TELECOM CHURN CASE STUDY

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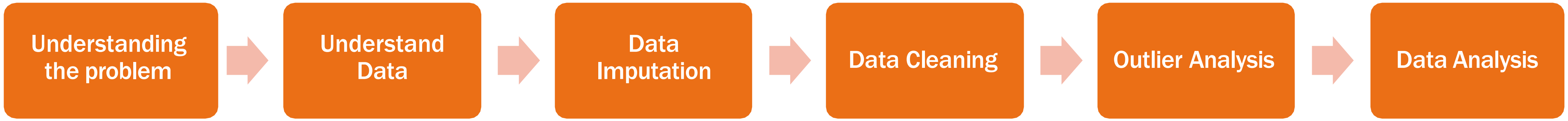
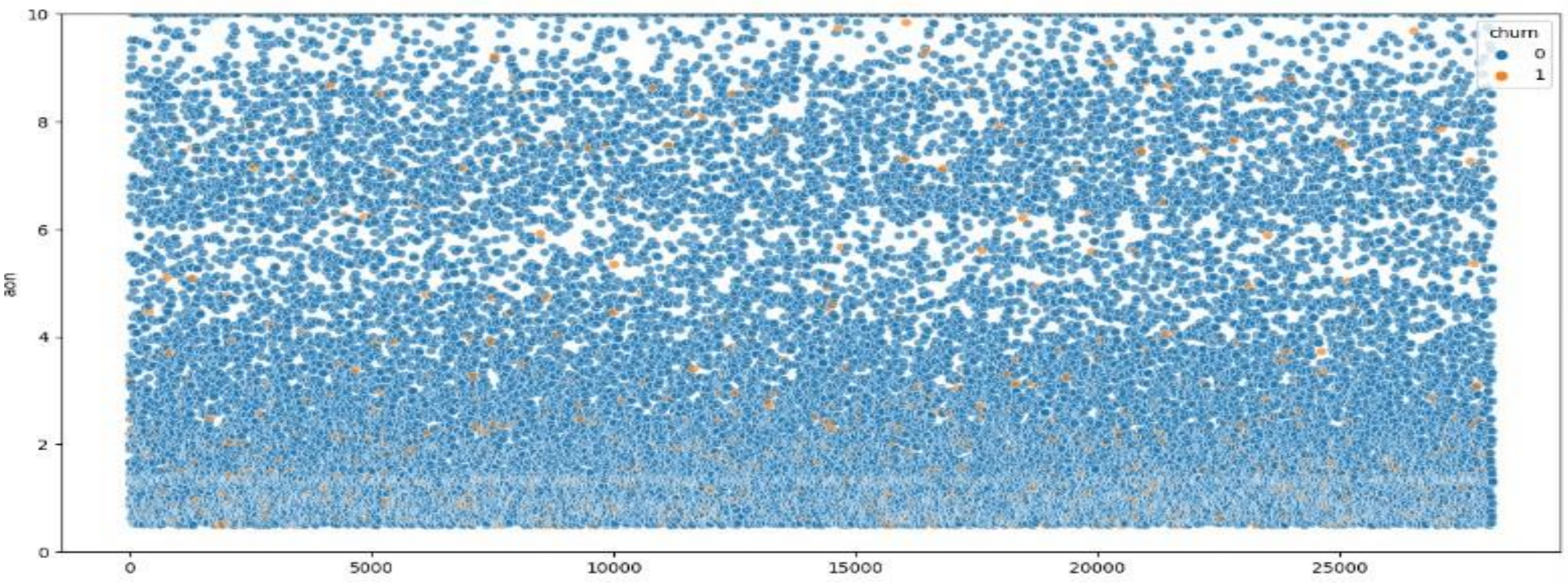
PROBLEM STATEMENT

- 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 a new customer than to retain an existing one, customer retention has now become even more important than customer acquisition. In this project, we defined high-value customers based on a certain metric and predicted churn only on high-value customers.

