

CUSTOMER BEHAVIOUR

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

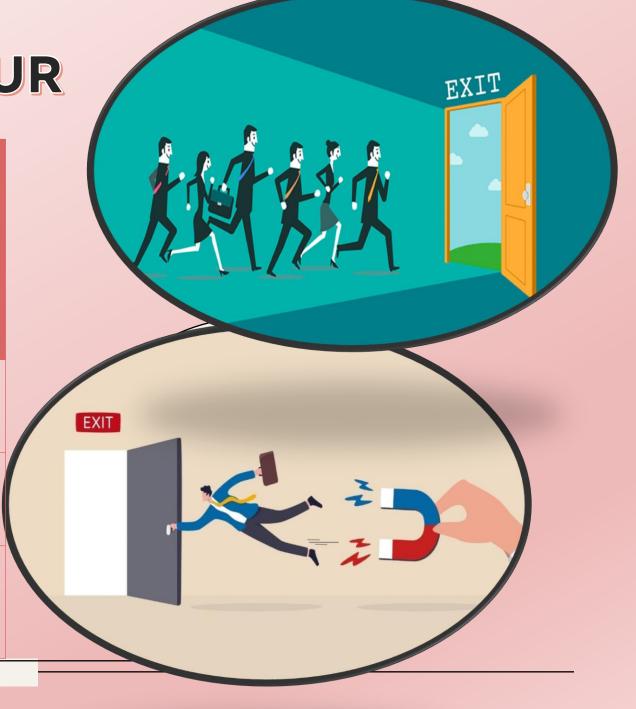
Good Phase The customer is happy with the service

Action Phase

The customer experience starts to become sore

Churn Phase

The customer is said to have churned



BUSINESS OBJECTIVE

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

In this case the dataset is over a four-month window

The first two months are the good phase – June July

The third month is the action phase - August

The fourth month is the churn phase -September



TELECOM CHURN

STEPS INVOLVED

Filter High Value Customers

Identify high-value customers based on their recharge amounts in the first two months, ensuring a robust dataset for churn prediction.

Tag Churners

Label customers as churners based on their activity (or lack thereof) during the churn phase, and remove attributes corresponding to this phase from the dataset.

Deal with Missing Values

Drop columns which are more than 40% and delete the rows which are having null values less than 6%.

Build Model

Predictive Model using Random Forest Classifier

Logistic Regression Model to identify predictor variables

Test Model

Deploy the model on the test set

FILTER HIGH-VALUE CUSTOMERS



As mentioned earlier the need to predict churn is only for high-value customers.

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).

After filtering the highvalue customers there are about 30011 rows.

TAG CHURNERS

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

The attributes you need to use to tag churners are:

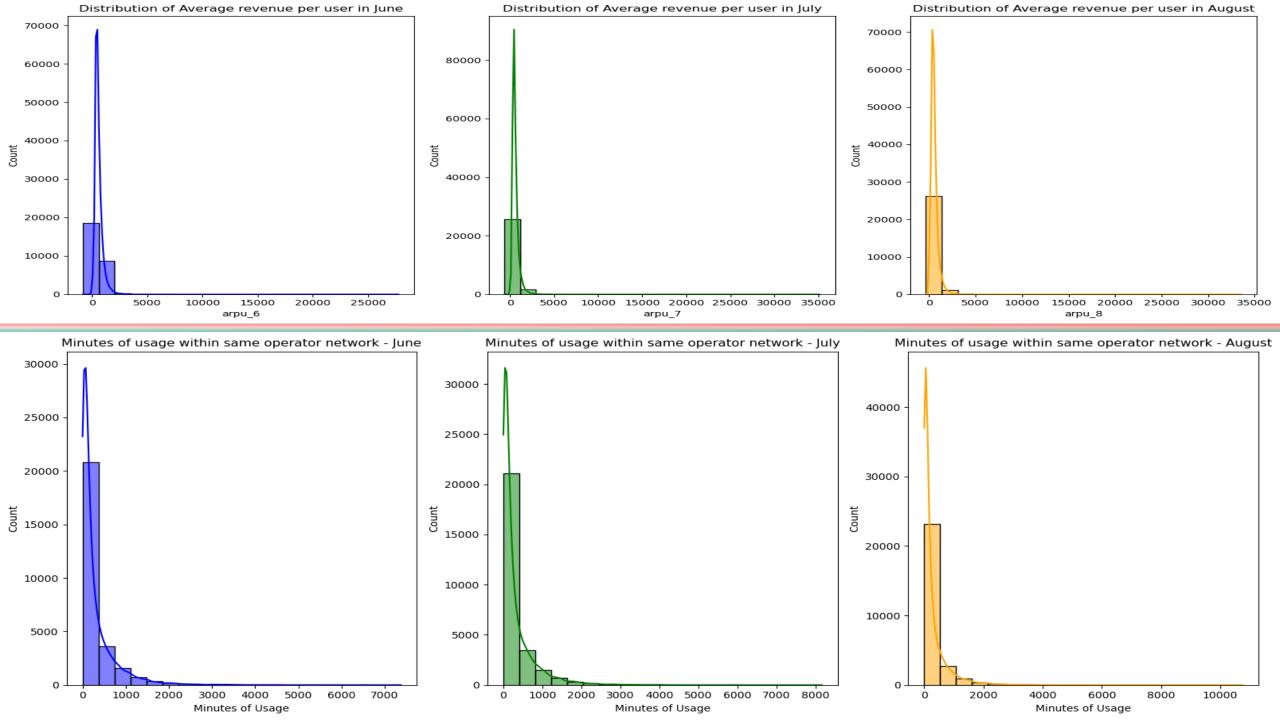
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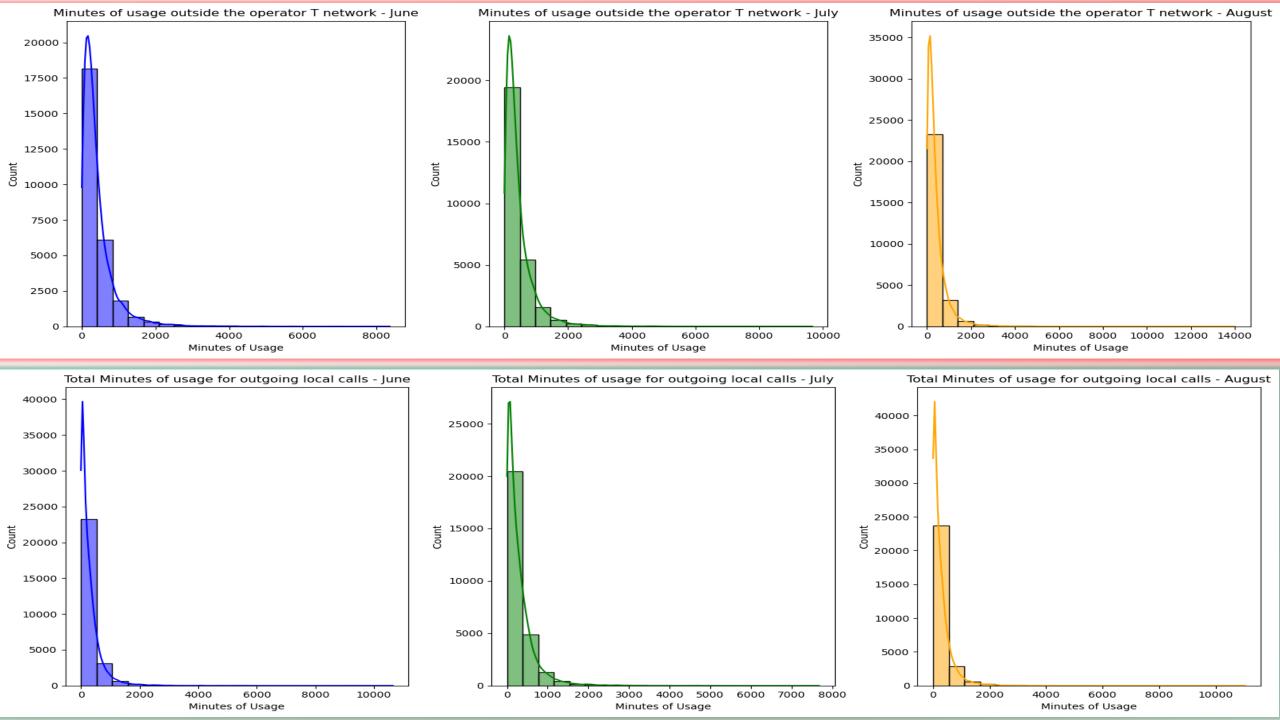
total_og_mou_9

