decreased while evaluating the model on the test set. However, the accuracy and specificity is quite good in the test set.

### **2.4.1 Final conclusion with PCA**

After trying several models we can see that for achieving the best sensitivity, which was our ultimate goal, the classic Logistic regression or the SVM models performs well. For both the models the sensitivity was approx 81%. Also we have good accuracy of approx 85%.

## **3 Without PCA**

### **3.1 Logistic regression with No PCA**

```
[169]: ##### Importing stats model
import statsmodels.api as sm
```

```
[170]: # Instantiate the model
# Adding the constant to X_train
log_no_pca = sm.GLM(y_train,(sm.add_constant(X_train)), family=sm.families.
    ↪Binomial())
```

```
[171]: # Fit the model
log_no_pca = log_no_pca.fit().summary()
```

```
[172]: # Summary
log_no_pca
```

```
[172]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                        Generalized Linear Model Regression Results
=====
Dep. Variable:          churn    No. Observations:          42850
Model:                  GLM      Df Residuals:              42720
Model Family:           Binomial  Df Model:                129
Link Function:          logit     Scale:                  1.0000
Method:                 IRLS      Log-Likelihood:          nan
```

Date: Sat, 16 May 2020 Deviance: nan  
Time: 17:56:38 Pearson chi2: 3.70e+05  
No. Iterations: 100  
Covariance Type: nonrobust

	coef	std err	z	P> z	[0.025
0.975]					
-----					
-----					
const	-73.1903	4452.100	-0.016	0.987	-8799.145
8652.765					
loc_og_t2o_mou	7.163e-07	4.32e-05	0.017	0.987	-8.39e-05
8.53e-05					
std_og_t2o_mou	2.572e-07	1.42e-05	0.018	0.986	-2.75e-05
2.81e-05					
loc_ic_t2o_mou	1.441e-06	6.09e-05	0.024	0.981	-0.000
0.000					
arpu_6	-0.0338	0.081	-0.418	0.676	-0.192
0.124					
arpu_7	0.0855	0.086	0.994	0.320	-0.083
0.254					
arpu_8	0.0909	0.110	0.828	0.407	-0.124
0.306					
onnet_mou_6	15.5129	3.573	4.342	0.000	8.510
22.516					
onnet_mou_7	-4.3251	1.817	-2.380	0.017	-7.886
-0.764					
onnet_mou_8	2.3528	1.825	1.289	0.197	-1.225
5.930					
offnet_mou_6	15.0874	3.361	4.489	0.000	8.500
21.674					
offnet_mou_7	-1.7629	1.721	-1.024	0.306	-5.136
1.611					
offnet_mou_8	-0.5496	1.883	-0.292	0.770	-4.240
3.141					
roam_ic_mou_6	0.1622	0.036	4.473	0.000	0.091
0.233					
roam_ic_mou_7	-0.0099	0.052	-0.189	0.850	-0.112
0.093					
roam_ic_mou_8	0.2041	0.044	4.663	0.000	0.118
0.290					
roam_og_mou_6	-5.1505	1.131	-4.554	0.000	-7.367
-2.934					
roam_og_mou_7	0.8855	0.474	1.867	0.062	-0.044
1.815					
roam_og_mou_8	0.0927	0.531	0.175	0.861	-0.948

1.133					
loc_og_t2t_mou_6	-3302.8216	656.377	-5.032	0.000	-4589.297
-2016.346					
loc_og_t2t_mou_7	-1474.6175	679.783	-2.169	0.030	-2806.968
-142.267					
loc_og_t2t_mou_8	5516.1251	628.160	8.781	0.000	4284.953
6747.297					
loc_og_t2m_mou_6	-3342.4429	664.131	-5.033	0.000	-4644.116
-2040.770					
loc_og_t2m_mou_7	-1392.1079	641.104	-2.171	0.030	-2648.649
-135.567					
loc_og_t2m_mou_8	5887.3829	670.271	8.784	0.000	4573.677
7201.089					
loc_og_t2f_mou_6	-285.2245	56.710	-5.030	0.000	-396.373
-174.076					
loc_og_t2f_mou_7	-123.0165	56.677	-2.171	0.030	-234.101
-11.933					
loc_og_t2f_mou_8	487.3991	55.519	8.779	0.000	378.584
596.214					
loc_og_t2c_mou_6	0.0433	0.022	1.982	0.048	0.000
0.086					
loc_og_t2c_mou_7	0.0099	0.021	0.463	0.643	-0.032
0.052					
loc_og_t2c_mou_8	0.0673	0.023	2.988	0.003	0.023
0.111					
loc_og_mou_6	3756.2132	1269.036	2.960	0.003	1268.947
6243.479					
loc_og_mou_7	5686.5575	1330.512	4.274	0.000	3078.802
8294.313					
loc_og_mou_8	-265.7885	1351.069	-0.197	0.844	-2913.835
2382.258					
std_og_t2t_mou_6	-1.309e+04	1867.084	-7.011	0.000	-1.67e+04
-9430.445					
std_og_t2t_mou_7	-9674.1364	1822.022	-5.310	0.000	-1.32e+04
-6103.040					
std_og_t2t_mou_8	5854.8113	1510.088	3.877	0.000	2895.093
8814.530					
std_og_t2m_mou_6	-1.214e+04	1732.071	-7.011	0.000	-1.55e+04
-8749.312					
std_og_t2m_mou_7	-9438.8725	1777.374	-5.311	0.000	-1.29e+04
-5955.284					
std_og_t2m_mou_8	5966.0664	1538.126	3.879	0.000	2951.394
8980.739					
std_og_t2f_mou_6	-255.4281	36.393	-7.019	0.000	-326.757
-184.099					
std_og_t2f_mou_7	-213.5957	40.259	-5.306	0.000	-292.502
-134.689					

