

# TELECOM CHURN CASE STUDY

## **Group Members:**

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Bayireddy**

# BACKGROUND

## Telecom Churn Case Study

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



# BUSINESS OBJECTIVE

## Telecom Churn Case Study

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

# PROCESS FOR SOLVING CASE STUDY

**DATA  
SET**

Data  
Understanding  
and EDA

Handling the  
class imbalance

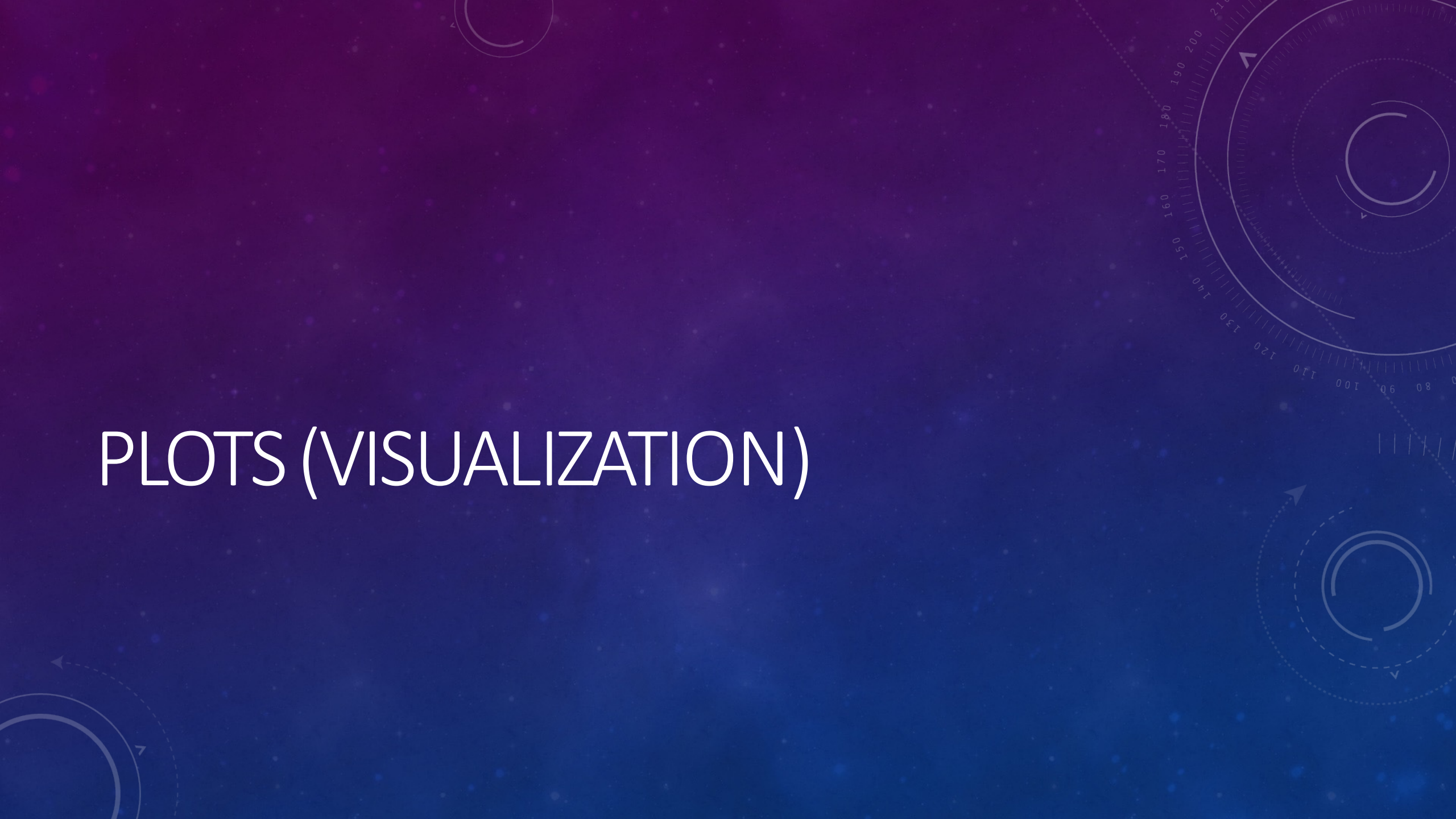
Model Building  
Using Logistic  
Regression and  
Decision Tree

