Telecom Churn Case Study
Author: Nidhi Sharma & Wayam Soni

Assignment Summary:

Problem Statement:-

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

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

Buisness Objective:- To reduce customer churn, telecom companies need to predict which customers are at high risk of churn.

Our Objective:- 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.

The steps are broadly:

1. Reading and understanding the data
   - shape(99999 rows and 226 columns), info, describe, duplicate values check
2. Cleaning the data
   - 2.1) Identifying the categorical and numerical variables.
     - 2.1.1) Identifying the categorical variables and treating them.

       ```
       - Features whose missing value is higher , drop them
       ```

     - 2.1.2) Identifying the important numerical variables which can be imputed with zero.

       ```
       - a) recharge amount
       - b) Minutes of usage - voice calls columns
       ```

     - 2.1.3) Identifying the variables having more than 50% missing values and dropping it
   - 2.2) Preprocess data (convert columns to appropriate formats, handle missing values, etc.)
     - 2.2.1) Converting columns to appropriate formats

       ```
       - object datatype columns , fill missing values with its mode and convert into date type
       ```

     - 2.2.2) Handling missing values of rets of the features

       ```
       - numerical columns are there and missing values are filled with median
       ```

3. Data preparation
   - 3.1) Derive new features

     ```
     - total_rech_data_amt_x ,
     ```

   - 3.2) Filter high-value customers
   - 3.3) Tag churners and remove attributes of the churn phase

     ```
     - 3.3.1) Tag churners
     - 3.3.2) Remove attributes of the churn phase
     ```

- 3.4) Check the columns with unique values and drop such columns

```
- drop date columns too
```

- 3.5) Feature Engineering (Derive some new feautres from the existing columns)

```
- b) Tenure Analysis for Customers
```

4. Visualization of data

- correlation
- 4.1) Univariate Analysis
- 4.2) Multivariate Analysis

```
- Visualising Numerical - Numerical Variables
- Visualising Numerical - Categorical Variables
```

- 4.3) Conducting appropriate exploratory analysis to extract useful insights (whether directly useful for business or for eventual modelling/feature engineering).

```
- 4.3.1) Exploring ARPU
- 4.3.2)Exploring RECHARGES
- 4.3.3) Exploring MOU
- 4.3.4) Scatetr Plots
        - Scatter plot between Total recharge number and Average revenue per use
        - Scatter plot between Tenure and Average revenue per use
- 4.3.5) Subplots
        - Avg. incoming calls  V/S  Month
        - Avg. outgoing call  V/S Month
        - Avg. recharge  V/S Month
```

5. preparation of data for modelling

- 5.1) Checking for Outliers and treat them

```
- drop columns whose contain only values as zero
```

- 5.2) Splitting the Data into X & y
- 5.3) Test-Train Split
- 5.4) Feature Scaling
- 5.5) Looking at Correlations
- 5.6) Checking for Class imbalance in Train & Test and treating it

```
- using SMOTE
```

6. Modelling

```
Model 1: Logistic Regression (with RFE)
Model 2: Decision Tree
    - Model 2.1: Decision Tree  (Default Hyperparameters)
    - Model 2.2: Decision Tree  (Hyperparameter Tuning)
Model 3: Random Forest
    - Model 3.1: Random Forest (Default Hyperparameters)
    - Model 3.2: Random Forest (Hyperparameters Tuning)
```

7. Final analysis
8. H. Recommendation of strategies to manage customer churn based on our observations.

Step 1: Reading and understanding the Data

In [1]:

```
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:80% !important; }</style>"))
```

In [2]:

```
# Lets import the required libraries and packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Lets Supress unnecessary warnings
import warnings
warnings.filterwarnings("ignore")
```

In [3]:

```
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
```

In [4]:

```python
# Lets import and read the dataset
tele_data = pd.read_csv('telecom_churn_data.csv')
tele_data
```

Out[4]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	last_date_of_month_6	last_date_of_month_7	last_date_of_month_8	last_date_of_month_9	arpu_6	arpu_7	arpu_8	arpu_9	onnet_mou_6	onnet_mou_7	onnet_mou_8	onnet_mou_9	offnet_mou_6	offnet_mou_7	offnet_mou_
0	7000842753	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	197.385	214.816	213.803	21.100	NaN	NaN	0.00	NaN	NaN	NaN	0.0
1	7001865778	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	34.047	355.074	268.321	86.285	24.11	78.68	7.68	18.34	15.74	99.84	304.7
2	7001625959	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	167.690	189.058	210.226	290.714	11.54	55.24	37.26	74.81	143.33	220.59	208.3
3	7001204172	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	221.338	251.102	508.054	389.500	99.91	54.39	310.98	241.71	123.31	109.01	71.6
4	7000142493	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	261.636	309.876	238.174	163.426	50.31	149.44	83.89	58.78	76.96	91.88	124.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
99994	7001548952	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	18.471	69.161	57.530	29.950	5.40	3.36	5.91	0.00	15.19	54.46	52.7
99995	7000607688	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	112.201	77.811	79.081	140.835	29.26	18.13	16.06	49.49	100.83	69.01	66.3
99996	7000087541	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	229.187	0.000	0.000	0.000	1.11	NaN	NaN	NaN	21.04	NaN	Na
99997	7000498689	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	322.991	303.386	606.817	731.010	0.00	0.00	0.00	0.00	0.00	0.00	0.0
99998	7001905007	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	687.065	0.000	0.000	0.000	84.34	NaN	NaN	NaN	166.46	NaN	Na

In [5]:

```python
# Lets see the head of our dataset
tele_data.head()
```

Out[5]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	last_date_of_month_6	last_date_of_month_7	last_date_of_month_8	last_date_of_month_9	arpu_6	arpu_7	arpu_8	arpu_9	onnet_mou_6	onnet_mou_7	onnet_mou_8	onnet_mou_9	offnet_mou_6	offnet_mou_7	offnet_mou_8
0	7000842753	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	197.385	214.816	213.803	21.100	NaN	NaN	0.00	NaN	NaN	NaN	0.00
1	7001865778	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	34.047	355.074	268.321	86.285	24.11	78.68	7.68	18.34	15.74	99.84	304.76
2	7001625959	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	167.690	189.058	210.226	290.714	11.54	55.24	37.26	74.81	143.33	220.59	208.36
3	7001204172	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	221.338	251.102	508.054	389.500	99.91	54.39	310.98	241.71	123.31	109.01	71.68
4	7000142493	109	0.0	0.0	0.0	6/30/2014	7/31/2014	8/31/2014	9/30/2014	261.636	309.876	238.174	163.426	50.31	149.44	83.89	58.78	76.96	91.88	124.26

In [6]:

```python
# Lets check the info to see the types of the feature variables and the null values present
tele_data.info(verbose=1)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Data columns (total 226 columns):
 #   Column                Dtype  
---  ------                -----  
 0   mobile_number         int64  
 1   circle_id             int64  
 2   loc_og_t2o_mou        float64
 3   std_og_t2o_mou        float64
 4   loc_ic_t2o_mou        float64
 5   last_date_of_month_6  object 
 6   last_date_of_month_7  object 
 7   last_date_of_month_8  object 
 8   last_date_of_month_9  object 
 9   arpu_6                float64
 10  arpu_7                float64
 11  arpu_8                float64
 12  arpu_9                float64
 13  onnet_mou_6           float64
```

Inference:- There are 99999 rows and 226 columns in the data. Lot of the columns are numeric type, but we need to inspect which are the categorical columns.

In [7]:
```
# Lets check the summary of the dataset
tele_data.describe(include='all')
```

Out[7]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	last_date_of_month_6	last_date_of_month_7	last_date_of_month_8	last_date_of_month_9
count	9.999900e+04	99999.0	98981.0	98981.0	98981.0	99999	99398	98899	98340
unique	NaN	NaN	NaN	NaN	NaN	1	1	1	1
top	NaN	NaN	NaN	NaN	NaN	6/30/2014	7/31/2014	8/31/2014	9/30/2014
freq	NaN	NaN	NaN	NaN	NaN	99999	99398	98899	98340
mean	7.001207e+09	109.0	0.0	0.0	0.0	NaN	NaN	NaN	NaN
std	6.956694e+05	0.0	0.0	0.0	0.0	NaN	NaN	NaN	NaN
min	7.000000e+09	109.0	0.0	0.0	0.0	NaN	NaN	NaN	NaN
25%	7.000606e+09	109.0	0.0	0.0	0.0	NaN	NaN	NaN	NaN
50%	7.001205e+09	109.0	0.0	0.0	0.0	NaN	NaN	NaN	NaN
75%	7.001812e+09	109.0	0.0	0.0	0.0	NaN	NaN	NaN	NaN
max	7.002411e+09	109.0	0.0	0.0	0.0	NaN	NaN	NaN	NaN

	arpu_6	arpu_7	arpu_8	arpu_9	onnet_mou_6	onnet_mou_7	onnet_mou_8	onnet_mou_9	offnet_mou_6	offn
count	99999.000000	99999.000000	99999.000000	99999.000000	96062.000000	96140.000000	94621.000000	92254.000000	96062.000000	961
unique	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
top	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
freq	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
mean	282.987358	278.536648	279.154731	261.645069	132.395875	133.670805	133.018098	130.302327	197.935577	19
std	328.439770	338.156291	344.474791	341.998630	297.207406	308.794148	308.951589	308.477668	316.851613	32
min	-2258.709000	-2014.045000	-945.808000	-1899.505000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	93.411500	86.980500	84.126000	62.685000	7.380000	6.660000	6.460000	5.330000	34.730000	3
50%	197.704000	191.640000	192.080000	176.849000	34.310000	32.330000	32.360000	29.840000	96.310000	9
75%	371.060000	365.344500	369.370500	353.466500	118.740000	115.595000	115.860000	112.130000	231.860000	22
max	27731.088000	35145.834000	33543.624000	38805.617000	7376.710000	8157.780000	10752.560000	10427.460000	8362.360000	96

Now lets check if the dataset has any duplicates.

In [8]:
```
# checking duplicates
sum(tele_data.duplicated(subset = 'mobile_number')) == 0
```

Out[8]: True

In [9]:
```
# Lets check the dimensions of the dataset
tele_data.shape
```

Out[9]: (99999, 226)

In [10]:
```
tele_data.drop_duplicates()
tele_data.shape
```

Out[10]: (99999, 226)

Inference:- No duplicate values

Step 2: Cleaning the data

In [11]:
```
# Lets check the null values present in the dataset
print(round(100*(tele_data.isnull().sum()/len(tele_data.index)), 2).sort_values(ascending = False))
```

```
count_rech_2g_6           74.85
date_of_last_rech_data_6  74.85
count_rech_3g_6           74.85
av_rech_amt_data_6        74.85
max_rech_data_6           74.85
total_rech_data_6         74.85
arpu_3g_6                 74.85
arpu_2g_6                 74.85
night_pck_user_6          74.85
fb_user_6                 74.85
arpu_3g_7                 74.43
count_rech_2g_7           74.43
fb_user_7                 74.43
count_rech_3g_7           74.43
arpu_2g_7                 74.43
av_rech_amt_data_7        74.43
max_rech_data_7           74.43
night_pck_user_7          74.43
total_rech_data_7         74.43
```

In [12]:
```
# Identifying if any column exists with only null values
tele_data.isnull().all(axis=0).any()
```

Out[12]: False

In [13]:
```
# Lets again check the dimensions of the dataset
tele_data.shape
```

Out[13]: (99999, 226)

2.1) Identifying the categorical and numerical variables.¶

In [14]:
```python
# create column name list by types of columns
id_cols = ['mobile_number', 'circle_id']

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',
             'date_of_last_rech_data_6',
             'date_of_last_rech_data_7',
             'date_of_last_rech_data_8',
             'date_of_last_rech_data_9'
            ]

cat_cols =  ['night_pck_user_6',
             'night_pck_user_7',
             'night_pck_user_8',
             'night_pck_user_9',
             'fb_user_6',
             'fb_user_7',
             'fb_user_8',
             'fb_user_9'
            ]

num_cols = [column for column in tele_data.columns if column not in id_cols + date_cols + cat_cols]

# print the number of columns in each list
print("#ID cols: %d\n#Date cols:%d\n#Numeric cols:%d\n#Category cols:%d" % (len(id_cols), len(date_cols), len(num_cols), len(cat_cols)))

# check if we have missed any column or not
print(len(id_cols) + len(date_cols) + len(num_cols) + len(cat_cols) == tele_data.shape[1])
```

```
#ID cols: 2
#Date cols:12
#Numeric cols:204
#Category cols:8
True
```

2.1.1) Identifying the categorical variables and treating them.¶

In [15]:
```python
for i in tele_data.columns:
    if tele_data[i].nunique() == 2:
        print("\nColumn",i,"is a categorical variable, since it has", tele_data[i].nunique(),"unique value")
```

```
Column night_pck_user_6 is a categorical variable, since it has 2 unique value

Column night_pck_user_7 is a categorical variable, since it has 2 unique value

Column night_pck_user_8 is a categorical variable, since it has 2 unique value

Column night_pck_user_9 is a categorical variable, since it has 2 unique value

Column fb_user_6 is a categorical variable, since it has 2 unique value

Column fb_user_7 is a categorical variable, since it has 2 unique value

Column fb_user_8 is a categorical variable, since it has 2 unique value

Column fb_user_9 is a categorical variable, since it has 2 unique value
```

In [16]:
```python
# Lets check the missing values in percentage
(tele_data[cat_cols].isnull().sum()*100/tele_data[cat_cols].shape[0]).sort_values(ascending = False)
```

Out[16]:
```
fb_user_6           74.846748
night_pck_user_6    74.846748
fb_user_7           74.428744
night_pck_user_7    74.428744
fb_user_9           74.077741
night_pck_user_9    74.077741
fb_user_8           73.660737
night_pck_user_8    73.660737
dtype: float64
```

In [17]:
```python
# Lets check the mode
tele_data[cat_cols].mode()
```

Out[17]:

	night_pck_user_6	night_pck_user_7	night_pck_user_8	night_pck_user_9	fb_user_6	fb_user_7	fb_user_8	fb_user_9
0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0

Inference:- We will delete the categorical variables, as it is having high missing values in it.

In [18]:
```
#tele_data.drop(tele_data[cat_cols])
tele_data.drop(cat_cols, axis=1, inplace=True)
tele_data.shape
```

Out[18]:
```
(99999, 218)
```

2.1.2) Identifying the important numerical variables which can be imputed with zero.

a) Recharge columns

In [19]:
```
# Let us first extract list of columns containing recharge amount, recharge data
rech_cols =  tele_data.columns[tele_data.columns.str.contains('rech_amt|rech_data')]
rech_cols
```

Out[19]:
```
Index(['total_rech_amt_6', 'total_rech_amt_7', 'total_rech_amt_8',
       'total_rech_amt_9', 'max_rech_amt_6', 'max_rech_amt_7',
       'max_rech_amt_8', 'max_rech_amt_9', 'date_of_last_rech_data_6',
       'date_of_last_rech_data_7', 'date_of_last_rech_data_8',
       'date_of_last_rech_data_9', 'total_rech_data_6', 'total_rech_data_7',
       'total_rech_data_8', 'total_rech_data_9', 'max_rech_data_6',
       'max_rech_data_7', 'max_rech_data_8', 'max_rech_data_9',
       'av_rech_amt_data_6', 'av_rech_amt_data_7', 'av_rech_amt_data_8',
       'av_rech_amt_data_9'],
      dtype='object')
```

In [20]:
```
# lets check the null values present in the rech_cols
round(100*(tele_data[rech_cols].isnull().sum()/len(tele_data[rech_cols].index)), 2).sort_values(
                                                                    ascending =False)
```

Out[20]:
```
av_rech_amt_data_6          74.85
date_of_last_rech_data_6    74.85
max_rech_data_6             74.85
total_rech_data_6           74.85
total_rech_data_7           74.43
av_rech_amt_data_7          74.43
date_of_last_rech_data_7    74.43
max_rech_data_7             74.43
av_rech_amt_data_9          74.08
date_of_last_rech_data_9    74.08
total_rech_data_9           74.08
max_rech_data_9             74.08
total_rech_data_8           73.66
av_rech_amt_data_8          73.66
date_of_last_rech_data_8    73.66
max_rech_data_8             73.66
max_rech_amt_9               0.00
max_rech_amt_8               0.00
max_rech_amt_7               0.00
max_rech_amt_6               0.00
total_rech_amt_9             0.00
total_rech_amt_8             0.00
total_rech_amt_7             0.00
total_rech_amt_6             0.00
dtype: float64
```

In [21]:
```
# create a list of recharge columns where we will impute missing values with zeroes

zero_impute = ['total_rech_data_6','total_rech_data_7','total_rech_data_8','total_rech_data_9',
            'max_rech_data_6','max_rech_data_7','max_rech_data_8','max_rech_data_9',
            'av_rech_amt_data_6','av_rech_amt_data_7','av_rech_amt_data_8','av_rech_amt_data_9']
```

In [22]:
```
tele_data[zero_impute].describe()
```

Out[22]:

	total_rech_data_6	total_rech_data_7	total_rech_data_8	total_rech_data_9	max_rech_data_6	max_rech_data_7	max_rech_data_8	max_rech_data_9	av_rech_amt_data_6	av_rech_amt_data_7	av_rech_amt_data_8	av_rech_amt_data_9
count	25153.000000	25571.000000	26339.000000	25922.000000	25153.000000	25571.000000	26339.000000	25922.00000	25153.000000	25571.000000	26339.000000	25922.000000
mean	2.463802	2.666419	2.651999	2.441170	126.393392	126.729459	125.717301	124.94144	192.600982	200.981292	197.526489	192.734315
std	2.789128	3.031593	3.074987	2.516339	108.477235	109.765267	109.437851	111.36376	192.646318	196.791224	191.301305	188.400286
min	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00000	1.000000	0.500000	0.500000	1.000000
25%	1.000000	1.000000	1.000000	1.000000	25.000000	25.000000	25.000000	25.00000	82.000000	92.000000	87.000000	69.000000
50%	1.000000	1.000000	1.000000	2.000000	145.000000	145.000000	145.000000	145.00000	154.000000	154.000000	154.000000	164.000000
75%	3.000000	3.000000	3.000000	3.000000	177.000000	177.000000	179.000000	179.00000	252.000000	252.000000	252.000000	252.000000
max	61.000000	54.000000	60.000000	84.000000	1555.000000	1555.000000	1555.000000	1555.00000	7546.000000	4365.000000	4076.000000	4061.000000

Inference: In the recharge variables where minumum value is 1, we can impute missing values with zeroes since it means customer didn't recharge their number that month.

In [23]:
```
# Lets check the missing values in percentage

print("Missing value ratio:\n")
(tele_data[zero_impute].isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```

```
Missing value ratio:
```

Out[23]:
```
av_rech_amt_data_6    74.846748
max_rech_data_6       74.846748
total_rech_data_6     74.846748
av_rech_amt_data_7    74.428744
max_rech_data_7       74.428744
total_rech_data_7     74.428744
av_rech_amt_data_9    74.077741
max_rech_data_9       74.077741
total_rech_data_9     74.077741
av_rech_amt_data_8    73.660737
max_rech_data_8       73.660737
total_rech_data_8     73.660737
dtype: float64
```

In [24]:
```
#impute missing values with 0

tele_data[zero_impute] = tele_data[zero_impute].apply(lambda x: x.fillna(0))
```

In [25]:
```
# now, let's make sure values are imputed correctly

print("Missing value ratio:\n")
print(tele_data[zero_impute].isnull().sum()*100/len(tele_data.shape))
```

```
Missing value ratio:

total_rech_data_6     0.0
total_rech_data_7     0.0
total_rech_data_8     0.0
total_rech_data_9     0.0
max_rech_data_6       0.0
max_rech_data_7       0.0
max_rech_data_8       0.0
max_rech_data_9       0.0
av_rech_amt_data_6    0.0
av_rech_amt_data_7    0.0
av_rech_amt_data_8    0.0
av_rech_amt_data_9    0.0
dtype: float64
```

In [26]:
```
# Lets again check the dimensions of the dataset
tele_data.shape
```

Out[26]:
```
(99999, 218)
```

In [27]:
```
# lets check the null values present in the dataset
(tele_data.isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```

Out[27]:
```
count_rech_3g_6             74.846748
count_rech_2g_6             74.846748
arpu_2g_6                   74.846748
arpu_3g_6                   74.846748
date_of_last_rech_data_6    74.846748
date_of_last_rech_data_7    74.428744
arpu_2g_7                   74.428744
arpu_3g_7                   74.428744
count_rech_2g_7             74.428744
count_rech_3g_7             74.428744
arpu_2g_9                   74.077741
arpu_3g_9                   74.077741
count_rech_3g_9             74.077741
count_rech_2g_9             74.077741
date_of_last_rech_data_9    74.077741
date_of_last_rech_data_8    73.660737
arpu_3g_8                   73.660737
count_rech_3g_8             73.660737
arpu_2g_8                   73.660737
```

b) Minutes of usage - voice calls columns

In [28]:
```
# create a list of mou columns where we will impute missing values with zeroes

mou_cols = tele_data.columns[tele_data.columns.str.contains('mou')]
mou_cols
```

Out[28]:
```
Index(['loc_og_t2o_mou', 'std_og_t2o_mou', 'loc_ic_t2o_mou', 'onnet_mou_6',
       'onnet_mou_7', 'onnet_mou_8', 'onnet_mou_9', 'offnet_mou_6',
       'offnet_mou_7', 'offnet_mou_8',
       ...
       'total_ic_mou_8', 'total_ic_mou_9', 'spl_ic_mou_6', 'spl_ic_mou_7',
       'spl_ic_mou_8', 'spl_ic_mou_9', 'isd_ic_mou_6', 'isd_ic_mou_7',
       'isd_ic_mou_8', 'isd_ic_mou_9'],
      dtype='object', length=119)
```

In [29]:
```
# Lets check the missing values in percentage

print("Missing value ratio:\n")
(tele_data[mou_cols].isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```

```
Missing value ratio:
```

Inference: For all minutes of usage columns the maximum missing % is 7.75 , means in these case the customer has not used at all, that particular call type, thus we can fill the missing values with zero

In [30]:
```
# replacing missing values by 0 for minutes of usage variables

tele_data[mou_cols] = tele_data[mou_cols].apply(lambda x: x.fillna(0))
```

In [31]:
```
# now, let's make sure values are imputed correctly

print("Missing value ratio:\n")
(tele_data[mou_cols].isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```

```
Missing value ratio:
```

In [32]:
```
# Lets again check the dimensions of the dataset
tele_data.shape
```

Out[32]:
```
(99999, 218)
```

In [33]:

```
# lets check the null values present in the dataset
(tele_data.isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```

Out[33]:

```
arpu_2g_6                  74.846748
arpu_3g_6                  74.846748
count_rech_3g_6            74.846748
date_of_last_rech_data_6   74.846748
count_rech_2g_6            74.846748
arpu_3g_7                  74.428744
arpu_2g_7                  74.428744
count_rech_3g_7            74.428744
date_of_last_rech_data_7   74.428744
count_rech_2g_7            74.428744
count_rech_3g_9            74.077741
date_of_last_rech_data_9   74.077741
count_rech_2g_9            74.077741
arpu_3g_9                  74.077741
arpu_2g_9                  74.077741
arpu_3g_8                  73.660737
count_rech_3g_8            73.660737
date_of_last_rech_data_8   73.660737
arpu_2g_8                  73.660737
```

2.1.3) Identifying the variables having more than 50% missing values and dropping it

In [34]:

```
# we will drop the columns having more than 50% NA values

tele_data= tele_data.drop(tele_data.loc[:,list(round(100*(tele_data.isnull().sum()/len(tele_data.index)),2)>50)].columns,1)

# Lets again check the dimensions of the dataset
tele_data.shape
```

Out[34]: (99999, 198)

In [35]:

```
# lets check the null values present in the dataset
(tele_data.isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```

Out[35]:

```
og_others_9             7.745077
ic_others_9             7.745077
og_others_8             5.378054
ic_others_8             5.378054
date_of_last_rech_9     4.760048
og_others_6             3.937039
ic_others_6             3.937039
ic_others_7             3.859039
og_others_7             3.859039
date_of_last_rech_8     3.622036
date_of_last_rech_7     1.767018
last_date_of_month_9    1.659017
date_of_last_rech_6     1.607016
last_date_of_month_8    1.100011
last_date_of_month_7    0.601006
std_og_t2f_mou_7        0.000000
std_og_t2f_mou_9        0.000000
std_og_t2c_mou_6        0.000000
std_og_t2c_mou_7        0.000000
```

2.2) Preprocess data (convert columns to appropriate formats, handle missing values, etc.)

2.2.1) Converting columns to appropriate formats

In [36]:

```
# lets check for columns that can be changed to integers, floats or date types
date_col_data = tele_data.select_dtypes('object').columns
date_col_data = date_col_data.tolist()
date_col_data
```

Out[36]:

```
['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']
```

In [37]:
```
tele_data[date_col_data].describe()
```
Out[37]:

	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
count	99999	99398	98899	98340	98392	98232	96377	95239
unique	1	1	1	1	30	31	31	30
top	6/30/2014	7/31/2014	8/31/2014	9/30/2014	6/30/2014	7/31/2014	8/31/2014	9/29/2014
freq	99999	99398	98899	98340	16960	17288	14706	22623

In [38]:
```
# lets check the null values present in the object_col_data
print("Missing value ratio:\n")
(tele_data[date_col_data].isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```
```
Missing value ratio:
```
Out[38]:
```
date_of_last_rech_9     4.760048
date_of_last_rech_8     3.622036
date_of_last_rech_7     1.767018
last_date_of_month_9    1.659017
date_of_last_rech_6     1.607016
last_date_of_month_8    1.100011
last_date_of_month_7    0.601006
last_date_of_month_6    0.000000
dtype: float64
```

Inference:- The above columns are dates columns, thus we can fill the missing values with mode

In [39]:
```
for col in date_col_data:
    tele_data[col].fillna((tele_data[col].mode()[0]), inplace=True)
```

In [40]:
```
# now, let's make sure values are imputed correctly

print("Missing value ratio:\n")
(tele_data[date_col_data].isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```
```
Missing value ratio:
```
Out[40]:
```
date_of_last_rech_9     0.0
date_of_last_rech_8     0.0
date_of_last_rech_7     0.0
date_of_last_rech_6     0.0
last_date_of_month_9    0.0
last_date_of_month_8    0.0
last_date_of_month_7    0.0
last_date_of_month_6    0.0
dtype: float64
```

In [41]:
```
tele_data[date_col_data].describe()
```
Out[41]:

	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
count	99999	99999	99999	99999	99999	99999	99999	99999
unique	1	1	1	1	30	31	31	30
top	6/30/2014	7/31/2014	8/31/2014	9/30/2014	6/30/2014	7/31/2014	8/31/2014	9/29/2014
freq	99999	99999	99999	99999	18567	19055	18328	27383

Inference: All the above columns can be converted to date type

In [42]:
```
# converting to datetime format

for col in date_col_data:
    tele_data[col] = pd.to_datetime(tele_data[col])

tele_data.shape
```
Out[42]:
```
(99999, 198)
```

In [43]:
```
# Again checking the format of the data
tele_data.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Columns: 198 entries, mobile_number to sep_vbc_3g
dtypes: datetime64[ns](8), float64(155), int64(35)
memory usage: 151.1 MB
```

2.2.2) Handling missing values

In [44]:
```
# lets check the null values present in the dataset
(tele_data.isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```

Out[44]:
```
ic_others_9          7.745077
og_others_9          7.745077
ic_others_8          5.378054
og_others_8          5.378054
ic_others_6          3.937039
og_others_6          3.937039
og_others_7          3.859039
ic_others_7          3.859039
std_og_t2c_mou_6     0.000000
std_og_mou_8         0.000000
std_og_mou_7         0.000000
std_og_mou_6         0.000000
std_og_t2c_mou_9     0.000000
std_og_t2c_mou_8     0.000000
std_og_t2c_mou_7     0.000000
sep_vbc_3g           0.000000
std_og_t2f_mou_9     0.000000
isd_og_mou_6         0.000000
std_og_t2f_mou_8     0.000000
```

In [45]:
```
missing_cols = tele_data.columns[tele_data.isnull().sum()>0]
missing_cols
```

Out[45]:
```
Index(['og_others_6', 'og_others_7', 'og_others_8', 'og_others_9',
       'ic_others_6', 'ic_others_7', 'ic_others_8', 'ic_others_9'],
      dtype='object')
```

In [46]:
```
tele_data[missing_cols].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99999 entries, 0 to 99998
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   og_others_6  96062 non-null  float64
 1   og_others_7  96140 non-null  float64
 2   og_others_8  94621 non-null  float64
 3   og_others_9  92254 non-null  float64
 4   ic_others_6  96062 non-null  float64
 5   ic_others_7  96140 non-null  float64
 6   ic_others_8  94621 non-null  float64
 7   ic_others_9  92254 non-null  float64
dtypes: float64(8)
memory usage: 6.1 MB
```

Inference:- The above columns are numerical columns, thus we can fill the missing values with median column value.

In [47]:
```
missing_cols = tele_data.columns[tele_data.isnull().sum()>0]
for col in missing_cols:
    tele_data[col].fillna((tele_data[col].median()), inplace=True)
```

In [48]:
```
# lets check the null values present in the dataset
(tele_data.isnull().sum()*100/len(tele_data)).sort_values(ascending = False)
```

Out[48]:
```
sep_vbc_3g           0.0
spl_og_mou_6         0.0
isd_og_mou_8         0.0
isd_og_mou_7         0.0
isd_og_mou_6         0.0
std_og_mou_9         0.0
std_og_mou_8         0.0
std_og_mou_7         0.0
std_og_mou_6         0.0
std_og_t2c_mou_9     0.0
std_og_t2c_mou_8     0.0
std_og_t2c_mou_7     0.0
std_og_t2c_mou_6     0.0
std_og_t2f_mou_9     0.0
std_og_t2f_mou_8     0.0
std_og_t2f_mou_7     0.0
std_og_t2f_mou_6     0.0
std_og_t2m_mou_9     0.0
std_og_t2m_mou_8     0.0
```

In [49]:
```
tele_data.shape
```

Out[49]:
```
(99999, 198)
```

In churn prediction, we assume that there are three phases of customer lifecycle :

- The 'good' phase [Month 6 & 7] (the customer is happy with the service)
- The 'action' phase [Month 8] (The customer experience starts to sore in this phase, becomes unhappy with service quality etc.)
- The 'churn' phase [Month 9] (In this phase, the customer is said to have churned.)

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

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

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

High-value Churn:

In the Indian and the southeast Asian market, approximately 80% of revenue comes from the top 20% customers (called high-value customers). Thus, if we can reduce churn of the high-value customers, we will be able to reduce significant revenue leakage.

Step 3: Data Preparation

3.1) Derive new features

This is one of the most important parts of data preparation since good features are often the differentiators between good and bad models. Using our business understanding to derive features which we think could be important indicators of churn.

lets dervie features to extract high value customers

- We can create new feature as **total_rech_data_amt_x** using `total_rech_data_x` and `av_rech_amt_data_x` to capture total amount utilized by customer for data (x represents month here, would be either 6 or 7 or 8).

lets find out total amount spent by customers on data recharge,we have two columns available to find out this.

In [50]:
```
# first column is av_rech_amt_data_x (x represents month here, would be either 6 or 7 or 8)
# second column is total_rech_data_x (x represents month here, would be either 6 or 7 or 8)
# lets introduce a new column total_rech_data_amt_x which can be calculated as av_rech_amt_data_x*total_rech_data_x

tele_data['total_rech_data_amt_6'] = tele_data['av_rech_amt_data_6'] * tele_data['total_rech_data_6']
tele_data['total_rech_data_amt_7'] = tele_data['av_rech_amt_data_7'] * tele_data['total_rech_data_7']
tele_data['total_rech_data_amt_8'] = tele_data['av_rech_amt_data_8'] * tele_data['total_rech_data_8']
tele_data['total_rech_data_amt_9'] = tele_data['av_rech_amt_data_9'] * tele_data['total_rech_data_9']
```

In [51]:
```
# now we dont need columns av_rech_amt_data_x,total_rech_data_x (x = 6/7/8) , lets drop them

tele_data.drop(['total_rech_data_6','total_rech_data_7','total_rech_data_8','total_rech_data_9',
     'av_rech_amt_data_6','av_rech_amt_data_7','av_rech_amt_data_8','av_rech_amt_data_9'],axis = 1,inplace = True)
```

3.2) Filter high-value customers

High valued customers would bring in more revenue and having them churn would be a huge loss to business. Our aim is to identify the high valued customers and try not to make them churn. Let us first identify the high valued customers.

The steps would be :

1. For the first two months calculate the average amount of money spent on recharge.
2. Calcuate the 70 percentile and above that cut-off would be high valued customer.

3.2.1) Defining total average recharge amount for good phase for months 6 and 7 (the good phase)

In [52]:
```
# lets find out the average recharge done in the first two months(june & july) - the good phase
# total amount spend would be the sum of total data recharge done & total call/sms recharges

tele_data_av_rech_6n7 = (tele_data['total_rech_amt_6'] + tele_data['total_rech_amt_7']
                       + tele_data['total_rech_data_amt_6']+ tele_data['total_rech_data_amt_7'])/2
```

3.2.2) Define High Value customers as follows: Those who have recharged with an amount more than or equal to X, where X is the 70th percentile of the average recharge amount in the first two months (the good phase).

In [53]:
```
# create a filter for values greater than 70th percentile of total average recharge amount for good phase
high_value_filter = np.percentile(tele_data_av_rech_6n7, 70.0)
print('70 percentile of 6th and 7th months avg recharge amount: ', high_value_filter)