std_og_t2f_mou_8 214.502	142.4571	36.758	3.876	0.000	70.412
std_og_t2c_mou_6 0.000	-3.536e-06	0.000	-0.018	0.986	-0.000
std_og_t2c_mou_7 0.000	-2.353e-06	0.000	-0.014	0.989	-0.000
std_og_t2c_mou_8 0.000	-2.486e-06	0.000	-0.017	0.986	-0.000
std_og_mou_6 2.03e+04	1.446e+04	2966.600	4.875	0.000	8646.469
std_og_mou_7 2.71e+04	2.105e+04	3103.817	6.783	0.000	1.5e+04
std_og_mou_8 1.32e+04	7815.2524	2767.836	2.824	0.005	2390.393
isd_og_mou_6 6.620	-51.5636	29.686	-1.737	0.082	-109.747
isd_og_mou_7 148.693	94.2299	27.788	3.391	0.001	39.767
isd_og_mou_8 387.462	320.5622	34.133	9.392	0.000	253.663
spl_og_mou_6 10.495	-83.1552	47.782	-1.740	0.082	-176.805
spl_og_mou_7 362.586	229.8600	67.719	3.394	0.001	97.134
spl_og_mou_8 632.102	523.1539	55.587	9.411	0.000	414.206
og_others_6 1.312	-10.0916	5.818	-1.734	0.083	-21.496
og_others_7 25.255	15.6443	4.903	3.191	0.001	6.034
og_others_8 6.3e+05	-5276.7831	3.24e+05	-0.016	0.987	-6.41e+05
total_og_mou_6 7270.720	3406.4402	1971.608	1.728	0.084	-457.840
total_og_mou_7 -3307.343	-7829.5225	2307.277	-3.393	0.001	-1.24e+04
total_og_mou_8 -1.5e+04	-1.894e+04	2011.752	-9.413	0.000	-2.29e+04
loc_ic_t2t_mou_6 315.443	-471.9694	401.748	-1.175	0.240	-1259.382
loc_ic_t2t_mou_7 2908.161	2043.4379	441.193	4.632	0.000	1178.715
loc_ic_t2t_mou_8 7230.601	6411.9241	417.700	15.351	0.000	5593.247
loc_ic_t2m_mou_6 442.865	-662.3378	563.889	-1.175	0.240	-1767.540
loc_ic_t2m_mou_7	2751.5586	593.997	4.632	0.000	1587.346



3915.772					
loc_ic_t2m_mou_8	9239.7305	601.928	15.350	0.000	8059.973
1.04e+04					
loc_ic_t2f_mou_6	-130.8717	111.320	-1.176	0.240	-349.055
87.312					
loc_ic_t2f_mou_7	595.9951	128.711	4.630	0.000	343.725
848.265					
loc_ic_t2f_mou_8	1755.6262	114.390	15.348	0.000	1531.426
1979.826					
loc_ic_mou_6	-1472.7581	1056.667	-1.394	0.163	-3543.788
598.272					
loc_ic_mou_7	-2703.9336	1115.928	-2.423	0.015	-4891.113
-516.754					
loc_ic_mou_8	3460.7823	1136.224	3.046	0.002	1233.824
5687.740					
std_ic_t2t_mou_6	-2047.5989	316.623	-6.467	0.000	-2668.169
-1427.028					
std_ic_t2t_mou_7	-414.5246	317.544	-1.305	0.192	-1036.900
207.851					
std_ic_t2t_mou_8	-551.5337	227.041	-2.429	0.015	-996.526
-106.541					
std_ic_t2m_mou_6	-2117.6774	327.457	-6.467	0.000	-2759.481
-1475.874					
std_ic_t2m_mou_7	-425.3418	325.663	-1.306	0.192	-1063.630
212.946					
std_ic_t2m_mou_8	-844.5218	347.926	-2.427	0.015	-1526.445
-162.599					
std_ic_t2f_mou_6	-364.6880	56.406	-6.465	0.000	-475.242
-254.134					
std_ic_t2f_mou_7	-79.5903	61.102	-1.303	0.193	-199.347
40.167					
std_ic_t2f_mou_8	-138.8260	56.895	-2.440	0.015	-250.338
-27.314					
std_ic_t2o_mou_6	-5.826e-07	2.86e-05	-0.020	0.984	-5.67e-05
5.55e-05					
std_ic_t2o_mou_7	1.092e-06	7.95e-05	0.014	0.989	-0.000
0.000					
std_ic_t2o_mou_8	1.37e-06	8.38e-05	0.016	0.987	-0.000
0.000					
std_ic_mou_6	1980.5760	602.710	3.286	0.001	799.287
3161.865					
std_ic_mou_7	1297.3541	611.724	2.121	0.034	98.398
2496.310					
std_ic_mou_8	8343.2863	569.153	14.659	0.000	7227.768
9458.805					
total_ic_mou_6	2863.2928	942.847	3.037	0.002	1015.348
4711.238					

total_ic_mou_7 437.167	-1538.9468	1008.240	-1.526	0.127	-3515.061
total_ic_mou_8 -1.78e+04	-1.982e+04	1035.030	-19.153	0.000	-2.19e+04
spl_ic_mou_6 -0.435	-1.5369	0.562	-2.733	0.006	-2.639
spl_ic_mou_7 1.598	0.5833	0.518	1.127	0.260	-0.431
spl_ic_mou_8 5.785	5.2078	0.295	17.671	0.000	4.630
isd_ic_mou_6 -171.704	-483.9815	159.328	-3.038	0.002	-796.259
isd_ic_mou_7 626.482	274.3329	179.671	1.527	0.127	-77.816
isd_ic_mou_8 3866.794	3507.8222	183.152	19.153	0.000	3148.851
ic_others_6 -28.829	-81.0624	26.650	-3.042	0.002	-133.295
ic_others_7 97.014	42.4590	27.835	1.525	0.127	-12.096
ic_others_8 606.506	550.1144	28.772	19.120	0.000	493.723
total_rech_num_6 0.091	0.0224	0.035	0.638	0.523	-0.046
total_rech_num_7 0.151	0.0726	0.040	1.804	0.071	-0.006
total_rech_num_8 -0.560	-0.6403	0.041	-15.682	0.000	-0.720
total_rech_amt_6 0.774	0.6131	0.082	7.465	0.000	0.452
total_rech_amt_7 -0.060	-0.2171	0.080	-2.701	0.007	-0.375
total_rech_amt_8 0.442	0.2182	0.114	1.913	0.056	-0.005
max_rech_amt_6 -0.151	-0.2237	0.037	-6.053	0.000	-0.296
max_rech_amt_7 0.011	-0.0587	0.036	-1.645	0.100	-0.129
max_rech_amt_8 0.233	0.1475	0.043	3.398	0.001	0.062
last_day_rch_amt_6 -0.119	-0.1756	0.029	-6.043	0.000	-0.233
last_day_rch_amt_7 0.059	0.0028	0.029	0.098	0.922	-0.054
last_day_rch_amt_8 -0.445	-0.5102	0.033	-15.449	0.000	-0.575
vol_2g_mb_6	0.1398	0.030	4.724	0.000	0.082