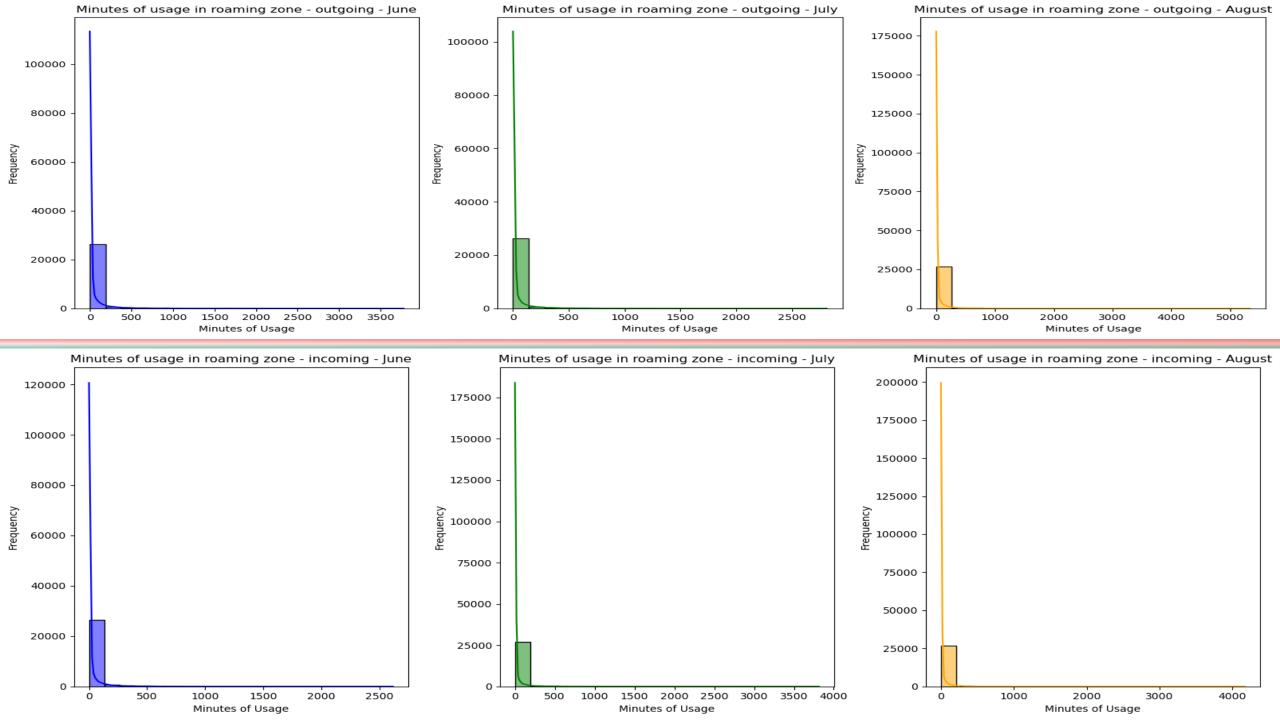
vol_2g_mb_9 vol_3g_mb_9

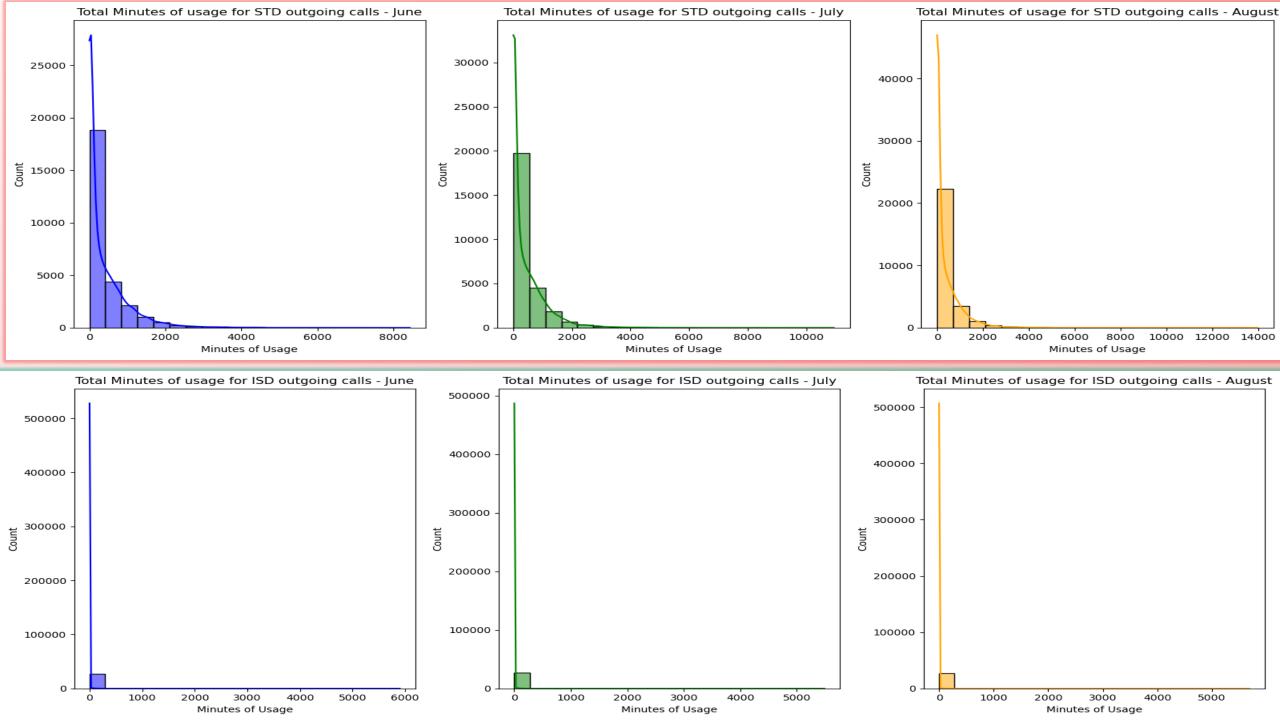
After tagging churners remove all the attributes corresponding to the churn phase (September)