# fitler the given data set based on 70th percentile
tele_data_hv_cust = tele_data[tele_data_av_rech_6n7 >= high_value_filter]
print('Dataframe Shape after Filtering High Value Customers: ', tele_data_hv_cust.shape)
```

```
70 percentile of 6th and 7th months avg recharge amount:  478.0
Dataframe Shape after Filtering High Value Customers:  (30001, 194)
```

Inference: There are 30001 rows and 194 columns for high value customers dataset.

3.3) Tag churners and remove attributes of the churn phase

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. The attributes you need to use to tag churners are:

`total_ic_mou_9`

`total_og_mou_9`

`vol_2g_mb_9`

`vol_3g_mb_9`

After tagging churners, remove all the attributes corresponding to the churn phase (all attributes having ' _9', etc. in their names).

3.3.1) Tag churners

In [54]:
```
# lets introduce a new column "churn", values would be either 1 (churn) or 0 (non-churn)
# we will calculate churn/non-churn based on the usage as mentioned in the problem statement

tele_data_hv_cust['churn'] = np.where(tele_data_hv_cust[['total_ic_mou_9','total_og_mou_9','vol_2g_mb_9','vol_3g_mb_9']].sum(axis=1) == 0, 1,0)
tele_data_hv_cust
```

Out[54]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	last_date_of_month_6	last_date_of_month_7	last_date_of_month_8	last_date_of_month_9	arpu_6	arpu_7	arpu_8	arpu_9	onnet_mou_6	onnet_mou_7	onnet_mou_8	onnet_mou_9	offnet_mou_6	offnet_mou_7	offnet_m
0	7000842753	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	197.385	214.816	213.803	21.100	0.00	0.00	0.00	0.00	0.00	0.00	
7	7000701601	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	1069.180	1349.850	3171.480	500.000	57.84	54.68	52.29	0.00	453.43	567.16	3
8	7001524846	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	378.721	492.223	137.362	166.787	413.69	351.03	35.08	33.46	94.66	80.63	1
21	7002124215	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	514.453	597.753	637.760	578.596	102.41	132.11	85.14	161.63	757.93	896.68	9
23	7000887461	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	74.350	193.897	366.966	811.480	48.96	50.66	33.58	15.74	85.41	89.36	2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
99981	7000630859	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	384.316	255.405	393.474	94.080	78.68	29.04	103.24	34.38	56.13	28.09	(
99984	7000661676	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	328.594	202.966	118.707	324.143	423.99	181.83	5.71	5.03	39.51	39.81	
99986	7001729035	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	644.973	455.228	564.334	267.451	806.73	549.36	775.41	692.63	784.76	617.13	5
99988	7002111859	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	312.558	512.932	402.080	533.502	199.89	174.46	2.46	7.16	175.88	277.01	2
99997	7000498689	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	2014-09-30	322.991	303.386	606.817	731.010	0.00	0.00	0.00	0.00	0.00	0.00	

30001 rows × 195 columns

In [55]:
```
# lets find out churn/non churn percentage
tele_data_hv_cust['churn'].value_counts()/len(tele_data_hv_cust)*100
```

Out[55]:
```
0    91.863605
1     8.136395
Name: churn, dtype: float64
```

Inference: 92% of the customers are not churn and only 8% of the customers are churn, this is a case of class imbalance, we will treat it later.

3.3.2) Remove attributes of the churn phase

After tagging churners, remove all the attributes corresponding to the churn phase (all attributes having ' _9', etc. in their names)

In [56]:
```
# Now we will delete 9th month columns because we would predict churn/non-churn later based on data from the 1st
# 3 months

churn_month_columns = [col for col in tele_data_hv_cust.columns if '_9' in col]
print(churn_month_columns)
print()
print(len(churn_month_columns))

tele_data_hv_cust.shape
```

```
['last_date_of_month_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
'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'
_ic_mou_9', 'isd_ic_mou_9', 'ic_others_9', 'total_rech_num_9', 'total_rech_amt_9', 'max_rech_amt_9', 'date_of_last_rech_9', 'last_day_rch_amt_9', 'max_rech_data_9', 'vol_2g_mb_9', 'vol_3g_mb_9', 'monthly_2g_9', 'sachet_2g_9', 'monthly_3g_9', 'sachet_3
mt_9']

46
```

Out[56]:
```
(30001, 195)
```

In [57]:
```python
# drop all columns corresponding to the churn phase
tele_data_hv_cust.drop(churn_month_columns,axis=1,inplace=True)
tele_data_hv_cust.drop('sep_vbc_3g',axis=1,inplace=True)

tele_data_hv_cust.shape
```

Out[57]: (30001, 148)

Inference: There are 30001 rows and 148 columns for high value customers dataset.

In [58]:
```python
tele_data_hv_cust
```

Out[58]:

	mobile_number	circle_id	loc_og_t2o_mou	std_og_t2o_mou	loc_ic_t2o_mou	last_date_of_month_6	last_date_of_month_7	last_date_of_month_8	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_
0	7000842753	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	197.385	214.816	213.803	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
7	7000701601	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	1069.180	1349.850	3171.480	57.84	54.68	52.29	453.43	567.16	325.91	16.23	33.49	
8	7001524846	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	378.721	492.223	137.362	413.69	351.03	35.08	94.66	80.63	136.48	0.00	0.00	
21	7002124215	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	514.453	597.753	637.760	102.41	132.11	85.14	757.93	896.68	983.39	0.00	0.00	
23	7000887461	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	74.350	193.897	366.966	48.96	50.66	33.58	85.41	89.36	205.89	0.00	0.00	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
99981	7000630859	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	384.316	255.405	393.474	78.68	29.04	103.24	56.13	28.09	61.44	0.00	0.00	
99984	7000661676	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	328.594	202.966	118.707	423.99	181.83	5.71	39.51	39.81	18.26	0.00	0.00	
99986	7001729035	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	644.973	455.228	564.334	806.73	549.36	775.41	784.76	617.13	595.44	0.00	0.00	
99988	7002111859	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	312.558	512.932	402.080	199.89	174.46	2.46	175.88	277.01	248.33	0.00	0.00	
99997	7000498689	109	0.0	0.0	0.0	2014-06-30	2014-07-31	2014-08-31	322.991	303.386	606.817	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

30001 rows × 148 columns

3.4) Check the columns with unique values and drop such columns

In [59]:

```python
# lets check the columns with no variance in their values and drop such columns
for i in tele_data_hv_cust.columns:
    if tele_data_hv_cust[i].nunique() == 1:
        print("\nColumn",i,"has no variance and contains only", tele_data_hv_cust[i].nunique(),"unique value")
        print("Dropping the column",i)
        tele_data_hv_cust.drop(i,axis=1,inplace = True)

# Lets again check the dimensions of the dataset
print("\nDimension of the updated dataset:",tele_data_hv_cust.shape)
```

```
Column circle_id has no variance and contains only 1 unique value
Dropping the column circle_id

Column loc_og_t2o_mou has no variance and contains only 1 unique value
Dropping the column loc_og_t2o_mou

Column std_og_t2o_mou has no variance and contains only 1 unique value
Dropping the column std_og_t2o_mou

Column loc_ic_t2o_mou has no variance and contains only 1 unique value
Dropping the column loc_ic_t2o_mou

Column last_date_of_month_6 has no variance and contains only 1 unique value
Dropping the column last_date_of_month_6

Column last_date_of_month_7 has no variance and contains only 1 unique value
Dropping the column last_date_of_month_7

Column last_date_of_month_8 has no variance and contains only 1 unique value
Dropping the column last_date_of_month_8

Column std_og_t2c_mou_6 has no variance and contains only 1 unique value
Dropping the column std_og_t2c_mou_6

Column std_og_t2c_mou_7 has no variance and contains only 1 unique value
Dropping the column std_og_t2c_mou_7

Column std_og_t2c_mou_8 has no variance and contains only 1 unique value
Dropping the column std_og_t2c_mou_8

Column std_ic_t2o_mou_6 has no variance and contains only 1 unique value
Dropping the column std_ic_t2o_mou_6

Column std_ic_t2o_mou_7 has no variance and contains only 1 unique value
Dropping the column std_ic_t2o_mou_7

Column std_ic_t2o_mou_8 has no variance and contains only 1 unique value
Dropping the column std_ic_t2o_mou_8

Dimension of the updated dataset: (30001, 135)
```

Inference:- Dropping above features with only one unique value as they will not add any value to our model building and analyis

In [60]:

```python
# lets check the dataset again
(tele_data_hv_cust.isnull().sum() * 100 / len(tele_data_hv_cust)).sort_values(ascending = False)
```

Out[60]:

```
churn                  0.0
og_others_6            0.0
std_og_t2m_mou_7       0.0
std_og_t2m_mou_8       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_mou_6           0.0
std_og_mou_7           0.0
std_og_mou_8           0.0
isd_og_mou_6           0.0
isd_og_mou_7           0.0
isd_og_mou_8           0.0
spl_og_mou_6           0.0
spl_og_mou_7           0.0
spl_og_mou_8           0.0
og_others_7            0.0
std_og_t2t_mou_8       0.0
og_others_8            0.0
```

In [61]:

```python
tele_data_hv_cust.shape
```

Out[61]:

```
(30001, 135)
```

In [62]:
```
tele_data_hv_cust.drop(tele_data_hv_cust.filter(regex='date_').columns,axis=1,inplace=True)

print (tele_data_hv_cust.shape)
```

```
(30001, 132)
```

In [63]:
```
tele_data_hv_cust.columns
```

Out[63]:
```
Index(['mobile_number', 'arpu_6', 'arpu_7', 'arpu_8', 'onnet_mou_6',
       'onnet_mou_7', 'onnet_mou_8', 'offnet_mou_6', 'offnet_mou_7',
       'offnet_mou_8',
       ...
       'sachet_3g_7', 'sachet_3g_8', 'aon', 'aug_vbc_3g', 'jul_vbc_3g',
       'jun_vbc_3g', 'total_rech_data_amt_6', 'total_rech_data_amt_7',
       'total_rech_data_amt_8', 'churn'],
      dtype='object', length=132)
```

3.5) Feature Engineering (Derive some new feautres from the existing columns)

- The AON variable was used to create tenure buckets. It was observed larger the tenure, lesser was the churn - as customers who are newly acquired to the network churned more as compared to the old customers.

In [64]:
```
tele_data_hv_cust
```

Out[64]:

	mobile_number	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t
0	7000842753	197.385	214.816	213.803	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
7	7000701601	1069.180	1349.850	3171.480	57.84	54.68	52.29	453.43	567.16	325.91	16.23	33.49	31.64	23.74	12.59	38.06	51.39	31.38	40.28	
8	7001524846	378.721	492.223	137.362	413.69	351.03	35.08	94.66	80.63	136.48	0.00	0.00	0.00	0.00	0.00	0.00	297.13	217.59	12.49	
21	7002124215	514.453	597.753	637.760	102.41	132.11	85.14	757.93	896.68	983.39	0.00	0.00	0.00	0.00	0.00	0.00	4.48	6.16	23.34	
23	7000887461	74.350	193.897	366.966	48.96	50.66	33.58	85.41	89.36	205.89	0.00	0.00	0.00	0.00	0.00	0.00	48.96	50.66	33.58	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
99981	7000630859	384.316	255.405	393.474	78.68	29.04	103.24	56.13	28.09	61.44	0.00	0.00	0.00	0.00	0.00	0.00	72.53	29.04	89.23	
99984	7000661676	328.594	202.966	118.707	423.99	181.83	5.71	39.51	39.81	18.26	0.00	0.00	0.00	0.00	0.00	0.00	423.99	181.83	5.71	
99986	7001729035	644.973	455.228	564.334	806.73	549.36	775.41	784.76	617.13	595.44	0.00	0.00	0.00	0.00	0.00	0.00	709.21	496.14	718.56	
99988	7002111859	312.558	512.932	402.080	199.89	174.46	2.46	175.88	277.01	248.33	0.00	0.00	0.00	0.00	0.00	0.00	170.28	146.48	2.46	
99997	7000498689	322.991	303.386	606.817	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

30001 rows × 132 columns

Tenure Analysis for Customers

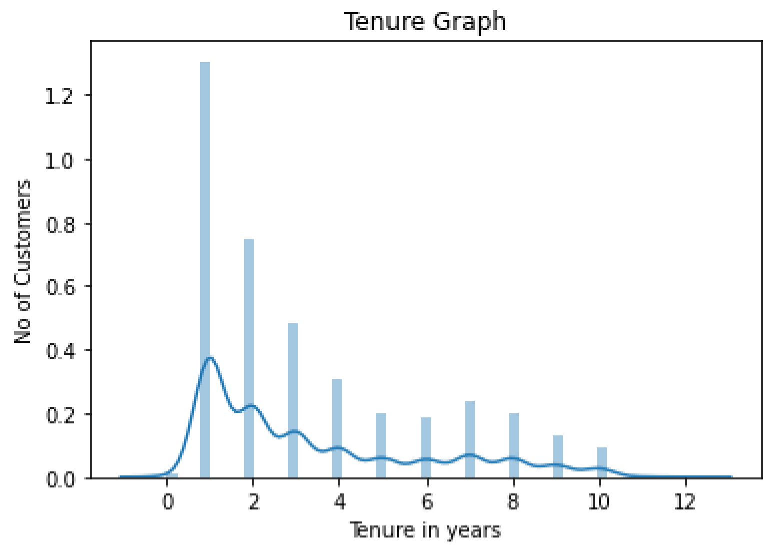
aon --> Age on network - number of days the customer is using the operator T network

In [65]:
```
# lets now convert AON in months

tele_data_hv_cust['Tenure'] = np.round(tele_data_hv_cust['aon']/365,0)
tele_data_hv_cust.drop('aon', axis=1, inplace=True)
tele_data_hv_cust['Tenure'].head()
```

Out[65]:
```
0     3.0
7     2.0
8     1.0
21    2.0
23    2.0
Name: Tenure, dtype: float64
```

In [66]:

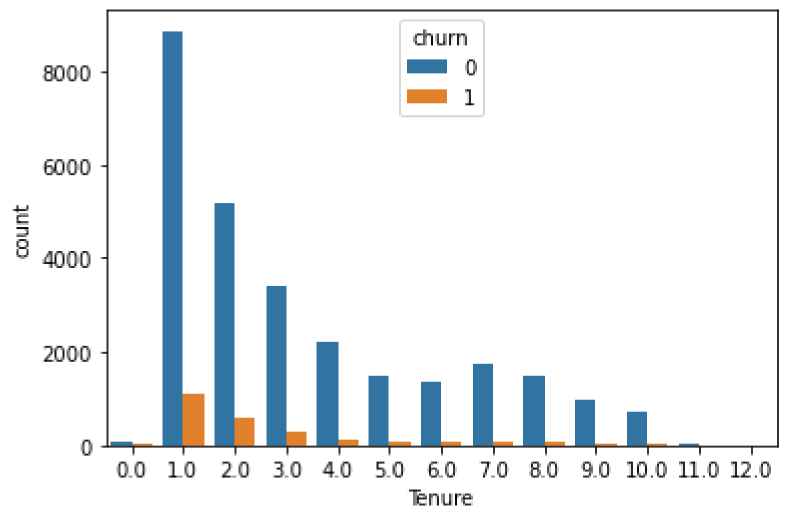
```
ax = sns.distplot(tele_data_hv_cust['Tenure'])
ax.set_ylabel('No of Customers')
ax.set_xlabel('Tenure in years')
ax.set_title('Tenure Graph')
plt.show()
```



Inference: Above graph shows the tenure of the customers and majority of customers falls under the tenure of 1 to 2 years.

In [67]:

```
#plt.figure(figsize=(5,8))
sns.countplot(x = 'Tenure', hue = 'churn',data =tele_data_hv_cust)
plt.show()
```



Inference:-

- From the above graph we can infer that majority of the churn people falls under the tenure of 1 to 2 years.
- The count of churn customers decreases as the tenure of the customers increases with the network.

In [68]:

```
tele_data_hv_cust.shape
```

Out[68]:

```
(30001, 132)
```

Step 4: Visualization of data (EDA)

Let's now spend some time doing what is arguably the most important step - **understanding the data**.

- If there is some obvious multicollinearity going on, this is the first place to catch it
- Here's where i will also identify if some predictors directly have a strong association with the outcome variable

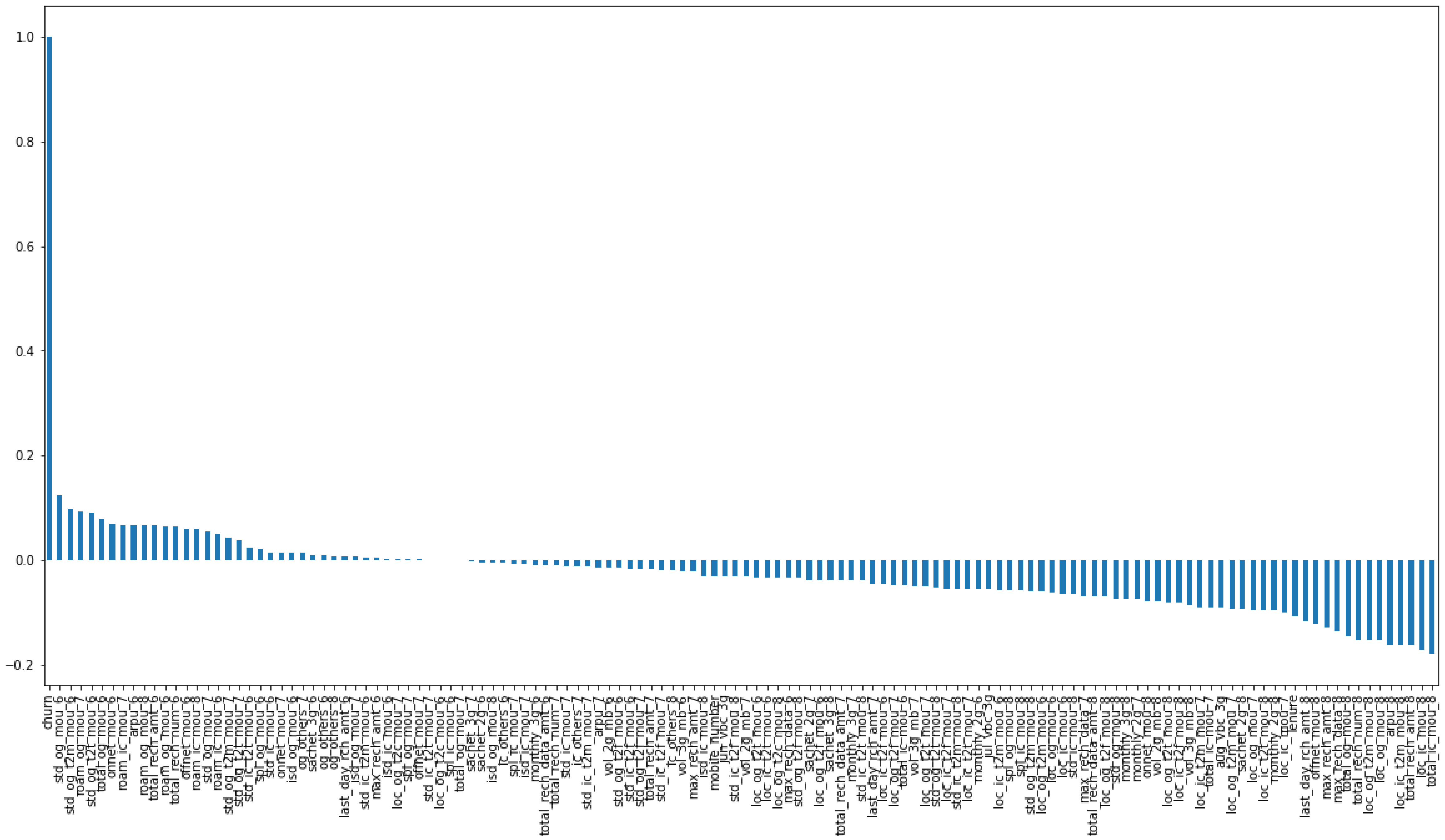
Checking the coorelations between the variables

In [69]:
```python
# lets check the correlation amongst the features
cor = tele_data_hv_cust.corr()
cor
```

Out[69]:

	mobile_number	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t
mobile_number	1.000000	0.033944	0.029496	0.034570	0.010576	0.006132	0.008436	0.022685	0.013701	0.020231	0.010688	-0.002337	0.005051	0.005742	-0.001444	-0.002998	0.047776	0.045378	0
arpu_6	0.033944	1.000000	0.671732	0.612617	0.342438	0.216136	0.186807	0.509280	0.339350	0.285100	0.126884	0.083484	0.090363	0.196086	0.143261	0.124994	0.167352	0.127683	0
arpu_7	0.029496	0.671732	1.000000	0.759858	0.211608	0.320818	0.270330	0.351713	0.490176	0.395668	0.092501	0.093692	0.093961	0.133520	0.179894	0.152217	0.106674	0.157926	0
arpu_8	0.034570	0.612617	0.759858	1.000000	0.151677	0.233728	0.347706	0.279066	0.377210	0.524798	0.087996	0.077709	0.110842	0.128323	0.141421	0.199114	0.101287	0.133167	0
onnet_mou_6	0.010576	0.342438	0.211608	0.151677	1.000000	0.750708	0.620316	0.090624	0.039540	0.037030	0.024517	0.024512	0.043989	0.077296	0.075410	0.072913	0.456971	0.356397	0
onnet_mou_7	0.006132	0.216136	0.320818	0.233728	0.750708	1.000000	0.806053	0.054915	0.085163	0.077621	0.038078	0.008422	0.037272	0.081178	0.068607	0.083913	0.345545	0.464012	0
onnet_mou_8	0.008436	0.186807	0.270330	0.347706	0.620316	0.806053	1.000000	0.063586	0.091316	0.130812	0.050134	0.020459	0.023086	0.096119	0.083938	0.095598	0.302415	0.384034	0
offnet_mou_6	0.022685	0.509280	0.351713	0.279066	0.090624	0.054915	0.063586	1.000000	0.739296	0.580516	0.048346	0.041570	0.057448	0.119801	0.101404	0.103824	0.081785	0.065119	0
offnet_mou_7	0.013701	0.339350	0.490176	0.377210	0.039540	0.085163	0.091316	0.739296	1.000000	0.767844	0.062289	0.038981	0.058858	0.112529	0.109432	0.120695	0.037634	0.063067	0
offnet_mou_8	0.020231	0.285100	0.395668	0.524798	0.037030	0.077621	0.130812	0.580516	0.767844	1.000000	0.069971	0.040871	0.047549	0.119067	0.095922	0.131054	0.048388	0.068537	0
roam_ic_mou_6	0.010688	0.126884	0.092501	0.087996	0.024517	0.038078	0.050134	0.048346	0.062289	0.069971	1.000000	0.510145	0.371946	0.645915	0.369125	0.241484	-0.016526	0.009238	0

In [70]:
```python
# lets check correlation of churn with other columns
plt.figure(figsize=(20,10))
tele_data_hv_cust.corr()['churn'].sort_values(ascending = False).plot(kind='bar')
plt.show()
```



Inference:

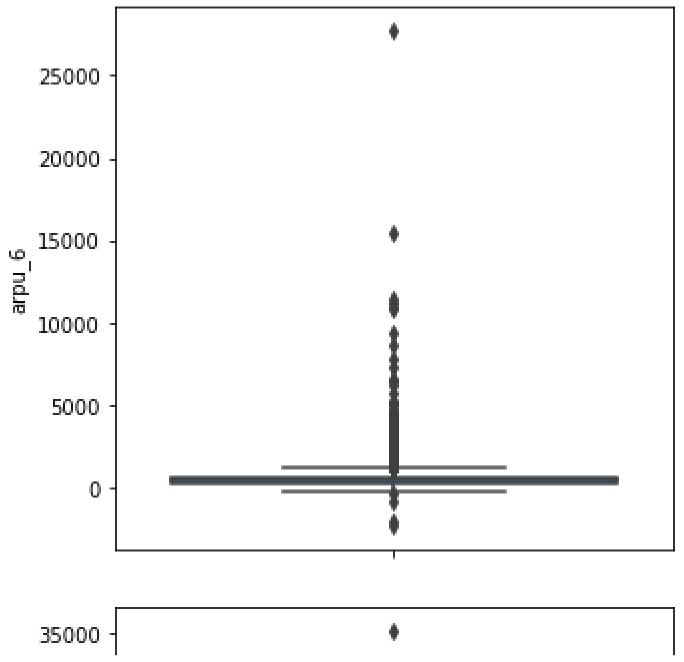
1. std_og_mou, roam_og_mou, std_og_t2m_mou, roam_ic_mou for 6 & 7th months are positively correlated with churn.
2. total_ic_mou, loc_ic_mou, total_rech_amt, loc_ic_t2m_mou for 8th month has negative correlation with churn.

4.1) Univariate Analysis

In [71]:
```
tele_data_hv_cust.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30001 entries, 0 to 99997
Columns: 132 entries, mobile_number to Tenure
dtypes: float64(106), int32(1), int64(25)
memory usage: 31.6 MB
```

In [72]:
```
cont_cols = [col for col in tele_data_hv_cust.columns if col not in ['churn','mobile_number']]

