TELECOM CHURN CASE STUDY

Author: Aesha Agrawal

DSC58 Batch

Overview

The telecom industry is characterized by fierce competition and high customer churn rates, with annual rates ranging from 15-25%. Given the substantial cost difference between acquiring new customers and retaining existing ones, reducing churn has become a top priority for telecom companies. Retaining high-profit customers is particularly crucial for incumbent operators.

In this project, we analyze customer-level data from a leading telecom firm to build predictive models that identify customers at high risk of churn.

Business Objective

The primary goal is to predict churn in the ninth month using data from the first three months. By accurately identifying customers likely to churn, the telecom company can proactively take retention measures such as offering special plans or improving service quality to retain these customers.

Another objective is to identify key indicators or factors that contribute to churn. By understanding these factors, the company can gain valuable insights into customer behavior and preferences, enabling them to tailor their retention strategies more effectively.

Overall, the project aims to help the telecom company reduce churn rates, improve customer retention, and enhance overall business performance.

Building the Model

Step 1

Identify customers who have recharged with an amount greater than or equal to the 70th percentile of the average recharge amount in the first two months.

Step 2

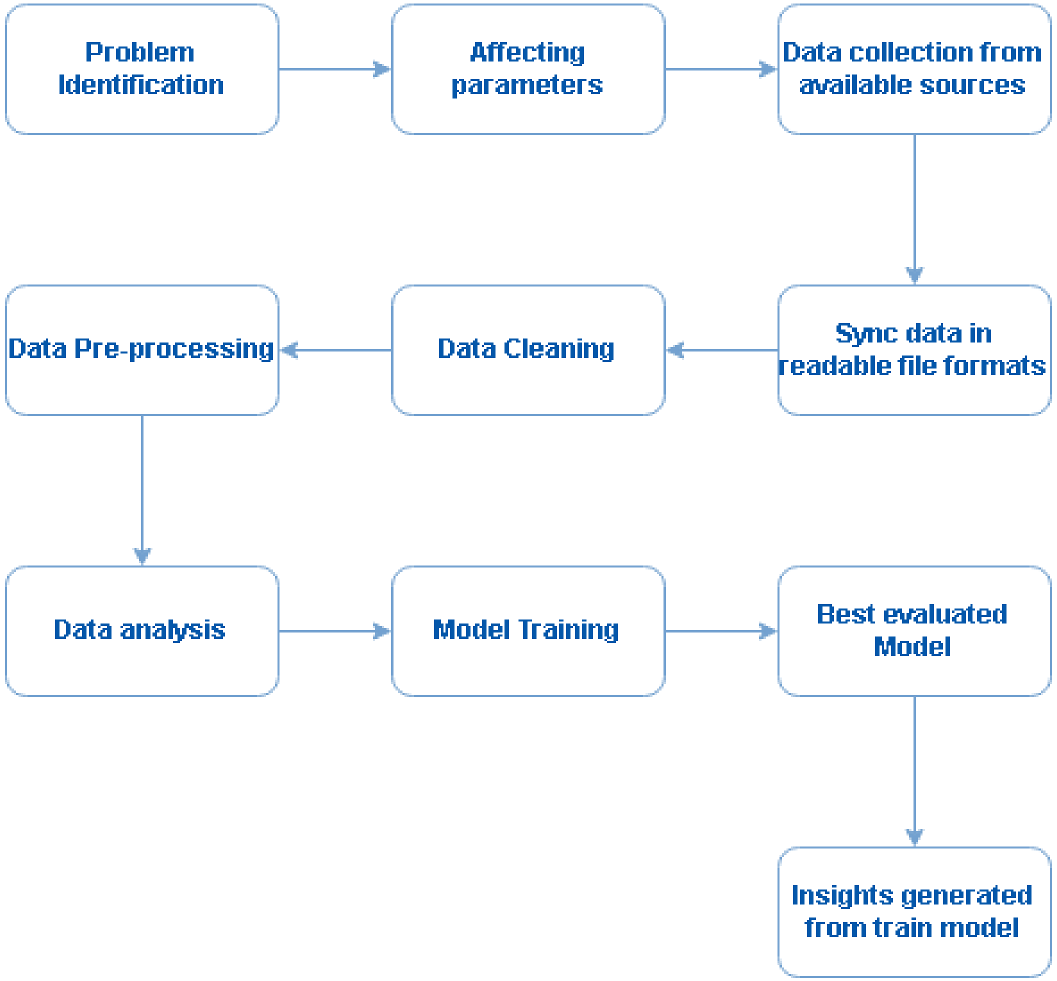
Build predictive models to forecast churn among high-value customers. Use techniques to handle class imbalance and identify important predictor attributes.