Feature Selection  
using RFECV

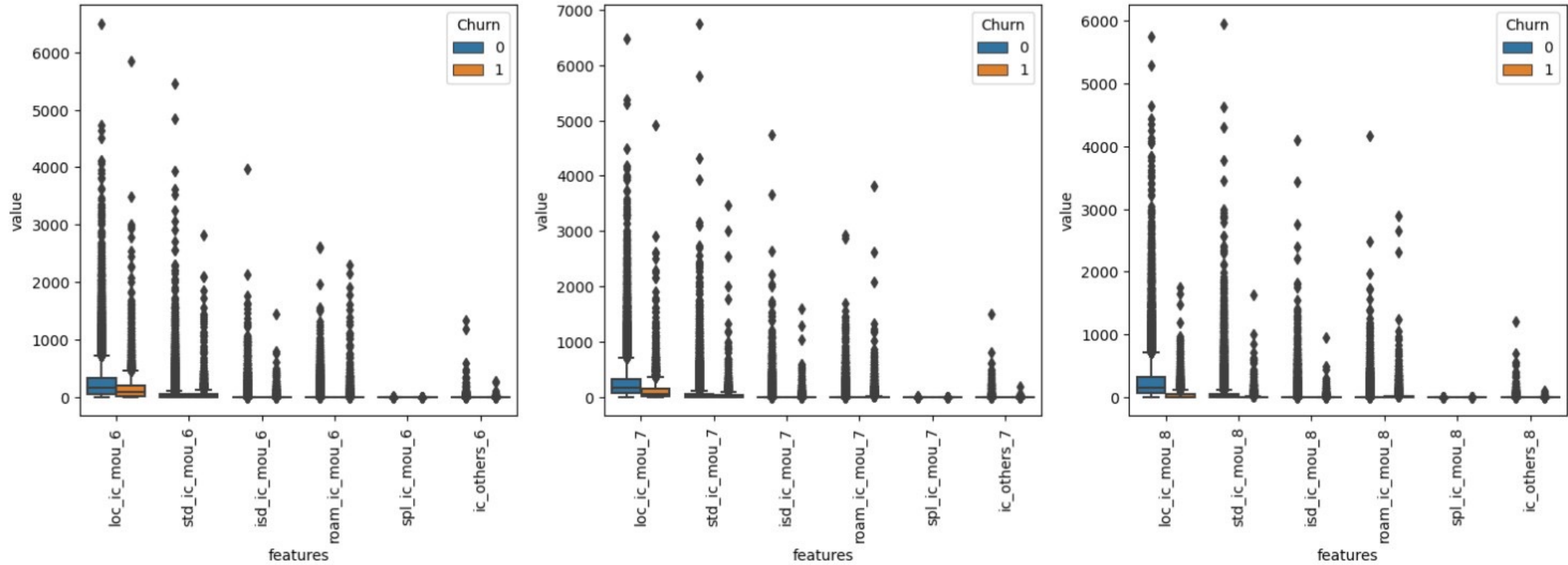
Business  
Recommendations



# PLOTS (VISUALIZATION)

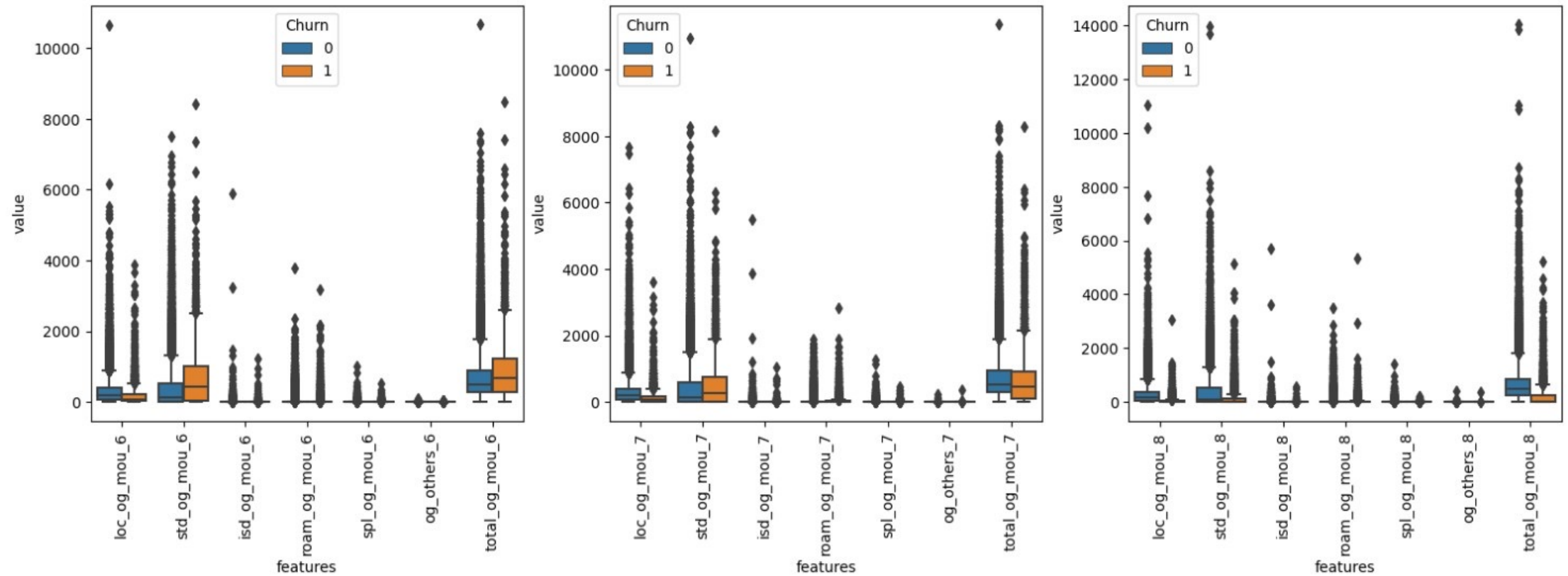