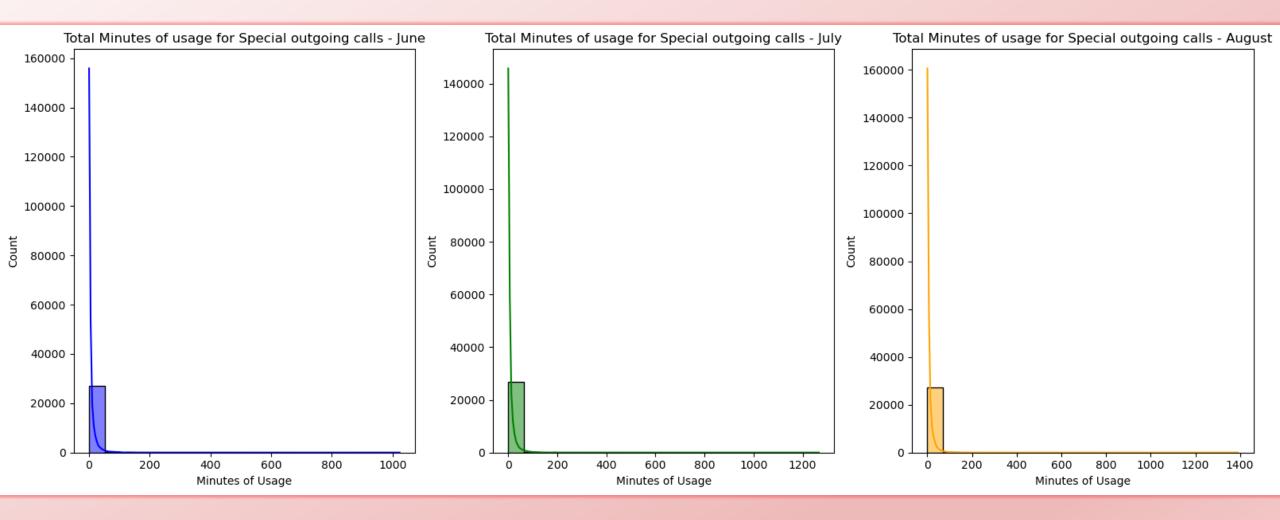


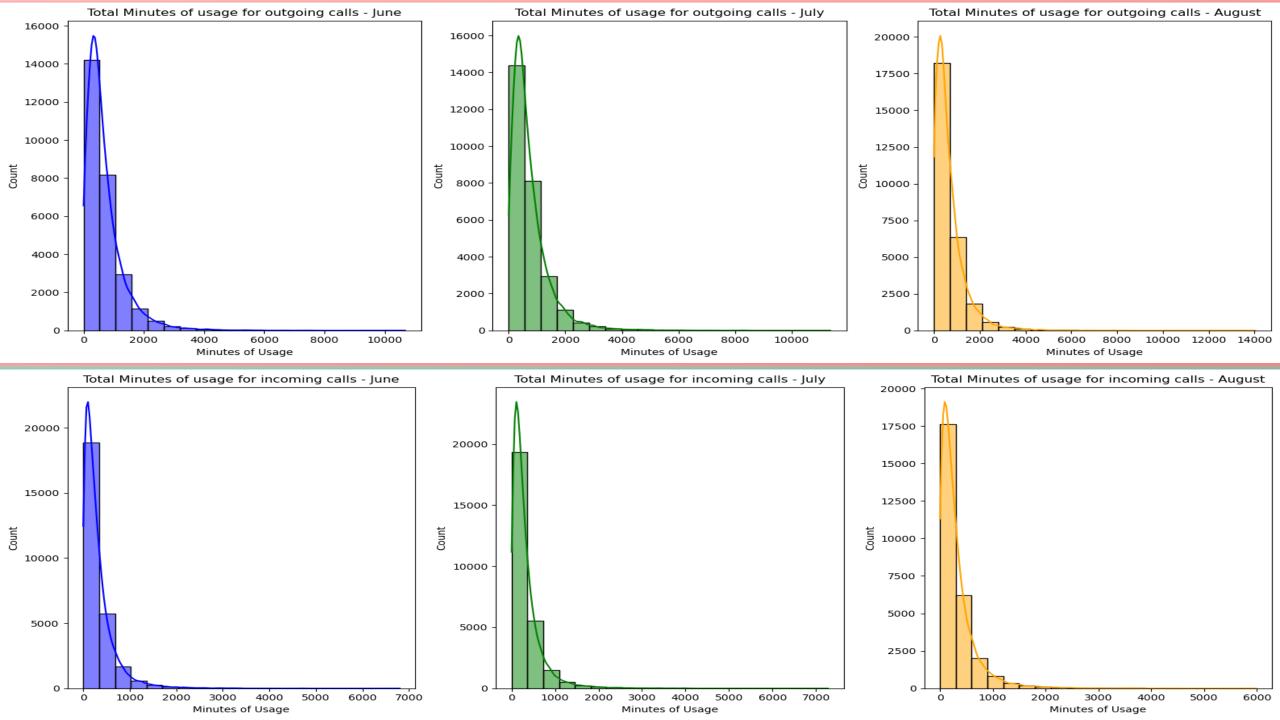


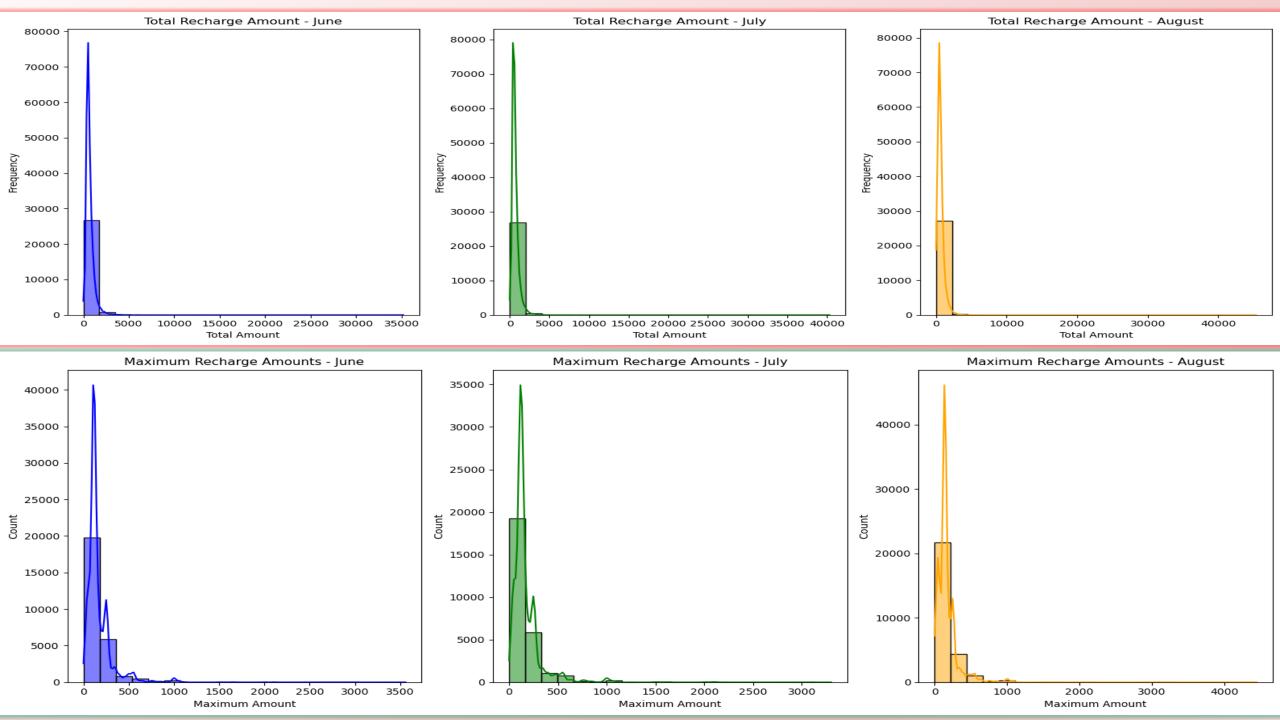


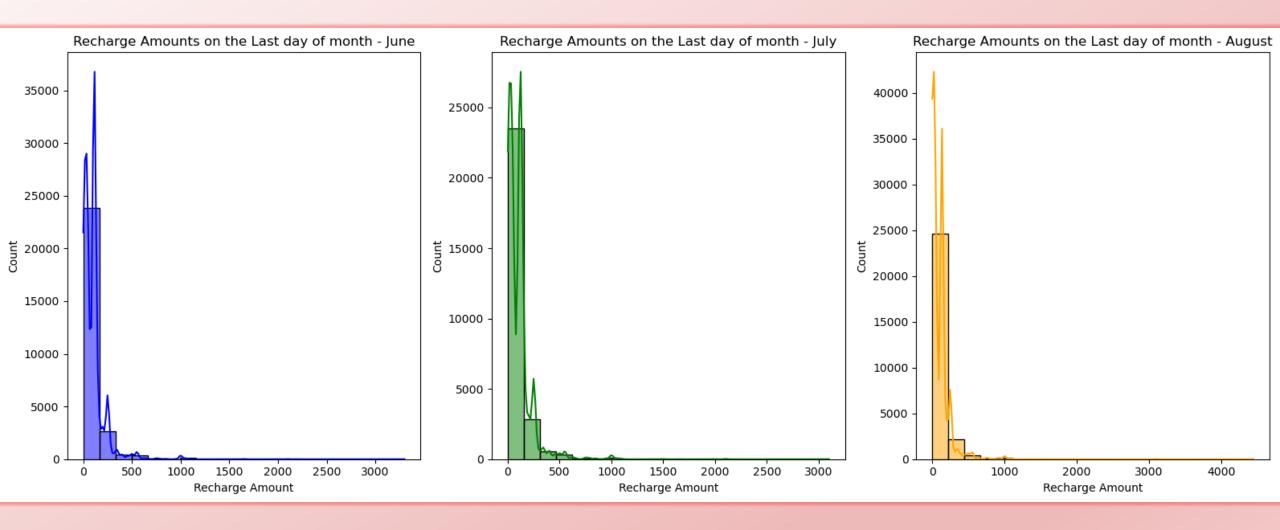