Visualize and interpret the key predictors to recommend strategies for reducing churn.

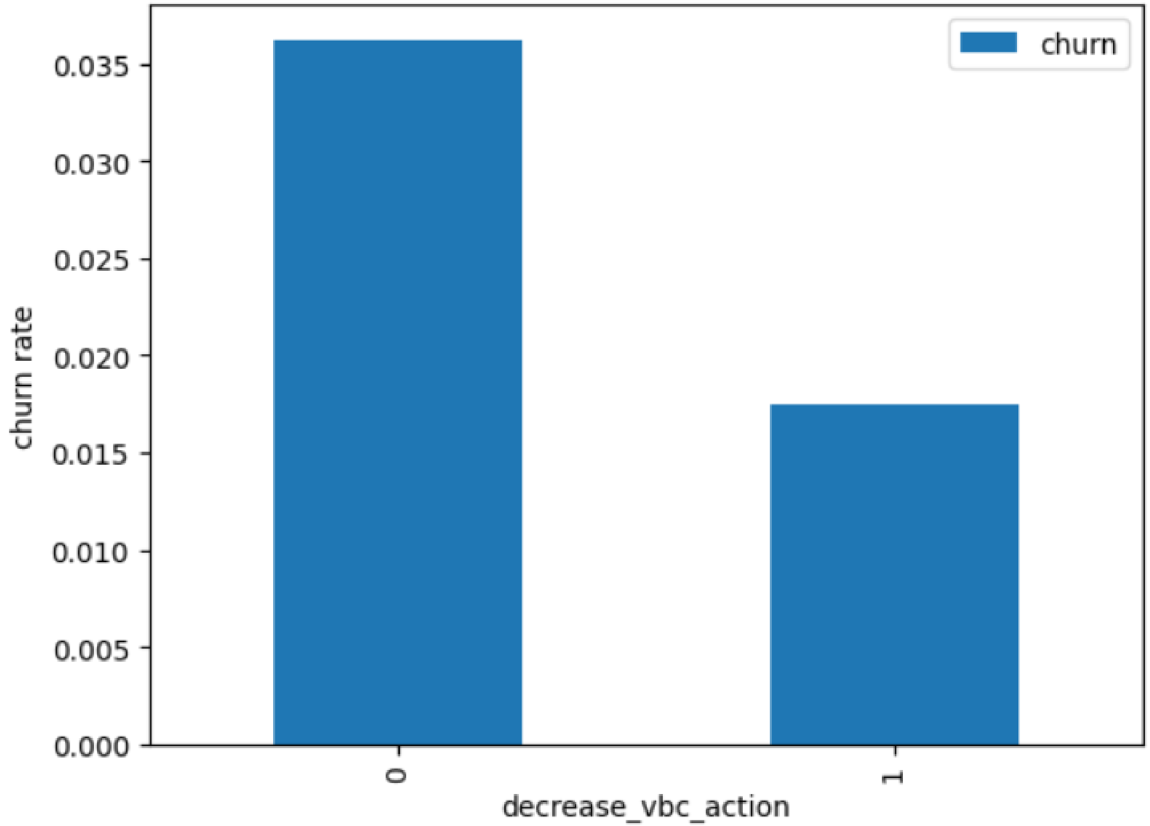
Step 3

Tag churned customers based on their activity in the fourth month, specifically looking at call and internet usage. Remove attributes corresponding to the churn phase to focus on relevant data.