0.198					
vol_2g_mb_7	0.0299	0.032	0.927	0.354	-0.033
0.093					
vol_2g_mb_8	0.0882	0.034	2.580	0.010	0.021
0.155					
vol_3g_mb_6	0.3625	0.044	8.158	0.000	0.275
0.450					
vol_3g_mb_7	0.4089	0.056	7.289	0.000	0.299
0.519					
vol_3g_mb_8	-0.1838	0.068	-2.700	0.007	-0.317
-0.050					
monthly_2g_6	-0.6068	0.045	-13.514	0.000	-0.695
-0.519					
monthly_2g_7	-0.4095	0.042	-9.834	0.000	-0.491
-0.328					
monthly_2g_8	-0.6419	0.059	-10.961	0.000	-0.757
-0.527					
sachet_2g_6	-0.0239	0.031	-0.773	0.439	-0.085
0.037					
sachet_2g_7	-0.2143	0.033	-6.464	0.000	-0.279
-0.149					
sachet_2g_8	-0.2391	0.032	-7.513	0.000	-0.301
-0.177					
monthly_3g_6	-0.3220	0.046	-6.989	0.000	-0.412
-0.232					
monthly_3g_7	-0.5808	0.052	-11.100	0.000	-0.683
-0.478					
monthly_3g_8	-0.8649	0.078	-11.083	0.000	-1.018
-0.712					
sachet_3g_6	-0.0281	0.032	-0.871	0.384	-0.091
0.035					
sachet_3g_7	-0.0829	0.042	-1.964	0.050	-0.166
-0.000					
sachet_3g_8	-0.1553	0.048	-3.222	0.001	-0.250
-0.061					
aon	-0.1564	0.022	-7.269	0.000	-0.199
-0.114					
aug_vbc_3g	-0.1965	0.057	-3.441	0.001	-0.308
-0.085					
jul_vbc_3g	-0.0522	0.047	-1.118	0.264	-0.144
0.039					
jun_vbc_3g	0.2364	0.047	5.007	0.000	0.144
0.329					
decrease_mou_action	-0.4989	0.053	-9.461	0.000	-0.602
-0.396					
decrease_rech_num_action	-1.0229	0.048	-21.429	0.000	-1.116
-0.929					

decrease_rech_amt_action	-0.3065	0.065	-4.720	0.000	-0.434
-0.179					
decrease_arpu_action	-0.1797	0.067	-2.701	0.007	-0.310
-0.049					
decrease_vbc_action	-1.7537	0.130	-13.538	0.000	-2.008
-1.500					

```
=====
=====
"""
```

**Model analysis** 1. We can see that there are few features have positive coefficients and few have negative. 2. Many features have higher p-values and hence became insignificant in the model.

### *Coarse tuning (Auto+Manual)*

We'll first eliminate a few features using Recursive Feature Elimination (RFE), and once we have reached a small set of variables to work with, we can then use manual feature elimination (i.e. manually eliminating features based on observing the p-values and VIFs).

#### 3.1.1 Feature Selection Using RFE

```
[173]: # Importing logistic regression from sklearn
from sklearn.linear_model import LogisticRegression
# Intantiate the logistic regression
logreg = LogisticRegression()
```

#### RFE with 15 columns

```
[174]: # Importing RFE
from sklearn.feature_selection import RFE

# Intantiate RFE with 15 columns
rfe = RFE(logreg, 15)

# Fit the rfe model with train set
rfe = rfe.fit(X_train, y_train)
```

```
[175]: # RFE selected columns
rfe_cols = X_train.columns[rfe.support_]
print(rfe_cols)
```

```
Index(['offnet_mou_7', 'offnet_mou_8', 'roam_og_mou_8', 'std_og_t2m_mou_8',
      'isd_og_mou_8', 'og_others_7', 'og_others_8', 'loc_ic_t2f_mou_8',
      'loc_ic_mou_8', 'std_ic_t2f_mou_8', 'ic_others_8', 'total_rech_num_8',
      'monthly_2g_8', 'monthly_3g_8', 'decrease_vbc_action'],
      dtype='object')
```

### 3.1.2 Model-1 with RFE selected columns

```
[176]: # Adding constant to X_train
X_train_sm_1 = sm.add_constant(X_train[rfe_cols])

#Instantiate the model
log_no_pca_1 = sm.GLM(y_train, X_train_sm_1, family=sm.families.Binomial())

# Fit the model
log_no_pca_1 = log_no_pca_1.fit()

log_no_pca_1.summary()
```

```
[176]: <class 'statsmodels.iolib.summary.Summary'>
      """
              Generalized Linear Model Regression Results
=====
Dep. Variable:          churn    No. Observations:          42850
Model:                  GLM      Df Residuals:              42834
Model Family:           Binomial Df Model:                  15
Link Function:          logit    Scale:                  1.0000
Method:                 IRLS     Log-Likelihood:         nan
Date:                   Sat, 16 May 2020    Deviance:              nan
Time:                   18:04:18    Pearson chi2:          4.49e+06
No. Iterations:         100
Covariance Type:        nonrobust
=====
=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----
const          -58.6610    4419.624     -0.013     0.989    -8720.965
8603.643
offnet_mou_7      0.6096      0.026     23.449     0.000      0.559
0.661
offnet_mou_8     -3.2532      0.106    -30.548     0.000     -3.462
-3.045
roam_og_mou_8      1.2482      0.032     39.496     0.000      1.186
1.310
std_og_t2m_mou_8   2.4408      0.094     26.101     0.000      2.258
2.624
isd_og_mou_8     -1.0212      0.194     -5.271     0.000     -1.401
-0.641
og_others_7       -1.1915      0.862     -1.382     0.167     -2.881
0.498
og_others_8     -4191.9652    3.22e+05     -0.013     0.990    -6.35e+05
=====
```

```

6.27e+05
loc_ic_t2f_mou_8      -0.7547      0.072      -10.487      0.000      -0.896
-0.614
loc_ic_mou_8          -1.9744      0.066      -30.078      0.000      -2.103
-1.846
std_ic_t2f_mou_8      -0.7922      0.075      -10.607      0.000      -0.939
-0.646
ic_others_8           -1.4913      0.132      -11.305      0.000      -1.750
-1.233
total_rech_num_8      -0.4840      0.018      -26.977      0.000      -0.519
-0.449
monthly_2g_8          -0.9031      0.043      -20.851      0.000      -0.988
-0.818
monthly_3g_8          -0.9871      0.043      -22.711      0.000      -1.072
-0.902
decrease_vbc_action   -1.3078      0.073      -17.956      0.000      -1.451
-1.165
=====
=====
"""

```

### Checking VIFs

```

[177]: # Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor

[178]: # Create a dataframe that will contain the names of all the feature variables,
        ↪ and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[rfe_cols].columns
vif['VIF'] = [variance_inflation_factor(X_train[rfe_cols].values, i) for i in
        ↪ range(X_train[rfe_cols].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif

```

```

[178]:
      Features  VIF
1  offnet_mou_8  7.45
3  std_og_t2m_mou_8  6.27
0  offnet_mou_7  1.92
8  loc_ic_mou_8  1.68
7  loc_ic_t2f_mou_8  1.21
11 total_rech_num_8  1.19
2  roam_og_mou_8  1.16
14 decrease_vbc_action  1.08
13 monthly_3g_8  1.06
6  og_others_8  1.05