Incoming Calls Usage



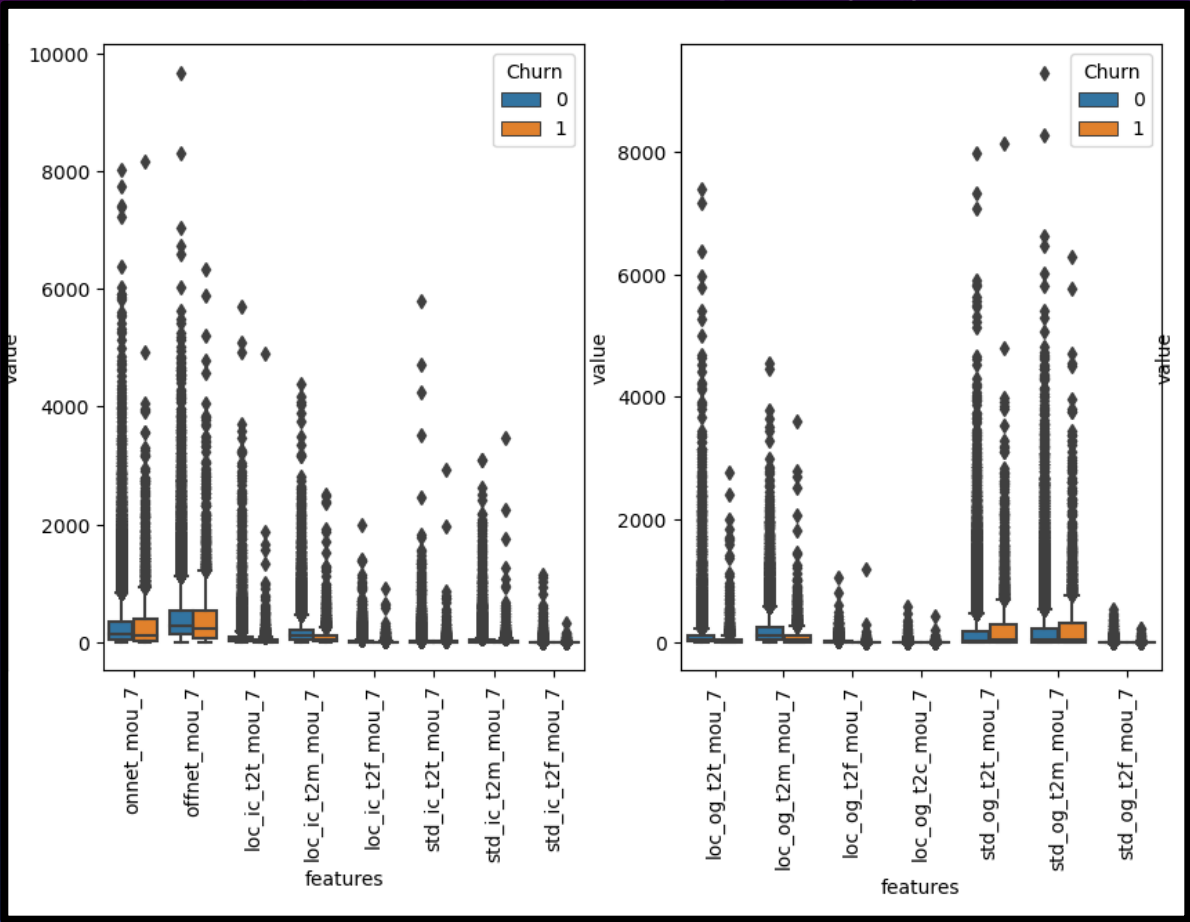
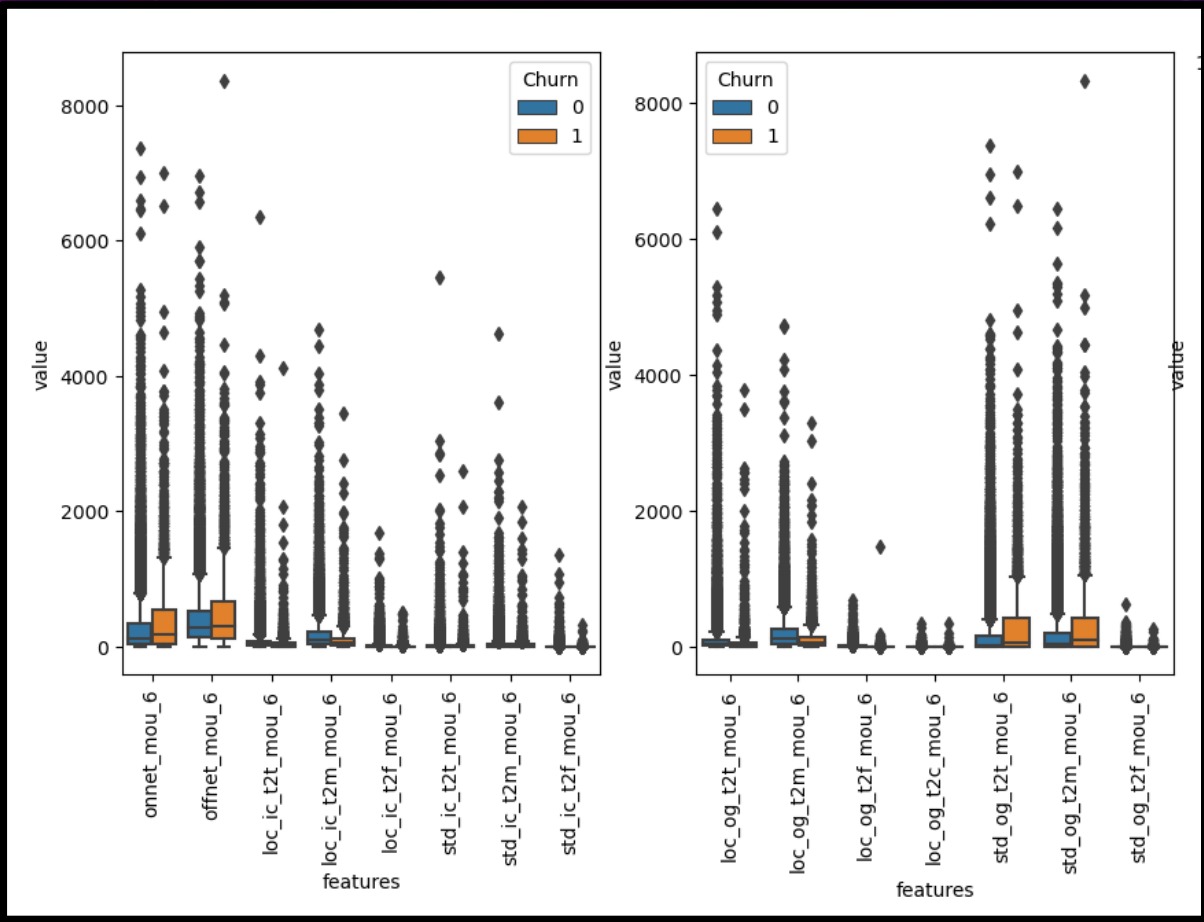
EDA box plot for the incoming call usage