Analysis View

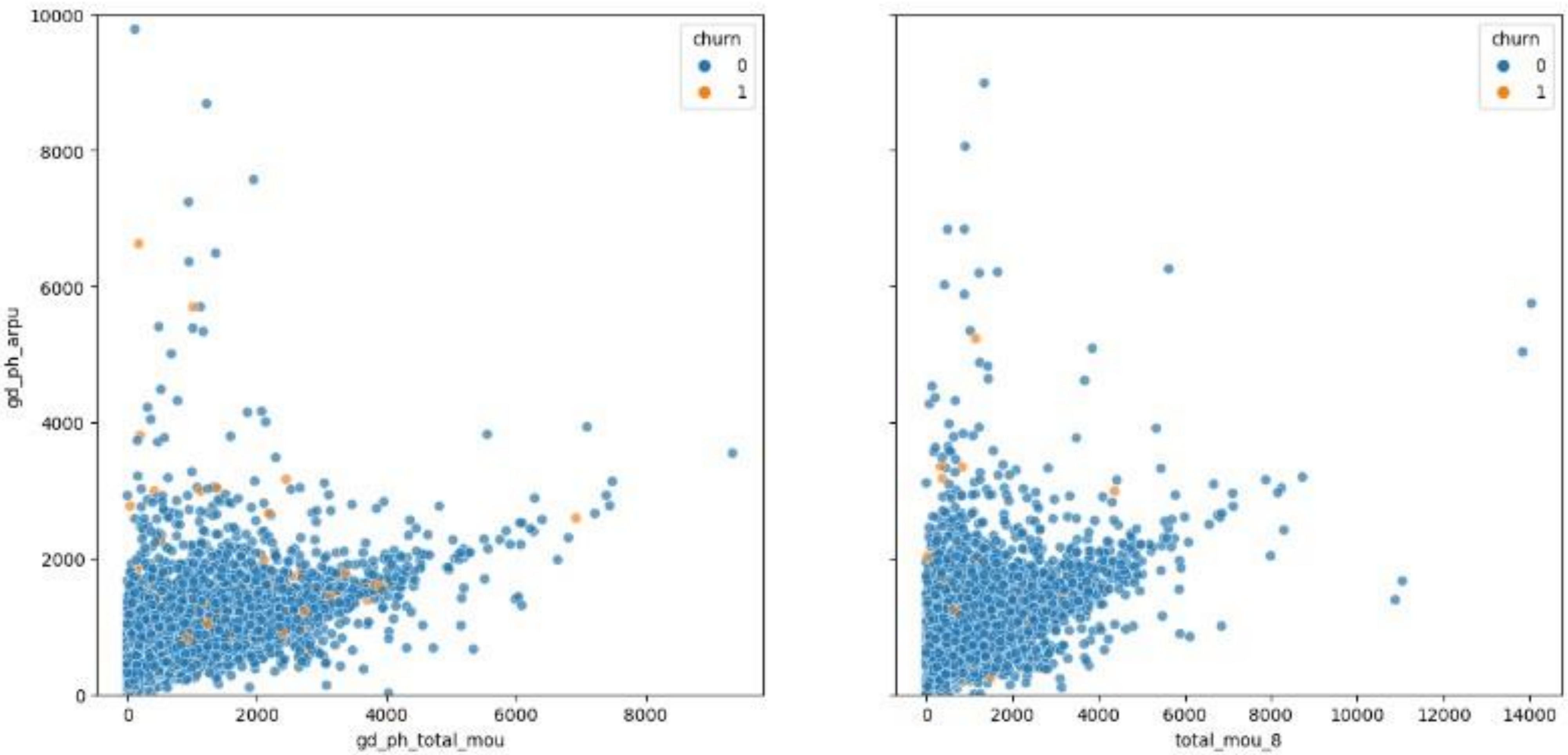


Checking churn based on tenure



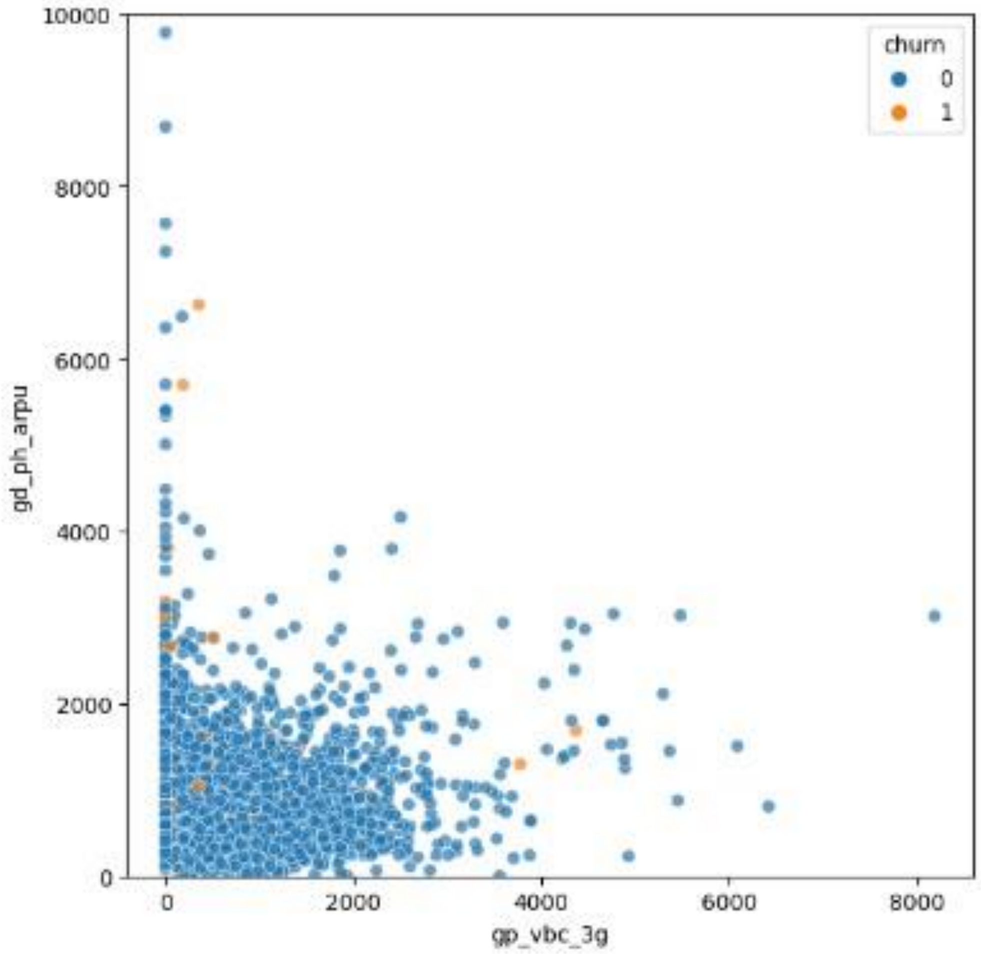
Athough we cannot see a pattern here, one can notice that the most of churners had a tenure less than 4 years.

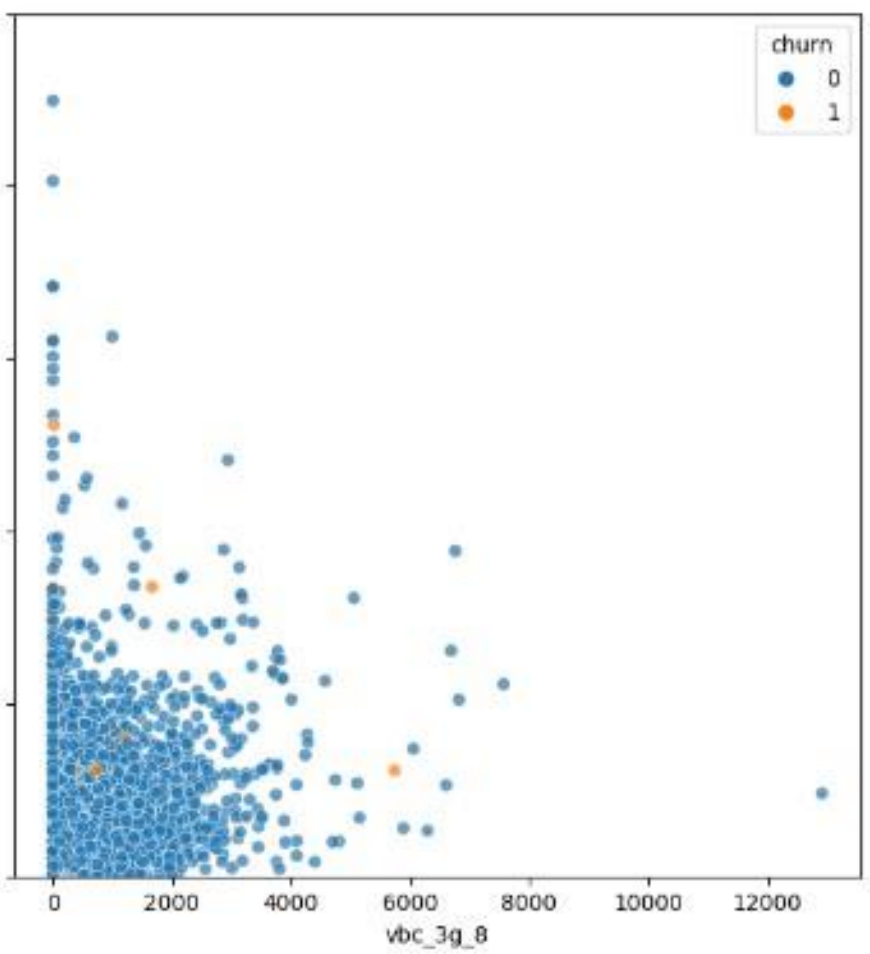
Lets check how the total_mou effects the revenue



It is clear from the plot that MOU have dropped significantly for the churners in the action pahse, thus affecting the revenue generated from them. Also, it should be noted that though the MOU is between 0-2000, the revenue is highest in that region. It informs us that these users had other services that were boosting the revenue.