```

```

12      monthly_2g_8  1.05
5       og_others_7   1.04
9      std_ic_t2f_mou_8 1.02
10     ic_others_8    1.02
4      isd_og_mou_8   1.01

```

Removing column `og_others_8`, which is insignificant as it has the highest p-value 0.99

```

[179]: # Removing og_others_8 column
log_cols = rfe_cols.to_list()
log_cols.remove('og_others_8')
print(log_cols)

```

```

['offnet_mou_7', 'offnet_mou_8', 'roam_og_mou_8', 'std_og_t2m_mou_8',
'isd_og_mou_8', 'og_others_7', 'loc_ic_t2f_mou_8', 'loc_ic_mou_8',
'std_ic_t2f_mou_8', 'ic_others_8', 'total_rech_num_8', 'monthly_2g_8',
'monthly_3g_8', 'decrease_vbc_action']

```

### 3.1.3 Model-2

Building the model after removing `og_others_8` variable.

```

[180]: # Adding constant to X_train
X_train_sm_2 = sm.add_constant(X_train[log_cols])

#Instantiate the model
log_no_pca_2 = sm.GLM(y_train, X_train_sm_2, family=sm.families.Binomial())

# Fit the model
log_no_pca_2 = log_no_pca_2.fit()

log_no_pca_2.summary()

```

```

[180]: <class 'statsmodels.iolib.summary.Summary'>
      ""

```

```

                        Generalized Linear Model Regression Results
=====
Dep. Variable:          churn      No. Observations:          42850
Model:                  GLM        Df Residuals:              42835
Model Family:           Binomial   Df Model:                 14
Link Function:          logit      Scale:                   1.0000
Method:                 IRLS       Log-Likelihood:          -15034.
Date:                   Sat, 16 May 2020    Deviance:                30068.
Time:                   18:06:36    Pearson chi2:            4.51e+06
No. Iterations:         11
Covariance Type:        nonrobust
=====

```

```

=====
                                coef      std err          z      P>|z|      [0.025
0.975]
-----
const                -1.1052      0.031    -35.342      0.000      -1.167
-1.044
offnet_mou_7         0.6081      0.026     23.427      0.000       0.557
0.659
offnet_mou_8        -3.2557      0.106    -30.603      0.000     -3.464
-3.047
roam_og_mou_8        1.2491      0.031     39.747      0.000       1.188
1.311
std_og_t2m_mou_8     2.4428      0.093     26.146      0.000       2.260
2.626
isd_og_mou_8        -1.0982      0.196     -5.590      0.000     -1.483
-0.713
og_others_7         -1.8793      0.818     -2.299      0.022     -3.482
-0.277
loc_ic_t2f_mou_8    -0.7548      0.072    -10.491      0.000     -0.896
-0.614
loc_ic_mou_8        -1.9714      0.066    -30.058      0.000     -2.100
-1.843
std_ic_t2f_mou_8    -0.8020      0.075    -10.727      0.000     -0.949
-0.655
ic_others_8         -1.4871      0.132    -11.278      0.000     -1.746
-1.229
total_rech_num_8    -0.4864      0.018    -27.146      0.000     -0.522
-0.451
monthly_2g_8        -0.9066      0.043    -20.866      0.000     -0.992
-0.821
monthly_3g_8        -0.9862      0.043    -22.700      0.000     -1.071
-0.901
decrease_vbc_action -1.3097      0.073    -17.994      0.000     -1.452
-1.167
=====
=====
"""

```

### Checking VIF for Model-2

```

[181]: # Create a dataframe that will contain the names of all the feature variables
        ↪and their respective VIFs
vif = pd.DataFrame()
vif['Features'] = X_train[log_cols].columns
vif['VIF'] = [variance_inflation_factor(X_train[log_cols].values, i) for i in
        ↪range(X_train[log_cols].shape[1])]

```



```
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

```
[181]:
```

	Features	VIF
1	offnet_mou_8	7.45
3	std_og_t2m_mou_8	6.27
0	offnet_mou_7	1.92
7	loc_ic_mou_8	1.68
6	loc_ic_t2f_mou_8	1.21
10	total_rech_num_8	1.19
2	roam_og_mou_8	1.16
13	decrease_vbc_action	1.08
12	monthly_3g_8	1.06
11	monthly_2g_8	1.05
8	std_ic_t2f_mou_8	1.02
4	isd_og_mou_8	1.01
9	ic_others_8	1.01
5	og_others_7	1.00

As we can see from the model summary that all the variables p-values are significant and offnet\_mou\_8 column has the highest VIF 7.45. Hence, deleting offnet\_mou\_8 column.

```
[182]: # Removing offnet_mou_8 column
log_cols.remove('offnet_mou_8')
```

### 3.1.4 Model-3

Model after removing offnet\_mou\_8 column.

```
[183]: # Adding constant to X_train
X_train_sm_3 = sm.add_constant(X_train[log_cols])

#Instantiate the model
log_no_pca_3 = sm.GLM(y_train, X_train_sm_3, family=sm.families.Binomial())

# Fit the model
log_no_pca_3 = log_no_pca_3.fit()

log_no_pca_3.summary()
```

```
[183]: <class 'statsmodels.iolib.summary.Summary'>
"""

                        Generalized Linear Model Regression Results
=====
Dep. Variable:          churn    No. Observations:          42850
Model:                  GLM      Df Residuals:              42836
Model Family:          Binomial  Df Model:                  13
```

```

Link Function:          logit      Scale:          1.0000
Method:                IRLS       Log-Likelihood: -15720.
Date:                  Sat, 16 May 2020 Deviance:      31440.
Time:                  18:07:30   Pearson chi2:   3.92e+06
No. Iterations:        11
Covariance Type:      nonrobust

```

```

=====
=====
              coef      std err          z      P>|z|      [0.025
0.975]
-----
-----
const          -1.2058      0.032    -37.536      0.000     -1.269
-1.143
offnet_mou_7     0.3665      0.022     16.456      0.000      0.323
0.410
roam_og_mou_8     0.7135      0.024     29.260      0.000      0.666
0.761
std_og_t2m_mou_8 -0.2474      0.022    -11.238      0.000     -0.291
-0.204
isd_og_mou_8     -1.3811      0.212     -6.511      0.000     -1.797
-0.965
og_others_7      -2.4711      0.872     -2.834      0.005     -4.180
-0.762
loc_ic_t2f_mou_8 -0.7102      0.075     -9.532      0.000     -0.856
-0.564
loc_ic_mou_8     -3.3287      0.057    -58.130      0.000     -3.441
-3.216
std_ic_t2f_mou_8 -0.9503      0.078    -12.181      0.000     -1.103
-0.797
ic_others_8      -1.5131      0.129    -11.771      0.000     -1.765
-1.261
total_rech_num_8 -0.5060      0.018    -28.808      0.000     -0.540
-0.472
monthly_2g_8     -0.9279      0.044    -21.027      0.000     -1.014
-0.841
monthly_3g_8     -1.0943      0.046    -23.615      0.000     -1.185
-1.004
decrease_vbc_action -1.3293      0.072    -18.478      0.000     -1.470
-1.188
=====
=====
"""

```

### VIF Model-3