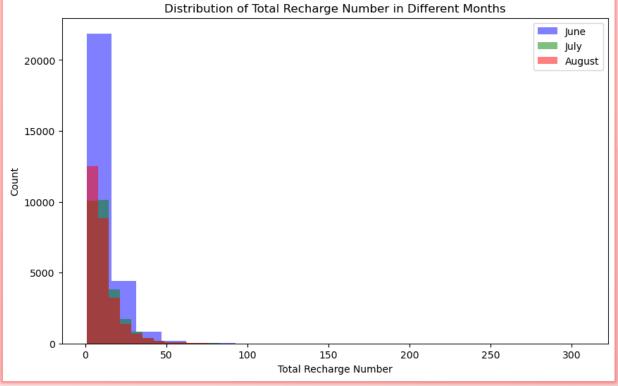


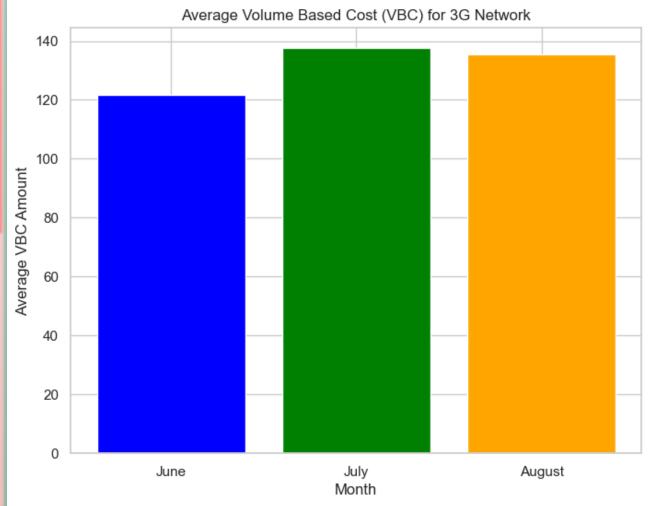






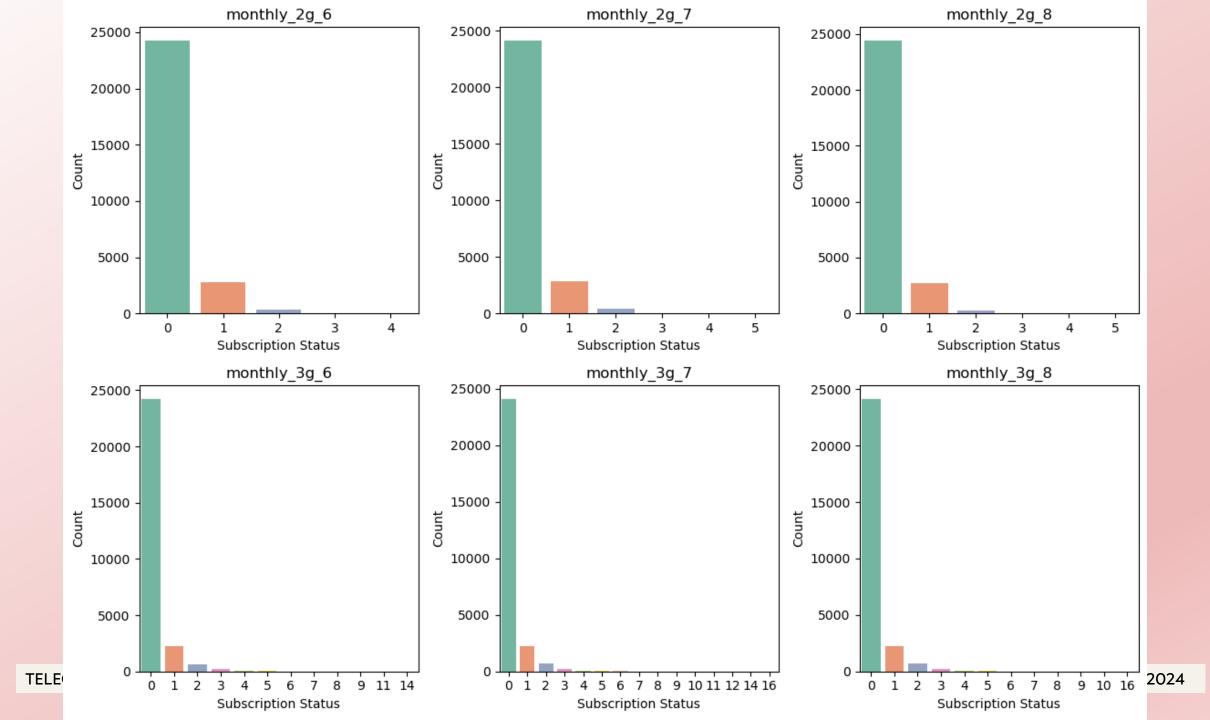


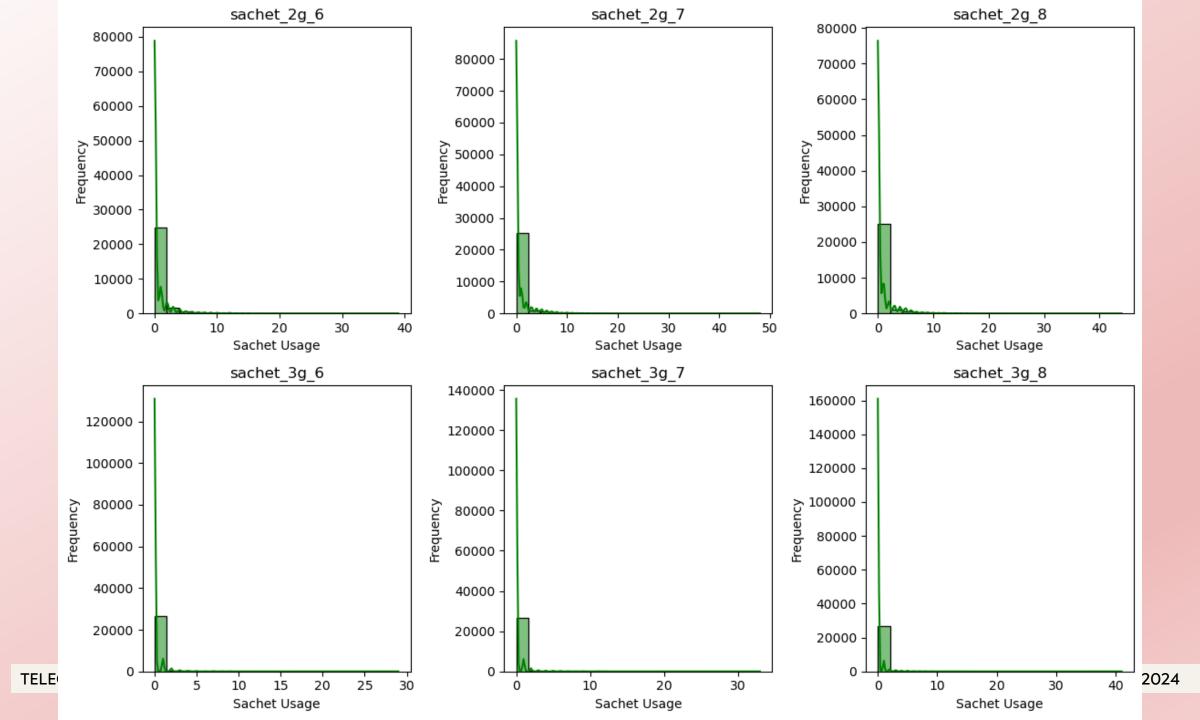