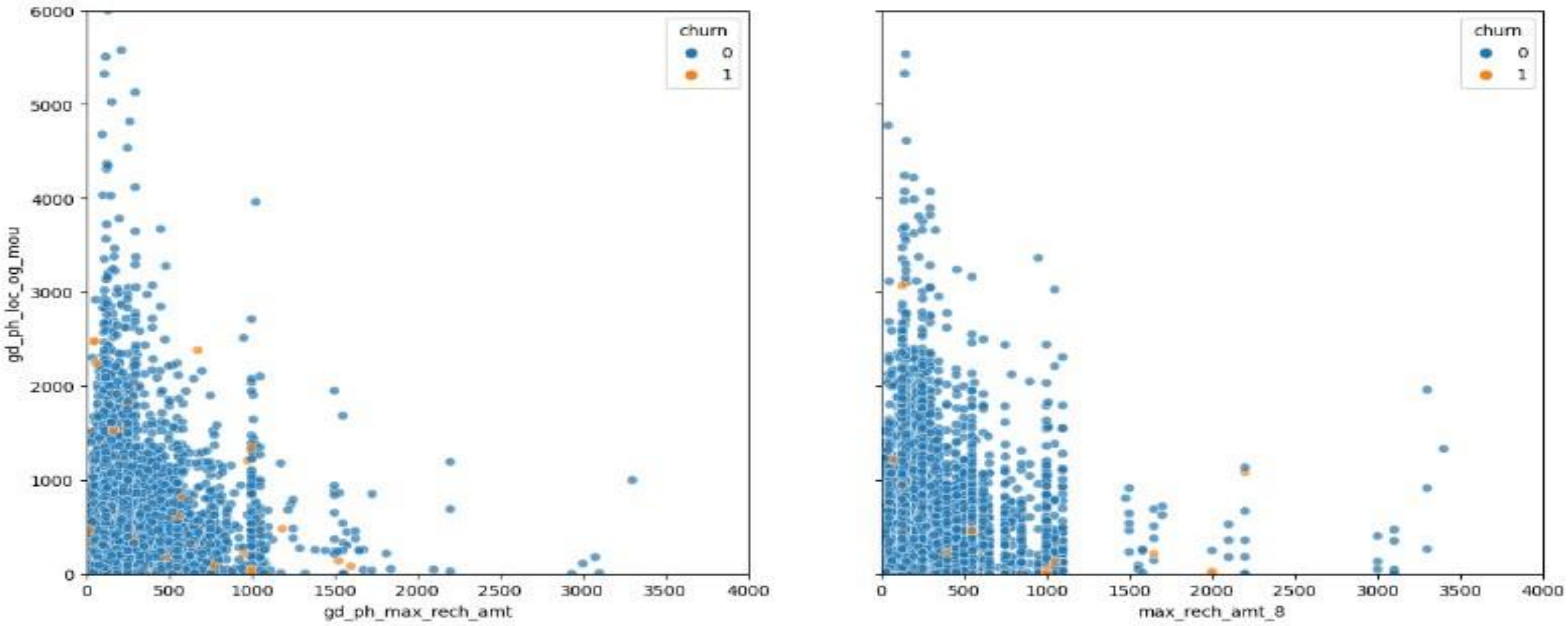
Lets check how the VBC effects the revenue