Outgoing Calls Usage



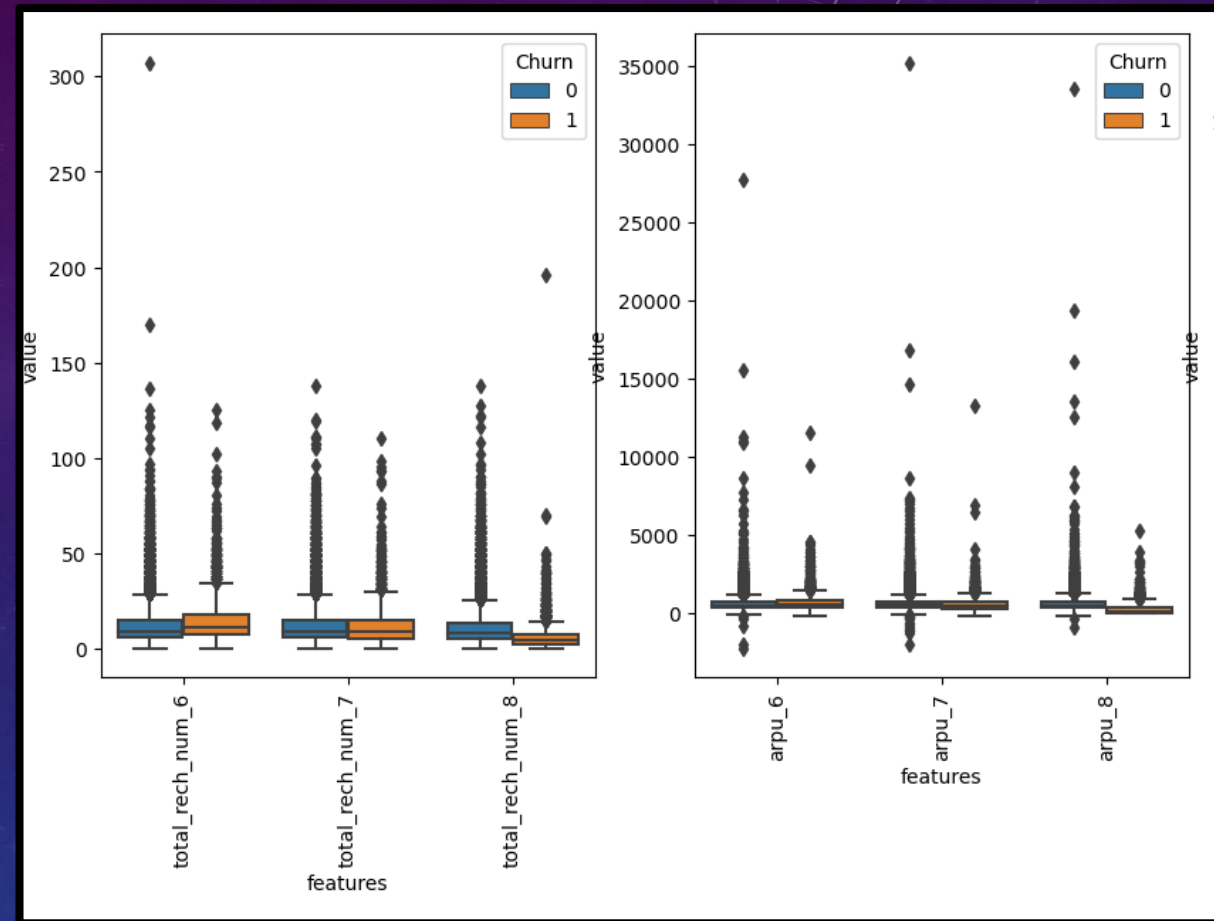
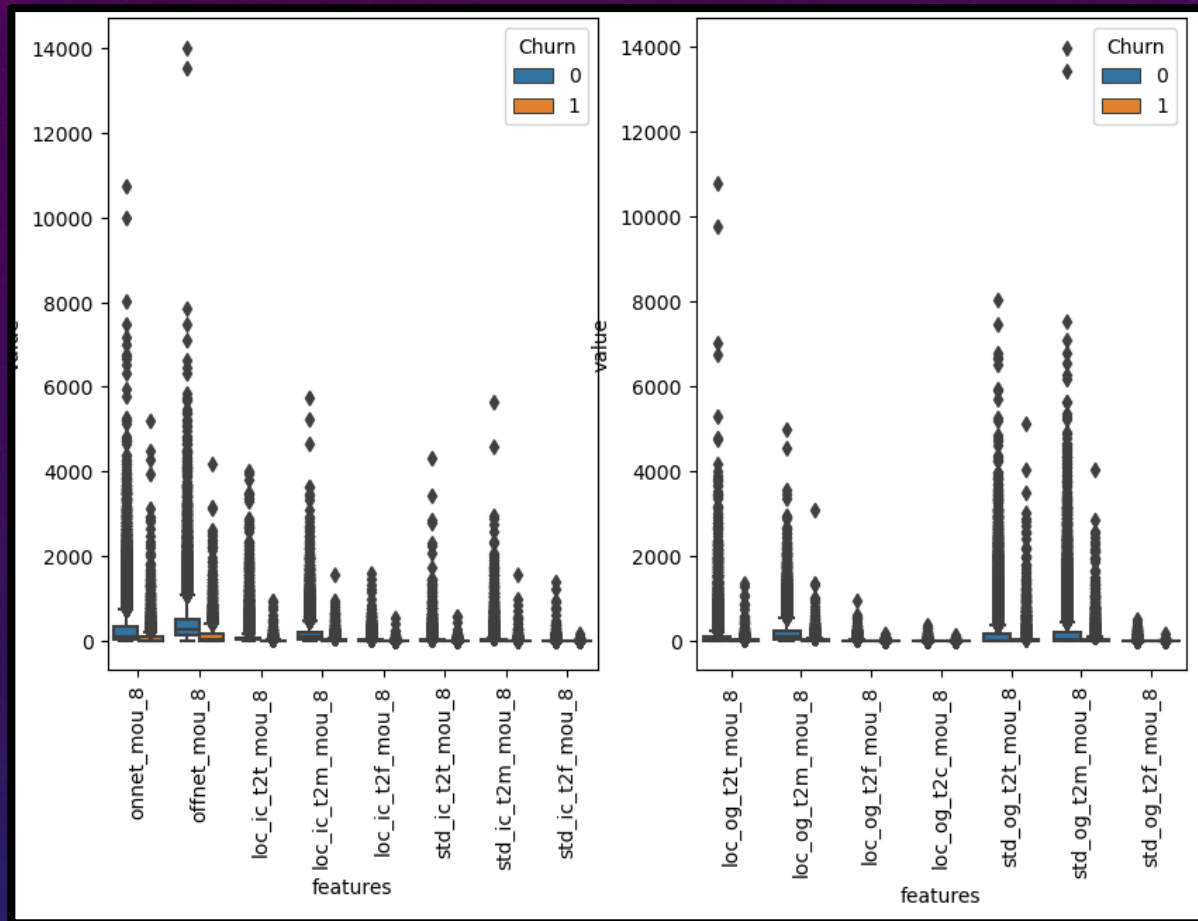
EDA box plot for the Outgoing call usage