Project WorkFlow

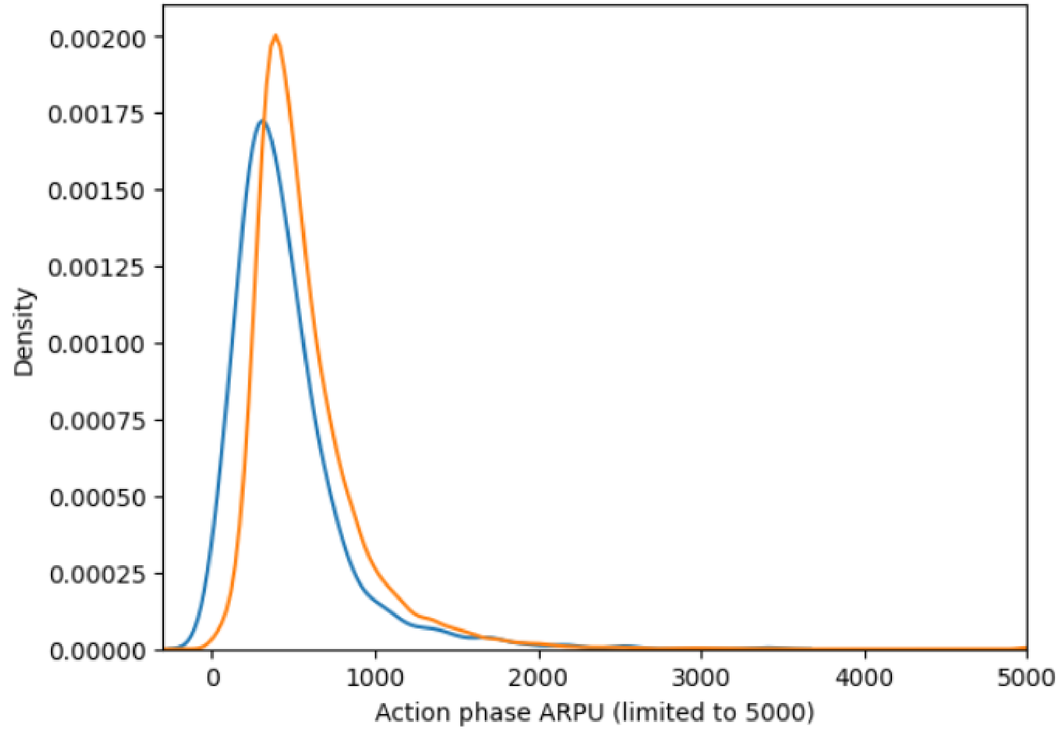


Churn rate on the basis whether the customer decreased her/his volume based cost in action month



Customers who experience an increase in volume-based costs during the action phase are more likely to churn. This suggests that customers tend to recharge less frequently during this phase, possibly indicating dissatisfaction or a readiness to switch to another service provider.