for col in cont_cols:
    plt.figure(figsize=(5, 5))
    sns.boxplot(y=col, data=tele_data_hv_cust)

```

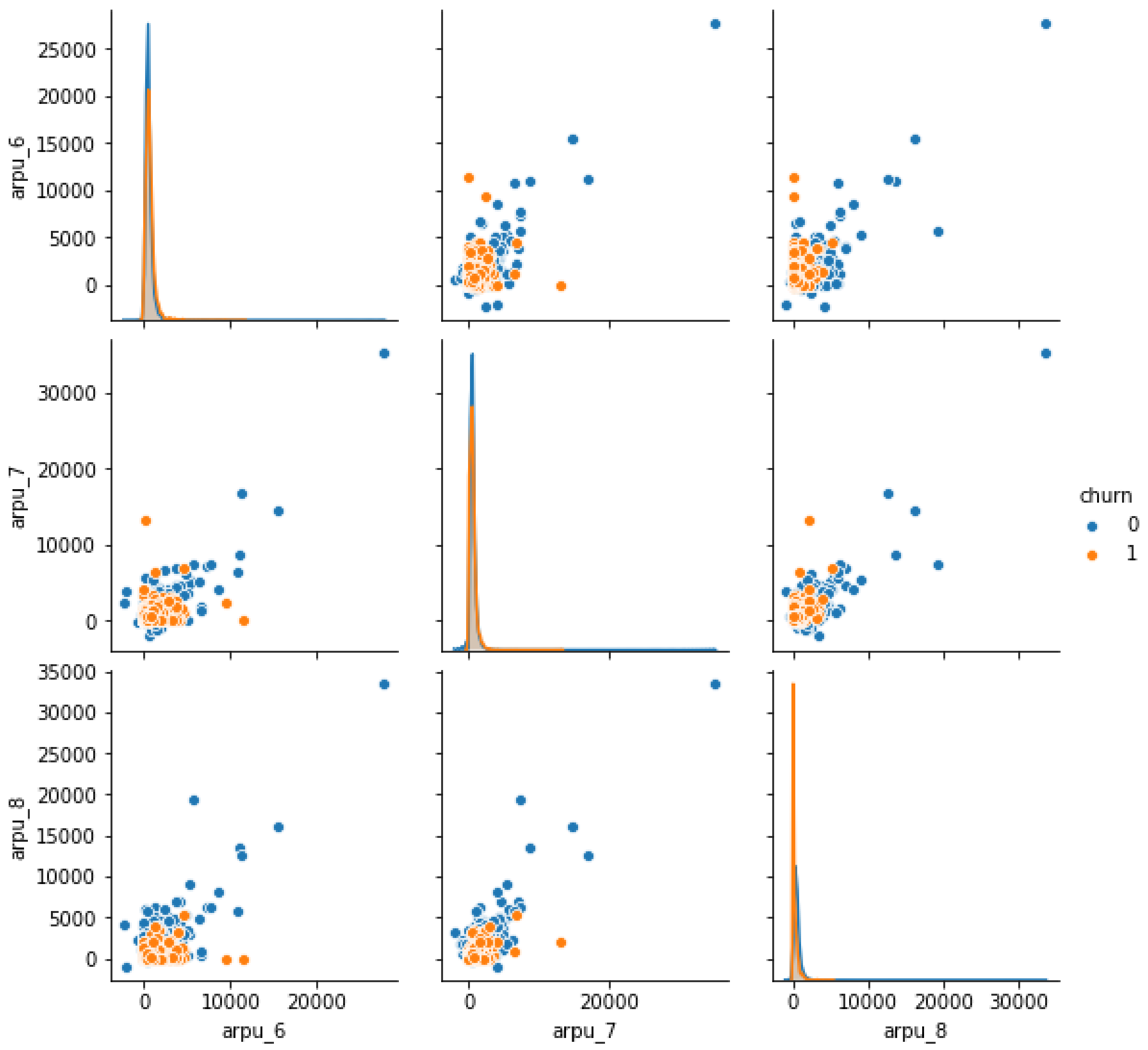


4.2) Multivariate Analysis

Visualising Numerical - Numerical Variables

In [73]:
```
# Plotting Average Revenue per User vs Churn
plt.figure(figsize=(12,12))
sns.pairplot(data=tele_data_hv_cust[['arpu_6', 'arpu_7','arpu_8','churn']],hue='churn')
plt.show()
```

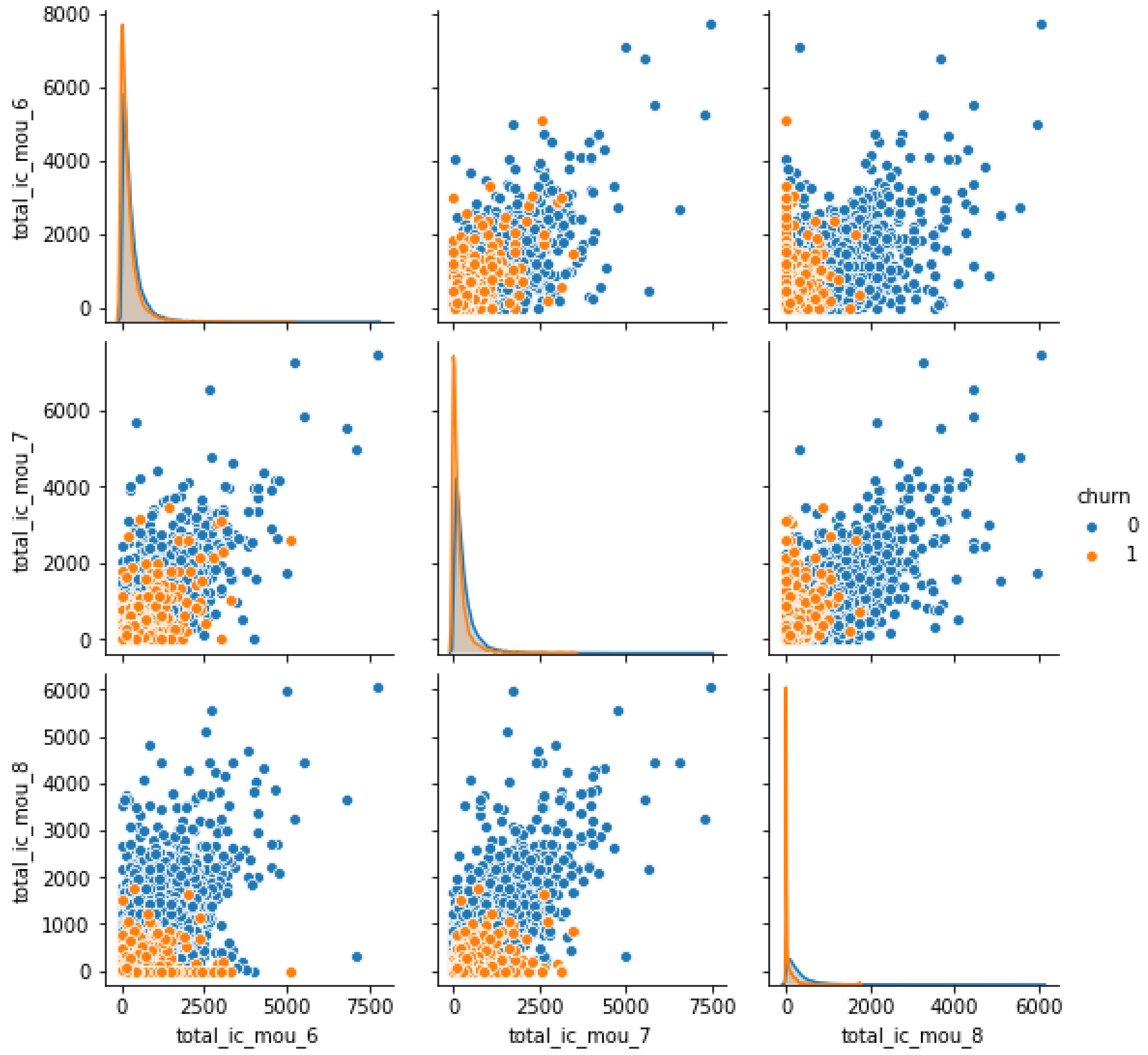
```
<Figure size 864x864 with 0 Axes>
```



Inference: We could see the drop in the ARPU for churned customer in the 8th Month (Action Phase).

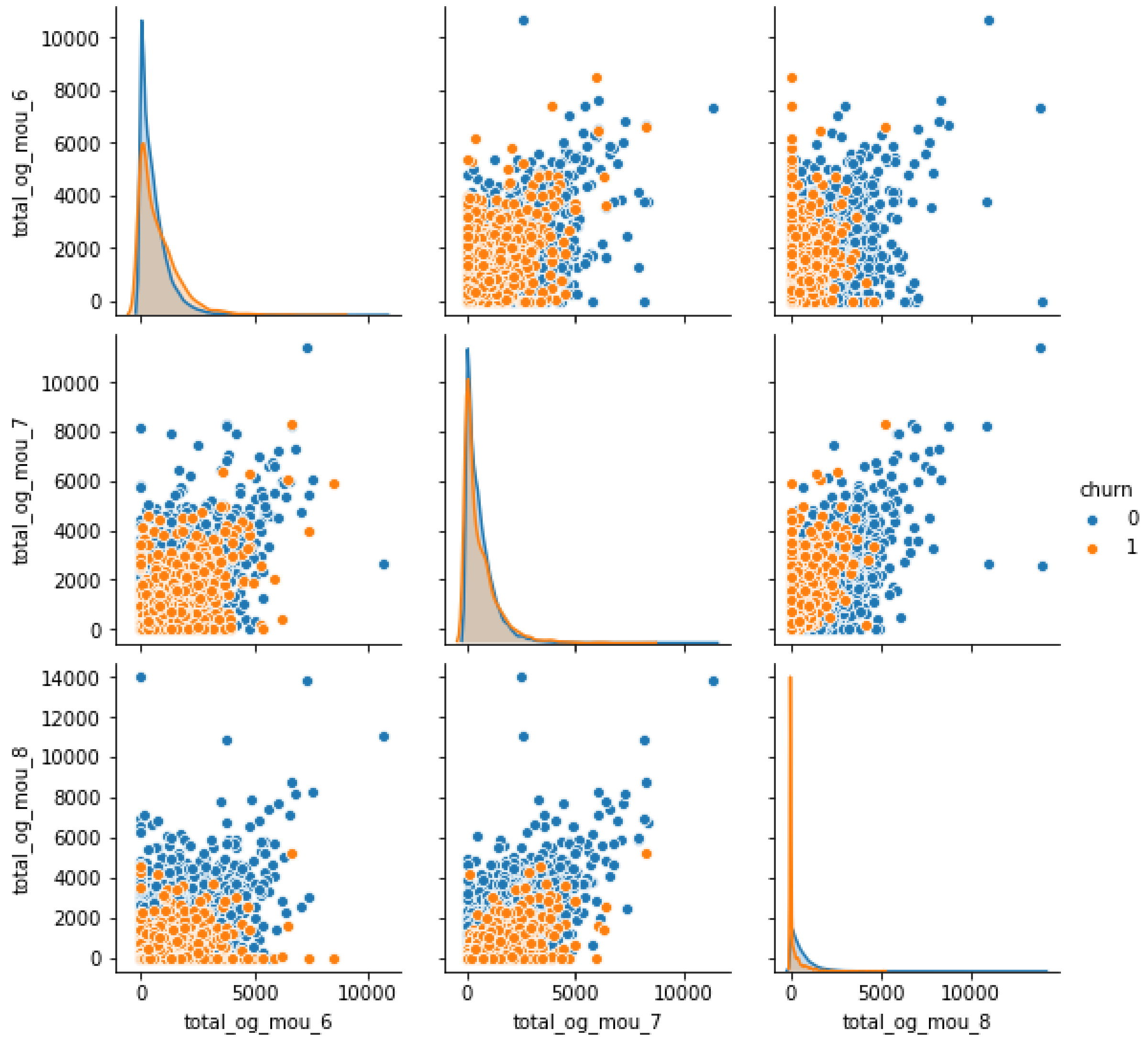
In [74]:

```
#Total Incoming calls vs Churn
sns.pairplot(data=tele_data_hv_cust[['total_ic_mou_6','total_ic_mou_7','total_ic_mou_8',
                                    'churn']],hue='churn')
plt.show()
```



In [75]:

```
#Total Outgoing calls vs Churn
sns.pairplot(data=tele_data_hv_cust[['total_og_mou_6','total_og_mou_7','total_og_mou_8','churn']],
             hue='churn')
plt.show()
```

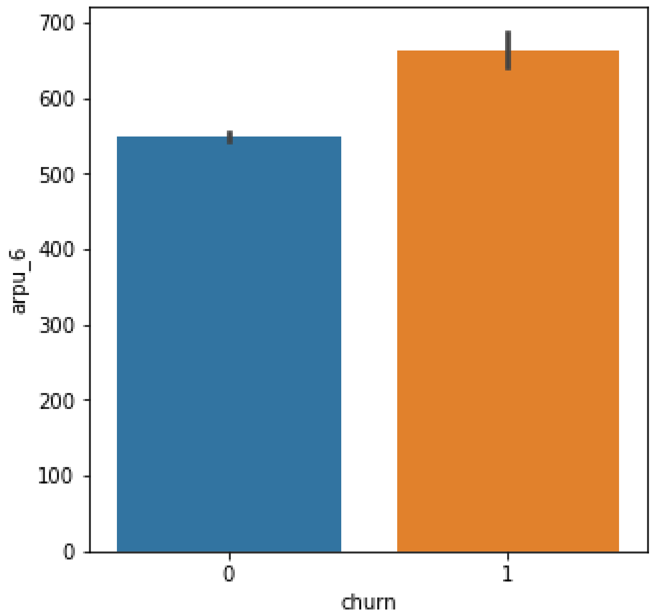


Inference: We could see the drop in the MOU for churned customer in the 8th Month (Action Phase).

Visualising Numerical - Categorical Variables

In [76]:

```
for col in cont_cols:
    plt.figure(figsize=(5, 5))
    sns.barplot(x='churn', y=col, data=tele_data_hv_cust)
    plt.show()
```



4.3) Conducting appropriate exploratory analysis to extract useful insights (whether directly useful for business or for eventual modelling/feature engineering).

4.3.1) Exploring ARPU

In [77]:

```
# create box plot for  6th, 7th and 8th month
def plot_bar_chart(attribute):
    plt.figure(figsize=(12,5))
    df = tele_data_hv_cust
    plt.subplot(1,3,1)
    #"avg_"+col+"_avg6n7"
    sns.barplot(x='churn', y=attribute+"_6", data=tele_data_hv_cust,palette=("bright"))
    plt.subplot(1,3,2)
    sns.barplot(x='churn', y=attribute+"_7", data=tele_data_hv_cust,palette=("bright"))
    plt.subplot(1,3,3)
    sns.barplot(x='churn', y=attribute+"_8", data=tele_data_hv_cust,palette=("bright"))
    plt.tight_layout()
    plt.show()
```

In [78]:

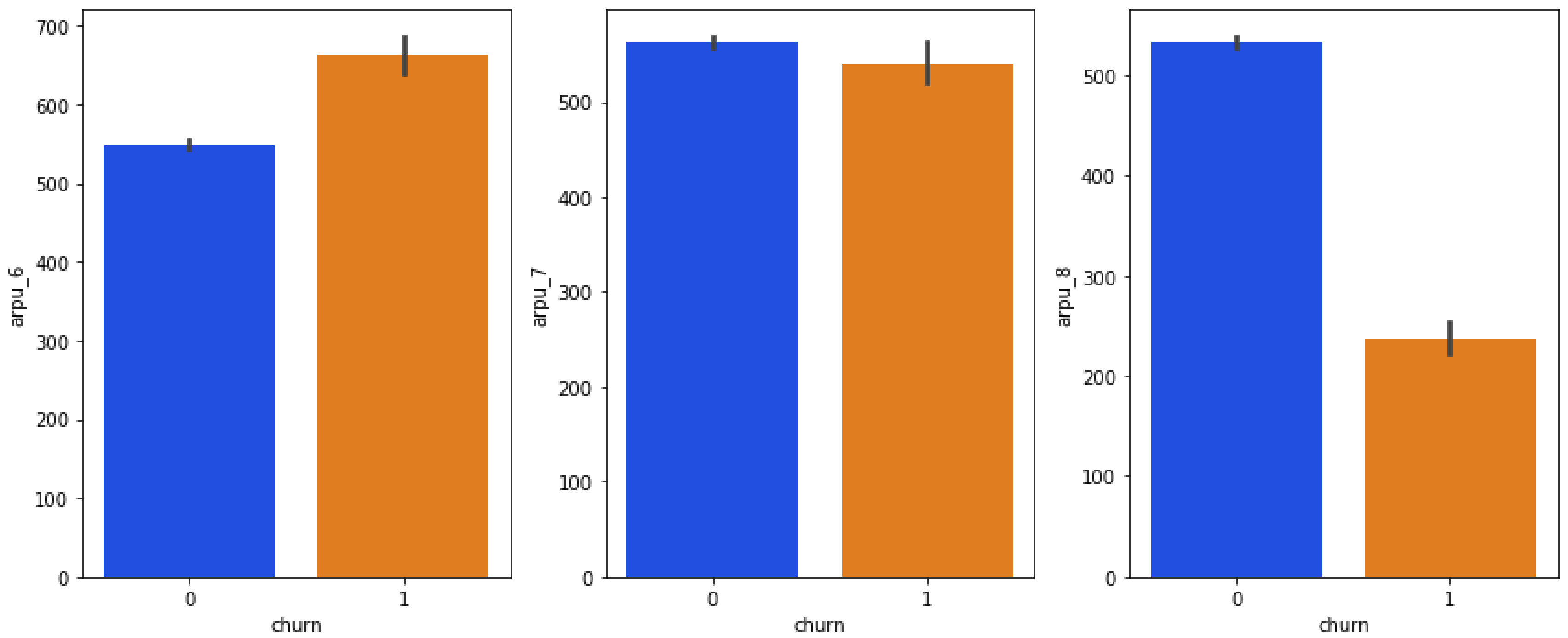
```
ARPU = [col for col in tele_data_hv_cust.columns if 'arpu_' in col]
print(ARPU)
```

```
['arpu_6', 'arpu_7', 'arpu_8']
```

Plotting ARPU for Voice Calls

In [79]:

```
plot_bar_chart('arpu')
```



INSIGHT:

We could see the drop in the ARPU for churned customer in the 8th Month (Action Phase).

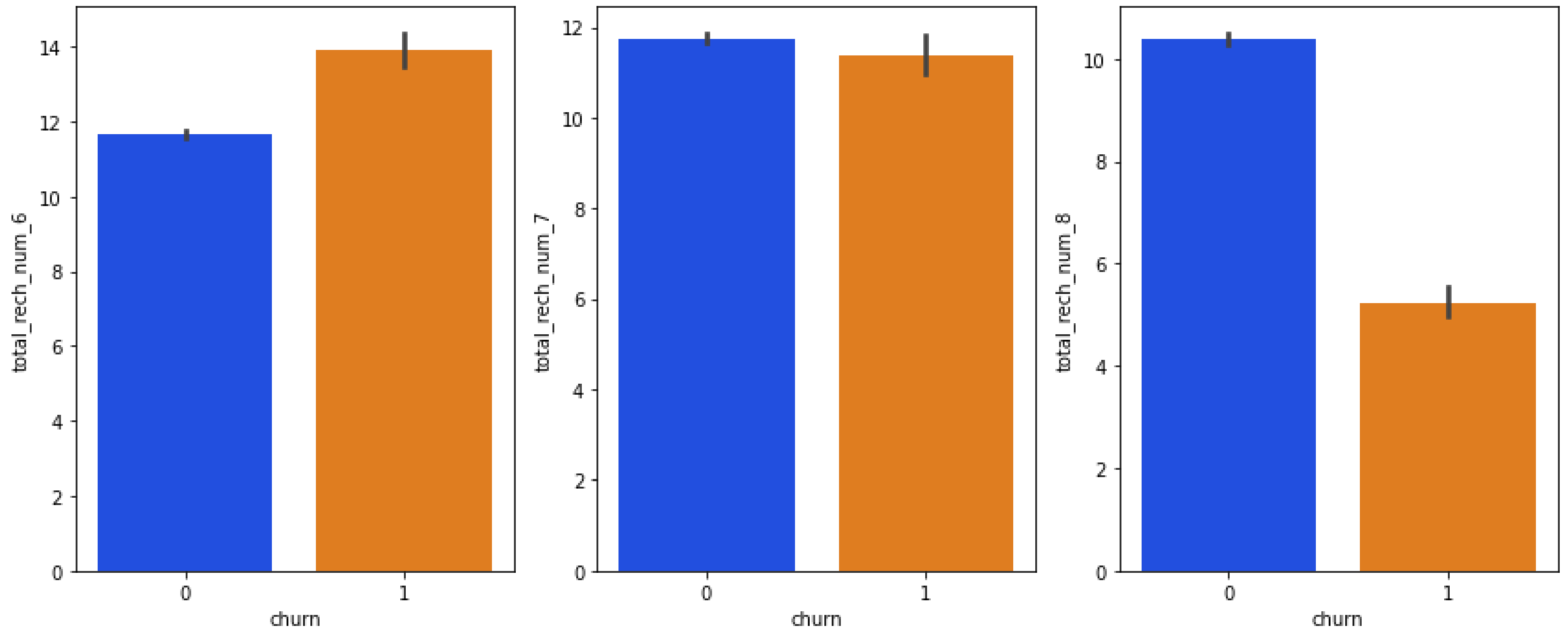
4.3.2)Exploring RECHARGES

In [80]:
```
RECHARGE = [col for col in tele_data_hv_cust.columns if '_rech_' in col]
print(RECHARGE)
```

```
['total_rech_num_6', 'total_rech_num_7', 'total_rech_num_8', 'total_rech_amt_6', 'total_rech_amt_7', 'total_rech_amt_8', 'max_rech_amt_6', 'max_rech_amt_7', 'max_rech_amt_8', 'max_rech_data_6', 'max_rech_data_7', 'max_rech_data_8', 'total_rech_data_amt
mt_7', 'total_rech_data_amt_8']
```

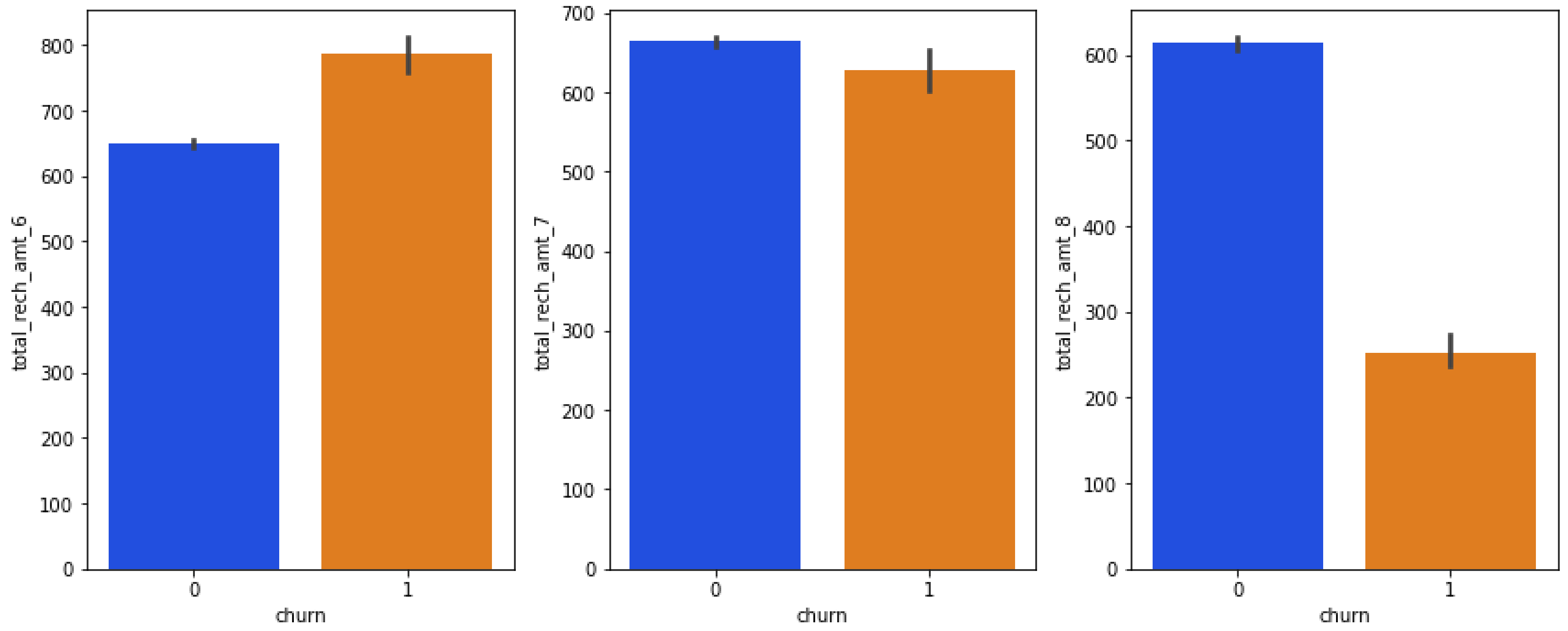
Plotting Recharge Numbers/Frequency per Phase (Good / Action)

In [81]:
```
plot_bar_chart('total_rech_num')
```



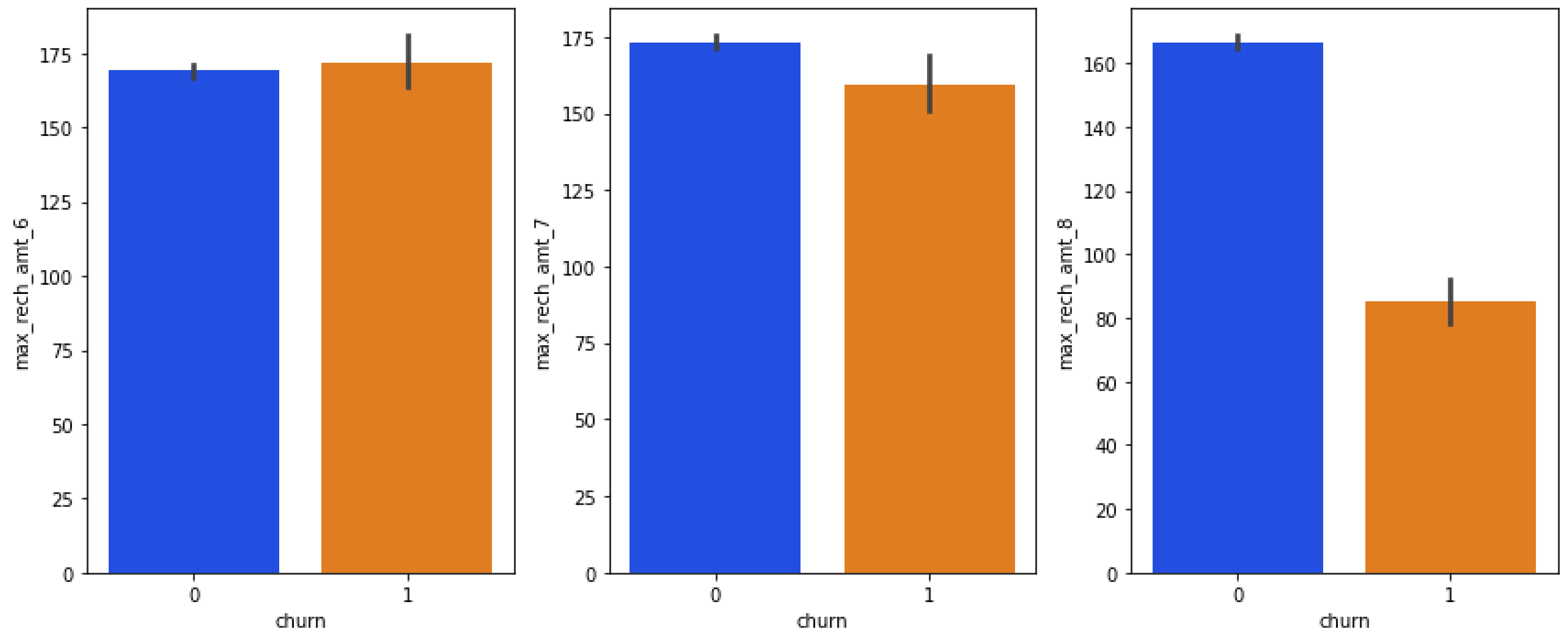
Plotting Total Recharge Amount per Phase (Good / Action)

In [82]:
```
plot_bar_chart('total_rech_amt')
```



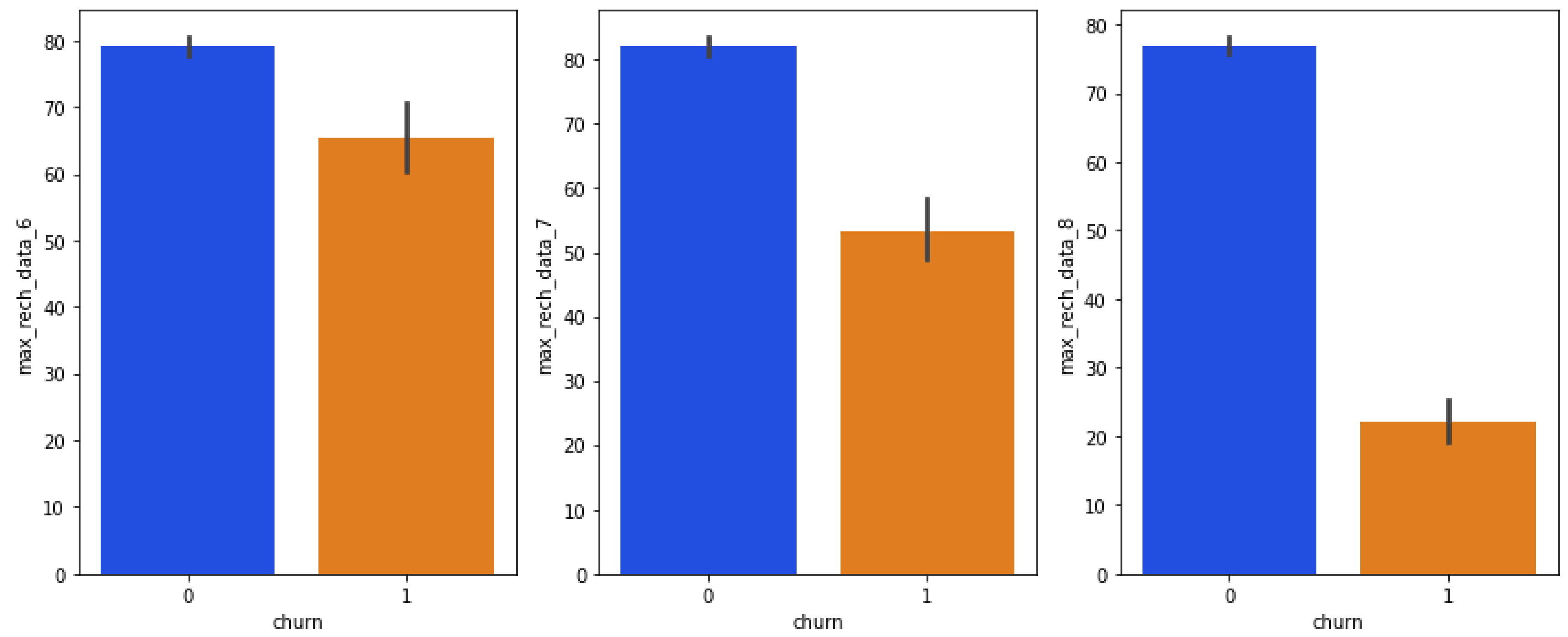
Plotting Max Recharge Amount per Phase (Good / Action)

In [83]:
```
plot_bar_chart('max_rech_amt')
```



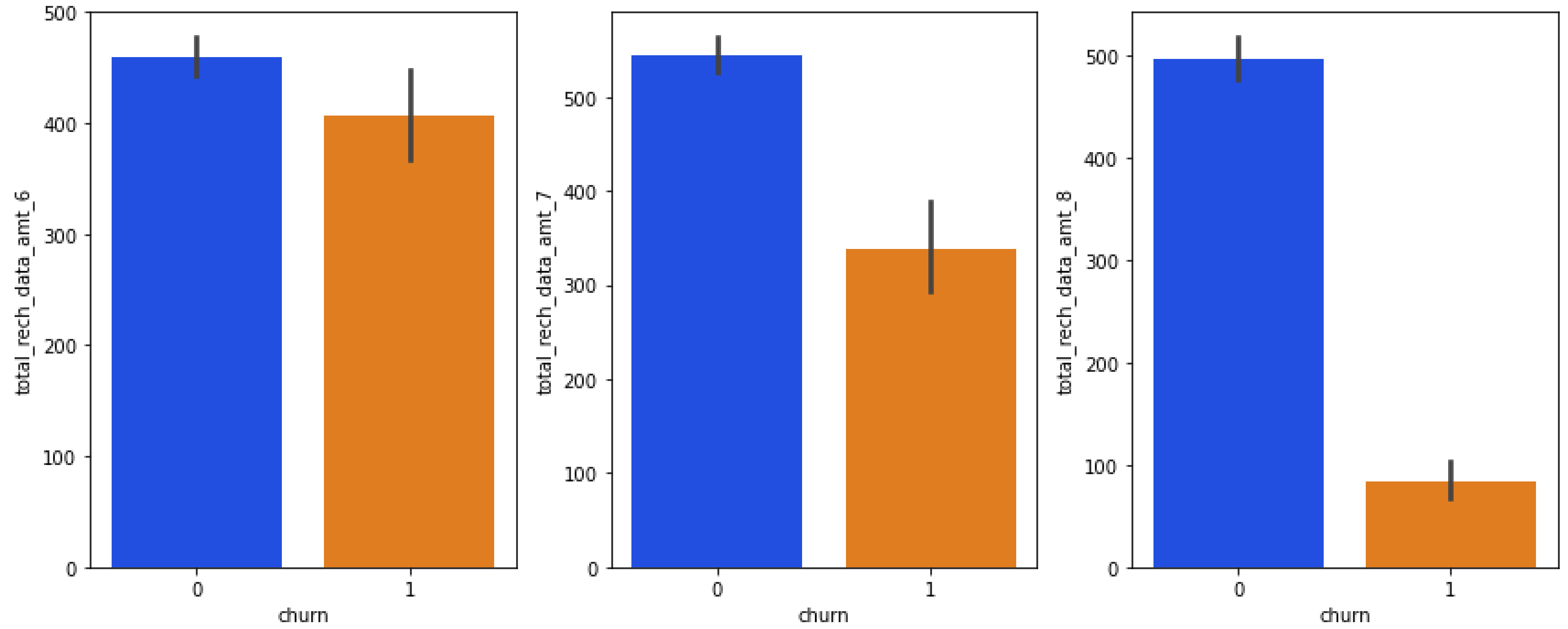
Plotting Max Recharge Data per Phase (Good / Action)

In [84]:
```
1 plot_bar_chart('max_rech_data')
```



Plotting Total Recharge Data Amount per Phase (Good / Action)

In [85]:
```
1 plot_bar_chart('total_rech_data_amt')
```



INSIGHT:

1. We could see a drop in the Recharge (Frequency & Amount) for the churned customer in the 8th Month (Action Phase).
2. We could see a drop in the Total Recharge amount for churned customers in the 8th Month (Action Phase).
3. We could see a drop in Maximum Recharge amount for churned customers in the 8th month (action phase).
4. We could see a drop in Maximum Recharge data for churned customers in the 8th month (action phase).
5. We could see a drop in Total Recharge amount for data for churned customers in the 8th month (action phase).

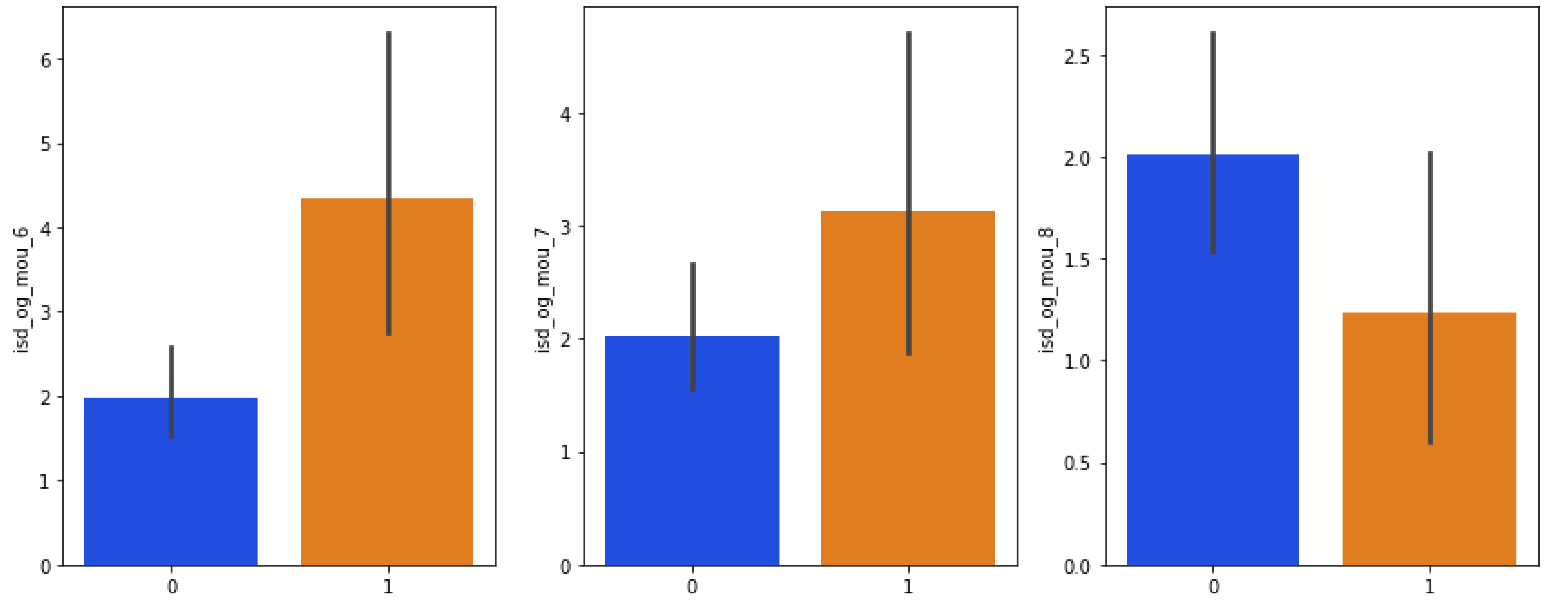
4.3.3) Exploring MOU

In [86]:
```
1 MOU = [col for col in tele_data_hv_cust.columns if '_mou_' in col]
2
3 print(MOU)
```