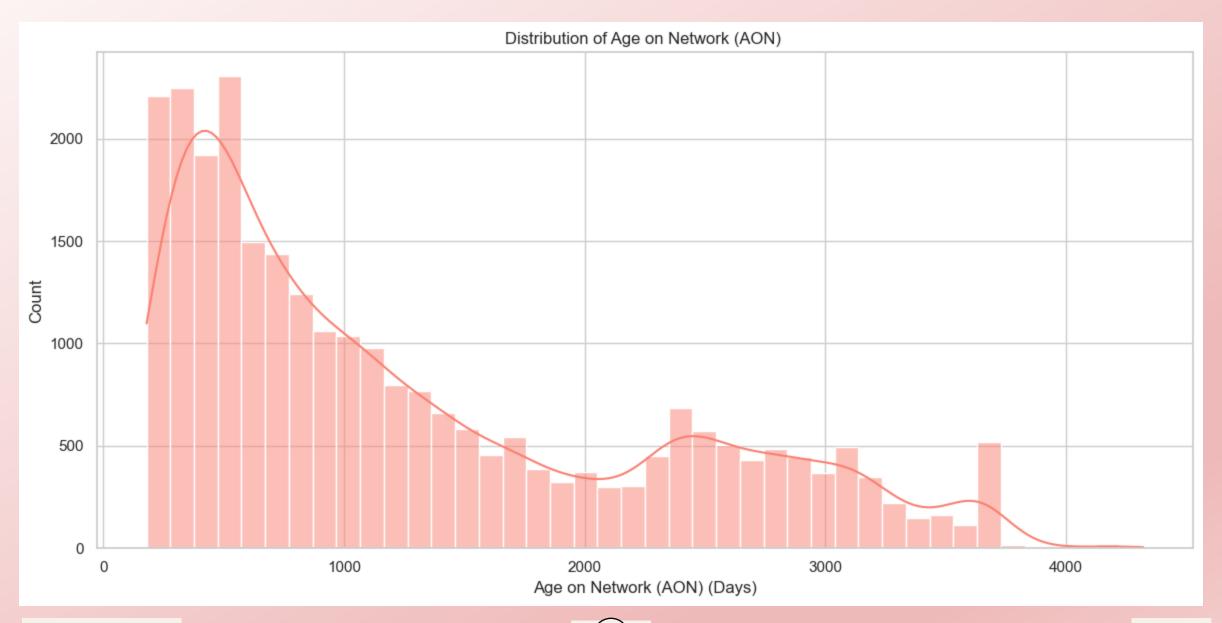


TELECOM CHURN

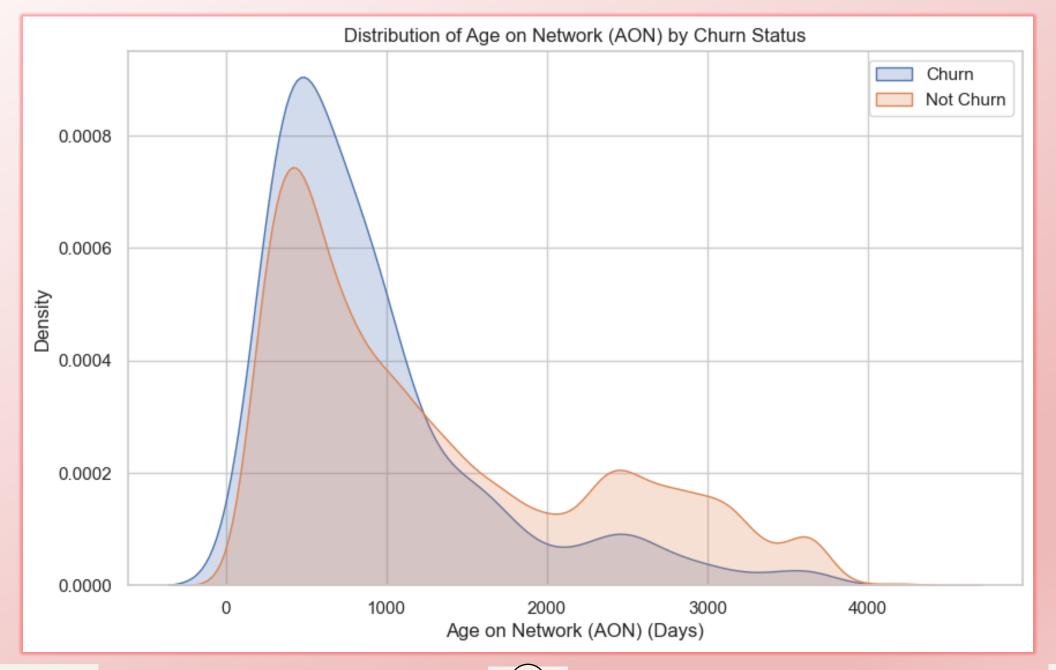
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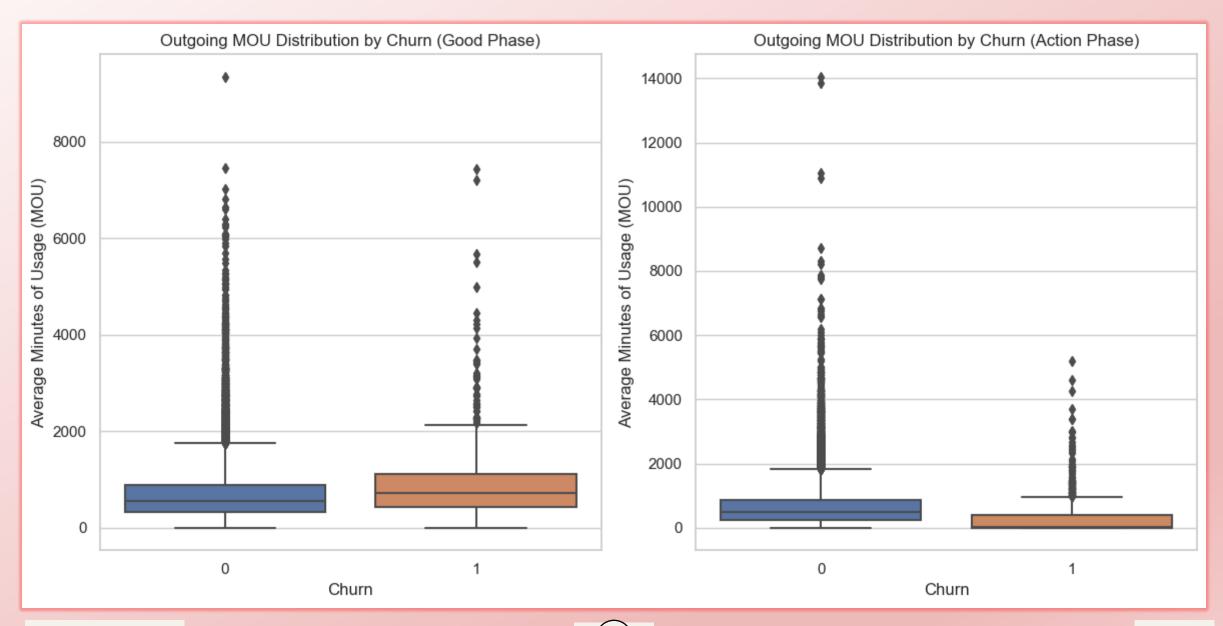