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

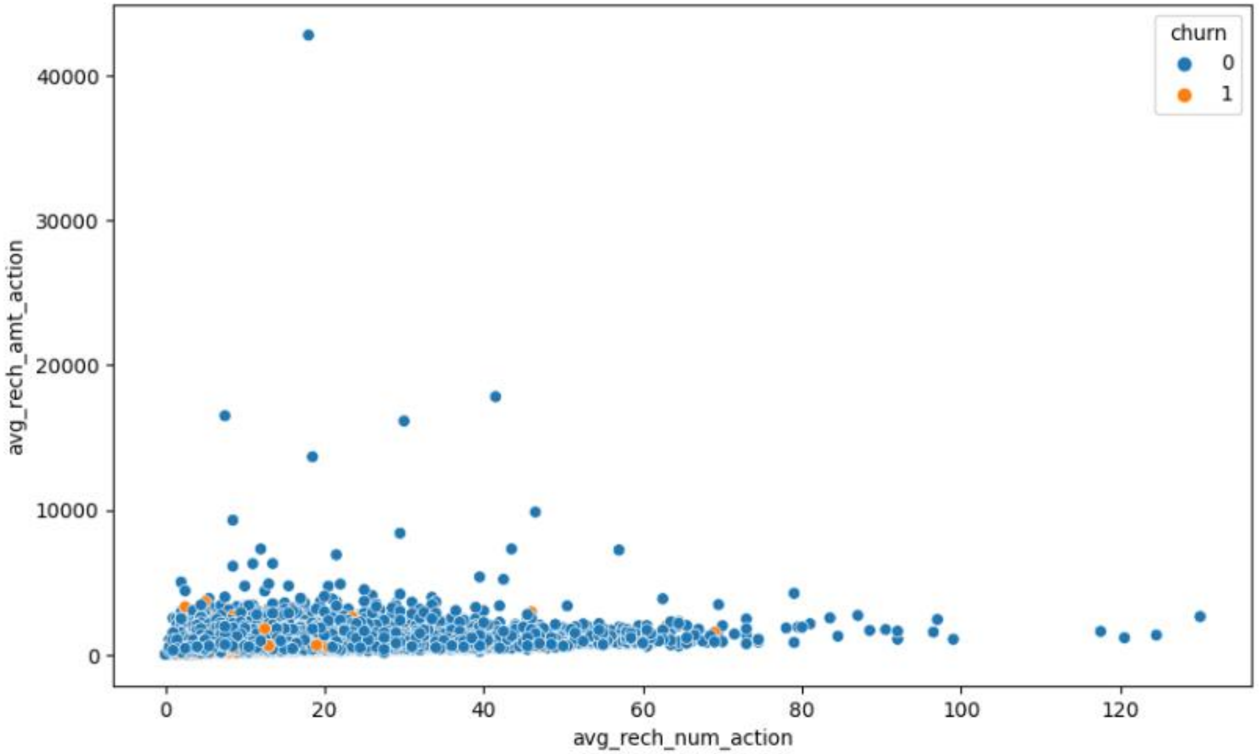


The analysis shows that for churned customers, the Average Revenue Per User (ARPU) is concentrated between 0 and 900, with fewer customers having higher ARPU.

This suggests that customers with lower ARPU are more likely to churn.

In contrast, for non-churned customers, the ARPU is mostly concentrated between 0 and 1000.

Analysis of recharge amount and number of recharge in action month



From the graph below the analysis reveals a clear pattern: the number of recharges and the total recharge amount are positively correlated. This means that customers who recharge more frequently also tend to recharge higher amounts.