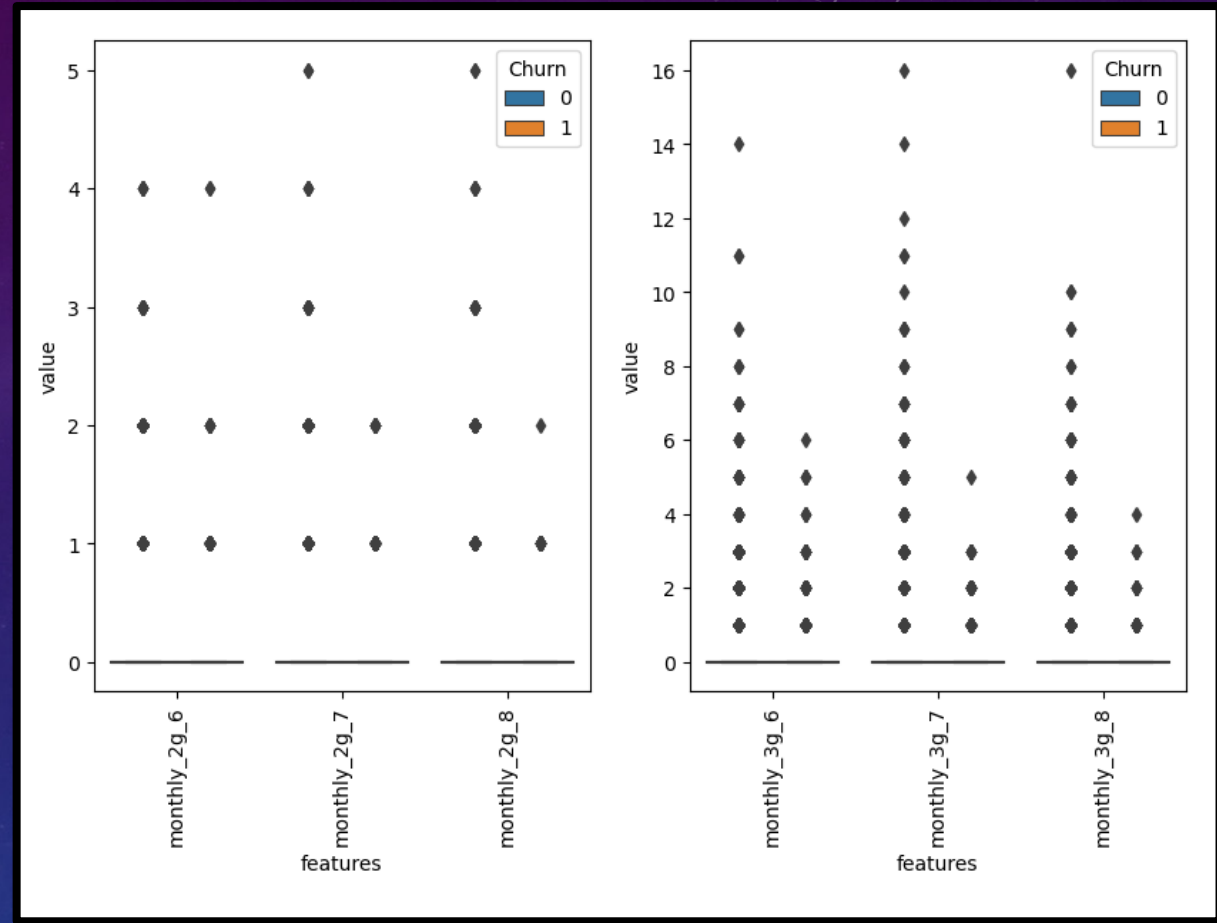
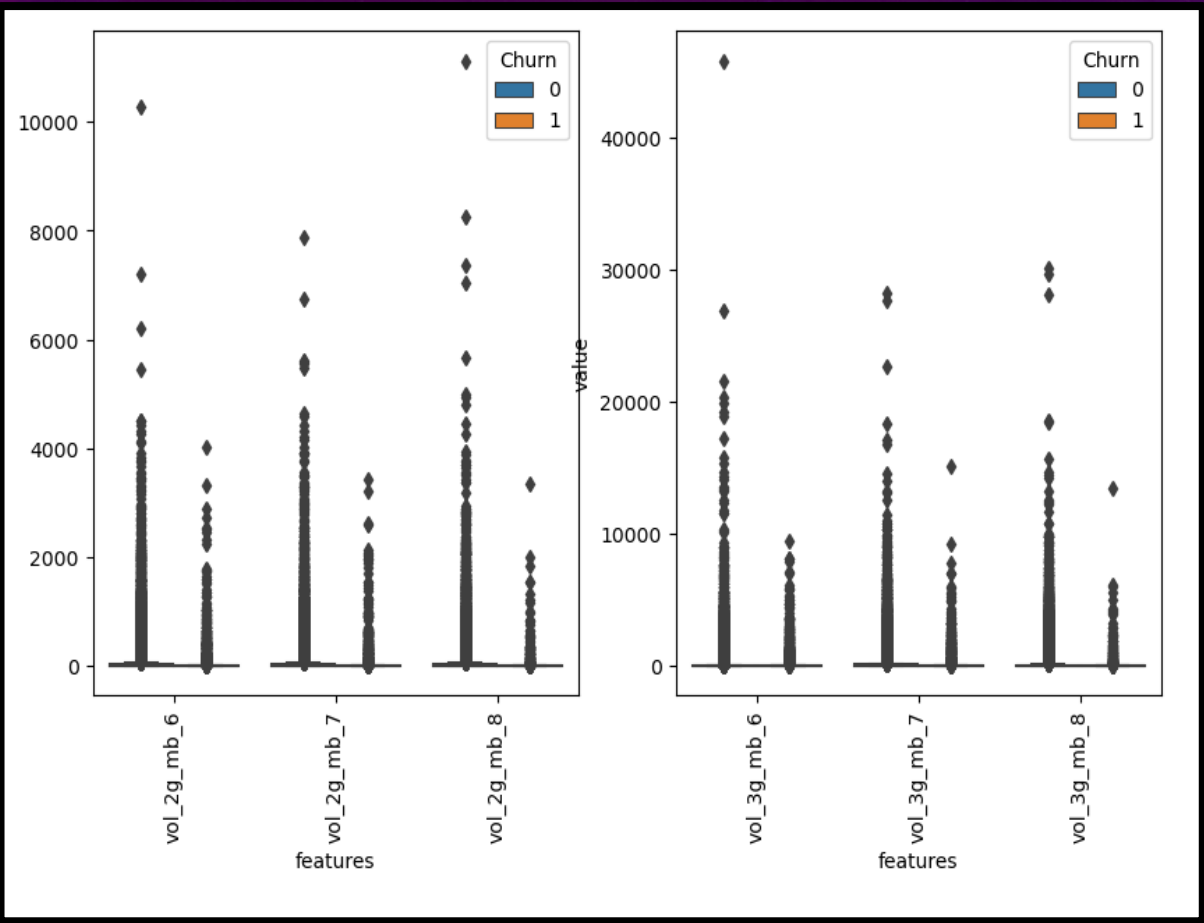