```
[184]: vif = pd.DataFrame()
vif['Features'] = X_train[log_cols].columns
vif['VIF'] = [variance_inflation_factor(X_train[log_cols].values, i) for i in
             range(X_train[log_cols].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

```
[184]:
```

	Features	VIF
2	std_og_t2m_mou_8	1.87
0	offnet_mou_7	1.72
6	loc_ic_mou_8	1.33
5	loc_ic_t2f_mou_8	1.21
9	total_rech_num_8	1.17
12	decrease_vbc_action	1.07
1	roam_og_mou_8	1.06
11	monthly_3g_8	1.06
10	monthly_2g_8	1.05
7	std_ic_t2f_mou_8	1.02
3	isd_og_mou_8	1.01
8	ic_others_8	1.01
4	og_others_7	1.00

Now from the model summary and the VIF list we can see that all the variables are significant and there is no multicollinearity among the variables.

Hence, we can concluded that *Model-3 log\_no\_pca\_3 will be the final model.*

### 3.1.5 Model performance on the train set

```
[185]: # Getting the predicted value on the train set
y_train_pred_no_pca = log_no_pca_3.predict(X_train_sm_3)
y_train_pred_no_pca.head()
```

```
[185]: 0    2.687411e-01
1    7.047483e-02
2    8.024370e-02
3    3.439222e-03
4    5.253815e-19
dtype: float64
```

Creating a dataframe with the actual churn and the predicted probabilities

```
[186]: y_train_pred_final = pd.DataFrame({'churn':y_train.values, 'churn_prob':
             y_train_pred_no_pca.values})

#Assigning Customer ID for each record for better readblity
#CustID is the index of each record.
```

```
y_train_pred_final['CustID'] = y_train_pred_final.index
y_train_pred_final.head()
```

```
[186]: churn churn_prob CustID
0      0  2.687411e-01      0
1      0  7.047483e-02      1
2      0  8.024370e-02      2
3      0  3.439222e-03      3
4      0  5.253815e-19      4
```

### Finding Optimal Probability Cutoff Point

```
[187]: # Creating columns for different probability cutoffs
prob_cutoff = [float(p/10) for p in range(10)]

for i in prob_cutoff:
    y_train_pred_final[i] = y_train_pred_final['churn_prob'].map(lambda x : 1
    ↪if x > i else 0)

y_train_pred_final.head()
```

```
[187]: churn churn_prob CustID 0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 \
0      0  2.687411e-01      0    1    1    1    0    0    0    0    0    0
1      0  7.047483e-02      1    1    0    0    0    0    0    0    0    0
2      0  8.024370e-02      2    1    0    0    0    0    0    0    0    0
3      0  3.439222e-03      3    1    0    0    0    0    0    0    0    0
4      0  5.253815e-19      4    1    0    0    0    0    0    0    0    0

0.9
0      0
1      0
2      0
3      0
4      0
```

Now let's calculate the accuracy sensitivity and specificity for various probability cutoffs.

```
[188]: # Creating a dataframe
cutoff_df = pd.DataFrame(columns=['probability', 'accuracy', 'sensitivity',
    ↪'specificity'])

for i in prob_cutoff:
    cm1 = metrics.confusion_matrix(y_train_pred_final['churn'],
    ↪y_train_pred_final[i] )
    total1=sum(sum(cm1))
```

```

accuracy = (cm1[0,0]+cm1[1,1])/total1

speci = cm1[0,0]/(cm1[0,0]+cm1[0,1])
sensi = cm1[1,1]/(cm1[1,0]+cm1[1,1])
cutoff_df.loc[i] =[ i ,accuracy,sensi,speci]
print(cutoff_df)

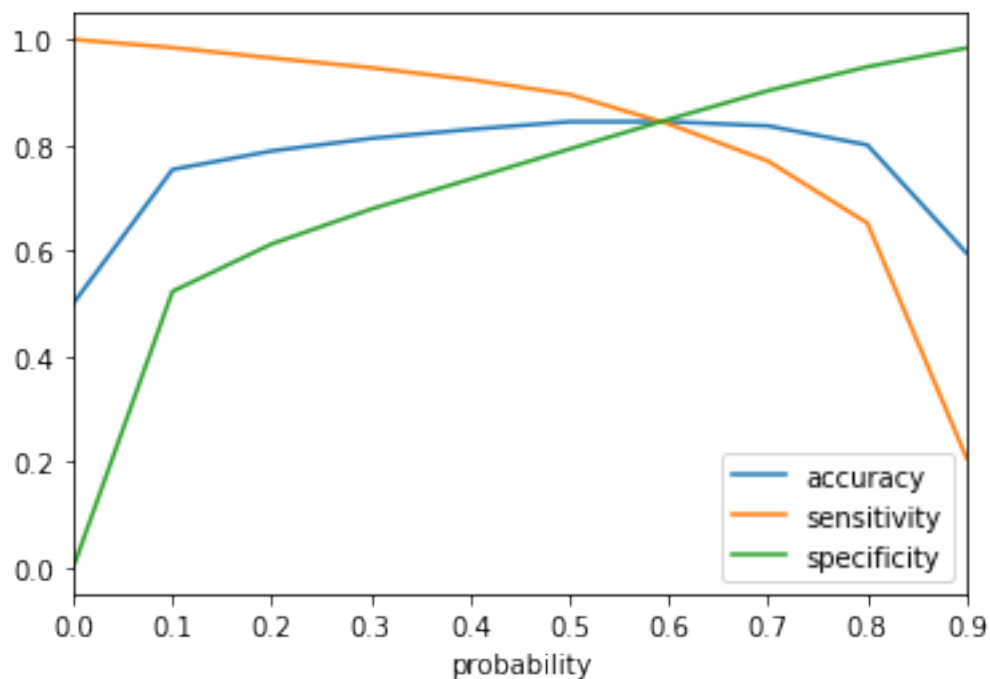
```

	probability	accuracy	sensitivity	specificity
0.0	0.0	0.500000	1.000000	0.000000
0.1	0.1	0.753629	0.984411	0.522847
0.2	0.2	0.788751	0.964714	0.612789
0.3	0.3	0.812509	0.946371	0.678646
0.4	0.4	0.829638	0.923874	0.735403
0.5	0.5	0.844131	0.895823	0.792439
0.6	0.6	0.844271	0.839860	0.848681
0.7	0.7	0.836173	0.769522	0.902824
0.8	0.8	0.800163	0.652275	0.948051
0.9	0.9	0.595426	0.207001	0.983851

```

[189]: # Plotting accuracy, sensitivity and specificity for different probabilities.
cutoff_df.plot('probability', ['accuracy','sensitivity','specificity'])
plt.show()

```



**Analysis of the above curve** Accuracy - Becomes stable around 0.6

Sensitivity - Decreases with the increased probability.