```
['onnet_mou_6', 'onnet_mou_7', 'onnet_mou_8', 'offnet_mou_6', 'offnet_mou_7', 'offnet_mou_8', 'roam_ic_mou_6', 'roam_ic_mou_7', 'roam_ic_mou_8', 'roam_og_mou_6', 'roam_og_mou_7', 'roam_og_mou_8', 'loc_og_t2t_mou_6', 'loc_og_t2t_mou_7', 'loc_og_t2t_mou_
'loc_og_t2m_mou_7', 'loc_og_t2m_mou_8', 'loc_og_t2f_mou_6', 'loc_og_t2f_mou_7', 'loc_og_t2f_mou_8', 'loc_og_t2c_mou_6', 'loc_og_t2c_mou_7', 'loc_og_t2c_mou_8', 'loc_og_mou_6', 'loc_og_mou_7', 'loc_og_mou_8', 'std_og_t2t_mou_6', 'std_og_t2t_mou_7', 'st
_t2m_mou_6', 'std_og_t2m_mou_7', 'std_og_t2m_mou_8', 'std_og_t2f_mou_6', 'std_og_t2f_mou_7', 'std_og_t2f_mou_8', 'std_og_mou_6', 'std_og_mou_7', 'std_og_mou_8', 'isd_og_mou_6', 'isd_og_mou_7', 'isd_og_mou_8', 'spl_og_mou_6', 'spl_og_mou_7', 'spl_og_mo
'total_og_mou_7', 'total_og_mou_8', 'loc_ic_t2t_mou_6', 'loc_ic_t2t_mou_7', 'loc_ic_t2t_mou_8', 'loc_ic_t2m_mou_6', 'loc_ic_t2m_mou_7', 'loc_ic_t2m_mou_8', 'loc_ic_t2f_mou_6', 'loc_ic_t2f_mou_7', 'loc_ic_t2f_mou_8', 'loc_ic_mou_6', 'loc_ic_mou_7', 'lo
_mou_6', 'std_ic_t2t_mou_7', 'std_ic_t2t_mou_8', 'std_ic_t2m_mou_6', 'std_ic_t2m_mou_7', 'std_ic_t2m_mou_8', 'std_ic_t2f_mou_6', 'std_ic_t2f_mou_7', 'std_ic_t2f_mou_8', 'std_ic_mou_6', 'std_ic_mou_7', 'std_ic_mou_8', 'total_ic_mou_6', 'total_ic_mou_7'
_ic_mou_6', 'spl_ic_mou_7', 'spl_ic_mou_8', 'isd_ic_mou_6', 'isd_ic_mou_7', 'isd_ic_mou_8']
```

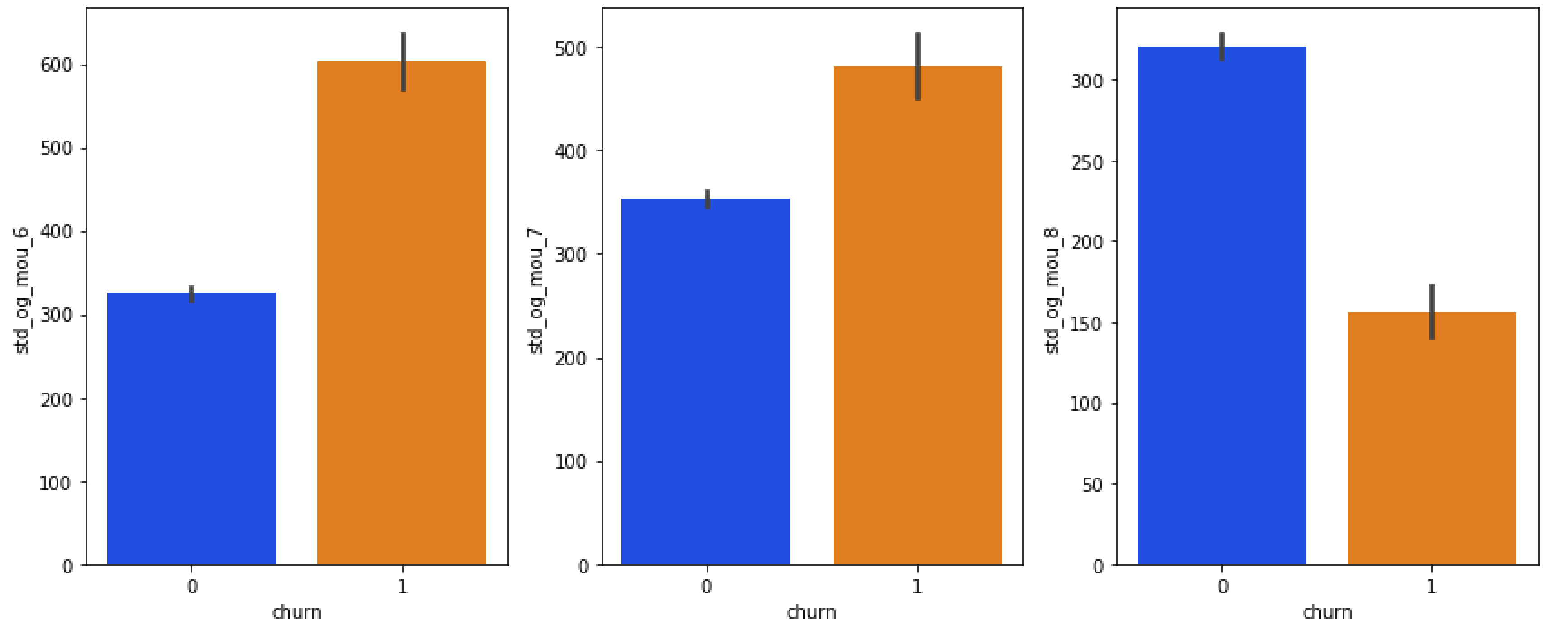
Plotting Outgoing International Minutes of Usage per Phase (Good / Action)

In [87]:
```
plot_bar_chart('isd_og_mou')
```



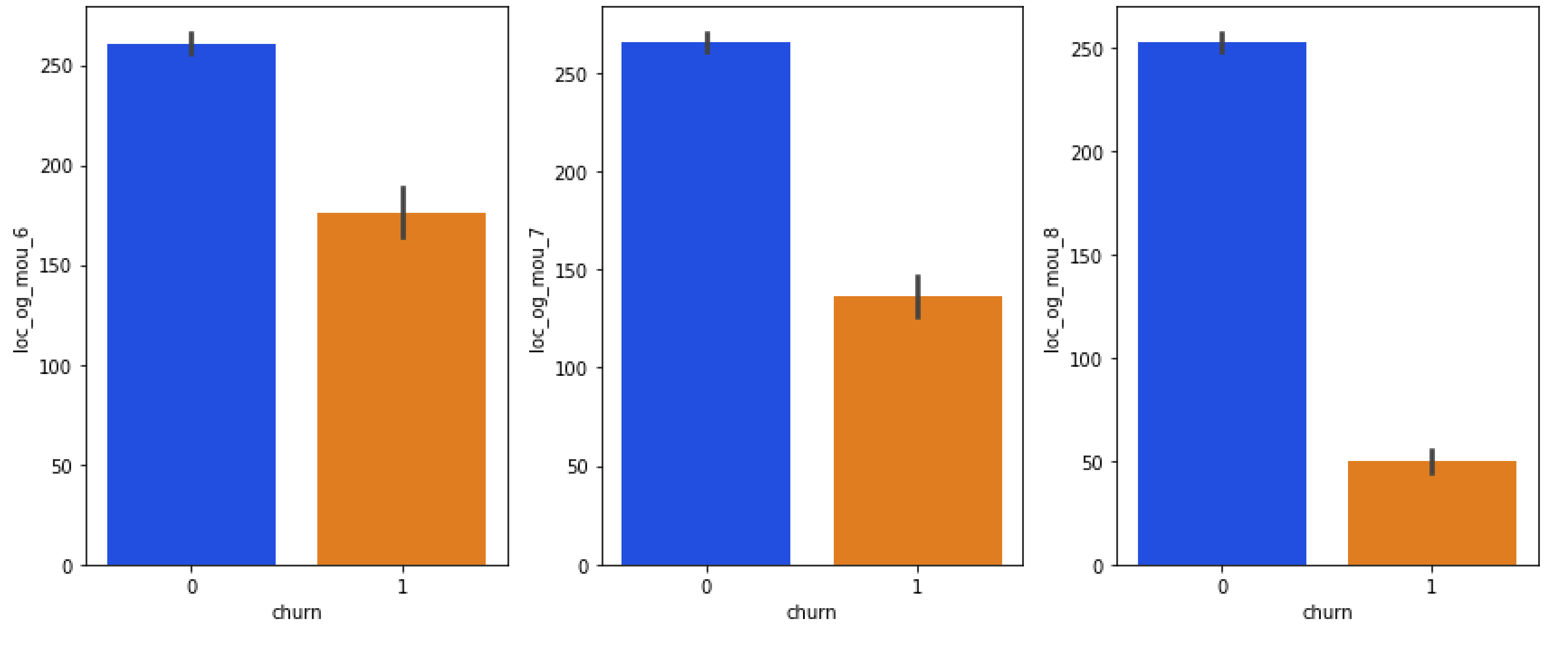
Plotting Outgoing STD Minutes of Usage per Phase (Good / Action)

In [88]:
```
plot_bar_chart('std_og_mou')
```



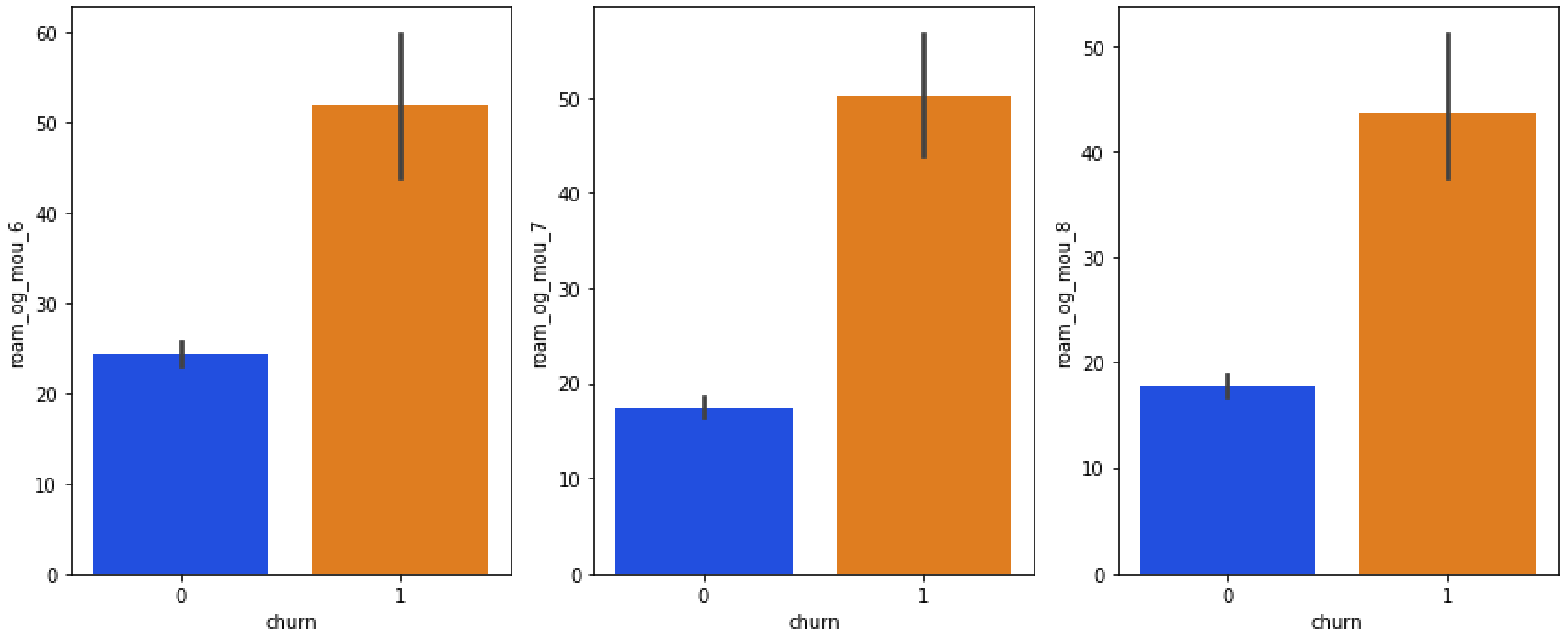
Plotting Outgoing Local Minutes of Usage per Phase (Good / Action)

In [89]:
```
plot_bar_chart('loc_og_mou')
```



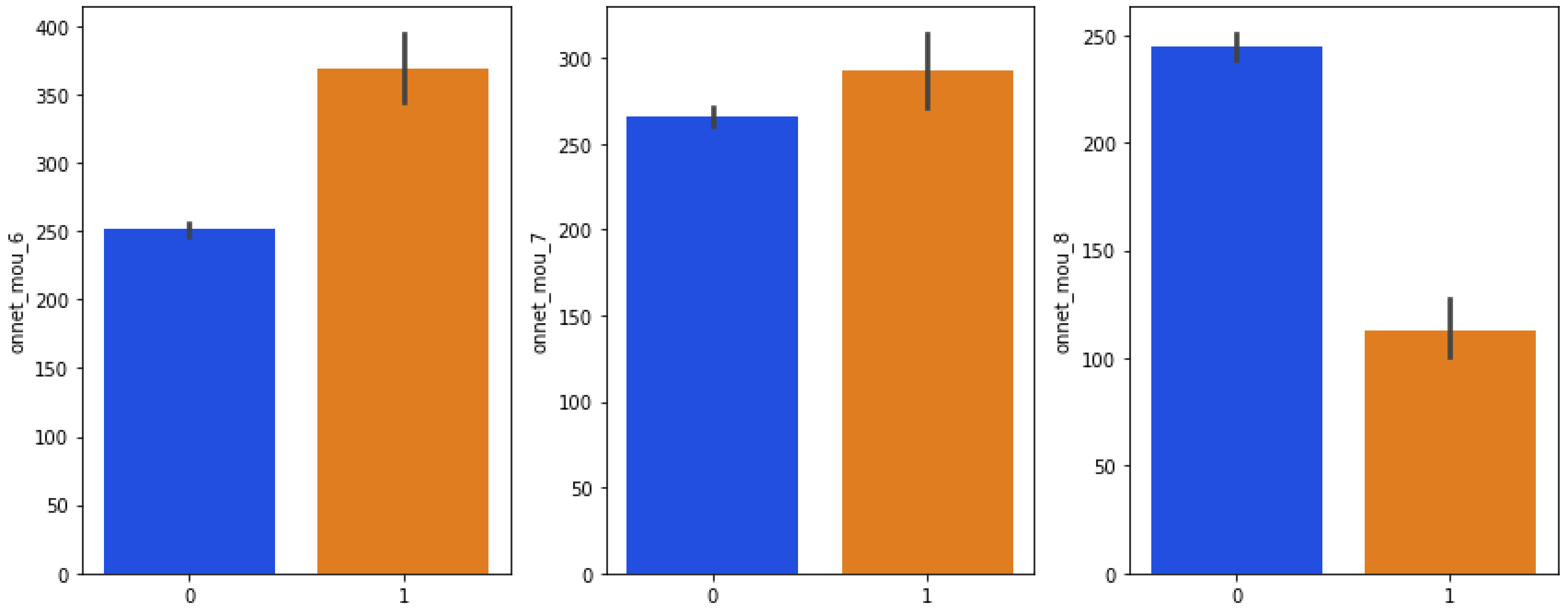
Plotting Outgoing Roaming Minutes of Usage per Phase (Good / Action)

```
In [90]: plot_bar_chart('roam_og_mou')
```



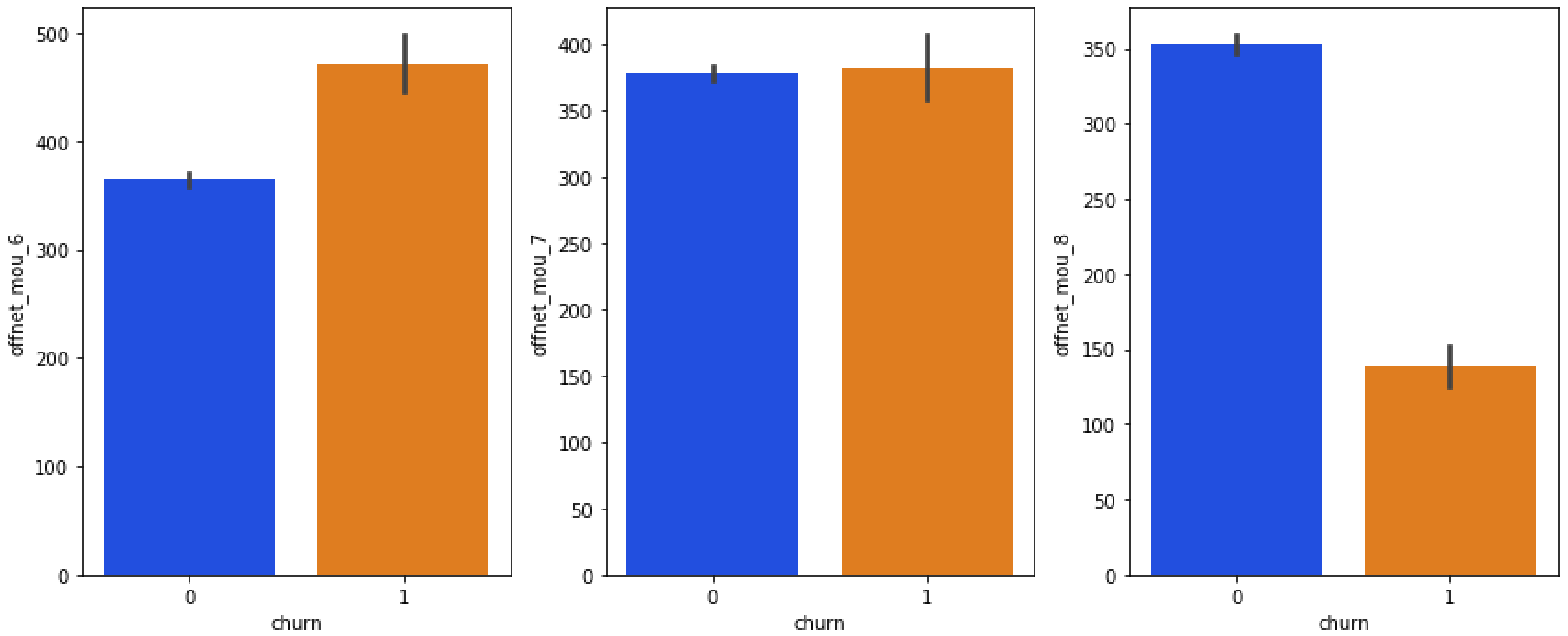
Plotting On-Net Minutes of Usage per Phase (Good / Action)

```
In [91]: plot_bar_chart('onnet_mou')
```



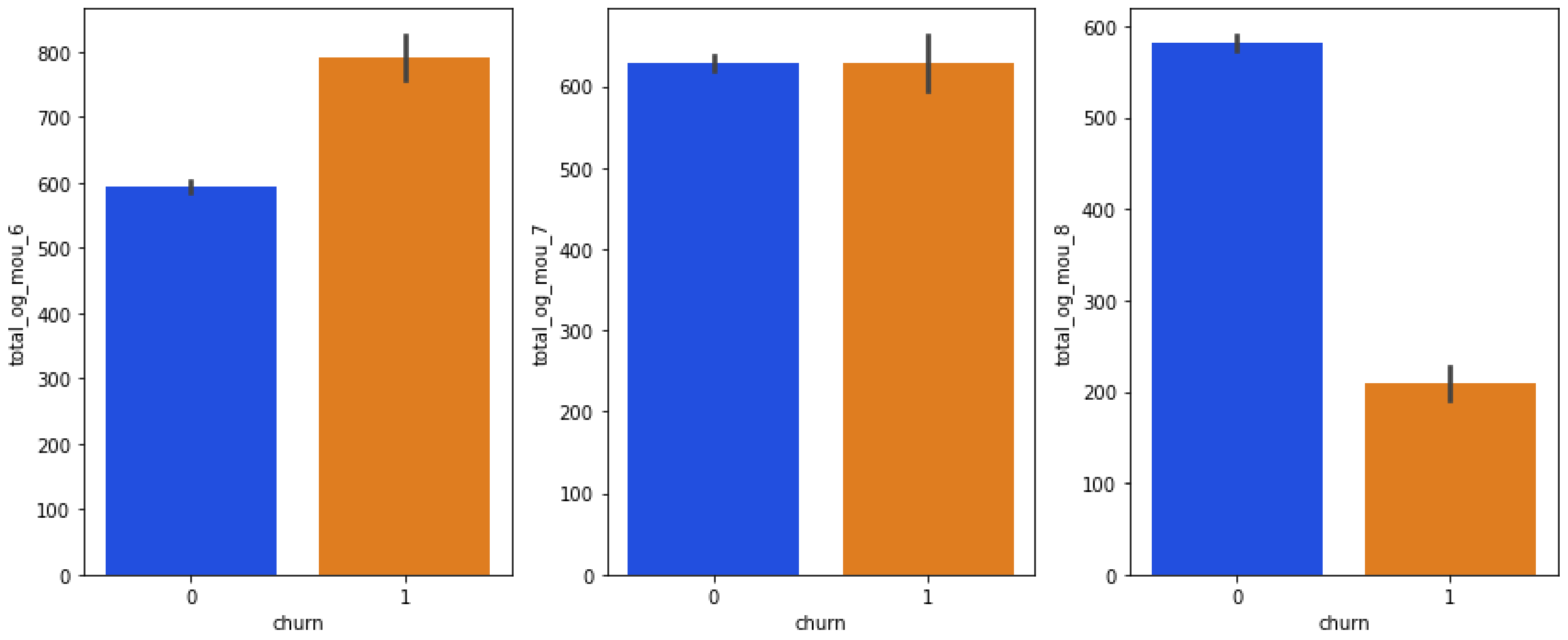
Plotting Off-Net Minutes of Usage per Phase (Good / Action)

```
In [92]: plot_bar_chart('offnet_mou')
```



Plotting Total Outgoing Minutes of Usage per Phase (Good / Action)

In [93]:
```python
plot_bar_chart('total_og_mou')
```

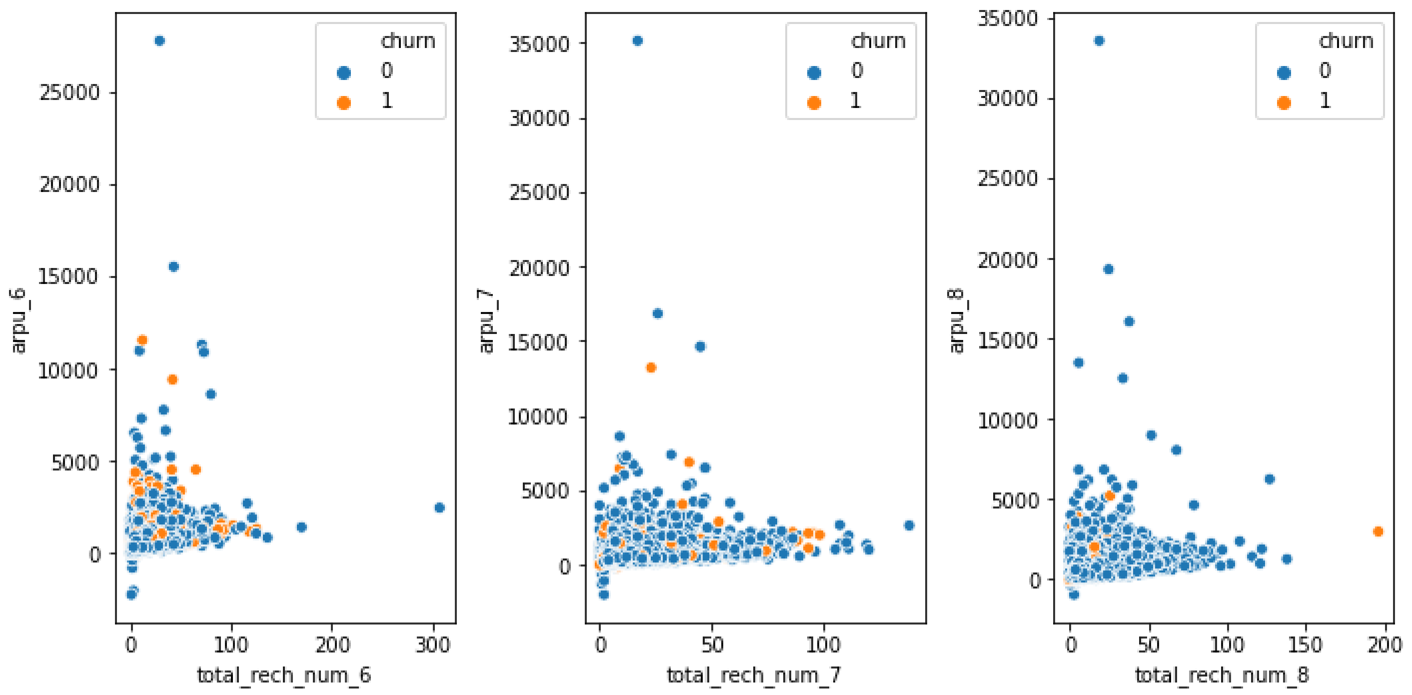


INSIGHT:

We could see a drop in all the MOU variables for the churned customer in the 8th Month (Action Phase).

Scatter plot between Total recharge number and Average revenue per use

In [94]:
```python
# lets now draw a scatter plot between total recharge number and Average revenue per use
fig= plt.figure(figsize=(10, 5))
plt.subplot(1, 3, 1)
sns.scatterplot(x='total_rech_num_6', y='arpu_6', data=tele_data_hv_cust, hue='churn')
plt.subplot(1, 3, 2)
sns.scatterplot(x='total_rech_num_7', y='arpu_7', data=tele_data_hv_cust, hue='churn')
plt.subplot(1, 3, 3)
sns.scatterplot(x='total_rech_num_8', y='arpu_8', data=tele_data_hv_cust, hue='churn')
fig.tight_layout()
plt.show()
```



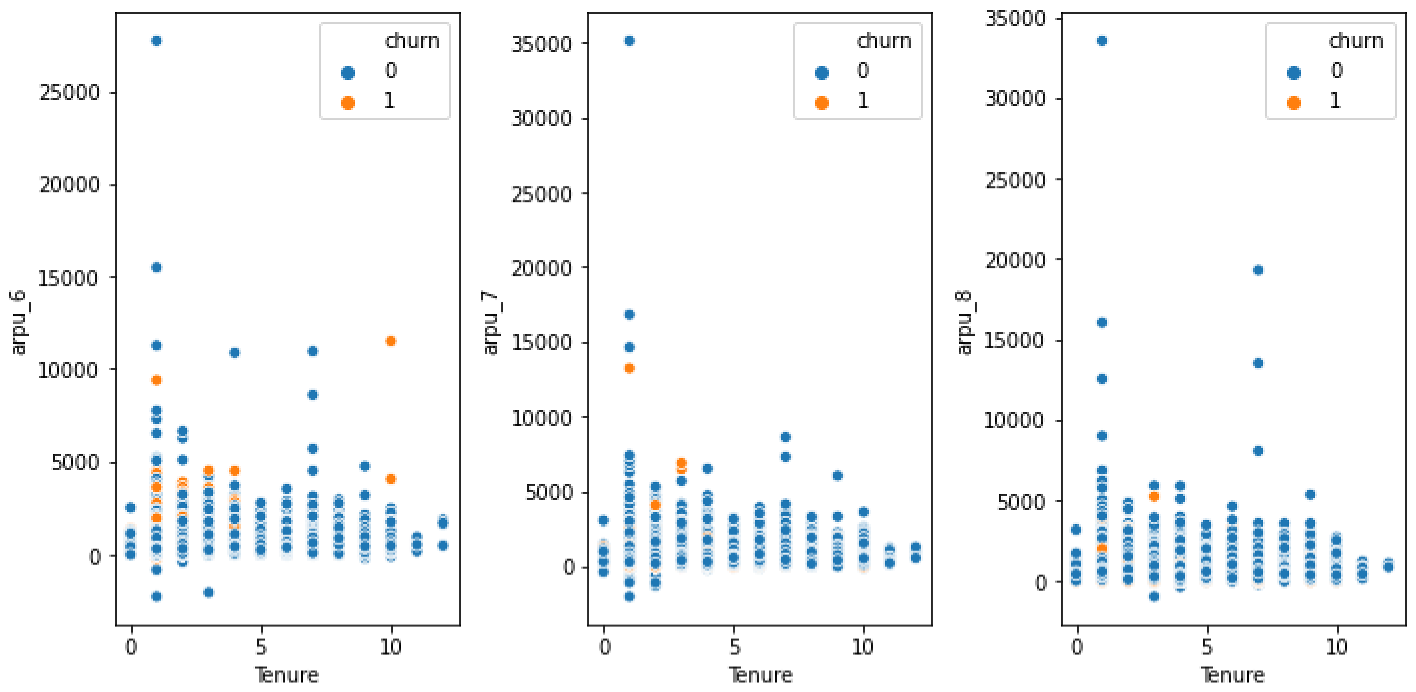
INSIGHT:

We could see a drop in arpu and total recharge number variables for the churned customer in the 8th Month (Action Phase).

Scatter plot between Tenure and Average revenue per use

In [95]:

```
# plot between Tenure and Average revenue per use
fig= plt.figure(figsize=(10, 5))
plt.subplot(1, 3, 1)
sns.scatterplot(x='Tenure', y='arpu_6', hue='churn', data=tele_data_hv_cust)
plt.subplot(1, 3, 2)
sns.scatterplot(x='Tenure', y='arpu_7', hue='churn', data=tele_data_hv_cust)
plt.subplot(1, 3, 3)
sns.scatterplot(x='Tenure', y='arpu_8', hue='churn', data=tele_data_hv_cust)
#plt.xlabel('Tenure_mon')
#plt.ylabel('arpu_8')
fig.tight_layout()
plt.show()
```



INSIGHT:

We could see a drop in arpu variables for the churned customer in the 8th Month (Action Phase) and recent joint cutomers are churning more.

We shall analyse the outgoing calls,incoming calls and the recharge done across the three months to see the increase and decrease in number

In [96]:

```
incoming_calls=tele_data_hv_cust.filter(regex='total_ic_mou').columns
avg_ic_mon_calls=pd.DataFrame(tele_data_hv_cust.groupby('Tenure',
                                                        as_index=False)[incoming_calls].mean())

avg_ic_mon_calls
```

Out[96]:

	Tenure	total_ic_mou_6	total_ic_mou_7	total_ic_mou_8
0	0.0	195.372444	218.856778	190.733111
1	1.0	235.291026	242.216376	224.551155
2	2.0	264.459021	269.386971	246.865465
3	3.0	285.800995	295.074208	278.132355
4	4.0	306.212811	314.826843	299.945626
5	5.0	352.835721	359.074788	337.883089
6	6.0	348.840431	354.301243	353.406368
7	7.0	379.912278	384.192625	368.345382
8	8.0	390.785042	399.027233	382.641345
9	9.0	376.461104	386.519779	377.644518
10	10.0	405.297881	408.511579	408.013227
11	11.0	464.702059	451.680588	415.940000
12	12.0	413.626667	396.713333	393.300000

In [97]:

```python
outgoing_calls = tele_data_hv_cust.filter(regex='total_og_mou').columns
avg_og_mon_calls = pd.DataFrame(tele_data_hv_cust.groupby('Tenure',as_index=False)[outgoing_calls].mean())

print(avg_og_mon_calls)
```

```
    Tenure  total_og_mou_6  total_og_mou_7  total_og_mou_8
0      0.0      687.816222      722.277222      591.782778
1      1.0      605.778611      630.292771      529.255129
2      2.0      654.083692      689.648883      585.166827
3      3.0      630.639118      639.796028      569.791793
4      4.0      616.946602      631.126602      566.979806
5      5.0      595.013475      599.259389      562.193134
6      6.0      585.840750      593.839549      563.441472
7      7.0      594.336846      602.048877      563.413979
8      8.0      550.788739      558.172004      523.573019
9      9.0      518.629367      512.549950      483.140321
10    10.0      556.344321      552.937632      532.899224
11    11.0      410.894706      414.671765      427.520882
12    12.0      489.610000      525.233333      406.490000
```

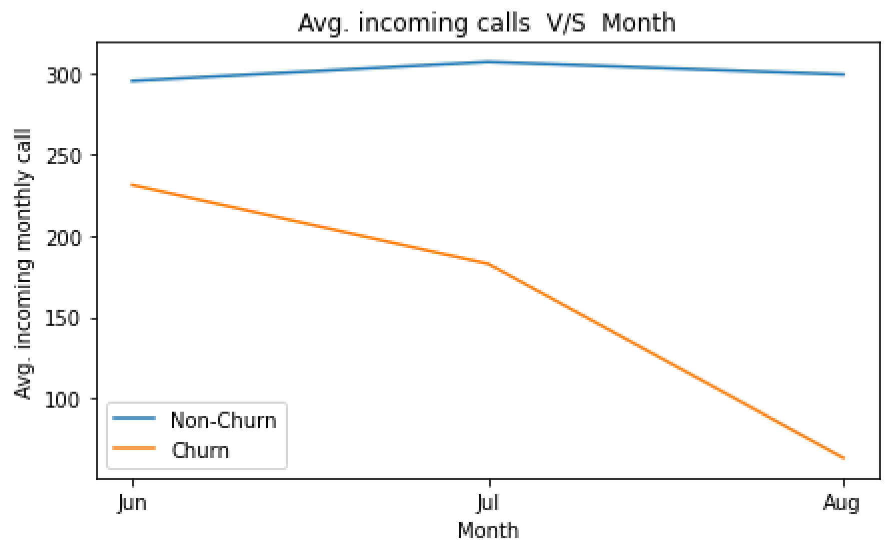
In [98]:

```python
total_rech_data_amt = tele_data_hv_cust.filter(regex='total_rech_data_amt').columns
avg_total_month_rech = pd.DataFrame(tele_data_hv_cust.groupby('Tenure',as_index=False)[total_rech_data_amt].mean())

print(avg_total_month_rech)
```

```
    Tenure  total_rech_data_amt_6  total_rech_data_amt_7  \
0      0.0             425.311111             575.711111
1      1.0             520.802021             588.549573
2      2.0             525.968126             601.355886
3      3.0             457.852623             534.129497
4      4.0             444.291843             535.603128
5      5.0             384.160232             463.669324
6      6.0             300.937153             398.269444
7      7.0             318.301046             362.039075
8      8.0             375.884939             456.117970
9      9.0             301.640562             345.785141
10    10.0             225.891967             291.988920
11    11.0             158.588235             160.617647
12    12.0            2688.000000             420.000000

    total_rech_data_amt_8
0              405.133333
1              512.589241
2              498.382116
3              497.890081
4              481.441669
5              417.626126
6              384.202431
7              306.202807
8              387.993859
9              317.119980
10             295.089335
11             258.441176
12             450.666667
```

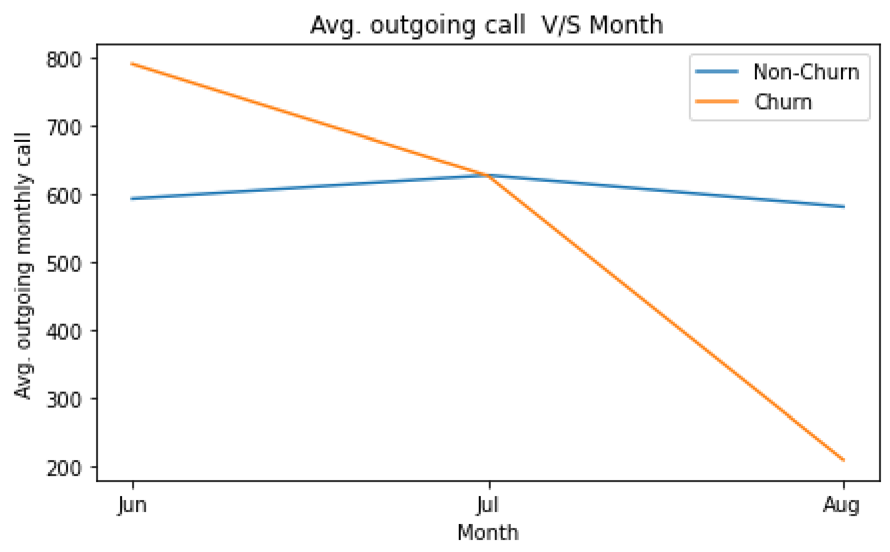
In [99]:

```python
fig, ax = plt.subplots(figsize=(7,4))
df=tele_data_hv_cust.groupby(['churn'])[incoming_calls].mean().T
plt.plot(df)
ax.set_xticklabels(['Jun','Jul','Aug'])
## Add legend
plt.legend(['Non-Churn', 'Churn'])
# Add titles
plt.title("Avg. incoming calls  V/S  Month",fontsize=12)
plt.xlabel("Month")
plt.ylabel("Avg. incoming monthly call")
plt.show()
```



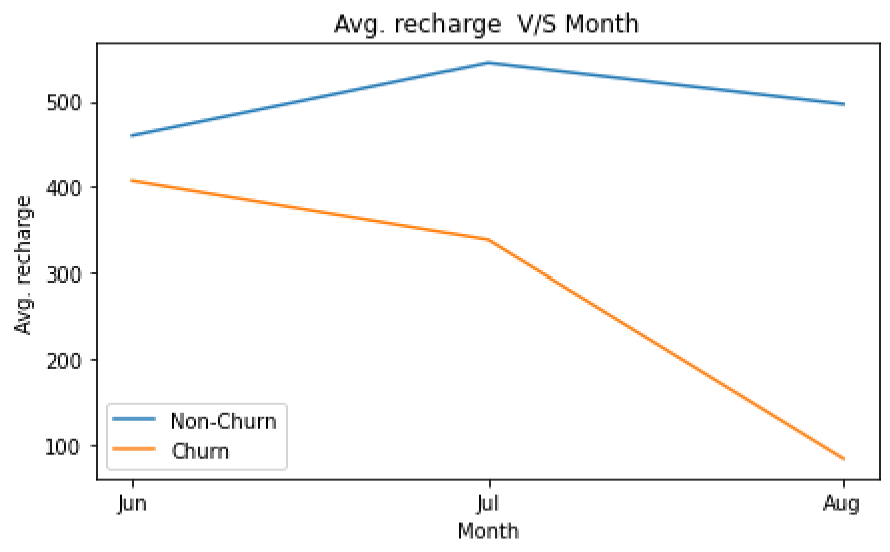
In [100]:

```
fig, ax = plt.subplots(figsize=(7,4))
df=tele_data_hv_cust.groupby(['churn'])[outgoing_calls].mean().T
plt.plot(df)
ax.set_xticklabels(['Jun','Jul','Aug'])
## Add legend
plt.legend(['Non-Churn', 'Churn'])
# Add titles
plt.title("Avg. outgoing call  V/S Month",fontsize=12)
plt.xlabel("Month")
plt.ylabel("Avg. outgoing monthly call")
plt.show()
```



In [101]:

```
fig, ax = plt.subplots(figsize=(7,4))
df=tele_data_hv_cust.groupby(['churn'])[total_rech_data_amt].mean().T
plt.plot(df)
ax.set_xticklabels(['Jun','Jul','Aug'])
## Add legend
plt.legend(['Non-Churn', 'Churn'])
# Add titles
plt.title("Avg. recharge  V/S Month",fontsize=12)
plt.xlabel("Month")
plt.ylabel("Avg. recharge")
plt.show()
```



INSIGHT:

- For churning customer we can observe that there are significant dropping from June to July and then dropping sharply from July to Aug that is almost trending 0.
- For Non Churning customers we can observe that there is an increase in number from June to July but again there is a slight decrease from July to August.
- The outgoing calls,incoming calls and total recharge have been decreasing for all the churning customers.

Step 5: Preparing the data for modelling

In [102]:

```
tele_data_hv_cust.shape
```

Out[102]:

```
(30001, 132)
```

In [103]:
```
tele_data_hv_cust
```

Out[103]:

	mobile_number	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t
0	7000842753	197.385	214.816	213.803	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
7	7000701601	1069.180	1349.850	3171.480	57.84	54.68	52.29	453.43	567.16	325.91	16.23	33.49	31.64	23.74	12.59	38.06	51.39	31.38	40.28	
8	7001524846	378.721	492.223	137.362	413.69	351.03	35.08	94.66	80.63	136.48	0.00	0.00	0.00	0.00	0.00	0.00	297.13	217.59	12.49	
21	7002124215	514.453	597.753	637.760	102.41	132.11	85.14	757.93	896.68	983.39	0.00	0.00	0.00	0.00	0.00	0.00	4.48	6.16	23.34	
23	7000887461	74.350	193.897	366.966	48.96	50.66	33.58	85.41	89.36	205.89	0.00	0.00	0.00	0.00	0.00	0.00	48.96	50.66	33.58	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
99981	7000630859	384.316	255.405	393.474	78.68	29.04	103.24	56.13	28.09	61.44	0.00	0.00	0.00	0.00	0.00	0.00	72.53	29.04	89.23	
99984	7000661676	328.594	202.966	118.707	423.99	181.83	5.71	39.51	39.81	18.26	0.00	0.00	0.00	0.00	0.00	0.00	423.99	181.83	5.71	
99986	7001729035	644.973	455.228	564.334	806.73	549.36	775.41	784.76	617.13	595.44	0.00	0.00	0.00	0.00	0.00	0.00	709.21	496.14	718.56	
99988	7002111859	312.558	512.932	402.080	199.89	174.46	2.46	175.88	277.01	248.33	0.00	0.00	0.00	0.00	0.00	0.00	170.28	146.48	2.46	
99997	7000498689	322.991	303.386	606.817	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

30001 rows × 132 columns

5.1) Checking for Outliers

In [104]:
```
# Lets check the outliers
tele_data_hv_cust.describe(percentiles=[0.01, 0.10,.25,.5,.75,.90,.95,.99])
```

Out[104]:

	mobile_number	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou
count	3.000100e+04	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.000000	30001.0000
mean	7.001206e+09	558.490824	560.782203	508.597957	260.793024	267.819295	234.112539	373.693961	378.103169	335.077044	16.110355	12.642504	12.500551	26.571547	20.152086	19.865615	84.484753	85.674287	78.0771
std	6.908784e+05	460.640461	479.776947	501.961981	459.644368	479.993989	458.448598	482.523558	498.923555	482.062509	76.302156	75.785903	74.125281	116.205525	96.100428	104.719009	228.794004	240.525999	227.3736
min	7.000000e+09	-2258.709000	-2014.045000	-945.808000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
1%	7.000026e+09	1.000000	0.700000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
10%	7.000251e+09	171.605000	177.886000	84.000000	0.700000	0.580000	0.000000	11.260000	10.430000	2.200000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
25%	7.000609e+09	309.865000	309.826000	231.473000	17.080000	16.030000	10.390000	71.610000	69.910000	46.740000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	4.380000	4.610000	2.5300
50%	7.001203e+09	481.694000	480.943000	427.585000	84.580000	82.810000	65.610000	222.540000	220.030000	182.790000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	24.330000	24.680000	20.7300
75%	7.001804e+09	699.943000	698.315000	661.491000	290.440000	290.240000	239.960000	487.940000	494.010000	438.890000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	77.980000	78.340000	72.0400
90%	7.002165e+09	994.099000	995.859000	977.345000	754.160000	784.480000	665.080000	895.830000	916.080000	823.680000	27.390000	14.290000	15.010000	50.430000	31.090000	28.880000	187.930000	190.840000	178.8400
95%	7.002285e+09	1240.964000	1261.272000	1255.019000	1135.440000	1185.790000	1074.590000	1256.610000	1272.290000	1167.540000	84.540000	55.640000	56.350000	145.410000	104.240000	100.510000	322.740000	324.390000	298.7800
99%	7.002386e+09	1985.115000	1999.500000	1986.622000	2151.740000	2201.960000	2159.110000	2326.360000	2410.890000	2193.130000	342.440000	280.460000	282.190000	530.710000	438.590000	427.030000	1006.360000	1018.530000	913.3300
max	7.002411e+09	27731.088000	35145.834000	33543.624000	7376.710000	8157.780000	10752.560000	8362.360000	9667.130000	14007.340000	2613.310000	3813.290000	4169.810000	3775.110000	2812.040000	5337.040000	6431.330000	7400.660000	10752.5600

Inference:- We can clearly see that there is a huge gap between the 99th percentile and the maximum values in most of the columns of the dataframe. This clearly means that there are outliers in the dataset and they need to be treated. Lets use capping technique to cap the outliers in this d

Capping outliers in all numeric variables

In [105]:
```
# Capping outliers in all numeric variables

cont_cols = [col for col in tele_data_hv_cust.columns if col not in ['churn','mobile_number']]

for col in cont_cols:

    Q1= tele_data_hv_cust[col].quantile(0.01)
    Q3= tele_data_hv_cust[col].quantile(0.99)
    IQR = Q3 - Q1
    tele_data_hv_cust=tele_data_hv_cust[(tele_data_hv_cust[col] >= Q1 - 1.5*IQR) & (
                                                            tele_data_hv_cust[col] <= Q3 + 1.5*IQR)]
tele_data_hv_cust.shape
```

Out[105]: (26859, 132)

In [106]:
```
len(cont_cols)
```

Out[106]: 130

In [107]:
```
tele_data_hv_cust.describe(percentiles=[0.01, 0.10,.25,.5,.75,.90,.95,.99])
```

Out[107]:

	mobile_number	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou
count	2.685900e+04	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.000000	26859.0000
mean	7.001205e+09	525.757944	523.030877	469.430064	249.831733	253.619678	219.429554	359.124963	361.401428	316.618361	12.784711	8.855358	8.897634	21.859126	15.226094	14.524715	75.206801	74.470481	67.5927
std	6.913275e+05	336.888778	332.326785	355.939570	415.726678	423.865684	399.172731	448.640778	458.671009	428.590568	52.507862	41.648307	40.497359	83.900066	63.574260	59.890547	165.922797	161.111030	145.6252
min	7.000000e+09	-810.661000	-897.035000	-345.129000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
1%	7.000026e+09	2.221440	0.515400	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
10%	7.000251e+09	167.873000	171.771200	78.183200	0.510000	0.400000	0.000000	9.904000	8.906000	1.630000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
25%	7.000608e+09	301.457000	299.139500	220.100000	16.220000	15.080000	9.540000	67.475000	65.640000	42.280000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	4.260000	4.460000	2.3600
50%	7.001199e+09	469.772000	467.459000	412.380000	82.810000	80.040000	62.860000	214.790000	211.330000	173.280000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	23.610000	23.930000	19.8100
75%	7.001804e+09	674.029500	668.561500	631.121000	286.350000	284.590000	233.065000	475.305000	478.920000	421.960000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	75.530000	75.170000	69.1900
90%	7.002165e+09	934.528600	927.686200	905.327200	740.064000	761.172000	642.994000	871.644000	891.024000	790.422000	24.080000	11.814000	12.742000	45.912000	26.940000	24.330000	178.782000	181.814000	170.1660
95%	7.002286e+09	1146.534600	1140.177700	1141.096100	1105.531000	1129.625000	1026.662000	1213.500000	1229.087000	1122.320000	72.094000	45.118000	45.713000	132.560000	90.198000	87.736000	304.377000	299.062000	276.8950
99%	7.002386e+09	1679.311100	1644.130660	1682.956200	1981.854200	1990.311800	1930.197600	2161.264600	2218.744000	2028.746000	276.649000	207.044000	209.540000	454.348400	339.224000	316.124600	838.168000	811.765000	711.1116
max	7.002411e+09	4497.680000	4212.269000	4822.844000	5012.190000	4730.640000	4744.480000	5081.010000	5194.830000	5184.110000	838.330000	653.480000	655.540000	1216.980000	921.690000	819.210000	2499.280000	2244.580000	1946.8600

In [108]:
```
# Identifying if any column exists with only null values
tele_data_hv_cust.isnull().all(axis=0).any()
```

Out[108]:
```
False
```

In [109]:
```
tele_data_hv_cust.og_others_8.value_counts()
```

Out[109]:
```
0.0    26859
Name: og_others_8, dtype: int64
```

In [110]:
```
# Dropping the 'og_others_8' variable, as it has zeroe values in all the rows
tele_data_hv_cust.drop('og_others_8', axis=1, inplace=True)
```

5.2) Splitting the Data into X & y

In [111]:
```
from sklearn.model_selection import train_test_split

# Putting feature variable to X
X = tele_data_hv_cust.drop(['churn','mobile_number'],axis=1)

# Putting response variable to y
y = tele_data_hv_cust['churn']
```

In [112]:
```
X
```

Out[112]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2m_mou_6	loc_(
0	197.385	214.816	213.803	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
7	1069.180	1349.850	3171.480	57.84	54.68	52.29	453.43	567.16	325.91	16.23	33.49	31.64	23.74	12.59	38.06	51.39	31.38	40.28	308.63	
8	378.721	492.223	137.362	413.69	351.03	35.08	94.66	80.63	136.48	0.00	0.00	0.00	0.00	0.00	0.00	297.13	217.59	12.49	80.96	
21	514.453	597.753	637.760	102.41	132.11	85.14	757.93	896.68	983.39	0.00	0.00	0.00	0.00	0.00	0.00	4.48	6.16	23.34	91.81	
23	74.350	193.897	366.966	48.96	50.66	33.58	85.41	89.36	205.89	0.00	0.00	0.00	0.00	0.00	0.00	48.96	50.66	33.58	82.94	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
99981	384.316	255.405	393.474	78.68	29.04	103.24	56.13	28.09	61.44	0.00	0.00	0.00	0.00	0.00	0.00	72.53	29.04	89.23	52.21	
99984	328.594	202.966	118.707	423.99	181.83	5.71	39.51	39.81	18.26	0.00	0.00	0.00	0.00	0.00	0.00	423.99	181.83	5.71	17.96	
99986	644.973	455.228	564.334	806.73	549.36	775.41	784.76	617.13	595.44	0.00	0.00	0.00	0.00	0.00	0.00	709.21	496.14	718.56	574.93	
99988	312.558	512.932	402.080	199.89	174.46	2.46	175.88	277.01	248.33	0.00	0.00	0.00	0.00	0.00	0.00	170.28	146.48	2.46	137.83	
99997	322.991	303.386	606.817	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

26859 rows × 129 columns

In [113]:
```
X.shape, y.shape
```

Out[113]:
```
((26859, 129), (26859,))
```

5.3) Test-Train Split

In [114]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.3,stratify = y,random_state=100)

print("X_train: ", X_train.shape)
print("y_train: ", y_train.shape)
print("X_test: ", X_test.shape)
print("y_test: ", y_test.shape)
```

```
X_train:  (18801, 129)
y_train:  (18801,)
X_test:  (8058, 129)
y_test:  (8058,)
```

In [115]:
```python
X_train
```

Out[115]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2m_mou_6
59748	187.046	192.482	157.962	0.44	2.44	2.53	1.99	12.51	4.56	0.00	0.00	0.00	0.00	0.00	0.0	0.44	2.44	2.53	1.99
31024	208.821	223.819	232.520	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00
78814	628.690	793.396	282.521	421.38	560.38	223.58	250.56	169.31	87.79	0.00	0.00	0.00	0.00	0.00	0.0	304.93	353.09	144.64	134.43
1005	425.771	840.149	618.523	97.66	153.91	317.21	387.84	653.16	577.73	0.00	296.23	45.83	0.00	172.24	36.4	74.23	102.29	210.18	335.11
27382	927.700	507.009	486.155	237.08	75.99	60.43	1212.84	629.81	1013.78	0.00	0.00	0.00	0.00	0.00	0.0	45.18	16.63	2.26	230.56
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
65754	568.124	1040.995	554.750	812.08	2159.98	876.46	108.56	262.83	161.53	0.00	0.00	0.00	0.00	0.00	0.0	47.79	88.88	43.16	43.14
43634	913.361	243.318	17.362	1197.63	122.19	10.56	1006.84	63.19	3.65	7.31	2.61	0.90	52.94	83.99	0.0	25.48	0.65	0.00	89.08
77376	1464.571	1153.011	867.697	138.58	255.83	934.76	2412.31	1061.64	764.83	0.00	0.00	0.00	0.28	0.00	0.0	136.28	255.83	934.76	2401.48
50660	362.989	252.285	126.547	46.61	5.96	61.04	118.11	81.94	57.06	0.00	0.00	0.00	0.00	0.00	0.0	6.83	5.96	14.91	54.06
83339	1123.783	20.500	835.120	676.38	0.58	511.04	1334.13	4.44	1450.39	15.59	8.08	0.51	148.41	5.03	0.0	48.66	0.00	10.24	139.14

18801 rows × 129 columns

Checking for Class imbalance in Train & Test

In [116]:
```python
y_train.value_counts(normalize=True)
```

Out[116]:
```
0    0.91926
1    0.08074
Name: churn, dtype: float64
```

In [117]:
```python
y_test.value_counts(normalize=True)
```

Out[117]:
```
0    0.919211
1    0.080789
Name: churn, dtype: float64
```

In [118]:
```python
X_test
```

Out[118]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2m_mou_6
1856	79.241	201.624	119.957	0.00	0.20	0.00	15.68	26.68	1.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	5.13
23195	101.428	179.197	64.824	2.64	7.93	0.23	47.69	50.54	8.94	0.00	0.00	0.00	0.00	0.00	0.00	2.64	7.93	0.23	46.36
39180	285.919	867.784	188.849	146.46	309.23	63.19	348.81	1275.84	362.03	0.00	0.00	0.00	0.00	0.00	5.98	4.41	137.38	30.51	28.06
51612	219.003	243.274	0.000	1.90	4.79	0.00	0.00	12.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
69554	303.511	379.953	395.028	11.06	20.33	50.13	99.14	111.03	212.66	0.00	0.00	0.00	0.00	0.00	0.00	11.06	18.59	49.81	82.68
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
83851	1036.564	119.738	86.119	236.23	49.69	0.98	397.74	21.78	39.34	11.74	20.44	18.09	19.54	71.48	40.33	3.73	0.00	0.00	177.08
98979	1419.971	748.026	586.043	128.13	171.99	72.91	1030.54	377.39	426.29	46.48	0.00	7.91	504.41	0.00	72.74	34.91	21.36	5.56	490.79
52980	722.922	681.043	685.221	530.31	656.91	701.08	689.29	493.86	540.08	0.00	0.00	0.00	0.00	0.00	0.00	29.76	32.14	20.18	29.59
96011	635.049	313.943	477.287	1047.38	602.34	704.39	311.49	98.66	77.44	0.00	28.24	75.08	0.00	17.43	179.76	83.43	51.54	56.21	78.53
86344	443.836	311.722	493.297	292.41	280.43	195.38	131.86	86.93	115.54	0.00	0.00	0.00	0.00	0.00	0.00	292.41	280.43	195.38	119.96

8058 rows × 129 columns

5.4) Feature Scaling

In [119]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18801 entries, 59748 to 83339
Columns: 129 entries, arpu_6 to Tenure
dtypes: float64(105), int64(24)
memory usage: 18.6 MB
```

In [120]:
```
# apply scaling on the dataset
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler

#numerical features
num_cols = [col for col in X_train.columns]