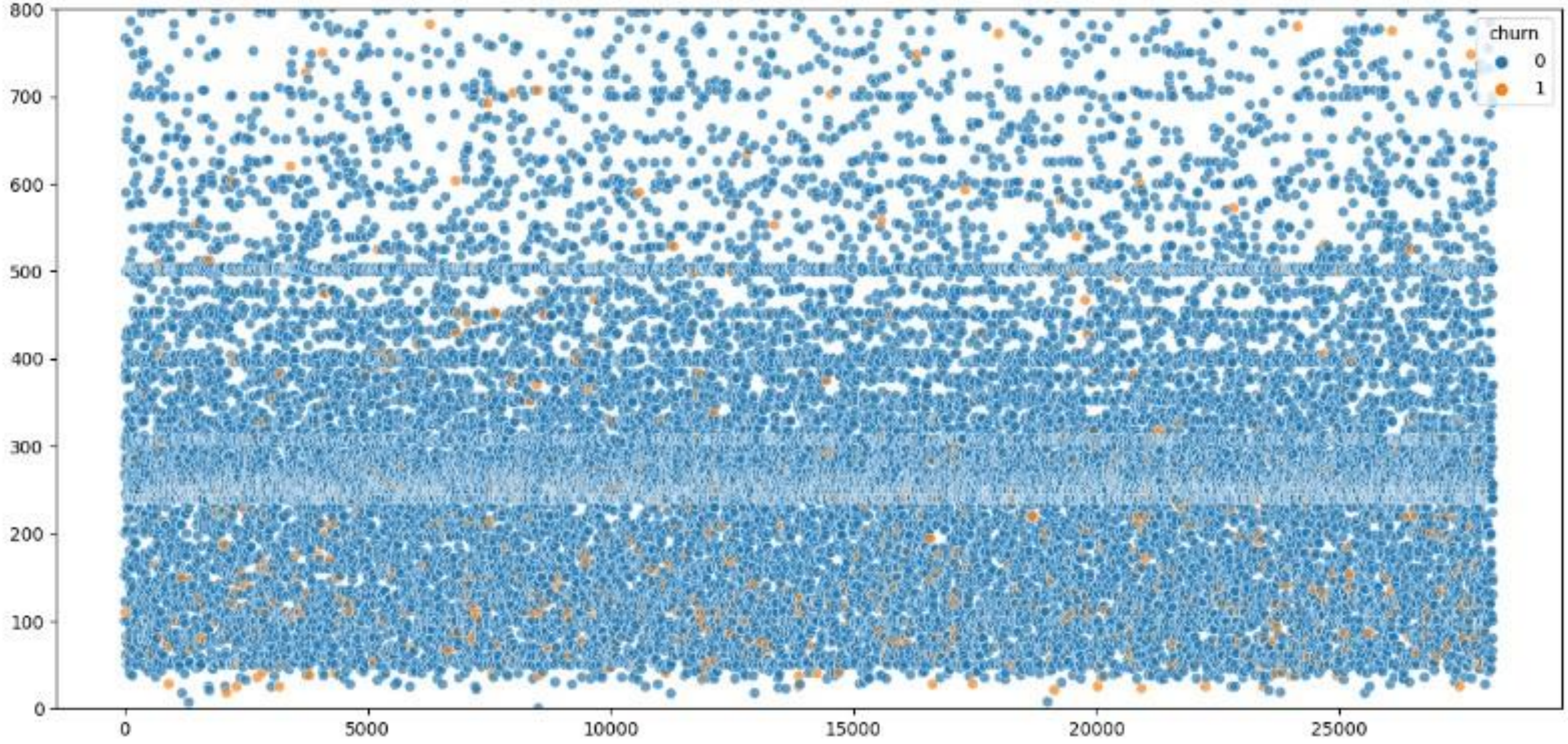
We observe that the users, who were using very less amount of VBC data, were generating high revenue churned. Again we see that the revenue is higher towards the lesser consumption side.

Checking the relation between recharge amount and local outgoing calls



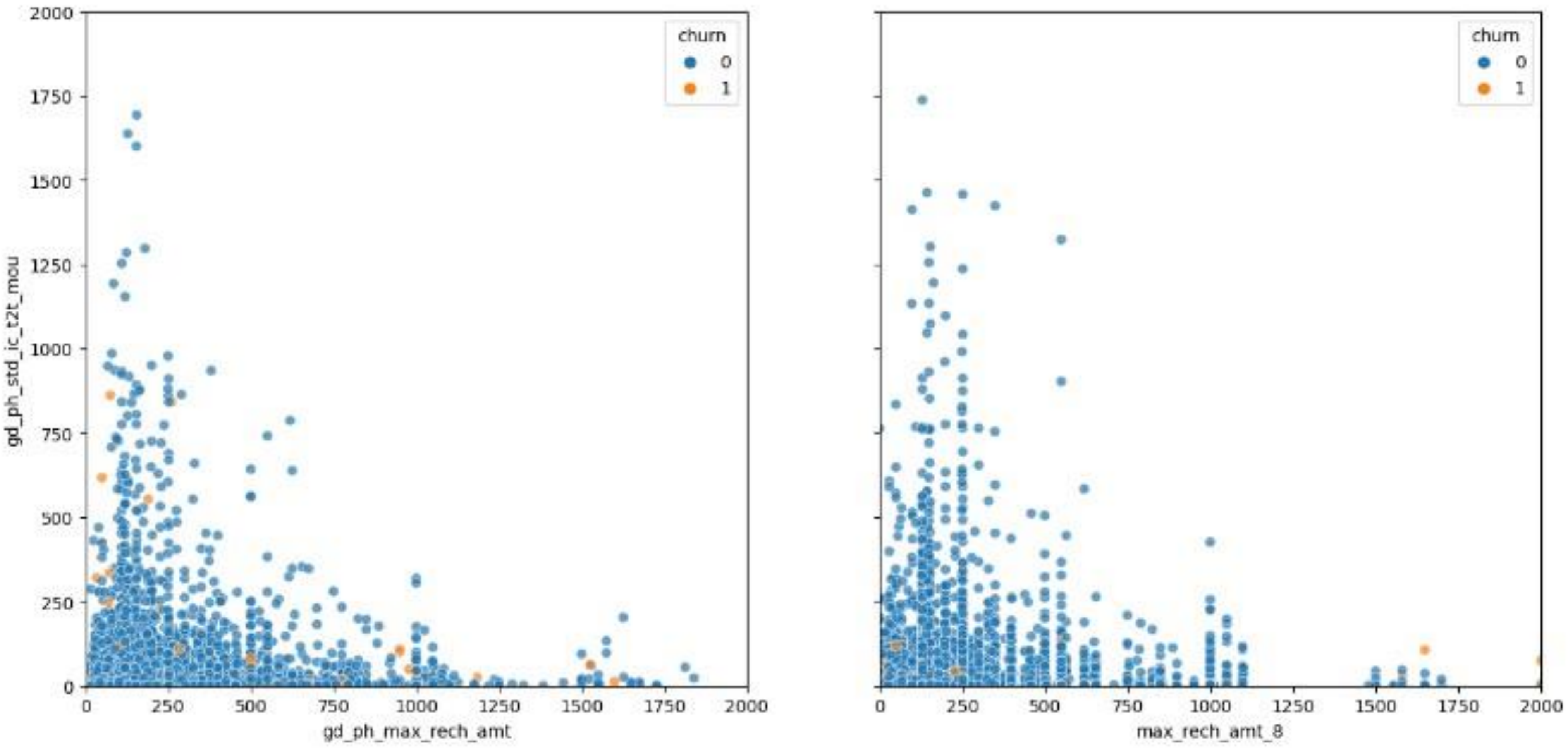
Those users, who were doing high amount recharging, were utilizing the service for local-use less when compared to user who did lesser amount of recharge. People whose max recharge amount, as well as local out going, were very less even in the good phase, churned more.