Specificity - Increases with the increasing probability.

At point 0.6 where the three parameters cut each other, we can see that there is a balance between sensitivity and specificity with a good accuracy.

Here we are intended to achieve better sensitivity than accuracy and specificity. Though as per the above curve, we should take 0.6 as the optimum probability cutoff, we are taking **0.5** for achieving higher sensitivity, which is our main goal.

```
[190]: # Creating a column with name "predicted", which is the predicted value for 0.5
        ↪ cutoff
y_train_pred_final['predicted'] = y_train_pred_final['churn_prob'].map(lambda x:
        ↪ 1 if x > 0.5 else 0)
y_train_pred_final.head()
```

```
[190]:   churn   churn_prob  CustID  0.0  0.1  0.2  0.3  0.4  0.5  0.6  0.7  0.8  \
0      0  2.687411e-01      0    1    1    1    0    0    0    0    0    0
1      0  7.047483e-02      1    1    0    0    0    0    0    0    0    0
2      0  8.024370e-02      2    1    0    0    0    0    0    0    0    0
3      0  3.439222e-03      3    1    0    0    0    0    0    0    0    0
4      0  5.253815e-19      4    1    0    0    0    0    0    0    0    0

      0.9  predicted
0      0          0
1      0          0
2      0          0
3      0          0
4      0          0
```

## Metrics

```
[191]: # Confusion metrics
confusion = metrics.confusion_matrix(y_train_pred_final['churn'],
        ↪ y_train_pred_final['predicted'])
print(confusion)
```

```
[[16978  4447]
 [ 2232 19193]]
```

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

```
[193]: # Accuracy
print("Accuracy:-", metrics.accuracy_score(y_train_pred_final['churn'],
        ↪ y_train_pred_final['predicted']))
```

```

# Sensitivity
print("Sensitivity:-", TP / float(TP+FN))

# Specificity
print("Specificity:-", TN / float(TN+FP))

```

Accuracy:- 0.8441306884480747  
Sensitivity:- 0.8958226371061844  
Specificity:- 0.792438739789965

We have got good accuracy, sensitivity and specificity on the train set prediction.

### Plotting the ROC Curve (Trade off between sensitivity & specificity)

```

[194]: # ROC Curve function

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

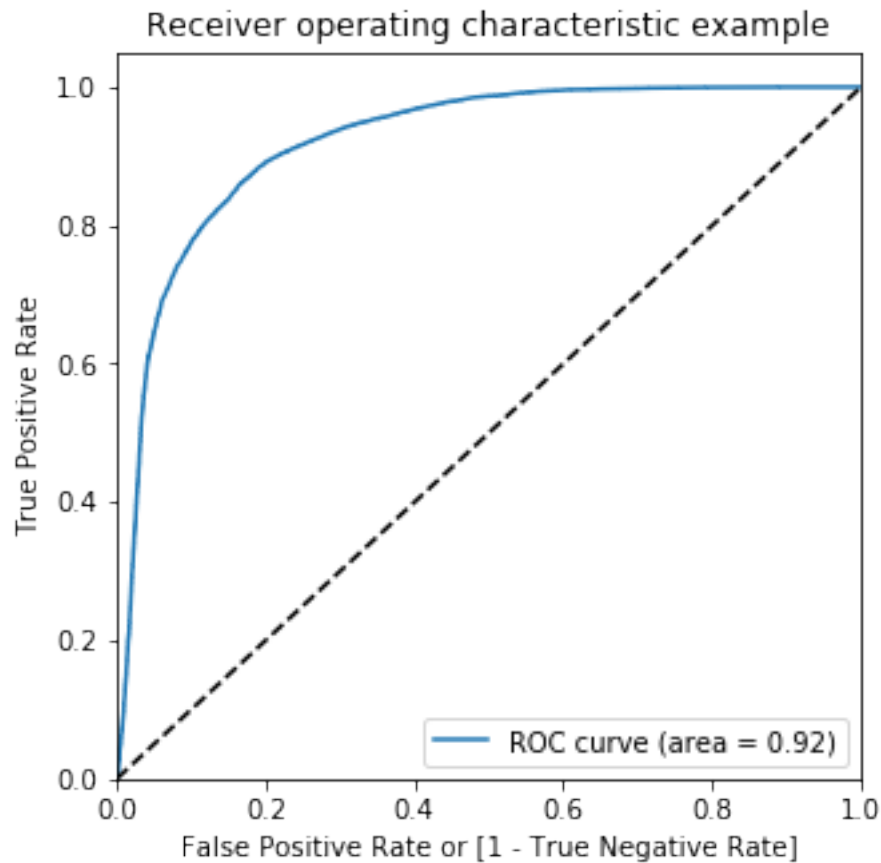
    return None

```

```

[195]: draw_roc(y_train_pred_final['churn'], y_train_pred_final['churn_prob'])

```



We can see the area of the ROC curve is closer to 1, which is the Gini of the model.

### 3.1.6 Testing the model on the test set

```
[196]: # Taking a copy of the test set
X_test_log = X_test.copy()
```

```
[198]: # Taking only the columns, which are selected in the train set after removing
↳insignificant and multicollinear variables
X_test_log = X_test_log[log_cols]
```

```
[199]: # Adding constant on the test set
X_test_sm = sm.add_constant(X_test_log)
```