# apply standardization on numerical features
for i in num_cols:

    # fit on training data column
    scale = StandardScaler()

    # transform the training data column
    X_train[i] = scale.fit_transform(X_train[[i]])

    # transform the testing data column
    X_test[i] = scale.transform(X_test[[i]])
```

In [121]:
```
X_train
```

Out[121]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2m_mou_6	loc
59748	-0.996811	-0.992722	-0.872609	-0.599102	-0.595687	-0.541702	-0.791725	-0.756289	-0.723297	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.447166	-0.446199	-0.446190	-0.669493	
31024	-0.932330	-0.897938	-0.661891	-0.600160	-0.601516	-0.548054	-0.796142	-0.783603	-0.733882	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.449800	-0.461364	-0.463646	-0.678057	
78814	0.311007	0.824839	-0.520576	0.413509	0.737264	0.013295	-0.240073	-0.413930	-0.530093	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	1.375520	1.733033	0.534285	-0.099557	
1005	-0.289887	0.966251	0.429043	-0.365230	-0.233816	0.248375	0.064593	0.642512	0.607220	-0.244438	6.899801	0.910412	-0.261172	2.519647	0.368152	-0.005457	0.174352	0.986472	0.764039	
27382	1.196451	-0.041385	0.054941	-0.029842	-0.419972	-0.396331	1.895520	0.591529	1.619436	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.179351	-0.358011	-0.448053	0.314124	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
65754	0.131656	1.573742	0.248806	1.353375	4.558801	1.652501	-0.555214	-0.209738	-0.358918	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.163728	0.091011	-0.165867	-0.492410	
43634	1.153989	-0.838960	-1.269977	2.280851	-0.309597	-0.521541	1.438343	-0.645633	-0.725409	-0.101292	-0.147821	-0.193392	0.371924	1.105352	-0.240127	-0.297276	-0.457324	-0.463646	-0.294714	
77376	2.786260	1.912552	1.133267	-0.266793	0.009676	1.798877	4.557510	1.534390	1.041541	-0.244438	-0.210468	-0.215502	-0.257824	-0.240672	-0.240127	0.365976	1.128578	5.985647	9.656352	
50660	-0.475800	-0.811838	-0.961395	-0.488035	-0.587277	-0.394799	-0.534020	-0.604695	-0.601427	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.408916	-0.424323	-0.360776	-0.445418	
83339	1.777101	-1.512909	1.041197	1.026935	-0.600131	0.735030	2.164699	-0.773909	2.632952	0.060848	-0.016527	-0.202973	1.513627	-0.160061	-0.240127	-0.158520	-0.461364	-0.392996	-0.079289	

18801 rows × 129 columns

In [122]:
```
X_test
```

Out[122]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_t2m_mou_6	loc
1856	-1.316049	-0.965070	-0.980020	-0.600160	-0.601038	-0.548054	-0.761343	-0.725350	-0.730795	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.449800	-0.460121	-0.463646	-0.655981	
23195	-1.250347	-1.032904	-1.135838	-0.593809	-0.582571	-0.547477	-0.690303	-0.673254	-0.713129	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.433997	-0.412080	-0.462059	-0.478553	
39180	-0.704023	1.049837	-0.785315	-0.247837	0.137252	-0.389401	-0.022026	2.002076	0.106509	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.140195	-0.423402	0.392430	-0.253145	-0.557305	
51612	-0.902178	-0.839093	-1.319046	-0.595590	-0.590073	-0.548054	-0.796142	-0.757271	-0.733882	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.449800	-0.461364	-0.463646	-0.678057	
69554	-0.651929	-0.425686	-0.202605	-0.573554	-0.552947	-0.422191	-0.576120	-0.541179	-0.240228	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.383595	-0.345830	-0.119986	-0.322256	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
83851	1.518824	-1.212748	-1.075654	-0.031887	-0.482804	-0.545594	0.086564	-0.736048	-0.642561	-0.014543	0.280144	0.228918	-0.027498	0.904867	0.433826	-0.427472	-0.461364	-0.463646	0.083980	
98979	2.654188	0.687610	0.337247	-0.291931	-0.190622	-0.364997	1.490941	0.040393	0.255678	0.665741	-0.210468	-0.021176	5.770944	-0.240672	0.975428	-0.240828	-0.328615	-0.425285	1.433984	
52980	0.590052	0.485009	0.617547	0.675550	0.967880	1.212169	0.733603	0.294695	0.519822	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	-0.271656	-0.261619	-0.324416	-0.550721	
96011	0.329838	-0.625344	0.029878	1.919411	0.837509	1.220480	-0.104851	-0.568188	-0.554118	-0.244438	0.467364	1.629002	-0.261172	0.038661	2.763834	0.049614	-0.141051	-0.075830	-0.340115	
86344	-0.236392	-0.632061	0.075126	0.103260	0.068447	-0.057507	-0.503504	-0.593799	-0.465676	-0.244438	-0.210468	-0.215502	-0.261172	-0.240672	-0.240127	1.300575	1.281463	0.884361	-0.161827	

8058 rows × 129 columns

5.5) Looking at Correlations

In [123]:

```python
# lets check the correlation amongst the features, drop the highly correlated ones
cor = X_train.corr()
cor
```

Out[123]:

	arpu_6	arpu_7	arpu_8	onnet_mou_6	onnet_mou_7	onnet_mou_8	offnet_mou_6	offnet_mou_7	offnet_mou_8	roam_ic_mou_6	roam_ic_mou_7	roam_ic_mou_8	roam_og_mou_6	roam_og_mou_7	roam_og_mou_8	loc_og_t2t_mou_6	loc_og_t2t_mou_7	loc_og_t2t_mou_8	loc_og_
arpu_6	1.000000	0.571898	0.480524	0.449459	0.279941	0.242136	0.605738	0.397304	0.337060	0.124146	0.091133	0.097359	0.188415	0.124597	0.128442	0.248554	0.194848	0.185805	
arpu_7	0.571898	1.000000	0.676494	0.296968	0.445740	0.374684	0.411703	0.602225	0.489366	0.089554	0.107377	0.104877	0.127723	0.154846	0.146231	0.168455	0.253111	0.222411	
arpu_8	0.480524	0.676494	1.000000	0.208298	0.318618	0.482737	0.307479	0.440947	0.636528	0.094341	0.066578	0.093153	0.125204	0.091568	0.158279	0.158627	0.215454	0.302755	
onnet_mou_6	0.449459	0.296968	0.208298	1.000000	0.751670	0.614024	0.085798	0.049731	0.043680	0.012432	0.036754	0.055323	0.066297	0.090078	0.096424	0.357029	0.265323	0.226352	
onnet_mou_7	0.279941	0.445740	0.318618	0.751670	1.000000	0.795589	0.036239	0.090463	0.084288	0.034371	0.003114	0.040088	0.079960	0.054944	0.086688	0.235015	0.339610	0.262871	
onnet_mou_8	0.242136	0.374684	0.482737	0.614024	0.795589	1.000000	0.052753	0.106389	0.155244	0.044423	0.013138	0.007287	0.092083	0.054747	0.058204	0.197236	0.260917	0.345020	
offnet_mou_6	0.605738	0.411703	0.307479	0.085798	0.036239	0.052753	1.000000	0.736987	0.583659	0.033224	0.042181	0.067900	0.080924	0.076790	0.092479	0.107497	0.083150	0.079115	
offnet_mou_7	0.397304	0.602225	0.440947	0.049731	0.090463	0.106389	0.736987	1.000000	0.774118	0.060981	0.025344	0.066341	0.100069	0.062581	0.098841	0.068499	0.100564	0.095644	
offnet_mou_8	0.337060	0.489366	0.636528	0.043680	0.084288	0.155244	0.583659	0.774118	1.000000	0.075596	0.018549	0.026455	0.106372	0.048940	0.075248	0.078634	0.105697	0.152836	
roam_ic_mou_6	0.124146	0.089554	0.094341	0.012432	0.034371	0.044423	0.033224	0.060981	0.075596	1.000000	0.398343	0.272827	0.713762	0.329740	0.230139	-0.010623	0.019282	0.044038	
roam_ic_mou_7	0.091133	0.107377	0.066578	0.036754	0.003114	0.013138	0.042181	0.025344	0.018549	0.398343	1.000000	0.479260	0.314753	0.725117	0.380113	0.005875	-0.019019	-0.001601	

In [124]:

```python
# lets check the correlation amongst the features, drop the highly correlated ones
import numpy as np
cor.loc[:,:] = np.tril(cor, k=-1)
cor = cor.stack()
cor[(cor > 0.70) | (cor < -0.70)].sort_values()
```

Out[124]:

```
total_ic_mou_8    loc_ic_mou_6        0.700225
total_og_mou_7    arpu_7              0.701246
loc_og_mou_7      loc_og_t2m_mou_6    0.701796
std_og_mou_8      onnet_mou_8         0.704907
total_og_mou_6    onnet_mou_6         0.705830
total_og_mou_7    total_og_mou_6      0.706988
                  onnet_mou_7         0.707055
total_ic_mou_6    loc_ic_mou_8        0.707493
loc_ic_t2m_mou_8  loc_ic_t2m_mou_6    0.708615
loc_og_mou_6      loc_og_t2m_mou_7    0.708769
total_rech_amt_8  total_og_mou_8      0.709013
total_ic_mou_7    loc_ic_t2m_mou_6    0.709496
loc_og_t2m_mou_8  loc_og_t2m_mou_6    0.712295
loc_og_mou_6      loc_og_t2t_mou_6    0.712514
std_ic_t2m_mou_8  std_ic_t2m_mou_7    0.713664
roam_og_mou_6     roam_ic_mou_6       0.713762
total_ic_mou_8    total_ic_mou_6      0.715310
loc_og_mou_7      loc_og_t2t_mou_7    0.715637
sachet_2g_8       sachet_2g_7         0.720124
```

In [125]:

```python
#To see which all are highly correlated with correlation value is equal or greater than 0.70
joincorr= X_train.corr()
X_train_corr = joincorr.stack().reset_index().sort_values(by = 0, ascending = False)
X_train_corr[((X_train_corr[0] < 1) & (X_train_corr[0] >= 0.7)) | ((X_train_corr[0] <= -0.7) & (X_train_corr[0] > -1))]
```

Out[125]:

	level_0	level_1	0
10047	total_ic_mou_8	loc_ic_mou_8	0.963875
8142	loc_ic_mou_8	total_ic_mou_8	0.963875
9789	total_ic_mou_6	loc_ic_mou_6	0.960416
7884	loc_ic_mou_6	total_ic_mou_6	0.960416
9918	total_ic_mou_7	loc_ic_mou_7	0.958802
8013	loc_ic_mou_7	total_ic_mou_7	0.958802
11906	total_rech_amt_8	arpu_8	0.950350
349	arpu_8	total_rech_amt_8	0.950350
11648	total_rech_amt_6	arpu_6	0.935805
91	arpu_6	total_rech_amt_6	0.935805
220	arpu_7	total_rech_amt_7	0.933405
11777	total_rech_amt_7	arpu_7	0.933405

highly correlated variables will be managed by RFE during modeling

In [126]:
```
print("X_train: ", X_train.shape)
print("y_train: ", y_train.shape)
print("X_test: ", X_test.shape)
print("y_test: ", y_test.shape)
```

```
X_train:  (18801, 129)
y_train:  (18801,)
X_test:  (8058, 129)
y_test:  (8058,)
```

In [127]:
```
X_train.shape, X_test.shape
```

Out[127]:
```
((18801, 129), (8058, 129))
```

5.6) Checking for Class imbalance in Train & Test and treating it

SMOTE - Synthetic Minority Oversampling Technique Creates new "Synthetic" observations

Process: -

1. Identify the feature vector and its nearest neighbour
2. Take the difference between the two
3. Multiply the difference with a random number between 0 and 1
4. Identify a new point on the line segment by adding the random number to feature vector
5. Repeat the process for identified feature vectors

In [128]:
```
# SMOTE
from imblearn.over_sampling import SMOTE
smt = SMOTE(random_state=45, k_neighbors=5)
X_train, y_train = smt.fit_resample(X_train, y_train)
len(X_train)
```

Out[128]:
```
34566
```

In [129]:
```
import collections
from collections import Counter
print(sorted(Counter(y_train).items()))
```

```
[(0, 17283), (1, 17283)]
```

In [130]:
```
y_train.value_counts(normalize=True)
```

Out[130]:
```
1    0.5
0    0.5
Name: churn, dtype: float64
```

In [131]:
```
print("X_train: ", X_train.shape)
print("y_train: ", y_train.shape)
print("X_test: ", X_test.shape)
print("y_test: ", y_test.shape)
```

```
X_train:  (34566, 129)
y_train:  (34566,)
X_test:  (8058, 129)
y_test:  (8058,)
```

Step 6: Modeling

6.1) Running our First Training Model

In [132]:

```python
import statsmodels.api as sm
# Logistic regression model
logm1 = sm.GLM(y_train,(sm.add_constant(X_train)), family = sm.families.Binomial())
logm1.fit().summary()
```

Out[132]:

Generalized Linear Model Regression Results

Dep. Variable:	churn	**No. Observations:**	34566
Model:	GLM	**Df Residuals:**	34437
Model Family:	Binomial	**Df Model:**	128
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-11843.
Date:	Mon, 31 Aug 2020	**Deviance:**	23686.
Time:	01:18:47	**Pearson chi2:**	8.94e+04
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.1293	0.034	-63.452	0.000	-2.195	-2.063

6.2) Feature Selection Using RFE

> RFE will also take care of highly correlated variables(not choosing them) and choose best varibales

In [133]:

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

from sklearn.feature_selection import RFE
rfe = RFE(logreg, 15)             # running RFE with 15 variables as output
rfe = rfe.fit(X_train, y_train)
```

In [134]:

```python
rfe.support_
```

Out[134]:

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

In [135]:

```python
list(zip(X_train.columns, rfe.support_, rfe.ranking_))
```

Out[135]:

```
[('arpu_6', False, 24),
 ('arpu_7', True, 1),
 ('arpu_8', False, 29),
 ('onnet_mou_6', False, 21),
 ('onnet_mou_7', False, 7),
 ('onnet_mou_8', True, 1),
 ('offnet_mou_6', False, 13),
 ('offnet_mou_7', False, 55),
 ('offnet_mou_8', False, 26),
 ('roam_ic_mou_6', False, 76),
 ('roam_ic_mou_7', False, 47),
 ('roam_ic_mou_8', False, 45),
 ('roam_og_mou_6', False, 113),
 ('roam_og_mou_7', False, 61),
 ('roam_og_mou_8', False, 30),
 ('loc_og_t2t_mou_6', False, 23),
 ('loc_og_t2t_mou_7', False, 20),
 ('loc_og_t2t_mou_8', False, 9),
 ('loc_og_t2m_mou_6', False, 15),
```

In [136]:

```python
col = X_train.columns[rfe.support_]
```

In [137]:
```
X_train.columns[~rfe.support_]
```

Out[137]:
```
Index(['arpu_6', 'arpu_8', 'onnet_mou_6', 'onnet_mou_7', 'offnet_mou_6',
       'offnet_mou_7', 'offnet_mou_8', 'roam_ic_mou_6', 'roam_ic_mou_7',
       'roam_ic_mou_8',
       ...
       'monthly_3g_8', 'sachet_3g_6', 'sachet_3g_7', 'sachet_3g_8',
       'jul_vbc_3g', 'jun_vbc_3g', 'total_rech_data_amt_6',
       'total_rech_data_amt_7', 'total_rech_data_amt_8', 'Tenure'],
      dtype='object', length=114)
```

Assessing the model with StatsModels

In [138]:
```
X_train_sm = sm.add_constant(X_train[col])
logm2 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm2.fit()
res.summary()
```

Out[138]:

Generalized Linear Model Regression Results

Dep. Variable:	churn	**No. Observations:**	34566
Model:	GLM	**Df Residuals:**	34550
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-13276.
Date:	Mon, 31 Aug 2020	**Deviance:**	26551.
Time:	01:20:24	**Pearson chi2:**	2.39e+05
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-2.2032	0.033	-65.972	0.000	-2.269	-2.138
arpu_7	0.4369	0.022	19.489	0.000	0.393	0.481
onnet_mou_8	1.4177	0.081	17.460	0.000	1.259	1.577
std_og_t2m_mou_8	1.3007	0.078	16.665	0.000	1.148	1.454
std_og_t2f_mou_8	-0.4170	0.058	-7.221	0.000	-0.530	-0.304
total_og_mou_8	-2.5010	0.128	-19.565	0.000	-2.752	-2.250
loc_ic_t2f_mou_8	-0.4334	0.055	-7.853	0.000	-0.542	-0.325
loc_ic_mou_7	0.6260	0.045	14.034	0.000	0.539	0.713
loc_ic_mou_8	-1.8368	0.073	-25.071	0.000	-1.980	-1.693
std_ic_mou_8	-0.6171	0.038	-16.082	0.000	-0.692	-0.542
spl_ic_mou_8	-0.7054	0.044	-16.048	0.000	-0.792	-0.619
total_rech_num_8	-0.6418	0.029	-21.823	0.000	-0.699	-0.584
last_day_rch_amt_8	-0.6479	0.023	-27.598	0.000	-0.694	-0.602
monthly_2g_8	-0.6870	0.030	-22.863	0.000	-0.746	-0.628
sachet_2g_8	-0.7103	0.031	-22.967	0.000	-0.771	-0.650
aug_vbc_3g	-0.7093	0.034	-20.789	0.000	-0.776	-0.642

In [139]:
```
# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm)
y_train_pred[:10]
```

Out[139]:
```
0    0.032924
1    0.160432
2    0.358339
3    0.000056
4    0.442205
5    0.080753
6    0.006519
7    0.419783
8    0.759136
9    0.369793
dtype: float64
```

In [140]:
```
y_train_pred = y_train_pred.values.reshape(-1)
y_train_pred[:10]
```

Out[140]:
```
array([3.29239032e-02, 1.60432021e-01, 3.58338968e-01, 5.55850809e-05,
       4.42204593e-01, 8.07525802e-02, 6.51903748e-03, 4.19783466e-01,
       7.59135524e-01, 3.69792666e-01])
```

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

In [141]:

```
y_train_pred_final = pd.DataFrame({'Churn':y_train.values, 'Churn_Prob':y_train_pred})
y_train_pred_final['mobile_number'] = y_train.index
y_train_pred_final.head()
```

Out[141]:

	Churn	Churn_Prob	mobile_number
0	0	0.032924	0
1	1	0.160432	1
2	0	0.358339	2
3	0	0.000056	3
4	0	0.442205	4

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

In [142]:

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

# Let's see the head
y_train_pred_final.head()
```

Out[142]:

	Churn	Churn_Prob	mobile_number	predicted
0	0	0.032924	0	0
1	1	0.160432	1	0
2	0	0.358339	2	0
3	0	0.000056	3	0
4	0	0.442205	4	0

In [143]:

```
from sklearn import metrics
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred_final.predicted )
print(confusion)
```

```
[[14028  3255]
 [ 2143 15140]]
```

In [144]:

```
# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.predicted))
```

```
0.8438349823526008
```

Checking VIFs

In [145]:

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

Out[145]:

	Features	VIF
4	total_og_mou_8	17.93
1	onnet_mou_8	7.55
2	std_og_t2m_mou_8	6.23
7	loc_ic_mou_8	4.47
6	loc_ic_mou_7	3.13
10	total_rech_num_8	1.96
0	arpu_7	1.55
5	loc_ic_t2f_mou_8	1.37
11	last_day_rch_amt_8	1.30
13	sachet_2g_8	1.30
8	std_ic_mou_8	1.23
14	aug_vbc_3g	1.18
12	monthly_2g_8	1.14
3	std_og_t2f_mou_8	1.08
9	spl_ic_mou_8	1.06

Inference:- There are a few variables with high VIF. It's best to drop these variables as they aren't helping much with prediction and unnecessarily making the model complex. The variable `'total_og_mou_8'` has the high VIF value. So let's start by dropping that.

Dropping the 1st Variable `'total_og_mou_8'` and Updating the Model

In [146]:
```
# Let's drop 'total_og_mou_8' since it has a high VIF value

col = col.drop('total_og_mou_8', 1)
col
```

Out[146]:
```
Index(['arpu_7', 'onnet_mou_8', 'std_og_t2m_mou_8', 'std_og_t2f_mou_8',
       'loc_ic_t2f_mou_8', 'loc_ic_mou_7', 'loc_ic_mou_8', 'std_ic_mou_8',
       'spl_ic_mou_8', 'total_rech_num_8', 'last_day_rch_amt_8',
       'monthly_2g_8', 'sachet_2g_8', 'aug_vbc_3g'],
      dtype='object')
```

In [147]:
```
# Let's re-run the model using the selected variables
X_train_sm = sm.add_constant(X_train[col])
logm3 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm3.fit()
res.summary()
```

Out[147]:

Generalized Linear Model Regression Results

Dep. Variable:	churn	**No. Observations:**	34566
Model:	GLM	**Df Residuals:**	34551
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-13520.
Date:	Mon, 31 Aug 2020	**Deviance:**	27040.
Time:	01:20:26	**Pearson chi2:**	1.04e+06
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-2.1928	0.034	-65.434	0.000	-2.259	-2.127
arpu_7	0.3777	0.022	17.537	0.000	0.335	0.420
onnet_mou_8	-0.1079	0.020	-5.399	0.000	-0.147	-0.069
std_og_t2m_mou_8	-0.1529	0.022	-6.902	0.000	-0.196	-0.109
std_og_t2f_mou_8	-0.5144	0.058	-8.801	0.000	-0.629	-0.400
loc_ic_t2f_mou_8	-0.4257	0.056	-7.546	0.000	-0.536	-0.315
loc_ic_mou_7	0.6846	0.045	15.244	0.000	0.597	0.773
loc_ic_mou_8	-2.5603	0.068	-37.447	0.000	-2.694	-2.426
std_ic_mou_8	-0.6072	0.038	-15.940	0.000	-0.682	-0.533
spl_ic_mou_8	-0.7063	0.044	-16.119	0.000	-0.792	-0.620
total_rech_num_8	-0.6847	0.029	-23.589	0.000	-0.742	-0.628
last_day_rch_amt_8	-0.6656	0.023	-28.417	0.000	-0.711	-0.620
monthly_2g_8	-0.6791	0.030	-22.660	0.000	-0.738	-0.620
sachet_2g_8	-0.6932	0.031	-22.487	0.000	-0.754	-0.633
aug_vbc_3g	-0.6875	0.034	-20.312	0.000	-0.754	-0.621

In [148]:
```
# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm).values.reshape(-1)
y_train_pred[:10]
```

Out[148]:
```
array([3.34048579e-02, 1.66689785e-01, 1.96691732e-01, 3.64185491e-05,
       4.48919943e-01, 8.48664461e-02, 6.53774375e-03, 3.96081104e-01,
       6.49588154e-01, 2.93454808e-01])
```

In [149]:
```
y_train_pred_final['Churn_Prob'] = y_train_pred
```

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

In [150]:

```
# Creating new column 'predicted' with 1 if Churn_Prob > 0.5 else 0
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()
```

Out[150]:

	Churn	Churn_Prob	mobile_number	predicted
0	0	0.033405	0	0
1	1	0.166690	1	0
2	0	0.196692	2	0
3	0	0.000036	3	0
4	0	0.448920	4	0

In [151]:

```
# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.predicted))
```

```
0.8394954579644738
```

So overall the accuracy hasn't dropped much.

Let's check the VIFs again

In [152]:

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

Out[152]:

	Features	VIF
6	loc_ic_mou_8	3.83
5	loc_ic_mou_7	3.13
9	total_rech_num_8	1.92
0	arpu_7	1.52
1	onnet_mou_8	1.38
2	std_og_t2m_mou_8	1.38
4	loc_ic_t2f_mou_8	1.37
12	sachet_2g_8	1.29
10	last_day_rch_amt_8	1.27
7	std_ic_mou_8	1.23
13	aug_vbc_3g	1.18
11	monthly_2g_8	1.14
3	std_og_t2f_mou_8	1.07
8	spl_ic_mou_8	1.06

Inference:- As you can notice some of the variable have high VIF values. Such variables are insignificant and should be dropped.

Dropping the 2nd Variable `loc_ic_mou_8` and Updating the Model

In [153]:

```
# Let's drop 'loc_ic_mou_8' since it has a high VIF value
col = col.drop('loc_ic_mou_8')
col
```

Out[153]:

```
Index(['arpu_7', 'onnet_mou_8', 'std_og_t2m_mou_8', 'std_og_t2f_mou_8',
       'loc_ic_t2f_mou_8', 'loc_ic_mou_7', 'std_ic_mou_8', 'spl_ic_mou_8',
       'total_rech_num_8', 'last_day_rch_amt_8', 'monthly_2g_8', 'sachet_2g_8',
       'aug_vbc_3g'],
      dtype='object')
```

In [154]:

```
# Let's re-run the model using the selected variables
X_train_sm = sm.add_constant(X_train[col])
logm4 = sm.GLM(y_train,X_train_sm, family = sm.families.Binomial())
res = logm4.fit()
res.summary()
```

Out[154]:

Generalized Linear Model Regression Results

Dep. Variable:	churn	**No. Observations:**	34566
Model:	GLM	**Df Residuals:**	34552
Model Family:	Binomial	**Df Model:**	13
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-14563.
Date:	Mon, 31 Aug 2020	**Deviance:**	29126.
Time:	01:20:28	**Pearson chi2:**	1.00e+06
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.8895	0.031	-61.236	0.000	-1.950	-1.829
arpu_7	0.4751	0.020	23.220	0.000	0.435	0.515
onnet_mou_8	-0.1951	0.020	-9.808	0.000	-0.234	-0.156
std_og_t2m_mou_8	-0.1822	0.022	-8.346	0.000	-0.225	-0.139
std_og_t2f_mou_8	-0.6705	0.062	-10.770	0.000	-0.793	-0.549
loc_ic_t2f_mou_8	-1.2152	0.059	-20.521	0.000	-1.331	-1.099
loc_ic_mou_7	-0.5205	0.025	-21.157	0.000	-0.569	-0.472
std_ic_mou_8	-0.8160	0.040	-20.519	0.000	-0.894	-0.738
spl_ic_mou_8	-0.7695	0.045	-17.136	0.000	-0.858	-0.681
total_rech_num_8	-0.9322	0.029	-32.395	0.000	-0.989	-0.876
last_day_rch_amt_8	-0.8746	0.024	-36.507	0.000	-0.922	-0.828
monthly_2g_8	-0.7239	0.029	-24.623	0.000	-0.782	-0.666
sachet_2g_8	-0.7193	0.031	-23.271	0.000	-0.780	-0.659
aug_vbc_3g	-0.7938	0.034	-23.111	0.000	-0.861	-0.726

In [155]:

```
# Getting the predicted values on the train set
y_train_pred = res.predict(X_train_sm).values.reshape(-1)
y_train_pred[:10]
```

Out[155]:

```
array([2.21276775e-02, 1.49432319e-01, 4.11680461e-01, 9.31728564e-05,
       3.67882662e-01, 5.34988669e-02, 5.44662490e-03, 4.81992838e-01,
       3.39347253e-01, 5.41797349e-01])
```

In [156]:

```
y_train_pred_final['Churn_Prob'] = y_train_pred
```

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

In [157]:

```
# Creating new column 'predicted' with 1 if Churn_Prob > 0.5 else 0
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()
```

Out[157]:

	Churn	Churn_Prob	mobile_number	predicted
0	0	0.022128	0	0
1	1	0.149432	1	0
2	0	0.411680	2	0
3	0	0.000093	3	0
4	0	0.367883	4	0

In [158]:

```
# Confusion matrix
confusion = metrics.confusion_matrix(y_train_pred_final.Churn, y_train_pred_final.predicted )
print(confusion)
```

```
[[13533  3750]
 [ 2499 14784]]
```

In [159]:

```
# Let's check the overall accuracy.
print(metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.predicted))
```

```
0.8192154139906266
```

So overall the accuracy hasn't dropped much.

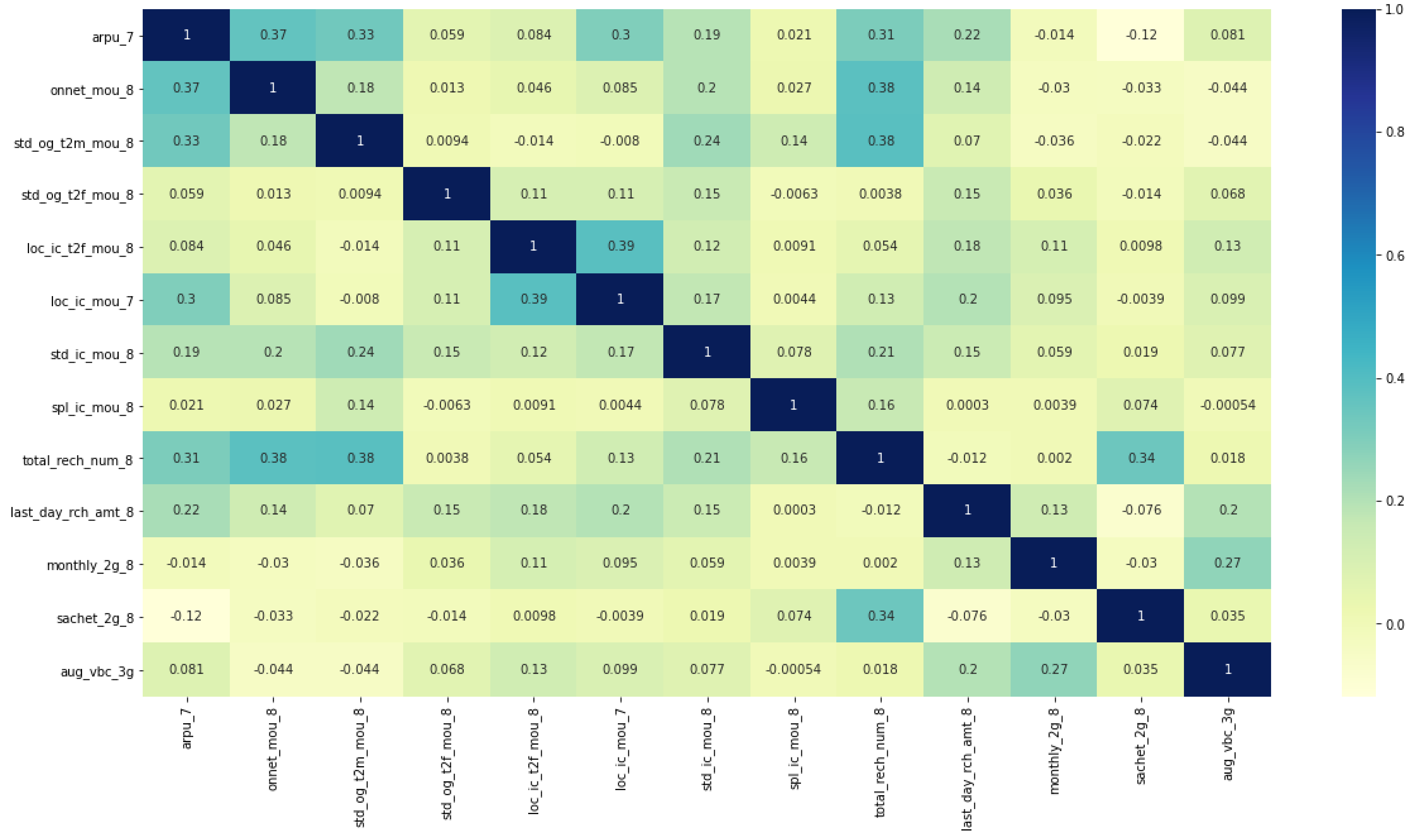
Let's now check the VIFs again

In [160]:
```
vif = pd.DataFrame()
vif['Features'] = X_train[col].columns
vif['VIF'] = [variance_inflation_factor(X_train[col].values, i) for i in range(X_train[col].shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[160]:

	Features	VIF
8	total_rech_num_8	1.85
0	arpu_7	1.50
5	loc_ic_mou_7	1.41
2	std_og_t2m_mou_8	1.38
1	onnet_mou_8	1.37
11	sachet_2g_8	1.29
4	loc_ic_t2f_mou_8	1.26
9	last_day_rch_amt_8	1.23
6	std_ic_mou_8	1.22
12	aug_vbc_3g	1.18
10	monthly_2g_8	1.13
3	std_og_t2f_mou_8	1.07
7	spl_ic_mou_8	1.05

In [161]:
```
plt.figure(figsize = (20,10))
cor= X_train[col].corr()
sns.heatmap(cor, annot=True, cmap="YlGnBu")
plt.show()
```



Our latest model have the following features:

- All variables have p-value < 0.05.
- All the features have very low VIF values, meaning, there is hardly any muliticollinearity among the features. This is also evident from the heat map.
- The overall accuracy of 81.92 at a probability threshold of 0.05 is also very acceptable.