Check the effect of max recharge amount on churn



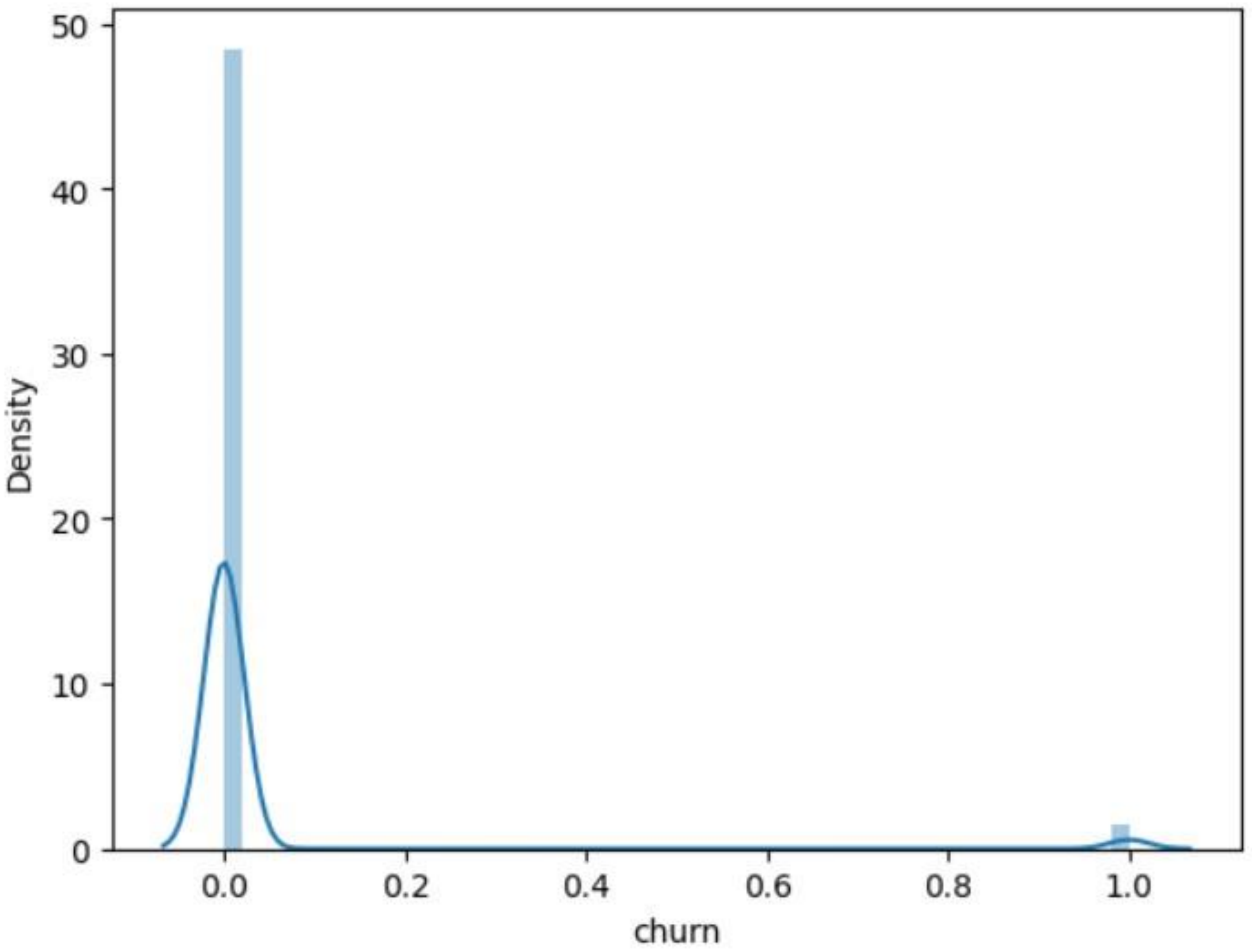
The plot shows that users who had the "max recharge amount" less than 200 churned more.