EDA box plot for the outliers



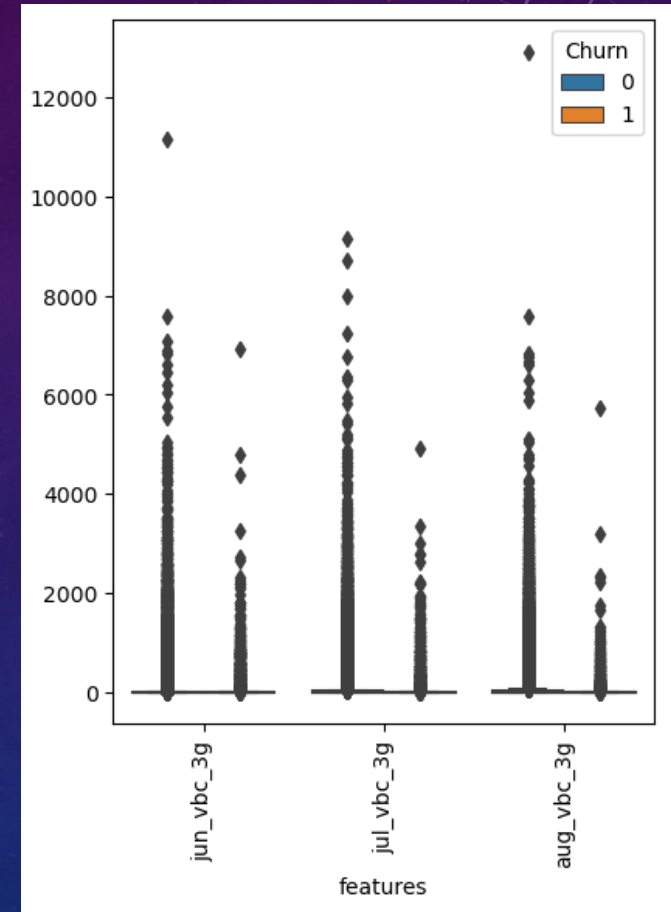
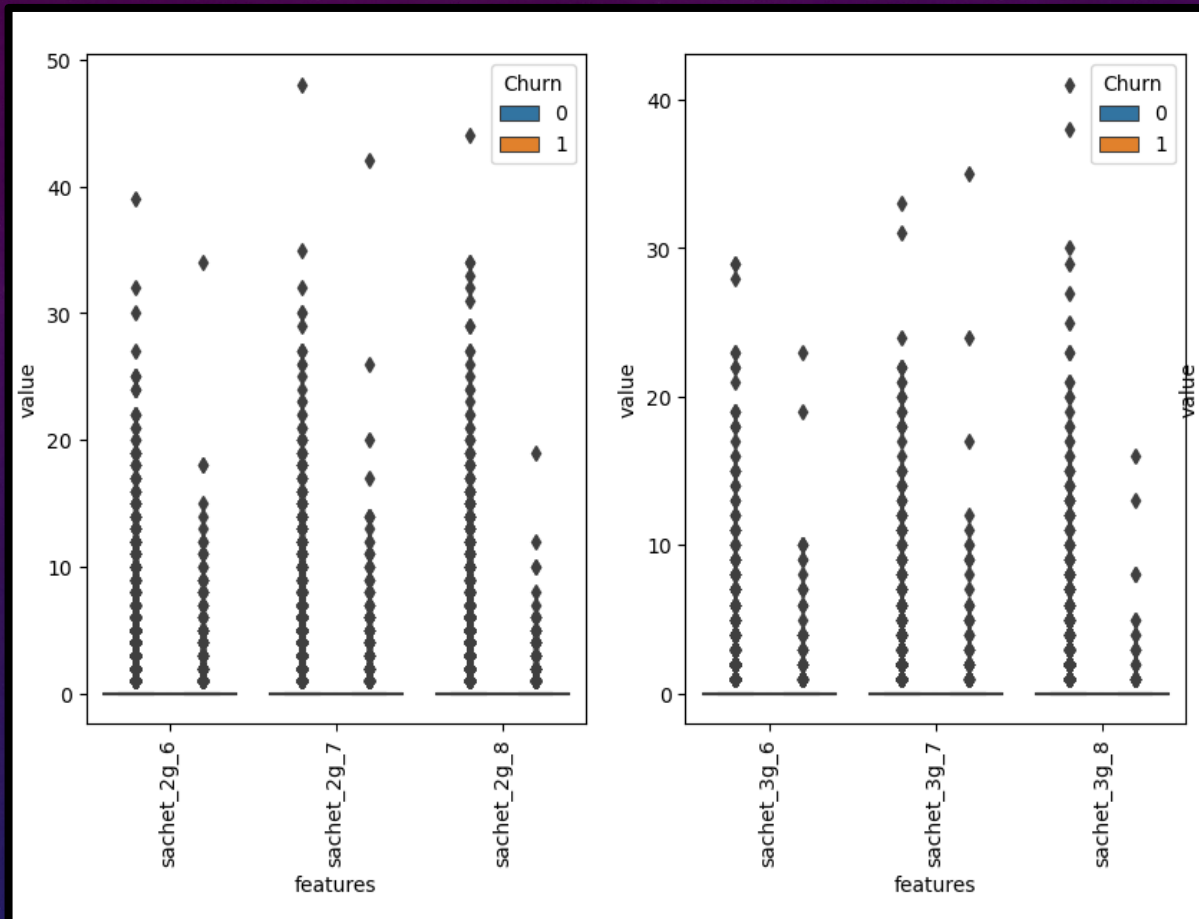