MODEL SUMMARY

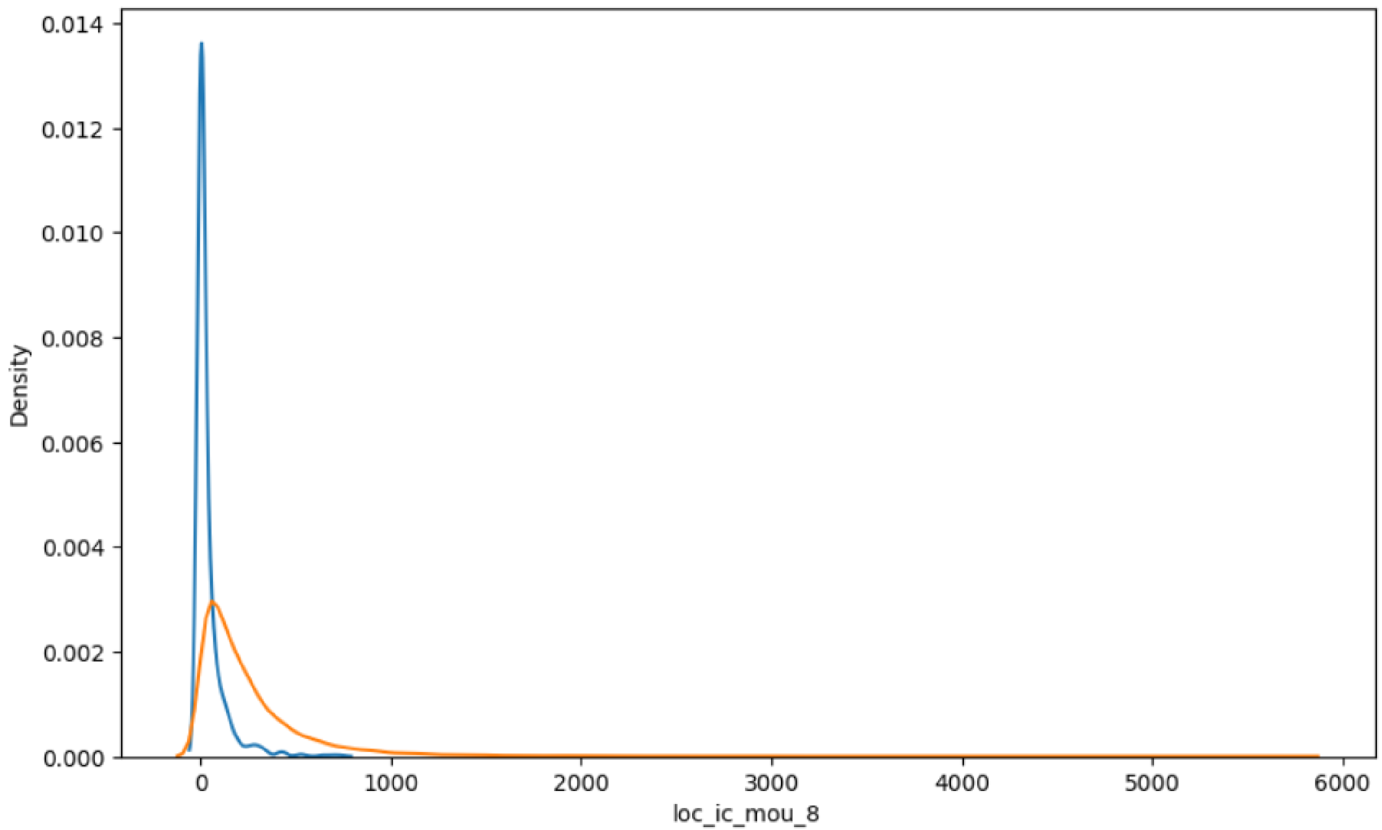
- **Train Set**
  1. Accuracy = 0.90
  2. Sensitivity = 0.91
  3. Specificity = 0.89

- **Test Set**
  1. Accuracy = 0.86
  2. Sensitivity = 0.64
  3. Specificity = 0.87

The model performs well on the training set, with high accuracy, sensitivity, and specificity. We can see from the model performance that the Sensitivity has been decreased while evaluating the model on the test set. However, the accuracy and specificity is quite good in the test set.