So we need not drop any more variables and we can proceed with making predictions using this model only

6.3) Calculating Metrics beyond simply accuracy

In [162]:
```
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives
```

In [163]:
```
# Let's check the overall accuracy.
print('Accuracy Score: ',metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.predicted))

# Let's see the sensitivity of our logistic regression model
print('Sensitivity: ', TP / float(TP+FN))

# Let us calculate specificity
print('Specificity: ',TN / float(TN+FP))

# Calculate false postive rate - predicting churn when customer does not have churned
print('false postive rate: ',FP/ float(TN+FP))

# positive predictive value
print('positive predictive value: ', TP / float(TP+FP))

# Negative predictive value
print('Negative predictive value: ',TN / float(TN+ FN))

## Misclassification rate
print('Misclassification Rate: ',(FN+FP)/(TP+TN+FP+FN))
```

```
Accuracy Score:  0.8192154139906266
Sensitivity:  0.8554070473876063
Specificity:  0.783023780593647
false postive rate:  0.21697621940635306
positive predictive value:  0.7976691485917773
Negative predictive value:  0.844124251497006
Misclassification Rate:  0.18078458600937336
```

6.4) Plotting the ROC Curve

An ROC curve demonstrates several things:

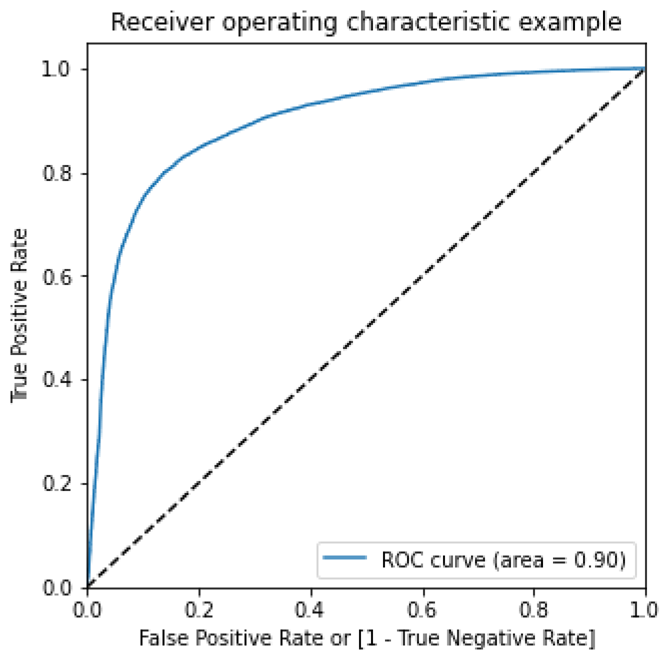
- It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).
- The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.
- The closer the curve comes to the 45-degree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

In [164]:
```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False)
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return None
```

In [165]:
```
fpr, tpr, thresholds = metrics.roc_curve( y_train_pred_final.Churn, y_train_pred_final.Churn_Prob, drop_intermediate = False )
```

In [166]:

```
draw_roc(y_train_pred_final.Churn, y_train_pred_final.Churn_Prob)
```



6.5) Calculating the area under the curve(GINI)

In [167]:

```
def auc_val(fpr,tpr):
    AreaUnderCurve = 0.
    for i in range(len(fpr)-1):
        AreaUnderCurve += (fpr[i+1]-fpr[i]) * (tpr[i+1]+tpr[i])
    AreaUnderCurve *= 0.5
    return AreaUnderCurve
```

In [168]:

```
auc = auc_val(fpr,tpr)
auc
```

Out[168]: 0.8970450102878165

As a rule of thumb, an AUC can be classed as follows,

- 0.90 - 1.00 = excellent
- 0.80 - 0.90 = good
- 0.70 - 0.80 = fair
- 0.60 - 0.70 = poor
- 0.50 - 0.60 = fail

Inference:- Since we got a value of 0.90, our model seems to be doing well on the train dataset.

6.6) Finding Optimal Cutoff Point

Optimal cutoff probability is that prob where we get balanced sensitivity and specificity

In [169]:

```python
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    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()
```

Out[169]:

	Churn	Churn_Prob	mobile_number	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	0	0.022128	0	0	1	0	0	0	0	0	0	0	0	0
1	1	0.149432	1	0	1	1	0	0	0	0	0	0	0	0
2	0	0.411680	2	0	1	1	1	1	1	0	0	0	0	0
3	0	0.000093	3	0	1	0	0	0	0	0	0	0	0	0
4	0	0.367883	4	0	1	1	1	1	0	0	0	0	0	0

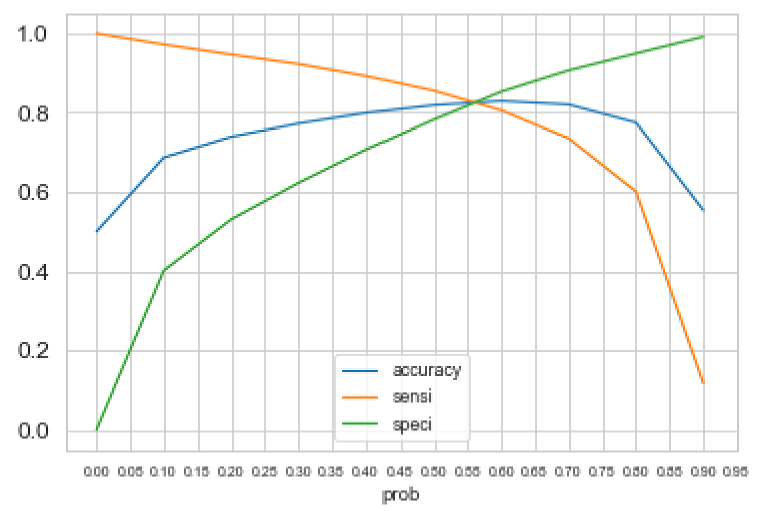
In [170]:

```python
# Now let's calculate accuracy sensitivity and specificity for various probability cutoffs.
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix

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

num = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
for i in num:
    cm1 = metrics.confusion_matrix(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)
```

```
     prob  accuracy     sensi     speci
0.0   0.0  0.500000  1.000000  0.000000
0.1   0.1  0.686773  0.972227  0.401319
0.2   0.2  0.738790  0.947058  0.530521
0.3   0.3  0.772898  0.922988  0.622809
0.4   0.4  0.799543  0.892553  0.706532
0.5   0.5  0.819215  0.855407  0.783024
0.6   0.6  0.829630  0.806052  0.853208
0.7   0.7  0.820778  0.734884  0.906671
0.8   0.8  0.775155  0.600822  0.949488
0.9   0.9  0.554273  0.117051  0.991495
```

In [171]:

```python
# Let's plot accuracy sensitivity and specificity for various probabilities.
import numpy as np
sns.set_style("whitegrid")
sns.set_context("paper")
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
plt.xticks(np.arange(0, 1, step=0.05), size = 7)
plt.yticks(size = 12)
plt.show()
```



Inference:- From the above curve, `0.55` is the point to take it as a cutoff probability. Since our requirement here is to identify almost all customers who are likely to churn as `our focus is on The recall (is intuitively the ability of the classifier to find all the positive s`

`Since we need to improve the recall value, So we will use 0.4 as our cutoff probability. as lower the cut off value will give me better recall value.`

So our threshold value will be 0.4

In [172]:
```
y_train_pred_final['final_predicted'] = y_train_pred_final.Churn_Prob.map(lambda x: 1 if x > 0.4 else 0)
y_train_pred_final.head()
```

Out[172]:

	Churn	Churn_Prob	mobile_number	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_predicted
0	0	0.022128	0	0	1	0	0	0	0	0	0	0	0	0	0
1	1	0.149432	1	0	1	1	0	0	0	0	0	0	0	0	0
2	0	0.411680	2	0	1	1	1	1	1	0	0	0	0	0	1
3	0	0.000093	3	0	1	0	0	0	0	0	0	0	0	0	0
4	0	0.367883	4	0	1	1	1	1	0	0	0	0	0	0	0

In [173]:
```
# Let's check the overall accuracy.
metrics.accuracy_score(y_train_pred_final.Churn, y_train_pred_final.final_predicted)
```

Out[173]: 0.7995429034311173

Precision and Recall

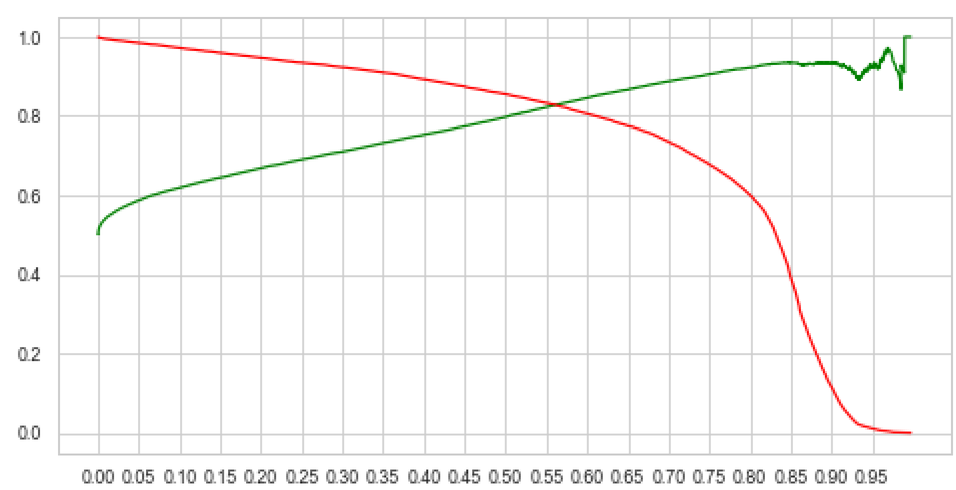
Precision and recall tradeoff

In [174]:
```
from sklearn.metrics import precision_recall_curve
y_train_pred_final.Churn, y_train_pred_final.final_predicted
```

Out[174]:
```
(0        0
 1        1
 2        0
 3        0
 4        0
         ..
 34561    1
 34562    1
 34563    1
 34564    1
 34565    1
 Name: Churn, Length: 34566, dtype: int32,
 0        0
 1        0
 2        1
 3        0
 4        0
         ..
 34561    1
 34562    1
 34563    1
 34564    1
 34565    1
 Name: final_predicted, Length: 34566, dtype: int64)
```

In [175]:
```
p, r, thresholds = precision_recall_curve(y_train_pred_final.Churn, y_train_pred_final.Churn_Prob)
```

In [176]:
```
plt.figure(figsize=(8, 4))
plt.plot(thresholds, p[:-1], "g-")
plt.plot(thresholds, r[:-1], "r-")
plt.xticks(np.arange(0, 1, step=0.05))
plt.show()
```



Inference:

From the above precision-recall graph, we get the optical threshold value as close to 0.55 which is same as that we got from accuracy,sensitivity and specificity cutoff.The recall is intuitively the ability of the classifier to find all the posit

Since we need to improve the recall value as we have to find the correctly predicted churn, So we will use 0.4 as our cutoff probability. as lower the cut off value will give me better recall value.

So our threshold value will be 0.4

Classification Report of train data (logestic regression)

In [177]:
```
from sklearn.metrics import classification_report
print(classification_report(y_train_pred_final.Churn, y_train_pred_final.final_predicted))
```

```
              precision    recall  f1-score   support

           0       0.87      0.71      0.78     17283
           1       0.75      0.89      0.82     17283

    accuracy                           0.80     34566
   macro avg       0.81      0.80      0.80     34566
weighted avg       0.81      0.80      0.80     34566
```

6.7) Making predictions on the test set

In [178]:
```
X_test = X_test[col]
X_test.head()
```

Out[178]:

	arpu_7	onnet_mou_8	std_og_t2m_mou_8	std_og_t2f_mou_8	loc_ic_t2f_mou_8	loc_ic_mou_7	std_ic_mou_8	spl_ic_mou_8	total_rech_num_8	last_day_rch_amt_8	monthly_2g_8	sachet_2g_8	aug_vbc_3g
1856	-0.965070	-0.548054	-0.412798	-0.204069	0.647239	-0.372933	-0.489144	-0.250255	0.039707	-0.532835	-0.382436	2.902547	-0.422089
23195	-1.032904	-0.547477	-0.412798	-0.204069	-0.404254	-0.256778	-0.489144	-0.250255	-0.533054	-0.662317	-0.382436	-0.018489	-0.422089
39180	1.049837	-0.389401	0.474691	-0.204069	-0.378988	0.127051	1.097210	-0.250255	-0.647607	-0.748637	-0.382436	-0.435779	-0.422089
51612	-0.839093	-0.548054	-0.412798	-0.204069	-0.404254	-0.829855	-0.489144	-0.250255	-0.876712	-0.748637	-0.382436	-0.435779	-0.422089
69554	-0.425686	-0.422191	-0.339691	0.229732	1.100748	2.021817	0.224364	-0.250255	0.268812	-0.532835	-0.382436	2.485256	-0.422089

In [179]:
```
y_test
```

Out[179]:
```
1856     0
23195    0
39180    1
51612    1
69554    0
        ..
83851    1
98979    0
52980    0
96011    0
86344    0
Name: churn, Length: 8058, dtype: int32
```

In [180]:
```
X_test_sm = sm.add_constant(X_test)
```

Making predictions on the test set

In [181]:
```
y_test_pred = res.predict(X_test_sm)
y_test_pred[:10]
```

Out[181]:
```
1856     0.044085
23195    0.701971
39180    0.648176
51612    0.874703
69554    0.004311
50382    0.076403
29273    0.005495
19229    0.536756
43755    0.067836
28811    0.412250
dtype: float64
```

In [182]:
```
# Converting y_pred to a dataframe which is an array
y_pred_1 = pd.DataFrame(y_test_pred)
# Let's see the head
y_pred_1.head()
```

Out[182]:

	0
1856	0.044085
23195	0.701971
39180	0.648176
51612	0.874703
69554	0.004311

In [183]:
```python
# Converting y_test to dataframe
y_test_df = pd.DataFrame(y_test)
# Putting CustID to index
y_test_df['mobile_number'] = y_test_df.index
```

In [184]:
```python
# Removing index for both dataframes to append them side by side
y_pred_1.reset_index(drop=True, inplace=True)
y_test_df.reset_index(drop=True, inplace=True)
```

In [185]:
```python
# Appending y_test_df and y_pred_1
y_pred_final = pd.concat([y_test_df, y_pred_1],axis=1)
y_pred_final.head()
```

Out[185]:

	churn	mobile_number	0
0	0	1856	0.044085
1	0	23195	0.701971
2	1	39180	0.648176
3	1	51612	0.874703
4	0	69554	0.004311

In [186]:
```python
# Renaming the column
y_pred_final= y_pred_final.rename(columns={ 0 : 'Churn_Prob', 'churn': 'Churn'})
# Rearranging the columns
y_pred_final = y_pred_final.reindex(['mobile_number','Churn','Churn_Prob'], axis=1)
# Let's see the head of y_pred_final
y_pred_final.head()
```

Out[186]:

	mobile_number	Churn	Churn_Prob
0	1856	0	0.044085
1	23195	0	0.701971
2	39180	1	0.648176
3	51612	1	0.874703
4	69554	0	0.004311

In [187]:
```python
y_pred_final['final_predicted'] = y_pred_final.Churn_Prob.map(lambda x: 1 if x > 0.4 else 0)
y_pred_final.head()
```

Out[187]:

	mobile_number	Churn	Churn_Prob	final_predicted
0	1856	0	0.044085	0
1	23195	0	0.701971	1
2	39180	1	0.648176	1
3	51612	1	0.874703	1
4	69554	0	0.004311	0

In [188]:
```python
# Let's check the overall accuracy.
metrics.accuracy_score(y_pred_final.Churn, y_pred_final.final_predicted)
```

Out[188]: 0.7190369818813601

Precision and Recall

Classification Report

In [189]:
```python
from sklearn.metrics import classification_report, r2_score
print(classification_report(y_pred_final.Churn, y_pred_final.final_predicted))
```

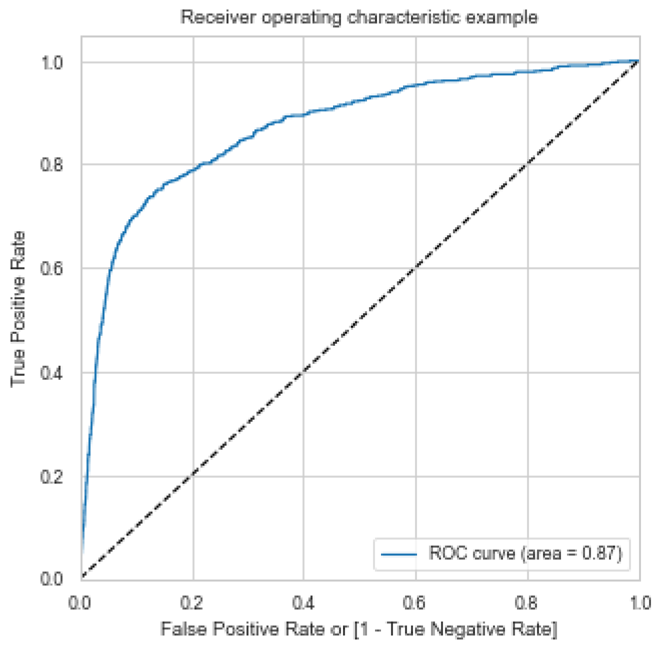
```
              precision    recall  f1-score   support

           0       0.98      0.71      0.82      7407
           1       0.20      0.85      0.33       651

    accuracy                           0.72      8058
   macro avg       0.59      0.78      0.58      8058
weighted avg       0.92      0.72      0.78      8058
```

Plotting the ROC Curve for Test Dataset

In [190]:
```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,
                                              drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(5, 5))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()

    return None
```

In [191]:
```
fpr, tpr, thresholds = metrics.roc_curve( y_pred_final.Churn, y_pred_final.Churn_Prob, drop_intermediate = False )
```

In [192]:
```
draw_roc(y_pred_final.Churn, y_pred_final.Churn_Prob)
```



Calculating the area under the curve(GINI)

In [193]:
```
def auc_val(fpr,tpr):
    AreaUnderCurve = 0.
    for i in range(len(fpr)-1):
        AreaUnderCurve += (fpr[i+1]-fpr[i]) * (tpr[i+1]+tpr[i])
    AreaUnderCurve *= 0.5
    return AreaUnderCurve
```

In [194]:
```
auc = auc_val(fpr,tpr)
auc
```

Out[194]: 0.8701916047778829

As a rule of thumb, an AUC can be classed as follows,

- 0.90 - 1.00 = excellent
- 0.80 - 0.90 = good
- 0.70 - 0.80 = fair
- 0.60 - 0.70 = poor
- 0.50 - 0.60 = fail

Inference:- Since we got a value of 0.87, our model seems to be doing well on the test dataset.

6.8) Determining Feature Importance

Selecting the coefficients of the selected features from our final model excluding the intercept

In [195]:

```
pd.options.display.float_format = '{:.2f}'.format
new_params = res.params[1:]
new_params
```

Out[195]:

```
arpu_7                0.48
onnet_mou_8          -0.20
std_og_t2m_mou_8     -0.18
std_og_t2f_mou_8     -0.67
loc_ic_t2f_mou_8     -1.22
loc_ic_mou_7         -0.52
std_ic_mou_8         -0.82
spl_ic_mou_8         -0.77
total_rech_num_8     -0.93
last_day_rch_amt_8   -0.87
monthly_2g_8         -0.72
sachet_2g_8          -0.72
aug_vbc_3g           -0.79
dtype: float64
```

Selecting Top 13 features which contribute most towards the probability of a customer getting churned.

In [196]:

```
feature_importance = new_params
imp_feat= pd.DataFrame(feature_importance).reset_index().sort_values(by=0,ascending=False)
imp_feat.rename(columns = {'index':'Varname', 0:'Imp'}, inplace = True)
imp_feat
```

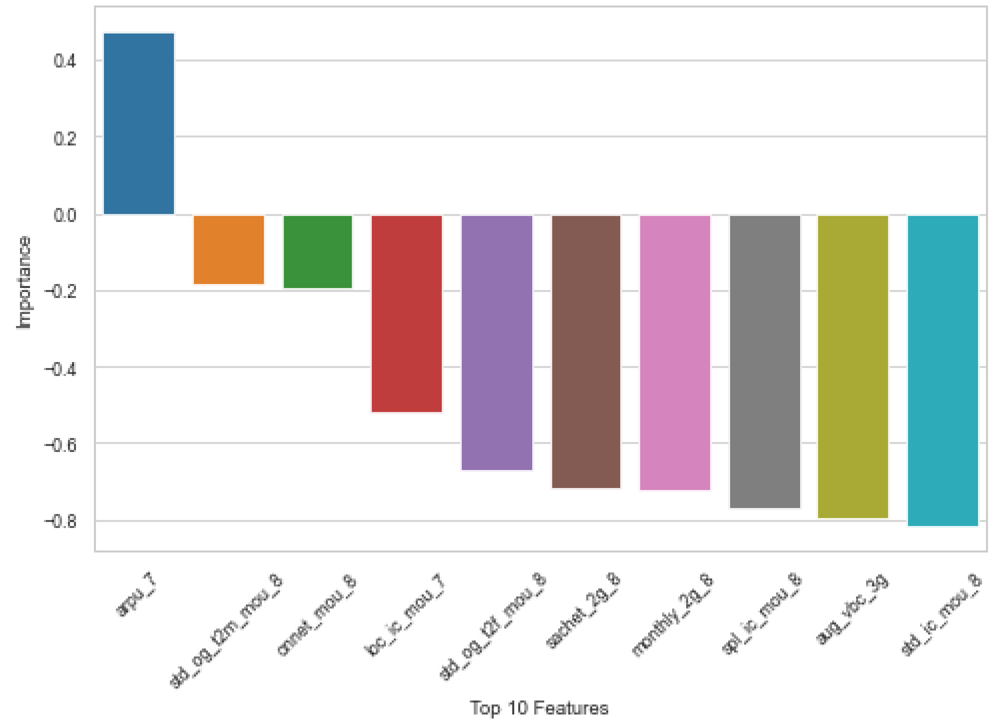
Out[196]:

	Varname	Imp
0	arpu_7	0.48
2	std_og_t2m_mou_8	-0.18
1	onnet_mou_8	-0.20
5	loc_ic_mou_7	-0.52
3	std_og_t2f_mou_8	-0.67
11	sachet_2g_8	-0.72
10	monthly_2g_8	-0.72
7	spl_ic_mou_8	-0.77
12	aug_vbc_3g	-0.79
6	std_ic_mou_8	-0.82
9	last_day_rch_amt_8	-0.87
8	total_rech_num_8	-0.93
4	loc_ic_t2f_mou_8	-1.22

Inference: We could see the Top 13 features which contribute most towards the probability of a customer getting churned.

In [197]:

```
plt.figure(figsize=(8, 5))

ax = sns.barplot(x='Varname', y= 'Imp', data=imp_feat[0:10])
ax.set(xlabel = 'Top 10 Features', ylabel = 'Importance')
plt.xticks(rotation=45)
plt.show()
```



Step 7: Conclusion

Based on our logical regression model, some features are identified which contribute most to a customer getting churned.

The conversion probability of a lead increases with increase in values of the following features in descending order:

Features with Positive Coefficient:

1) arpu_7: 0.48

The churn probability of a customer increases with decrease in values of the following features in descending order:

Features with Negative Coefficient:

1) std_og_t2m_mou_8: -0.18
2) onnet_mou_8: -0.20
3) loc_ic_mou_7: -0.52
4) std_og_t2f_mou_8: -0.67
5) sachet_2g_8: -0.72
6) monthly_2g_8: -0.72
7) spl_ic_mou_8: -0.77
8) aug_vbc_3g: -0.79
9) std_ic_mou_8: -0.82
10) last_day_rch_amt_8: -0.87
11) total_rech_num_8: -0.93
12) loc_ic_t2f_mou_8: -1.22

Train data

```
                accuracy: 0.80
            precision    recall  f1-score

         0       0.87      0.71      0.78
         1       0.75      0.89      0.82
```

Test data

```
                accuracy: 0.72
             precision    recall  f1-score

          0       0.98      0.71     0.82
          1       0.20      0.85     0.33
```

In [198]:
```
confusion_test = metrics.confusion_matrix(y_pred_final.Churn, y_pred_final.final_predicted )
confusion_test
```

Out[198]:
```
array([[5242, 2165],
       [  99,  552]], dtype=int64)
```

Model 2.1) Using Decision Trees (Default Hyperparameters)

In [199]:
```
from sklearn.metrics import precision_recall_curve, plot_roc_curve, roc_auc_score
from sklearn.metrics import precision_score, recall_score, confusion_matrix, classification_report
from sklearn.metrics import accuracy_score, f1_score
```

In [200]:
```
X_train,X_test,y_train, y_test = train_test_split(X, y,train_size=0.7,stratify = y,random_state=100)
```

In [201]:
```
X_train.shape, X_test.shape
```

Out[201]:
```
((18801, 129), (8058, 129))
```

In [202]:
```
y_train.shape, y_test.shape
```

Out[202]:
```
((18801,), (8058,))
```

In [203]:
```
y_train.value_counts(normalize=True)
```

Out[203]:
```
0   0.92
1   0.08
Name: churn, dtype: float64
```

In [204]:
```
y_test.value_counts(normalize=True)
```

Out[204]:
```
0    0.92
1    0.08
Name: churn, dtype: float64
```

Checking for Class imbalance in Train & Test and treating it

SMOTE - Synthetic Minority Oversampling Technique

Creates new "Synthetic" observations

Process: -

1. Identify the feature vector and its nearest neighbour
2. Take the difference between the two
3. Multiply the difference with a random number between 0 and 1
4. Identify a new point on the line segment by adding the random number to feature vector
5. Repeat the process for identified feature vectors

In [205]:
```
# SMOTE
from imblearn.over_sampling import SMOTE
smt = SMOTE(random_state=45, k_neighbors=5)
X_train, y_train = smt.fit_resample(X_train, y_train)
len(X_train)
```

Out[205]:
```
34566
```

In [206]:
```
import collections
from collections import Counter
print(sorted(Counter(y_train).items()))
```

```
[(0, 17283), (1, 17283)]
```

In [207]:
```
y_train.value_counts(normalize=True)
```

Out[207]:
```
1    0.50
0    0.50
Name: churn, dtype: float64
```

In [208]:
```
# Lets import decision tree libraries
from sklearn.tree import DecisionTreeClassifier

# Lets create a decision tree with the default hyper parameters
dt_default = DecisionTreeClassifier(random_state=42)
```

Fitting the decision tree with default hyperparameters

In [209]:
```
# Lets fit the decision tree with default hyperparameters
dt_default.fit(X_train, y_train)
```

Out[209]:
```
DecisionTreeClassifier(random_state=42)
```

In [210]:
```
y_train_pred_dt = dt_default.predict(X_train)
y_test_pred_dt = dt_default.predict(X_test)
```

In [211]:
```
# X_train.shape,X_test.shape,y_train_pred_dt_hp.shape,y_test_pred_dt_hp.
```

In [212]:
```
print(classification_report(y_train, y_train_pred_dt))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     17283
           1       1.00      1.00      1.00     17283

    accuracy                           1.00     34566
   macro avg       1.00      1.00      1.00     34566
weighted avg       1.00      1.00      1.00     34566
```

Making predictions on the test set

In [213]:
```
print ('\n clasification report:\n', classification_report(y_test, y_test_pred_dt))
```

```
 clasification report:
               precision    recall  f1-score   support

           0       0.96      0.91      0.94      7407
           1       0.37      0.61      0.46       651

    accuracy                           0.89      8058
   macro avg       0.67      0.76      0.70      8058
weighted avg       0.92      0.89      0.90      8058
```

Conclusion:- From Decision Tree (Default Hyperparameters)

Train data

```
                    accuracy:1.00
          precision    recall  f1-score   support

     0       1.00      1.00      1.00     17283
     1       1.00      1.00      1.00     17283
```

Test data

```
                    accuracy: 0.89
           precision    recall  f1-score   support

     0       0.96      0.91      0.94      7407
     1       0.37      0.61      0.46       651
```

Accuracy: 88.6%

F1 score: 46.3%

Recall: 61.0%

Precision: 37.3%

ROC for the test dataset: 76.0%

The accuracy values of train and test has huge difference which leads to overfitting .Hence for overfitting treatment we are using hyper-parameter tuning

Model 2.2) Hyper-parameter tuning for the Decision Tree

In [214]:
```
from sklearn.model_selection import GridSearchCV
```

In [215]:
```
dt = DecisionTreeClassifier(random_state=42)
```

In [216]:
```
params = {
    "max_depth": [2,3,5,10,20],
    "min_samples_leaf": [5,10,20,50,100,500],
    'criterion': ["gini", "entropy"]

}
```

In [217]:
```
grid_search = GridSearchCV(estimator=dt,
                           param_grid=params,
                           cv=4,
                           n_jobs=-1, verbose=1, scoring="recall")
```

In [218]:
```
%%time
grid_search.fit(X_train, y_train)
```

```
Fitting 4 folds for each of 60 candidates, totalling 240 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:   15.4s
[Parallel(n_jobs=-1)]: Done 192 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 240 out of 240 | elapsed:  2.9min finished

Wall time: 2min 59s
```

Out[218]:
```
GridSearchCV(cv=4, estimator=DecisionTreeClassifier(random_state=42), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [2, 3, 5, 10, 20],
                         'min_samples_leaf': [5, 10, 20, 50, 100, 500]},
             scoring='recall', verbose=1)
```

grid_search.cv_results_

This function helps us to try out different combinations of hyperparameters which ultimately eased our process of figuring out these best values.

In [219]:
```
score_dt = pd.DataFrame(grid_search.cv_results_)
score_dt.head()
```

Out[219]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_criterion	param_max_depth	param_min_samples_leaf	params	split0_test_score	split1_test_score	split2_test_score	split3_test_score	mean_test_score	std_test_score	rank_test_score
0	0.98	0.04	0.03	0.00	gini	2	5	{'criterion': 'gini', 'max_depth': 2, 'min_sam...	0.84	0.86	0.85	0.85	0.85	0.01	38
1	0.82	0.03	0.03	0.00	gini	2	10	{'criterion': 'gini', 'max_depth': 2, 'min_sam...	0.84	0.86	0.85	0.85	0.85	0.01	38
2	0.84	0.01	0.03	0.00	gini	2	20	{'criterion': 'gini', 'max_depth': 2, 'min_sam...	0.84	0.86	0.85	0.85	0.85	0.01	38
3	0.81	0.01	0.03	0.00	gini	2	50	{'criterion': 'gini', 'max_depth': 2, 'min_sam...	0.84	0.86	0.85	0.85	0.85	0.01	38
4	0.83	0.02	0.04	0.01	gini	2	100	{'criterion': 'gini', 'max_depth': 2, 'min_sam...	0.84	0.86	0.85	0.85	0.85	0.01	38

In [220]:
```
grid_search.best_score_
```

Out[220]:
```
0.9321885955325842
```

grid_search.best_estimator_ :

When the grid search is called with various params, it chooses the one with the highest score based on the given scorer func. Best estimator gives the info of the params that resulted in the highest score or in simple term Estimator that was chos i.e. estimator which gave highest score (or smallest loss if specified) on the left out data.

Inference:

Since we have selected recall for our scoring . So Grid search best estimator will provide us the best estimator which will give us the information of params that resulted in highest Recall score

We have selected recall for scoring as our buisness requirement is to identify almost all customers who are likely to churn. High recall means model will correctly identify almost all customers who are likely to churn.