EDA box plot for the outliers

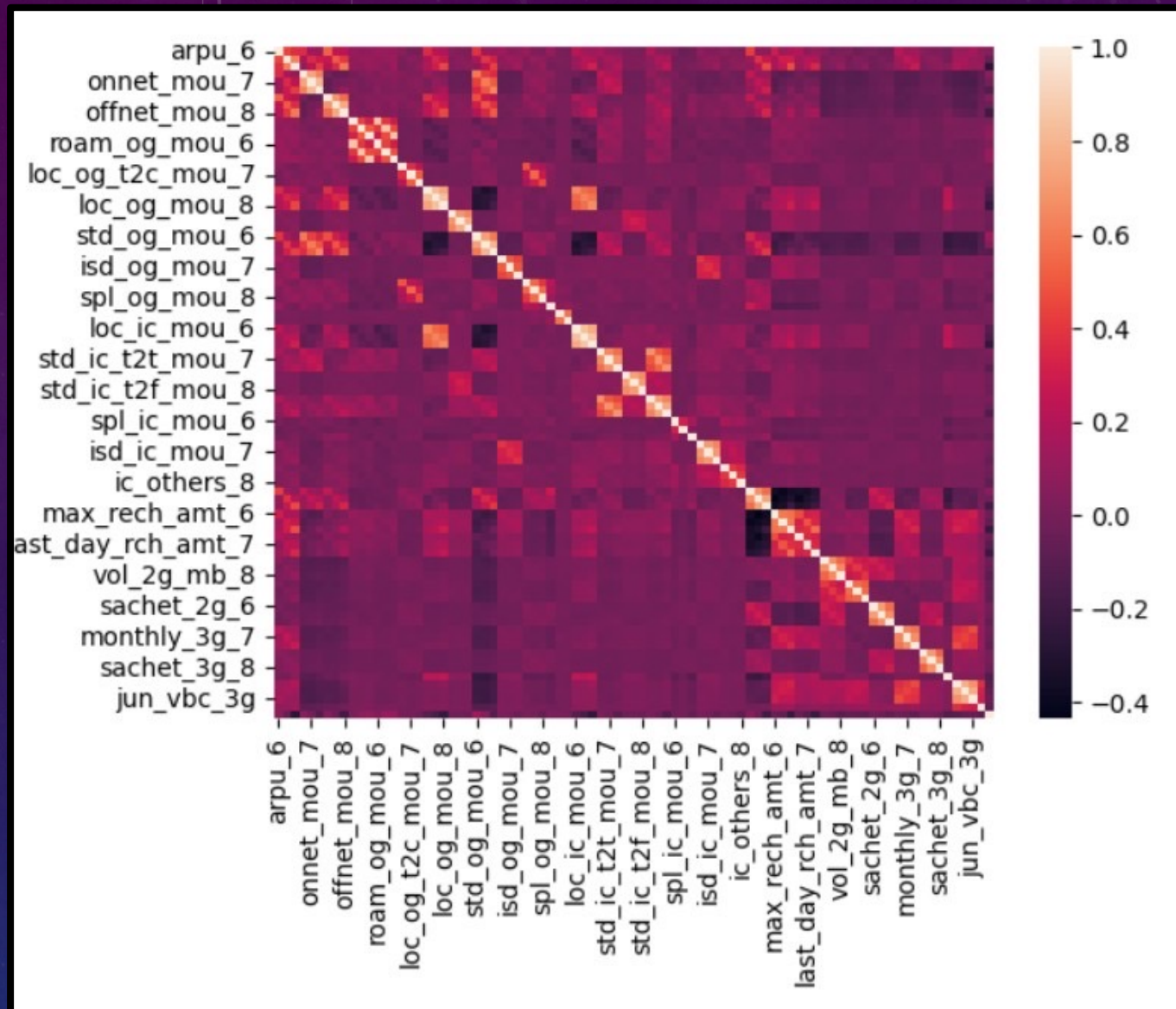


EDA box plot for the outliers



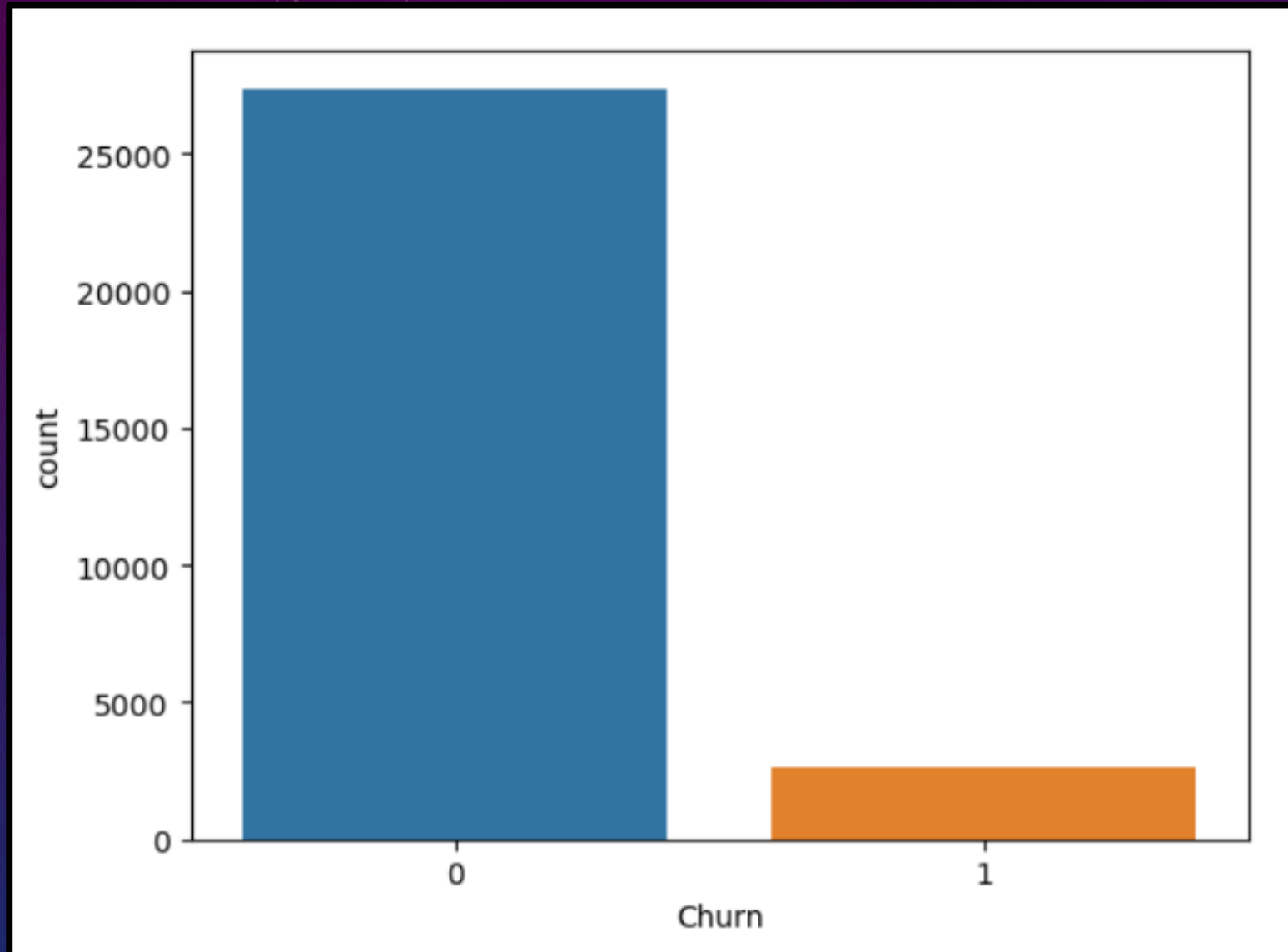


EDA box plot for the outliers



EDA plots depicting correlation (Heat Map) of all selected columns.





**EDA Box plot for Class imbalance.**

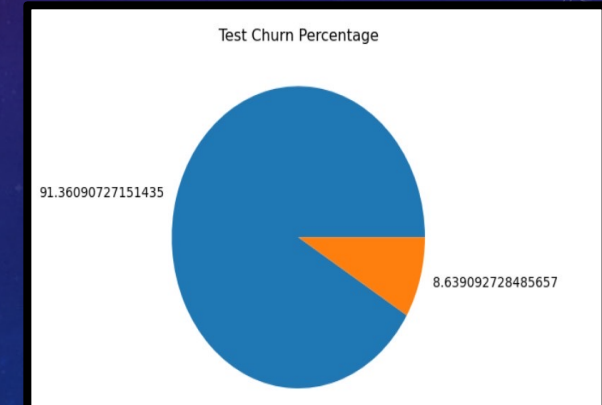
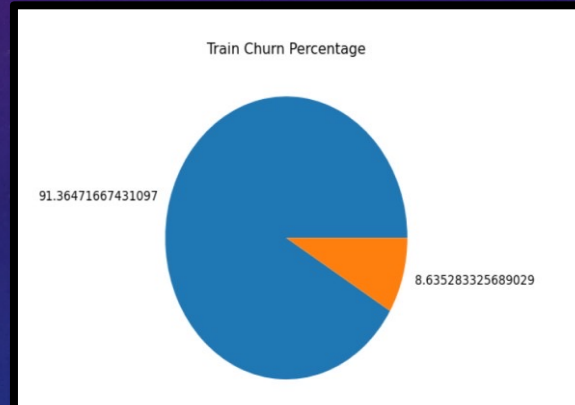
```
df2.shape
```

```
(29979, 87)
```

**Data Set Shape  
Before Splitting  
into Train - Test**

```
df_train.shape, df_test.shape
```

```
((23983, 87), (5996, 87))
```



**Data Shape**



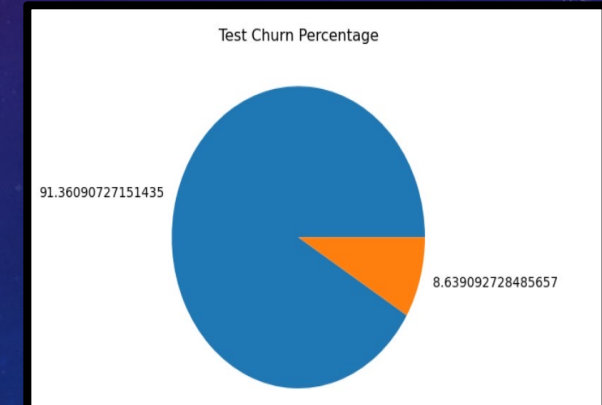
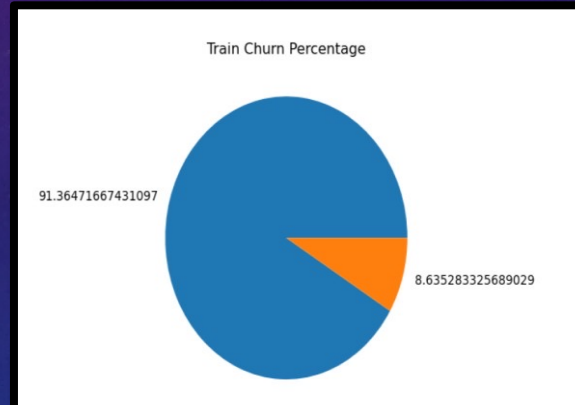
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**Data Shape**