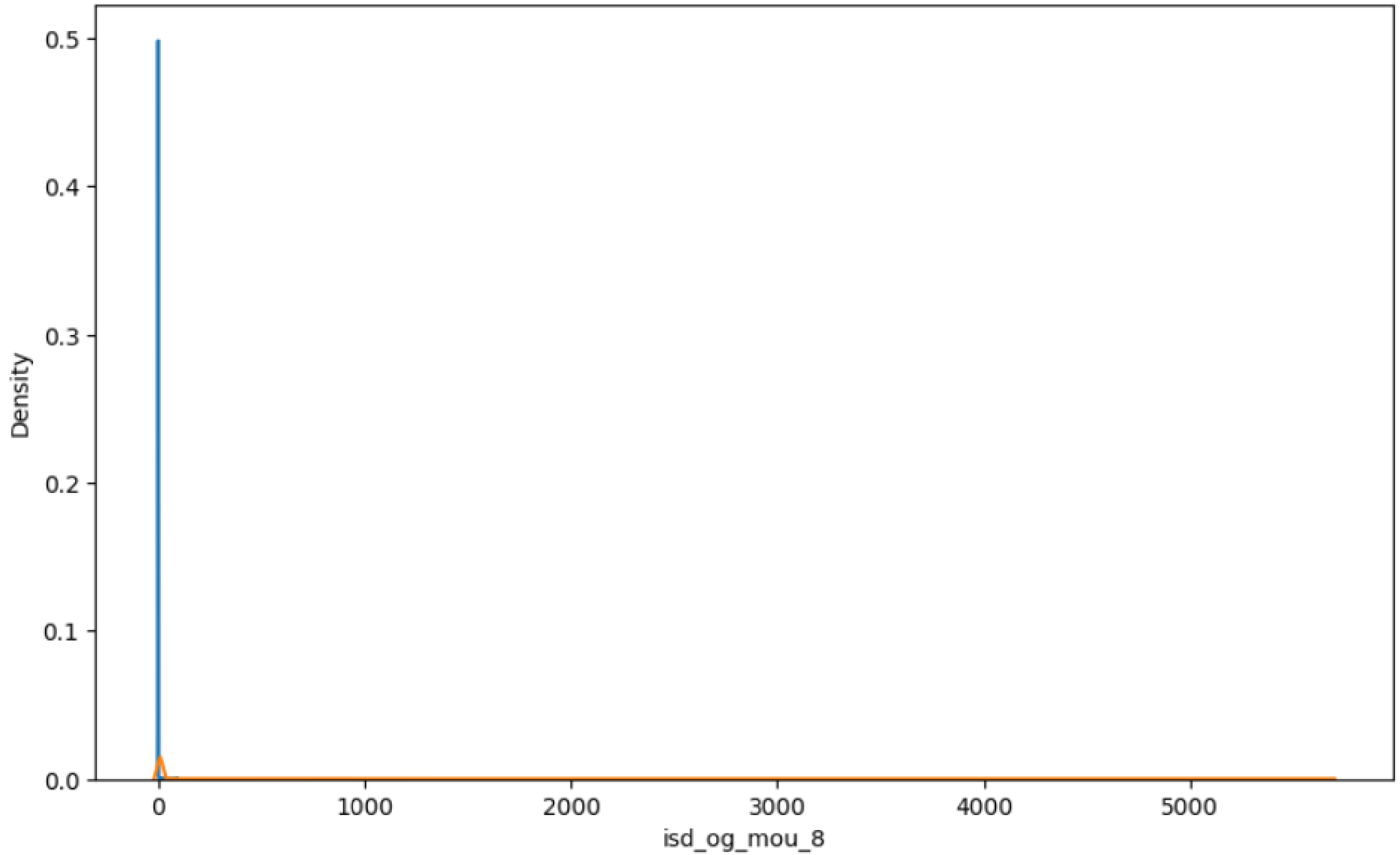
PLOTS OF IMPORTANT PREDICTORS FOR CHURN AND NON CHURN CUSTOMERS

Plotting loc_ic_mou_8 predictor for churn and not churn customers



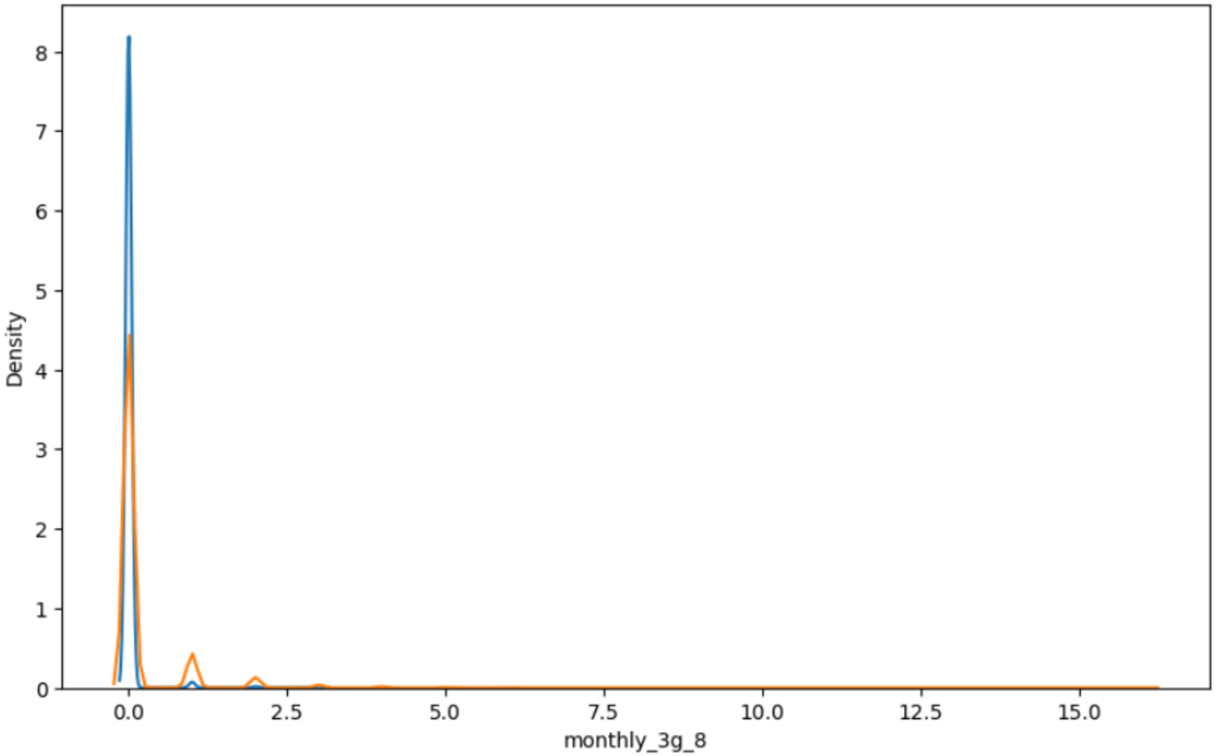
We can see that churned customers tend to have lower minutes of usage in August compared to non-churned customers.

Plotting isd_og_mou_8 predictor for churn and not churn customers



We can see that churned customers show minimal usage of ISD outgoing minutes in August, with a concentration around zero. In contrast, non-churned customers exhibit slightly higher ISD outgoing minutes compared to churned customers.

Plotting monthly_3g_8 predictor for churn and not churn customers



Churned customers have a high concentration of monthly 3G data around 1 for August, while non-churned customers show a more dispersed distribution across various values.
Similarly, we can plot the distribution of each variable with higher coefficients to visualize their impact on churn.

Business Recomendations

Target customers who exhibit the following behaviors in the action phase (August):

1. Decreased usage of incoming local calls and outgoing ISD calls.
2. Reduced outgoing others charge in July and incoming others charge in August.
3. Increased value-based cost in the action phase.
4. Higher monthly 3G recharge in August.
5. Decreased STD incoming minutes of usage for operators T to fixed lines of T in August.
6. Decreased monthly 2G usage in August.
7. Decreased incoming minutes of usage for operators T to fixed lines of T in August.
8. Increased roaming outgoing minutes of usage.

These behaviors suggest a higher likelihood of churn, making these customers potential targets for retention offers or strategies.

THANK YOU!