### Predictions on the test set with final model

```
[200]: # Predict on the test set
y_test_pred = log_no_pca_3.predict(X_test_sm)
```

```
[201]: y_test_pred.head()
```



```
[201]: 5704      0.034015
      64892    0.000578
      39613    0.513564
      93118    0.020480
      81235    0.034115
      dtype: float64
```

```
[202]: # Converting y_test_pred to a dataframe because y_test_pred is an array
      y_pred_1 = pd.DataFrame(y_test_pred)
      y_pred_1.head()
```

```
[202]:      0
      5704    0.034015
      64892    0.000578
      39613    0.513564
      93118    0.020480
      81235    0.034115
```

```
[203]: # Convetting y_test to a dataframe
      y_test_df = pd.DataFrame(y_test)
      y_test_df.head()
```

```
[203]:      churn
      5704      0
      64892      0
      39613      0
      93118      0
      81235      0
```

```
[204]: # Putting index to Customer ID
      y_test_df['CustID'] = y_test_df.index
```

```
[205]: # Removing index form the both dataframes for merging them side by side
      y_pred_1.reset_index(drop=True, inplace=True)
      y_test_df.reset_index(drop=True, inplace=True)
```

```
[206]: # Appending y_pred_1 and y_test_df
      y_test_pred_final = pd.concat([y_test_df, y_pred_1], axis=1)
```

```
[207]: y_test_pred_final.head()
```

```
[207]:      churn  CustID      0
      0      0    5704  0.034015
      1      0   64892  0.000578
      2      0   39613  0.513564
      3      0   93118  0.020480
      4      0   81235  0.034115
```

```
[208]: # Renaming the '0' column as churn probability
y_test_pred_final = y_test_pred_final.rename(columns={0: 'churn_prob'})
```

```
[209]: # Rearranging the columns
y_test_pred_final = y_test_pred_final.
↳reindex_axis(['CustID', 'churn', 'churn_prob'], axis=1)
```

```
[210]: y_test_pred_final.head()
```

```
[210]:   CustID  churn  churn_prob
0    5704     0    0.034015
1   64892     0    0.000578
2    39613     0    0.513564
3    93118     0    0.020480
4    81235     0    0.034115
```

```
[211]: # In the test set using probability cutoff 0.5, what we got in the train set
y_test_pred_final['test_predicted'] = y_test_pred_final['churn_prob'].
↳map(lambda x: 1 if x > 0.5 else 0)
```

```
[212]: y_test_pred_final.head()
```

```
[212]:   CustID  churn  churn_prob  test_predicted
0    5704     0    0.034015             0
1   64892     0    0.000578             0
2    39613     0    0.513564             1
3    93118     0    0.020480             0
4    81235     0    0.034115             0
```

## Metrics

```
[214]: # Confusion matrix
confusion = metrics.confusion_matrix(y_test_pred_final['churn'],
↳y_test_pred_final['test_predicted'])
print(confusion)
```

```
[[4190 1158]
 [ 34 159]]
```

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

```
[216]: # Accuracy
print("Accuracy:-", metrics.accuracy_score(y_test_pred_final['churn'],
↳y_test_pred_final['test_predicted']))
```

```
# Sensitivity
print("Sensitivity:-", TP / float(TP+FN))

# Specificity
print("Specificity:-", TN / float(TN+FP))
```

Accuracy:- 0.7848763761053962  
 Sensitivity:- 0.8238341968911918  
 Specificity:- 0.7834704562453254

### Model summary

- Train set
  - Accuracy = 0.84
  - Sensitivity = 0.81
  - Specificity = 0.83
- Test set
  - Accuracy = 0.78
  - Sensitivity = 0.82
  - Specificity = 0.78

Overall, the model is performing well in the test set, what it had learnt from the train set.

**Final conclusion with no PCA** We can see that the logistic model with no PCA has good sensitivity and accuracy, which are comparable to the models with PCA. So, we can go for the more simplistic model such as logistic regression with PCA as it explains the important predictor variables as well as the significance of each variable. The model also helps us to identify the variables which should be acted upon for making the decision of the to be churned customers. Hence, the model is more relevant in terms of explaining to the business.

## 3.2 Business recommendation

**Top predictors** Below are few top variables selected in the logistic regression model.

Variables	Coefficients
loc_ic_mou_8	-3.3287
og_others_7	-2.4711
ic_others_8	-1.5131
isd_og_mou_8	-1.3811
decrease_vbc_action	-1.3293
monthly_3g_8	-1.0943
std_ic_t2f_mou_8	-0.9503
monthly_2g_8	-0.9279
loc_ic_t2f_mou_8	-0.7102
roam_og_mou_8	0.7135

We can see most of the top variables have negative coefficients. That means, the variables are

inversely correlated with the churn probability.

E.g.:-

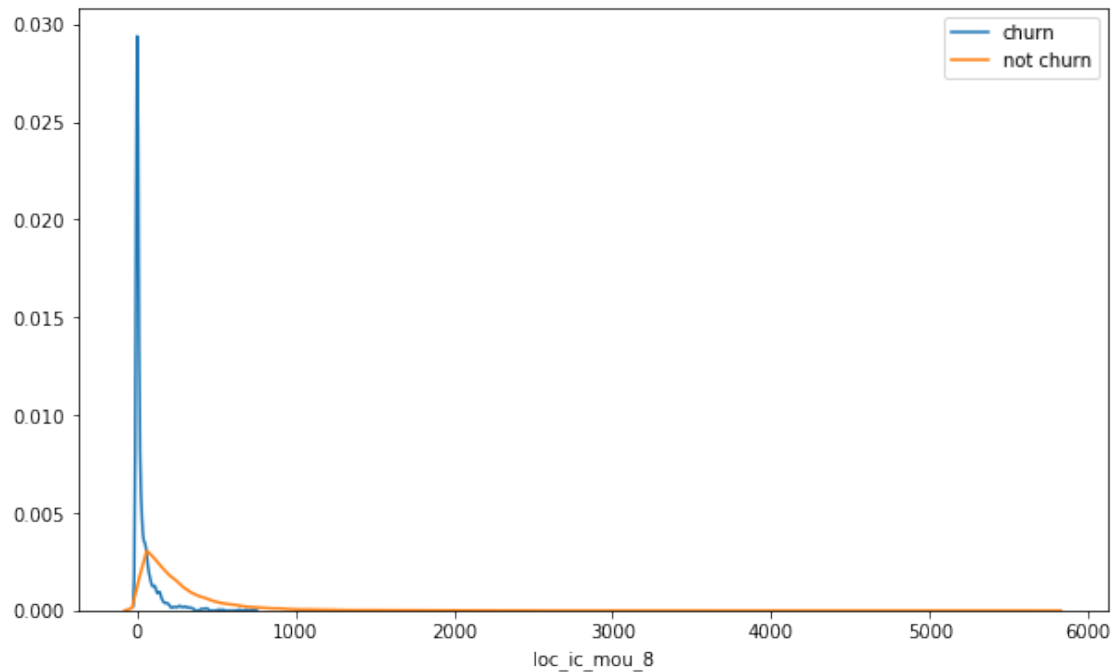
If the local incoming minutes of usage (loc\_ic\_mou\_8) is lesser in the month of August than any other month, then there is a higher chance that the customer is likely to churn.

### ***Recommendations***

1. Target the customers, whose minutes of usage of the incoming local calls and outgoing ISD calls are less in the action phase (mostly in the month of August).
2. Target the customers, whose outgoing others charge in July and incoming others on August are less.
3. Also, the customers having value based cost in the action phase increased are more likely to churn than the other customers. Hence, these customers may be a good target to provide offer.
4. Customers, whose monthly 3G recharge in August is more, are likely to be churned.
5. Customers having decreasing STD incoming minutes of usage for operators T to fixed lines of T for the month of August are more likely to churn.
6. Customers decreasing monthly 2g usage for August are most probable to churn.
7. Customers having decreasing incoming minutes of usage for operators T to fixed lines of T for August are more likely to churn.
8. roam\_og\_mou\_8 variables have positive coefficients (0.7135). That means for the customers, whose roaming outgoing minutes of usage is increasing are more likely to churn.