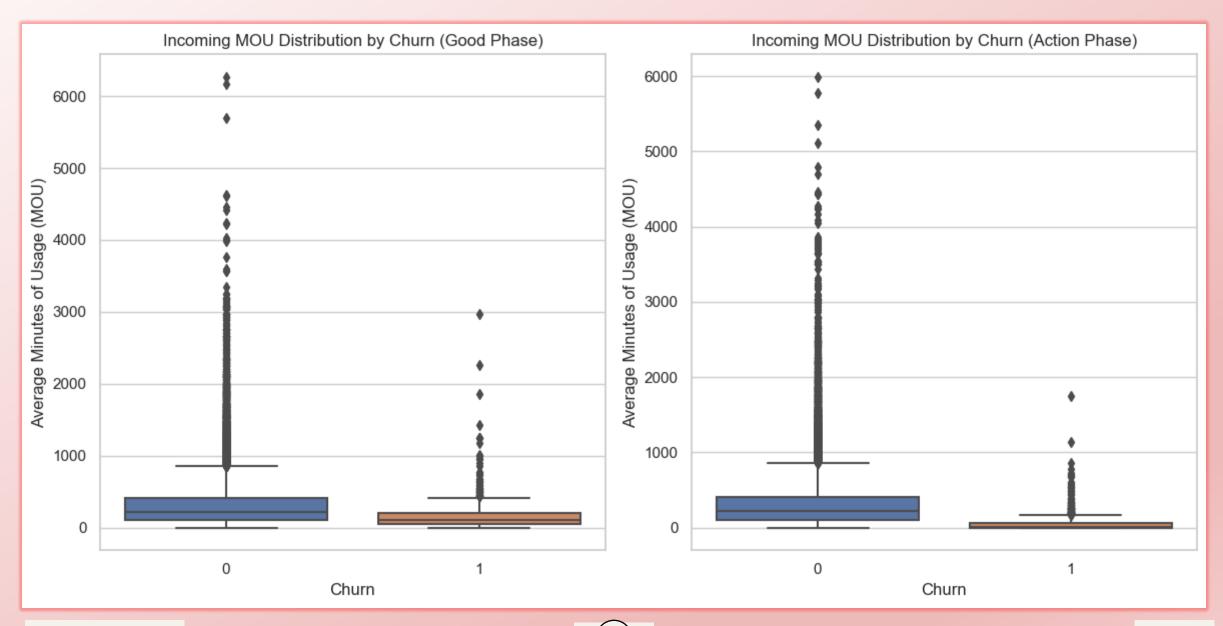


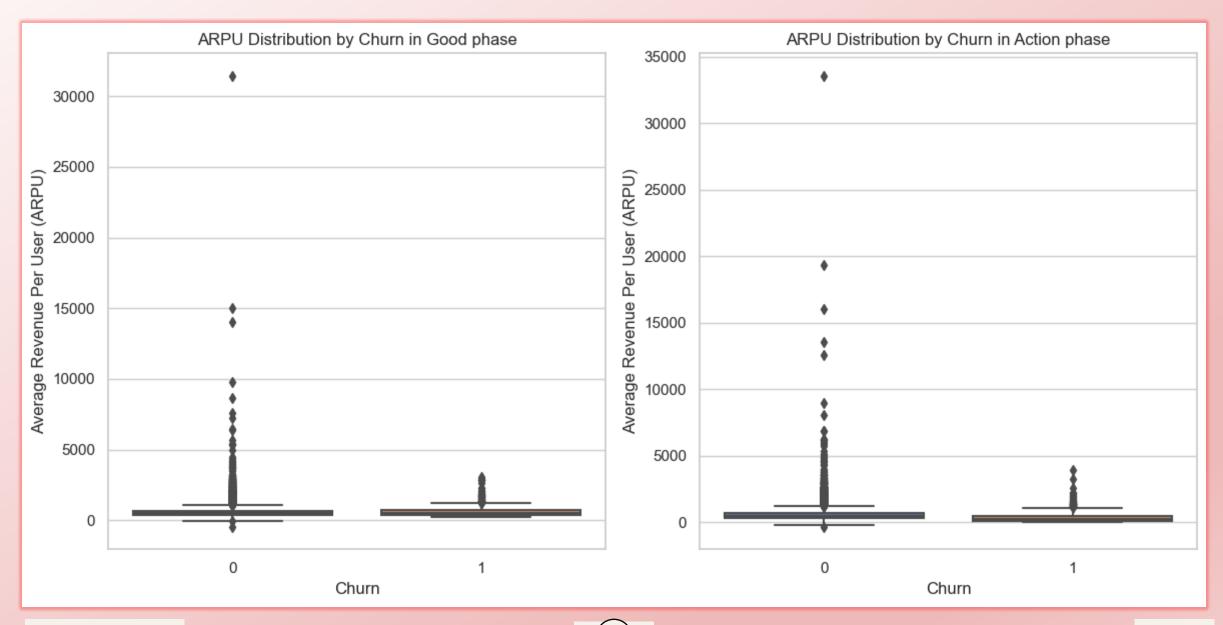


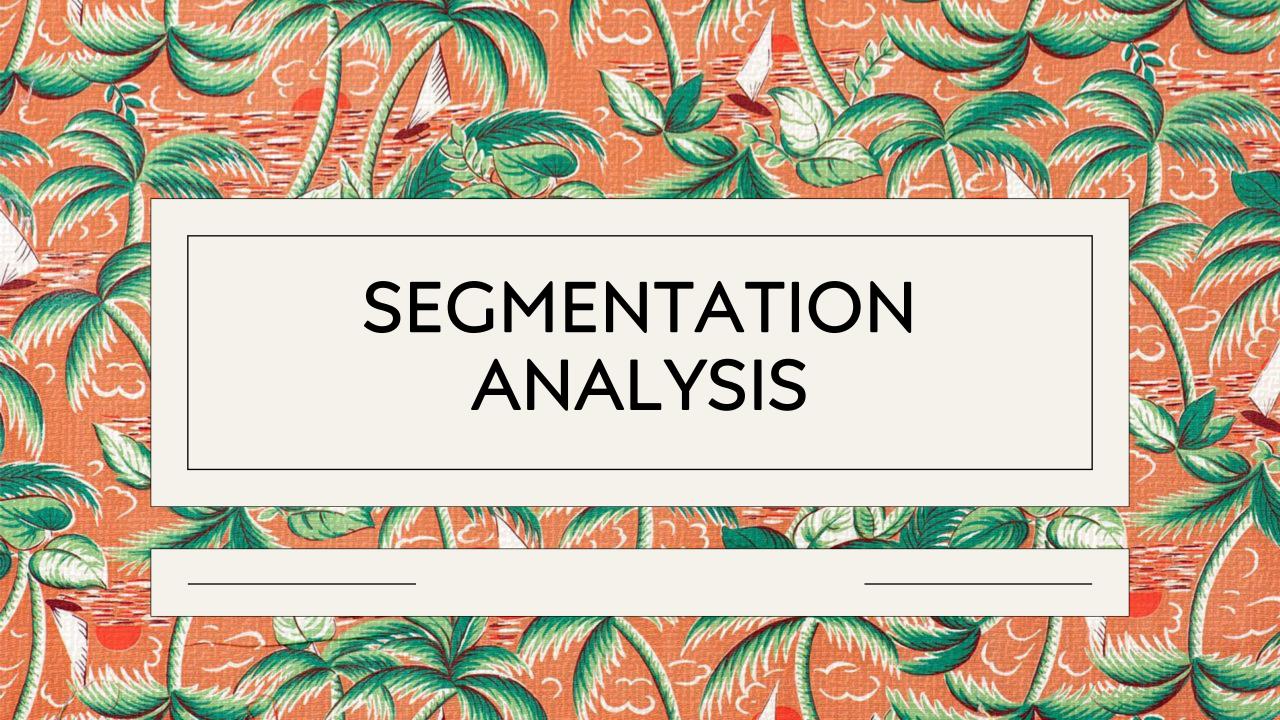


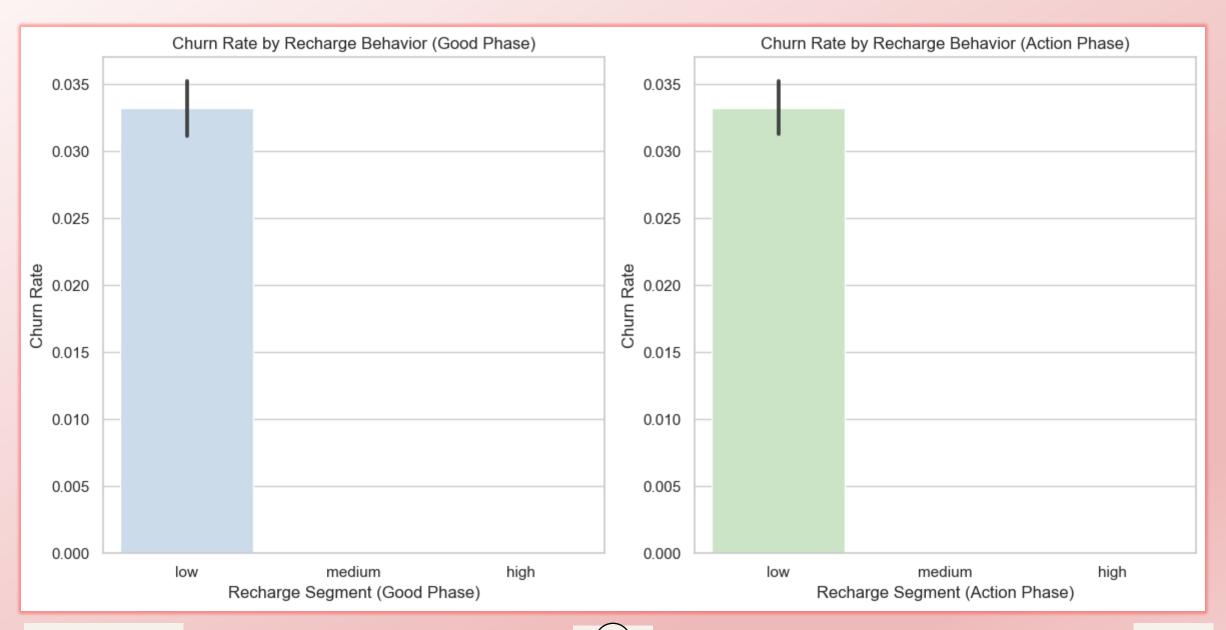


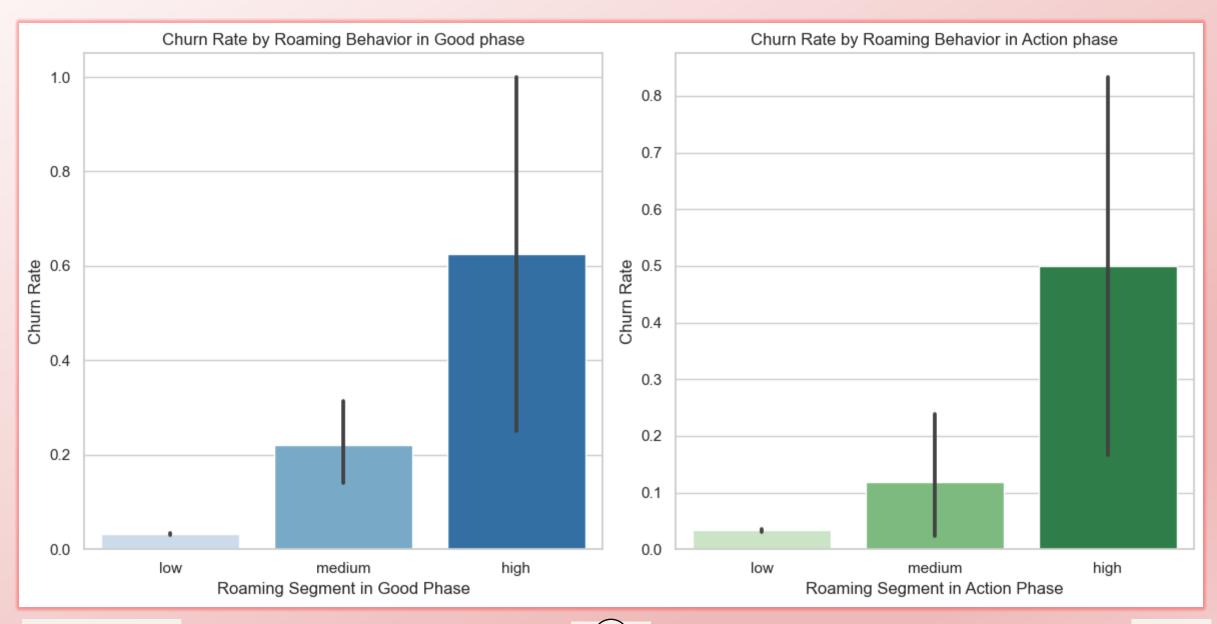


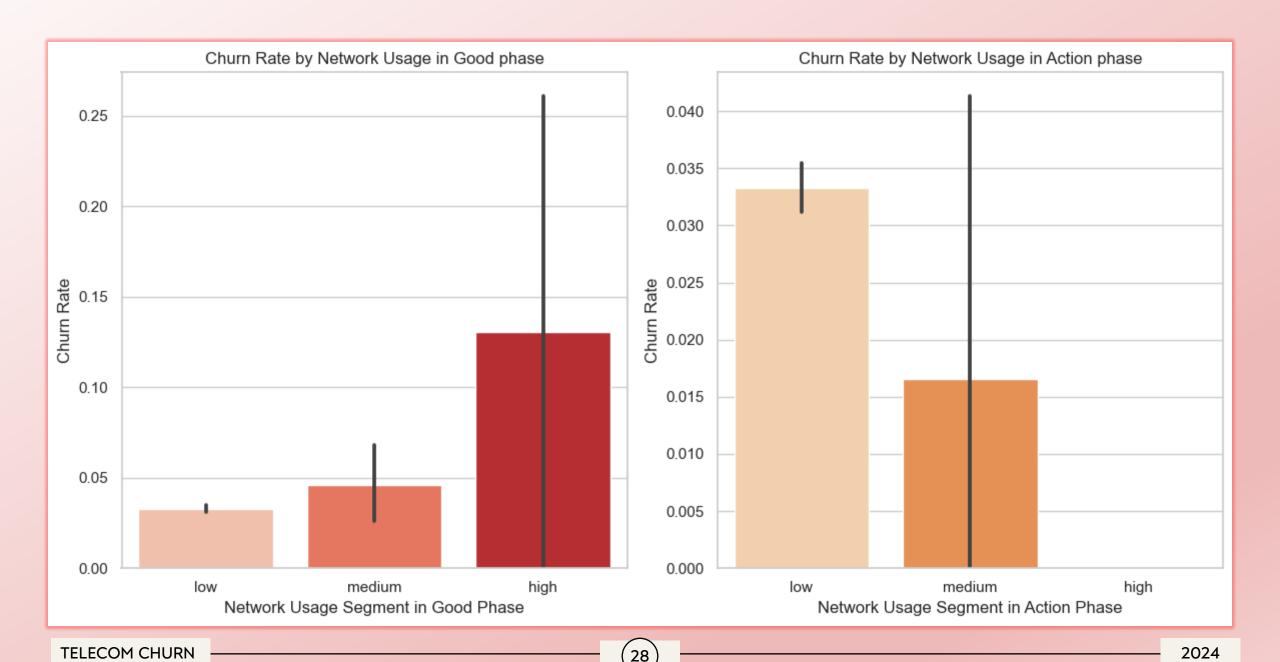












CHECKED HIGHLY CORRELATED VARIABLES

isd_og_mou_8
isd_og_mou_7
total_rech_amt_8
isd_og_mou_8
total_rech_amt_6
total_rech_amt_7
total_ic_mou_6
total_ic_mou_8
total_ic_mou_7
std_og_t2t_mou_8
std_og_t2m_mou_7
std_og_t2m_mou_8
std_og_t2t_mou_6

These variables were deleted as they were highly correlated.

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MODEL BUILDING

Cleaned dataset consists of 26495 rows and 112 columns.

Performed feature scaling on the dataset. Handled class imbalance using SMOTE

Conducted train-test split with a ratio of 80% for training data and 20% for testing data.

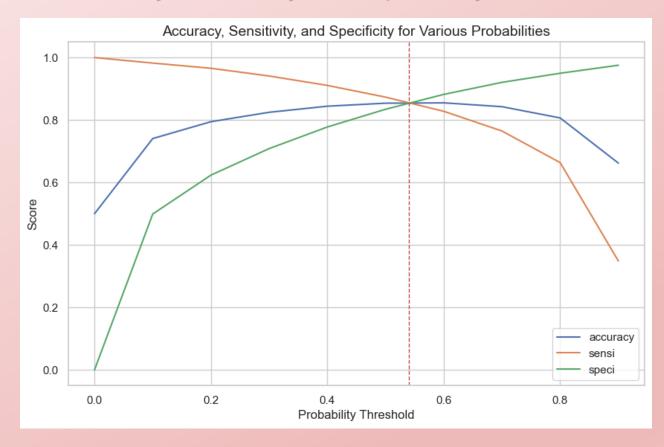
Utilized Logistic Regression model for prediction. Employed Recursive Feature Elimination (RFE) technique with 20 variables as output for feature selection.