In [221]:
```
dt_best = grid_search.best_estimator_
dt_best
```

Out[221]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=10, min_samples_leaf=5,
                       random_state=42)
```

Inference:- Based on the Grid Search Hyperparameter tuning method, we identified the best parameters for the Decision Tree from Grid search best estimator as:- criterion='entropy', max_depth=10, min_samples_leaf=5, min_samples_split=5.

- From these parameters (criterion='entropy') helps us to determines how the impurity of a split is measured, (max_depth) helps us to limit the max number of levels in each decision tree to 10, (min_samples_leaf) helps us to find min number of data points allowed in a leaf node to 5, (min_samples_split) help number of data points a node must contain in order to consider splitting i.e. to 5
- By applying these parameters and tuning the model, we will able to improve the metrics that we received from the default parametes of Decision Tree.

In [222]:
```
y_train_pred_dt_hp = dt_best.predict(X_train)

```

In [223]:
```
y_test_pred_dt_hp = dt_best.predict(X_test)
```

In [224]:
```
print(classification_report(y_train, dt_best.predict(X_train)))
```

```
              precision    recall  f1-score   support

           0       0.96      0.93      0.94     17283
           1       0.93      0.96      0.94     17283

    accuracy                           0.94     34566
   macro avg       0.94      0.94      0.94     34566
weighted avg       0.94      0.94      0.94     34566
```

Making predictions on the test set

In [225]:
```
print ('\n clasification report:\n', classification_report(y_test, y_test_pred_dt_hp))
```

```
 clasification report:
               precision    recall  f1-score   support

           0       0.97      0.89      0.93      7407
           1       0.37      0.73      0.49       651

    accuracy                           0.88      8058
   macro avg       0.67      0.81      0.71      8058
weighted avg       0.93      0.88      0.90      8058
```

In [226]:
```


print ('\n Confussion Matrix:\n',confusion_matrix(y_test, y_test_pred_dt_hp))
```

```
 confussion matrix:
 [[6739  668]
 [ 254  397]]
```

In [227]:
```
dt_best.feature_importances_
```

Out[227]:
```
array([7.51185441e-04, 9.36876245e-04, 4.38464673e-03, 0.00000000e+00,
       7.31165951e-04, 3.62261340e-03, 4.36768786e-03, 8.77102145e-04,
       0.00000000e+00, 2.12564307e-03, 2.93652703e-03, 9.08349238e-03,
       1.94983953e-03, 1.79514503e-03, 1.32306924e-01, 8.68379988e-04,
       2.18127537e-03, 1.25648265e-03, 6.27386515e-05, 2.42624208e-03,
       8.81910869e-04, 7.49836410e-04, 3.38119447e-03, 0.00000000e+00,
       1.99776679e-04, 7.72781335e-04, 1.06263016e-03, 2.42611113e-03,
       1.44197688e-03, 1.86475391e-03, 4.70219051e-03, 2.35063858e-03,
       9.13780568e-04, 0.00000000e+00, 1.23665862e-03, 6.18071964e-04,
       1.62987555e-03, 4.68823005e-03, 0.00000000e+00, 0.00000000e+00,
       7.08522321e-03, 2.61506781e-03, 3.91044804e-04, 4.14688141e-03,
       3.54404825e-03, 3.13624322e-03, 1.64180161e-02, 3.25209476e-03,
       7.33825722e-04, 0.00000000e+00, 1.86837245e-03, 1.14864075e-03,
       2.11219542e-02, 8.69158846e-03, 4.46605162e-03, 1.59992049e-03,
       1.39291916e-03, 2.36791599e-03, 1.55994028e-04, 2.05534162e-03,
       4.25835567e-03, 7.39968253e-04, 2.09267945e-04, 9.92918700e-04,
       1.41268388e-03, 8.23817662e-04, 0.00000000e+00, 6.36417296e-04,
       7.22696096e-04, 3.97005699e-03, 2.73717035e-03, 4.64496794e-04,
       1.58535986e-03, 9.26952364e-04, 2.67018678e-03, 9.00379592e-04,
       5.68011529e-03, 0.00000000e+00, 7.05774326e-03, 3.66766741e-01,
       1.36184696e-03, 1.02020655e-03, 2.82342098e-03, 2.80489784e-03,
       6.48217701e-04, 4.23794699e-04, 2.29291722e-03, 4.85634547e-03,
       1.72903739e-04, 1.70829322e-03, 3.69519953e-03, 1.71157234e-03,
       2.19655990e-03, 2.26673126e-03, 3.81739334e-02, 2.08756517e-03,
       6.67858362e-03, 8.06859773e-03, 4.88122696e-03, 3.23557466e-03,
       3.96003713e-02, 1.38236092e-03, 2.14569629e-03, 1.42510877e-02,
       3.52856138e-03, 7.35881563e-03, 3.87672744e-03, 1.90490495e-03,
       2.93942044e-03, 8.63465955e-04, 6.55878563e-04, 5.93650145e-03,
       1.41999121e-03, 0.00000000e+00, 0.00000000e+00, 4.63705446e-03,
       0.00000000e+00, 1.50382076e-03, 0.00000000e+00, 3.65679935e-03,
       2.27069518e-03, 0.00000000e+00, 2.47087399e-03, 8.61441428e-04,
       7.76496377e-04, 2.47476610e-03, 3.35165233e-03, 8.51509577e-02,
       2.55424131e-02])
```

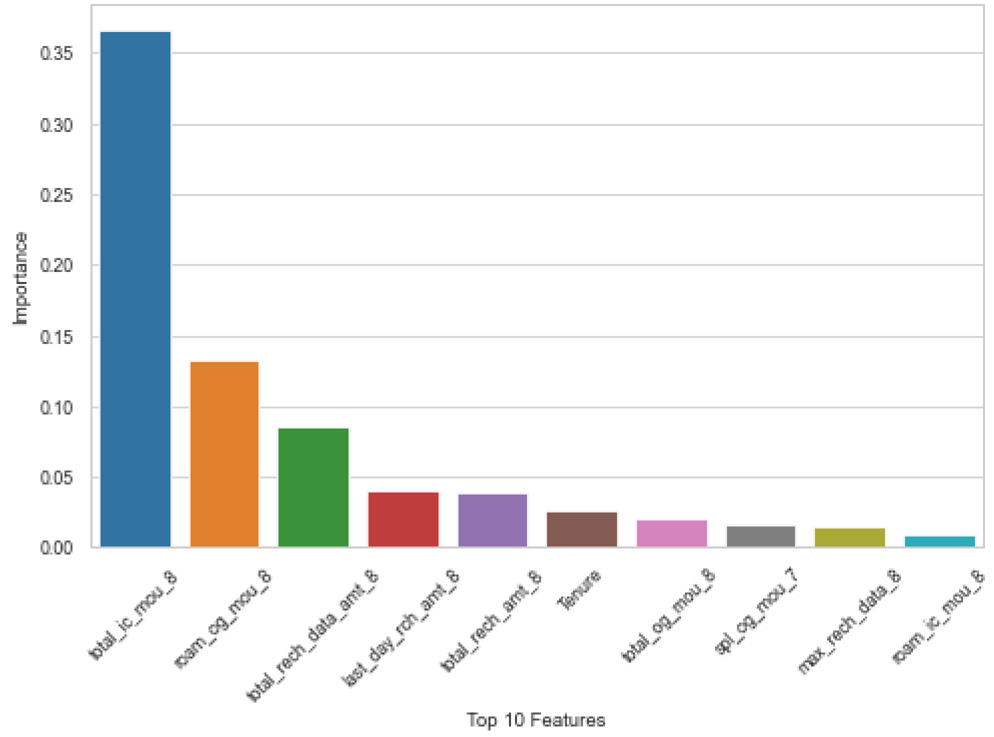
In [228]:
```
imp_df = pd.DataFrame({
    "Varname": X_train.columns,
    "Imp": dt_best.feature_importances_
})
```

In [229]:
```
imp_feat= imp_df.sort_values(by="Imp", ascending=False)
imp_feat.head(10)
```

Out[229]:

	Varname	Imp
79	total_ic_mou_8	0.37
14	roam_og_mou_8	0.13
127	total_rech_data_amt_8	0.09
100	last_day_rch_amt_8	0.04
94	total_rech_amt_8	0.04
128	Tenure	0.03
52	total_og_mou_8	0.02
46	spl_og_mou_7	0.02
103	max_rech_data_8	0.01
11	roam_ic_mou_8	0.01

In [230]:
```
plt.figure(figsize=(8, 5))

ax = sns.barplot(x='Varname', y= 'Imp', data=imp_feat[0:10])
ax.set(xlabel = 'Top 10 Features', ylabel = 'Importance')
plt.xticks(rotation=45)
plt.show()
```



Conclusion

Based on our Decision Tree (Hyperparameter Tuning) model, some features are identified which contribute most to a customer getting churned.

1) total_ic_mou_8 0.37
2) roam_og_mou_8 0.13
3) total_rech_data_amt_8 0.09
4) last_day_rch_amt_8 0.04
5) total_rech_amt_8 0.04
6) Tenure 0.03
7) total_og_mou_8 0.02
8) spl_og_mou_7 0.02
9) max_rech_data_8 0.01
10) roam_ic_mou_8 0.01

Train data

```
                  accuracy: 0.94

              precision    recall  f1-score
           0       0.96      0.93      0.94
           1       0.93      0.96      0.94
```

Test data

```
                                    accuracy: 0.88

                          precision    recall  f1-score
                    0       0.97      0.89      0.93
                    1       0.37      0.73      0.49
```

hence after Hyper-parameter tuning , overfitting has been traeted well and metrices(recall, accuracy) has improved on test data

Model 3.1) Using Random Forest (Default Hyperparameters)

In [231]:
```python
from sklearn.ensemble import RandomForestClassifier
rf_default = RandomForestClassifier(random_state=100, oob_score=True)
```

In [232]:
```python
%%time
rf_default.fit(X_train, y_train)
```

```
Wall time: 29.5 s
```

Out[232]:
```
RandomForestClassifier(oob_score=True, random_state=100)
```

In [233]:
```python
rf_default.oob_score_
```

Out[233]:
```
0.9661806399351964
```

In [234]:
```python
y_train_pred_rf = rf_default.predict(X_train)
y_test_pred_rf = rf_default.predict(X_test)
```

In [235]:
```python
print(classification_report(y_train, y_train_pred_rf))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     17283
           1       1.00      1.00      1.00     17283

    accuracy                           1.00     34566
   macro avg       1.00      1.00      1.00     34566
weighted avg       1.00      1.00      1.00     34566
```

Making predictions on the test set

In [236]:
```python
print ('\n clasification report:\n', classification_report(y_test, y_test_pred_rf))
confusion_rf = metrics.confusion_matrix( y_test, y_test_pred_rf)

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

# Let's see the sensitivity of our logistic regression model
print("Sensitivity: " ,'{:.1%}'.format(TP / float(TP+FN)))

# Let us calculate specificity
print("Specificity: " ,'{:.1%}'.format(TN / float(TN+FP)))

# Calculate false postive rate - predicting churn when customer does not have churned
print("False postive rate:" ,'{:.1%}'.format(FP/ float(TN+FP)))

# positive predictive value
print("Positive predictive value:" ,'{:.1%}'.format(TP / float(TP+FP)))

# Negative predictive value
print("Negative predictive value:" ,'{:.1%}'.format(TN / float(TN+ FN)))
```

```
 clasification report:
               precision    recall  f1-score   support

           0       0.97      0.96      0.96      7407
           1       0.56      0.65      0.61       651

    accuracy                           0.93      8058
   macro avg       0.77      0.80      0.78      8058
weighted avg       0.94      0.93      0.93      8058
```

Conclusion:- From Random Forest (Default Hyperparameters)

Train data

```
                      accuracy: 1.00
           precision    recall  f1-score

     0       1.00      1.00      1.00
     1       1.00      1.00      1.00
```

Test data

```
                     accuracy: 0.93
            precision    recall  f1-score

     0       0.97      0.96      0.96
     1       0.56      0.65      0.61
```

The accuracy values of train and test has huge difference which leads to overfitting .Hence for overfitting treatment we are using hyper-parameter tuning

Model 3.2) Hyper-parameter tuning for the Random Forest

In [237]:
```
rf = RandomForestClassifier(random_state=42, n_jobs=-1)
```

In [238]:
```
params = {
    'max_depth': [5,10,15,20,25,40],
    'min_samples_leaf': [5,10,20,50],
    'n_estimators': [25, 50, 100],
    'min_samples_split': [10,20,30],
    'criterion': ["gini", "entropy"]
}
```

In [239]:
```
grid_search = GridSearchCV(estimator=rf,
                           param_grid=params,
                           cv = 4,
                           n_jobs=-1, verbose=1, scoring="recall")
```

In [240]:
```
%%time
grid_search.fit(X_train, y_train)
```

```
Fitting 4 folds for each of 432 candidates, totalling 1728 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 192 tasks      | elapsed:  6.4min
[Parallel(n_jobs=-1)]: Done 442 tasks      | elapsed: 20.4min
[Parallel(n_jobs=-1)]: Done 792 tasks      | elapsed: 42.5min
[Parallel(n_jobs=-1)]: Done 1242 tasks      | elapsed: 73.1min
[Parallel(n_jobs=-1)]: Done 1728 out of 1728 | elapsed: 116.2min finished

Wall time: 1h 56min 21s
```

Out[240]:
```
GridSearchCV(cv=4, estimator=RandomForestClassifier(n_jobs=-1, random_state=42),
             n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [5, 10, 15, 20, 25, 40],
                         'min_samples_leaf': [5, 10, 20, 50],
                         'min_samples_split': [10, 20, 30],
                         'n_estimators': [25, 50, 100]},
             scoring='recall', verbose=1)
```

In [241]:
```
score_df = pd.DataFrame(grid_search.cv_results_)
score_df.head()
```

Out[241]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_criterion	param_max_depth	param_min_samples_leaf	param_min_samples_split	param_n_estimators	params	split0_test_score	split1_test_score	split2_test_score	split3_test_score	mean_test_score	std_test
0	2.94	0.03	0.15	0.01	gini	5	5	10	25	{'criterion': 'gini', 'max_depth': 5, 'min_sam...	0.83	0.87	0.85	0.88	0.86	
1	5.00	0.42	0.50	0.35	gini	5	5	10	50	{'criterion': 'gini', 'max_depth': 5, 'min_sam...	0.83	0.87	0.86	0.88	0.86	
2	10.23	0.43	0.62	0.43	gini	5	5	10	100	{'criterion': 'gini', 'max_depth': 5, 'min_sam...	0.84	0.87	0.86	0.88	0.86	
3	2.47	0.24	0.33	0.26	gini	5	5	20	25	{'criterion': 'gini', 'max_depth': 5, 'min_sam...	0.83	0.87	0.86	0.87	0.86	
4	4.73	0.38	0.59	0.11	gini	5	5	20	50	{'criterion': 'gini', 'max_depth': 5, 'min_sam...	0.83	0.87	0.86	0.87	0.86	

In [242]:
```
grid_search.best_score_
```

Out[242]:
```
0.9611183700189427
```

Grid_search.best_estimator_ :- When the grid search is called with various params, it chooses the one with the highest score based on the given scorer function. Best estimator gives the information of the params that resulted in the highest score or in simple term Estimator that was chos estimator which gave highest score (or smallest loss if specified) on the left out data.

Inference:- Since we have selected recall for our scoring, So Grid search best estimator will provide us the best estimator which will give us the information of the params that resulted in the highest `Recall` score.

We have selected recall for scoring as our buisness requirement is to identify almost all customers who are likely to churn. High recall means model will correctly identify almost all customers who are likely to churn.

In [243]:
```python
rf_best = grid_search.best_estimator_
rf_best
```

Out[243]:
```
RandomForestClassifier(criterion='entropy', max_depth=20, min_samples_leaf=5,
                       min_samples_split=10, n_estimators=50, n_jobs=-1,
                       random_state=42)
```

grid_search.best_estimator_ :

    Estimator that was chosen by the search, i.e. estimator which gave highest score (or smallest loss if specified) on the left out data.

Inference:- Based on the Grid Search Hyperparameter tuning method, we identified the best parameters for the Random Forest from Grid search best estimator as - criterion='entropy', max_depth=25, min_samples_leaf=5, min_samples_split=5, n_estimators=200, max_features=10.

- From these parameters (criterion='entropy') helps us to determines how the impurity of a split is measured, (max_depth) helps us to limit the max number of levels in each decision tree to 25, (min_samples_leaf) helps us to find min number of data points allowed in a leaf node to 5, (min_samples_split) help number of data points a node must contain in order to consider splitting i.e. to 5, (n_estimators) helps us to find number of trees in the forest to 200, (max_features) helps us to find number of features to consider when looking for the split to 10.
- By applying these parameters and tuning the model, we will able to improve the metrics that we received from the default parametes of Random Forest.

In [244]:
```python
y_train_pred_rf_hp = rf_best.predict(X_train)
y_test_pred_rf_hp = rf_best.predict(X_test)
```

In [245]:
```python
print(classification_report(y_train, rf_best.predict(X_train)))
```

```
              precision    recall  f1-score   support

           0       0.99      0.98      0.99     17283
           1       0.98      0.99      0.99     17283

    accuracy                           0.99     34566
   macro avg       0.99      0.99      0.99     34566
weighted avg       0.99      0.99      0.99     34566
```

Making predictions on the test set

In [246]:
```python

print ('\n clasification report:\n', classification_report(y_test, y_test_pred_rf_hp))

```

```
 clasification report:
               precision    recall  f1-score   support

           0       0.97      0.95      0.96      7407
           1       0.53      0.70      0.60       651

    accuracy                           0.93      8058
   macro avg       0.75      0.82      0.78      8058
weighted avg       0.94      0.93      0.93      8058
```

In [247]:
```python
print ('\n confussion matrix:\n',confusion_matrix(y_test, y_test_pred_dt_hp))
```

```
 confussion matrix:
 [[6615  792]
 [ 177  474]]
```

In [248]:

```
rf_best.feature_importances_
```

Out[248]:

```
array([0.00494432, 0.00631354, 0.03413472, 0.00365882, 0.00440676,
       0.00770009, 0.00397378, 0.00399256, 0.01891283, 0.00233509,
       0.00336025, 0.03792102, 0.00255051, 0.00690602, 0.05573015,
       0.00458003, 0.00424956, 0.0155642 , 0.00398294, 0.00451755,
       0.013623  , 0.00266462, 0.00287988, 0.00959769, 0.00163161,
       0.00241041, 0.0026381 , 0.00428058, 0.00684496, 0.02419486,
       0.00481613, 0.0052134 , 0.00280153, 0.00458094, 0.00504843,
       0.00400712, 0.00116868, 0.00080841, 0.00042316, 0.00526687,
       0.00666422, 0.00596019, 0.0006991 , 0.001162  , 0.00099055,
       0.00654254, 0.00865435, 0.00485748, 0.00411163, 0.        ,
       0.00443029, 0.00516039, 0.02222296, 0.00575158, 0.00526664,
       0.02043883, 0.00513688, 0.00613517, 0.04327228, 0.00373513,
       0.00356524, 0.00816932, 0.00446778, 0.00685159, 0.05570625,
       0.00427807, 0.00455275, 0.0027808 , 0.00365236, 0.00457457,
       0.00655779, 0.00169019, 0.00131135, 0.00222263, 0.00405265,
       0.00374897, 0.0100562 , 0.00533608, 0.00503769, 0.04327668,
       0.00347324, 0.00066461, 0.00259591, 0.00210441, 0.00233229,
       0.00149357, 0.00313328, 0.00276168, 0.00135222, 0.00421119,
       0.00449278, 0.01397691, 0.00461576, 0.00588225, 0.04120331,
       0.00500332, 0.00744068, 0.03454494, 0.00653725, 0.00576512,
       0.0282798 , 0.00342234, 0.00547647, 0.01677455, 0.00295984,
       0.00404517, 0.01020182, 0.00345974, 0.00367948, 0.00731208,
       0.0026149 , 0.0022056 , 0.00503792, 0.00117404, 0.00160778,
       0.00499264, 0.00040393, 0.00066383, 0.00159547, 0.0007875 ,
       0.00034627, 0.00069519, 0.00468044, 0.00273197, 0.00317133,
       0.00365323, 0.00521396, 0.03370725, 0.00780442])
```

grid_search.feature_importances_ :

Methods that use ensembles of decision trees (like Random Forest or Extra Trees) can also compute the relative importance of each attribute. These importance values can be used to inform a feature selection process.

In [249]:

```
imp_df = pd.DataFrame({
    "Varname": X_train.columns,
    "Imp": rf_best.feature_importances_
})
```

In [250]:

```
imp_feat= imp_df.sort_values(by="Imp", ascending=False)
imp_feat.head(10)
```

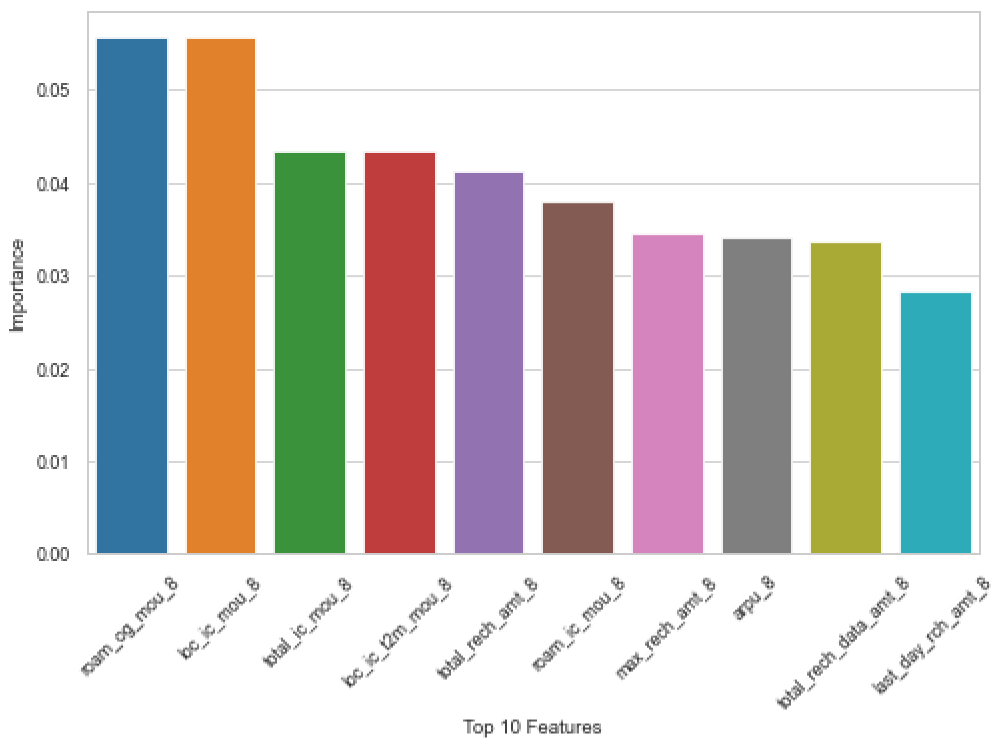
Out[250]:

	Varname	Imp
14	roam_og_mou_8	0.06
64	loc_ic_mou_8	0.06
79	total_ic_mou_8	0.04
58	loc_ic_t2m_mou_8	0.04
94	total_rech_amt_8	0.04
11	roam_ic_mou_8	0.04
97	max_rech_amt_8	0.03
2	arpu_8	0.03
127	total_rech_data_amt_8	0.03
100	last_day_rch_amt_8	0.03

In [251]:

```
plt.figure(figsize=(8,5))

ax = sns.barplot(x='Varname', y= 'Imp', data=imp_feat[0:10])
ax.set(xlabel = 'Top 10 Features', ylabel = 'Importance')
plt.xticks(rotation=45)
plt.show()
```



Conclusion

Based on our Random Forest (Hyperparameters Tuning) model, some features are identified which contribute most to a customer getting churned.

1) roam_og_mou_8 0.06
2) loc_ic_mou_8 0.06
3) total_ic_mou_8 0.04
4) loc_ic_t2m_mou_8 0.04
5) total_rech_amt_8 0.04
6) roam_ic_mou_8 0.04
7) max_rech_amt_8 0.03
8) arpu_8 0.03
9) total_rech_data_amt_8 0.03
10) last_day_rch_amt_8 0.03

Train data

```
                    accuracy: 0.99
            precision    recall  f1-score

       0       0.99      0.97      0.98
       1       0.97      0.99      0.98
```

Test data

```
                    accuracy: 0.93
           precision    recall  f1-score

       0       0.97      0.95      0.96
       1       0.53      0.70      0.60
```

after using hyper-parameter-tuning , recall has improved

7. Final Analysis on basis of Logistic Regression

churn =1 , not churn =0

Models	Test_Accuracy	Test_Recall	Test_Precision	Test_F1-Score
Logestic Regression(RFE)	72	85	20	33
Decision Tree(default)	89	61	37	46
Decision Tree(Hyer-paramter Tuning)	88	73	37	49
Random Forest(default)	93	65	56	61
Random Forest(Hyer-paramter Tuning)	93	70	53	60

Hence The Logestic Regression is the best model from above models

```
as in logestic regression model , as we have more focus on recall metrice rather than other .
Since our requirement here is to identify almost all customers who are likely to churn as
```

```
our focus is on The recall (is intuitively the ability of the classifier to find all the positive samples.)
```

Model Consideration:-

- Based on the accuracy, ROC and recall of different models, we will consider Logistic Regression as our final model.
- The test accuracy is 72%, recall is 85% and ROC is 87% .
- The recall for churn is 0.85, which is highest among all other models. **Since our buisness objective is more important to identify churners than the non-churners accurately. High recall means model will correctly identify almost all customers who are likely to churn.**
- Hence Logistic Regression model is chosen based on its performance on `Recall metric` .

  It is chosen based on its performance on Recall and Precision metric.

churn =1 , not churn =0 ### Compilation of models For Test data

Logistic Regression Model

Classification Report

	precision	recall	f1-score	support
0	0.98	0.71	0.82	7407
1	0.20	0.85	0.33	651

Accuracy: 71.9%¶

ROC: 87.0%

Decision Tree (Default Hyperparameters) Model

Clasification Report

	precision	recall	f1-score	support
0	0.96	0.91	0.94	7407
1	0.37	0.61	0.46	651

Accuracy: 88.6%¶

ROC: 76.0%

Decision Tree (Hyperparameter Tuning) Model

Clasification Report

	precision	recall	f1-score	support
0	0.97	0.89	0.93	7407
1	0.37	0.73	0.49	651

Accuracy: 88.0%¶

ROC: 84.8%

Random Forest (Default Hyperparameters) Model

Clasification Report

	precision	recall	f1-score	support
0	0.97	0.96	0.96	7407
1	0.56	0.65	0.61	651

Accuracy: 93.1%¶

ROC: 92.3%

Random Forest (Hyperparameters Tuning) Model

Clasification Report

	precision	recall	f1-score	support
0	0.97	0.95	0.96	7407
1	0.53	0.70	0.60	651

Accuracy: 92.6%

ROC: 92.8%

logistic regression model choosen

In [253]:

```
# lets find the most important predictor variables on basis of their coefficient to predict churn.

feature_importance = new_params
Final_imp_feat= pd.DataFrame(feature_importance).reset_index().sort_values(by=0,ascending=False)
Final_imp_feat.rename(columns = {'index':'Imp_feature', 0:'Imp'}, inplace = True)
Final_imp_feat
```

Out[253]:

	Imp_feature	Imp
0	arpu_7	0.48
2	std_og_t2m_mou_8	-0.18
1	onnet_mou_8	-0.20
5	loc_ic_mou_7	-0.52
3	std_og_t2f_mou_8	-0.67
11	sachet_2g_8	-0.72
10	monthly_2g_8	-0.72
7	spl_ic_mou_8	-0.77
12	aug_vbc_3g	-0.79
6	std_ic_mou_8	-0.82
9	last_day_rch_amt_8	-0.87
8	total_rech_num_8	-0.93
4	loc_ic_t2f_mou_8	-1.22

Inference: We could see the Top 13 features which contribute most towards the probability of a customer getting churned.

Based on our logical regression model, some features are identified which contribute most to a customer getting churned.
The churn probability of a customer increases with increase in values of the following features in descending order:

Features with Positive Coefficient:

1) arpu_7: 0.48
The churn probability of a customer increases with decrease in values of the following features in descending order:

Features with Negative Coefficient:

1) std_og_t2m_mou_8: -0.18
2) onnet_mou_8: -0.20
3) loc_ic_mou_7: -0.52
4) std_og_t2f_mou_8: -0.67
5) sachet_2g_8: -0.72
6) monthly_2g_8: -0.72
7) spl_ic_mou_8: -0.77
8) aug_vbc_3g: -0.79
9) std_ic_mou_8: -0.82
10) last_day_rch_amt_8: -0.87
11) total_rech_num_8: -0.93
12) loc_ic_t2f_mou_8: -1.22

Step 8: Business Insights and Recommendation of strategies to manage churn customer based on our observations.

```
1. Lesser the STD outgoing minute of usage to other operators mobile higher is the probability of getting churn. So Telecom company needs to provide offers to the customers, whose STD outgoing to other operators mobile had decreased.Offers such a
hich will help them to opt when they required. Telecom company can also provide "STD free minutes" which customer can opt as per his her requirements of STD calling.

2. Telecom company needs to pay attention to the onnet minutes of usage, lesser the onnet minutes of usage higher is the probability of getting churn. They should provide some plans like "Unlimited Calls" within same operator.

3. Telecom company should focus on local incoming calls. Lesser the local incoming minutes of usage higher is the probability of getting churn. In an ideal situation, lesser local incoming minutes might be due to poor network or call drop issue w
vised by adding more towers or working on connectivity issue.

4. Telecom company needs to provide offers to them whose STD outgoing to operator's fixed line had decreased. Lesser the STD outgoing minute of usage to fixed line higher is the probability of getting churn. Offers like "Fixed STD--plan which car
 customer whose major call attempts are done to Fixed line operator. And also "Fixed STD Minutes" which can be opt as per requirements which may not be monthly can be alternatively.

5. Telecom company should focus on 2g Sachet. Lesser the use of sachet for 2g higher is the probability of getting churn. We can introduce plans like "One Time Trial Pack" which can be used by consumer as per their daily net usage, plans like cha
d get 1 day some mb of 2g for free.

6. Telecom company should focus on 2g monthly. Lesser the use of 2g over monthly basis higher is the probability of getting churn. We can introduced plans like  "Pay for 30 & Use for 35 days". " Pay for 30 & Get CAshback of certain amount". We ca
vice providers like Paytm / Phone pe etc.

7. Telecom company should focus on Volume base cost for 3g. Lesser the use of 3g volume higher is the probability of getting churn. Telecom company should conduct a survey of such customer data which will help us to understand the details about t
gly we need to form a "Exclusive Well Trained Service Team" who will help to communicate about the best plan and offer customised plans as per thier requirements.

8. Telecom company should focus on Special incoming minute of usage. Lesser the use of Special incoming call higher is the probability of getting churn. Telecom company can offer them free calling to specific numbers may be 2, 4, 6 special number
 will definately increase the usage as there wont be any restrictions for calling. This can be done depending on customers credibilty.
```

In [ ]:
```
1
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In [ ]:
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In [ ]:
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