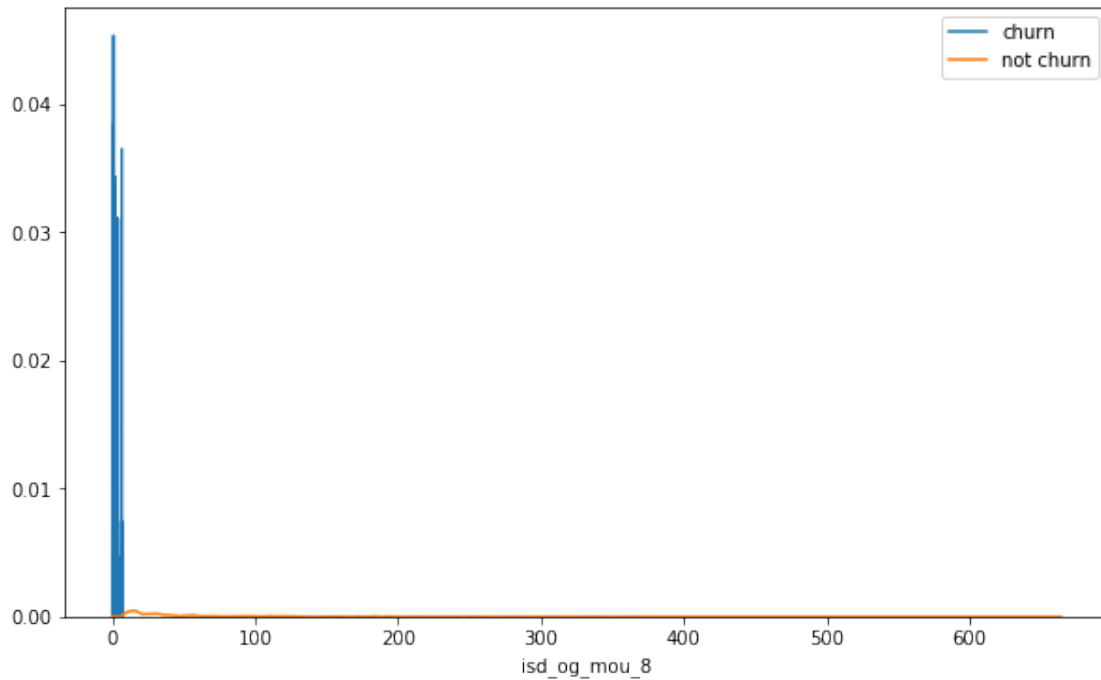
### **Plots of important predictors for churn and non churn customers**

```
[217]: # Plotting loc_ic_mou_8 predictor for churn and not churn customers
fig = plt.figure(figsize=(10,6))
sns.distplot(data_churn['loc_ic_mou_8'],label='churn',hist=False)
sns.distplot(data_non_churn['loc_ic_mou_8'],label='not churn',hist=False)
plt.show()
```



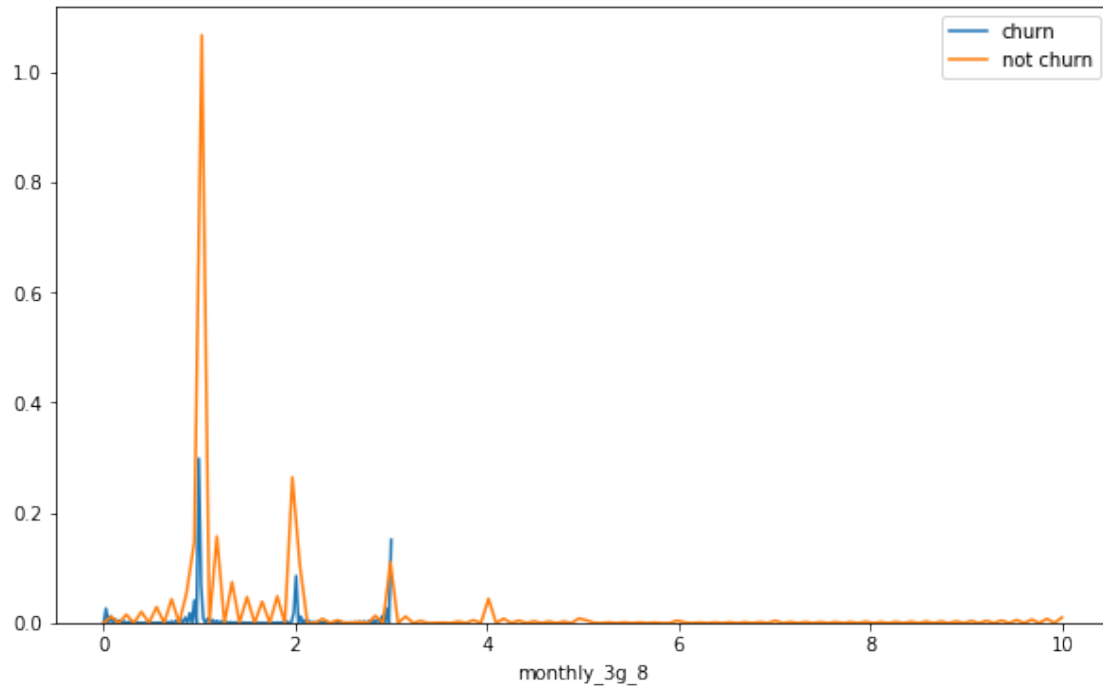
We can see that for the churn customers the minutes of usage for the month of August is mostly populated on the lower side than the non churn customers.

```
[218]: # Plotting isd_og_mou_8 predictor for churn and not churn customers
fig = plt.figure(figsize=(10,6))
sns.distplot(data_churn['isd_og_mou_8'],label='churn',hist=False)
sns.distplot(data_non_churn['isd_og_mou_8'],label='not churn',hist=False)
plt.show()
```



We can see that the ISD outgoing minutes of usage for the month of August for churn customers is denser approximately to zero. On the other hand for the non churn customers it is little more than the churn customers.

```
[219]: # Plotting monthly_3g_8 predictor for churn and not churn customers
fig = plt.figure(figsize=(10,6))
sns.distplot(data_churn['monthly_3g_8'],label='churn',hist=False)
sns.distplot(data_non_churn['monthly_3g_8'],label='not churn',hist=False)
plt.show()
```



The number of monthly 3g data for August for the churn customers are very much populated around 1, whereas for non-churn customers it is spread across various numbers.

Similarly, we can plot each variable, which has higher coefficients, to see the churn distribution.