Finalized model iteratively, removing features with p-values greater than 0.05 and Variance Inflation Factor (VIF) greater than 5 for Testing data.

ROC CURVE

Receiver operating characteristic example 1.0 0.8 True Positive Rate 0.2 ROC curve (area = 0.92) 0.0 0.0 0.2 0.4 0.6 0.8 1.0 False Positive Rate or [1 - True Negative Rate]

Accuracy, Sensitivity, And Specificity Curves



- With the current cut off as seen in the graph as **0.54**, the **accuracy** is **85.56**%, **sensitivity** is **85.59**% and **specificity** is **85.53**%
- > The precision is 85.54%, Recall is 85.59% and F1 score is 85.56%.

PREDICTIONS ON THE TEST DATA

Performed scaling on the required variables as part of preprocessing.

Trained the test set using the final model derived from the feature selection process.

Utilized the trained model to make predictions on the test data.

Employed a cutoff value of 0.54 for classification.

Achieved an Accuracy of 86.36% on the test data.

Sensitivity, representing the true positive rate, stood at 85.64%.

Specificity, representing the true negative rate, was measured at **86.38%**.

RECOMMENDATIONS

- ➤ Improve Network Coverage: Invest in improving network coverage and quality, especially for local and roaming calls, as these factors significantly influence churn.
- ➤ Roaming Services Enhancement: Enhance roaming services to provide a seamless experience for customers traveling outside their home network area.
- ➤ Recharge Offers: Design attractive recharge offers and schemes, focusing on the last day recharge amounts and the total number of recharges, to retain customers and incentivize usage.
- ➤ Service Scheme Customization: Offer personalized service schemes with validity equivalent to a month for both 2G and 3G networks, targeting specific customer segments based on usage patterns.
- ➤ Data Usage Optimization: Provide value-added services and data usage optimization tips to customers, considering factors like mobile internet usage volume for 2G network in August.
- ➤ Customer Engagement: Implement proactive customer engagement strategies, such as loyalty programs and personalized communication, to address customer needs and concerns effectively.

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