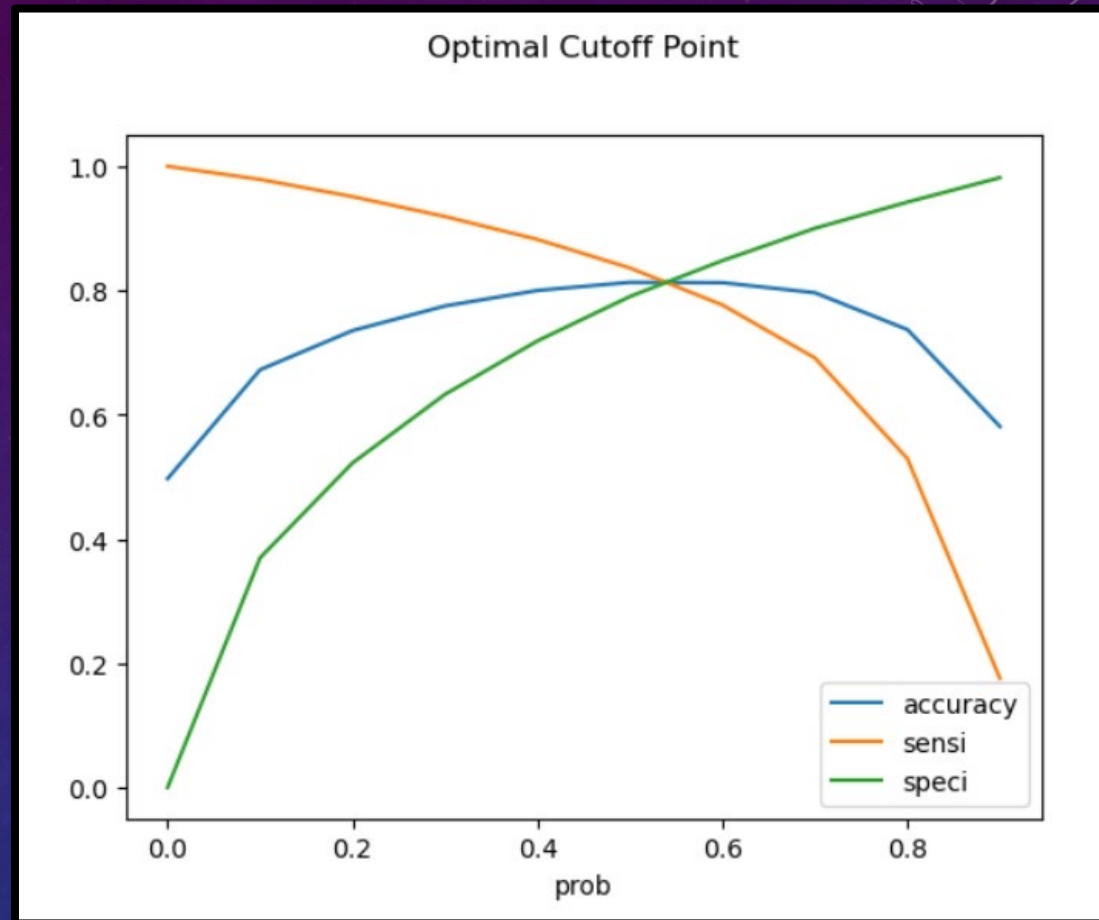
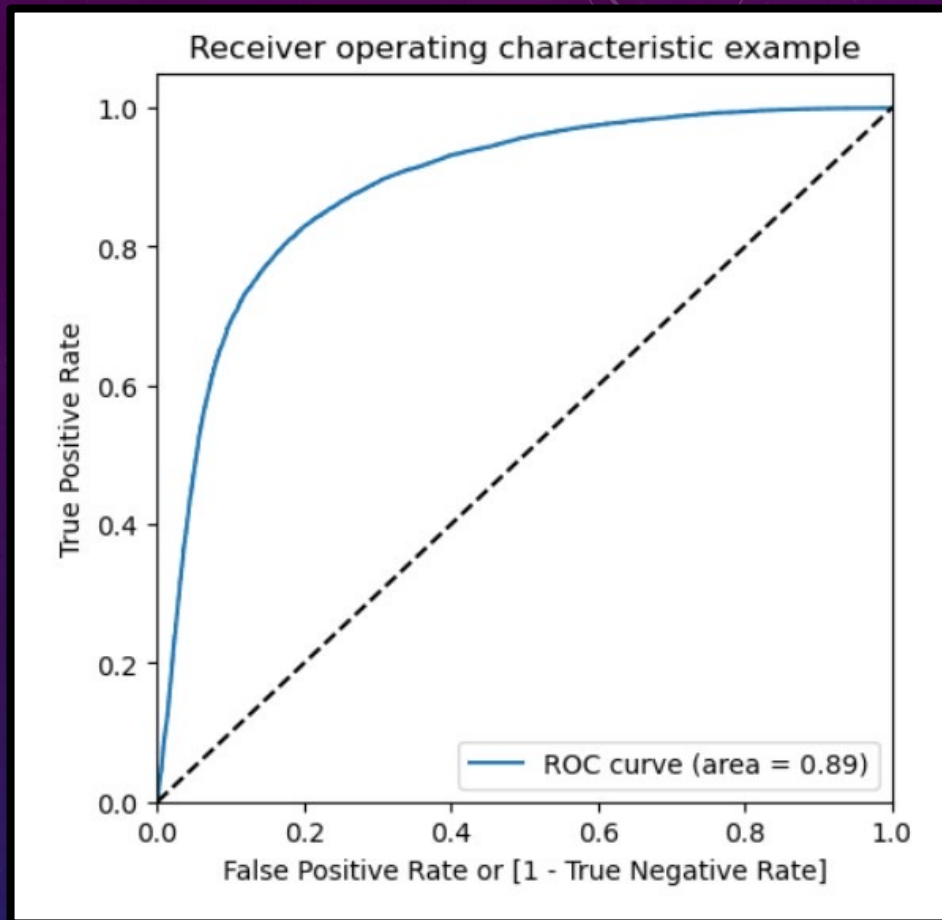
	Features	VIF
2	loc_og_mou_8	2.01
3	loc_ic_mou_7	1.64
7	last_day_rch_amt_8	1.45
6	total_rech_num_8	1.42
0	arpu_7	1.28
11	aon	1.21
4	std_ic_mou_8	1.16
9	sachet_2g_8	1.16
10	monthly_3g_8	1.14
1	roam_og_mou_8	1.09
12	sep_vbc_3g	1.09
8	monthly_2g_8	1.07
5	spl_ic_mou_8	1.03

**AFTER PROCESSING THE DATA FOR  
MODEL BUILDING USING LR, WE FOUND  
THE 4<sup>TH</sup> MODEL WHOSE HAVING GOOD  
LOW P- VALUE.**

```
Accuracy: 0.8131255164814984
F1 score: 0.8164415683975559
Recall: 0.8361814151117679
Precision: 0.7976122296136393
ROC_AUC_SCORE: 0.8132623030286843
```

**Model Building using Logistic Regression**





**Model Building using Logistic Regression**

- **After Processing the test data for model building using LR gives quite a good result on test data.**

```
Accuracy: 0.8275517011340894
F1 score: 0.45116772823779194
Recall: 0.8204633204633205
Precision: 0.31112737920937045
ROC_AUC_SCORE: 0.8243426496438545
```

- **The precision is too low but we can count on Recall which is good.**
- **We are preferring recall because it takes False negative Cases on count. Here we need to predict all churning customers. That's why we could not afford much False Negatives cases.**

**Model Building using Logistic Regression**



```
Accuracy: 0.8629086057371581  
F1 score: 0.4907063197026022  
Recall: 0.7644787644787645  
Precision: 0.3613138686131387  
ROC_AUC_SCORE: 0.8183474508775714
```

- **After doing feature selection using rfecv. We took only 12 most important features. After hyper tuning our recall, accuracy, precision value slightly improved but not good enough. Hence we will try for Random Forest**

**Model Building using Decision Tree**



Accuracy: 0.9127751834556371  
F1 score: 0.6111524163568773  
Recall: 0.7934362934362934  
Precision: 0.4969770253929867  
ROC\_AUC\_SCORE: 0.858748084651699

So most important features for our final model are all from action phase.

Top 10 are listed here

1. roam\_og\_mou\_8
2. loc\_ic\_mou\_8
3. roam\_ic\_mou\_8
4. arpu\_8
5. loc\_og\_mou\_8
6. last\_day\_rch\_amt\_8
7. max\_rech\_amt\_8
8. total\_rech\_num\_8
9. std\_ic\_mou\_8
10. onnet\_mou\_8

**Model Building using Random Forest**

# Business Recommendations

## Telecom Churn Case Study

- The company after identifying customers in action phase can give offers for increasing local incoming and outgoing minutes of usage.
- Customers are more keen towards the local incoming calls over anything so, We can provide more free incoming calls and also we can reduce the outgoing calls charges for better connectivity. This can provide an advantage over other operators in the market
- The roaming charges can be made lesser by giving offers. More importantly we can provide free incoming calls on roaming.
- We can provide attractive offers and packages for the customers.



THANK YOU