Incoming from the same service provider vs the recharge amount



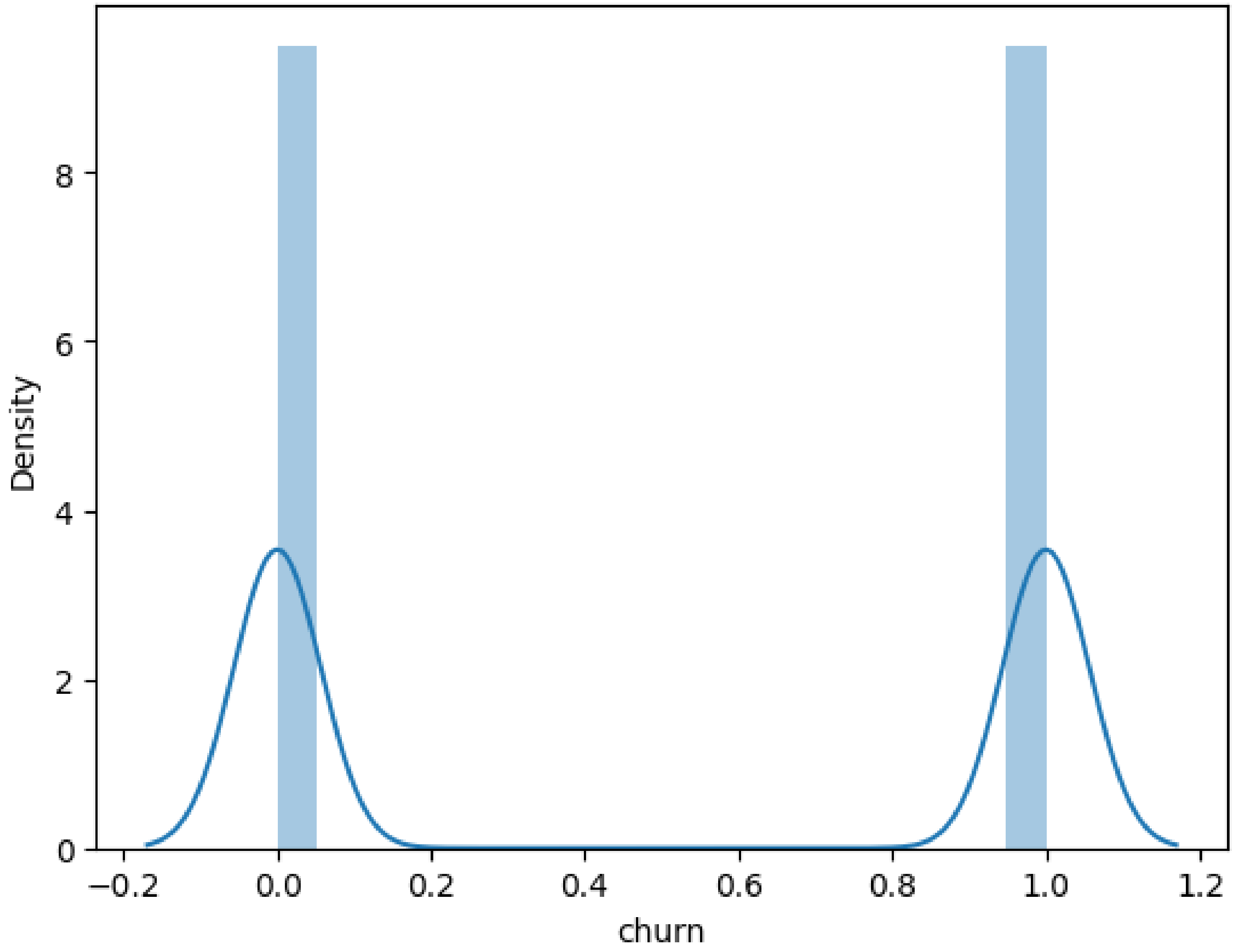
Users with "max recharge amount" on the higher end but have low incoming call mou during the good pahse, churned out more.

Distribution of target variable



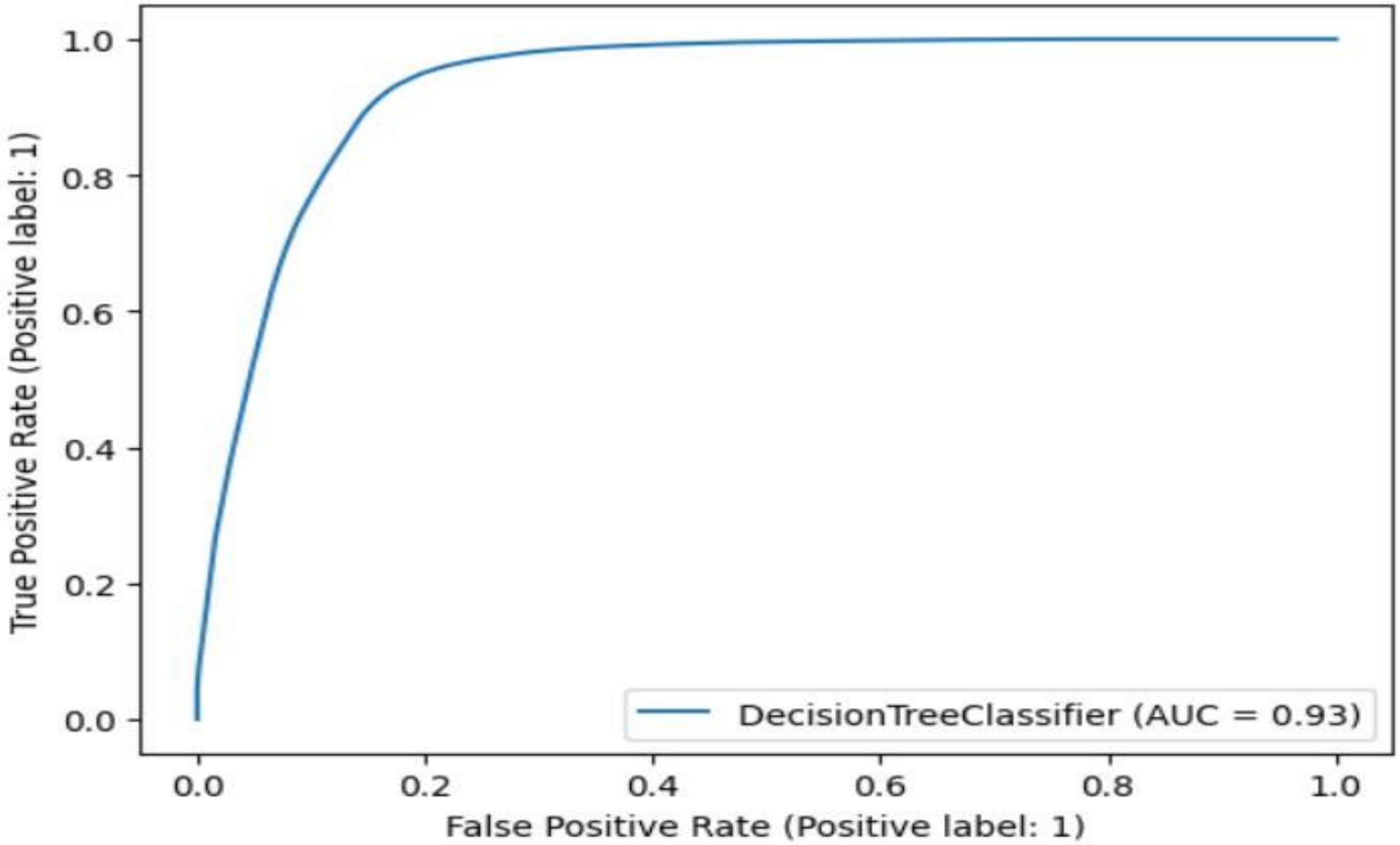
Though the varible is not skewed, it is higly imbalanced, the number of non-churners in the dataset is around 94%. To handle this imbalance, we used SMOTE algorithm.

Distribution of target variable: Handling imbalance

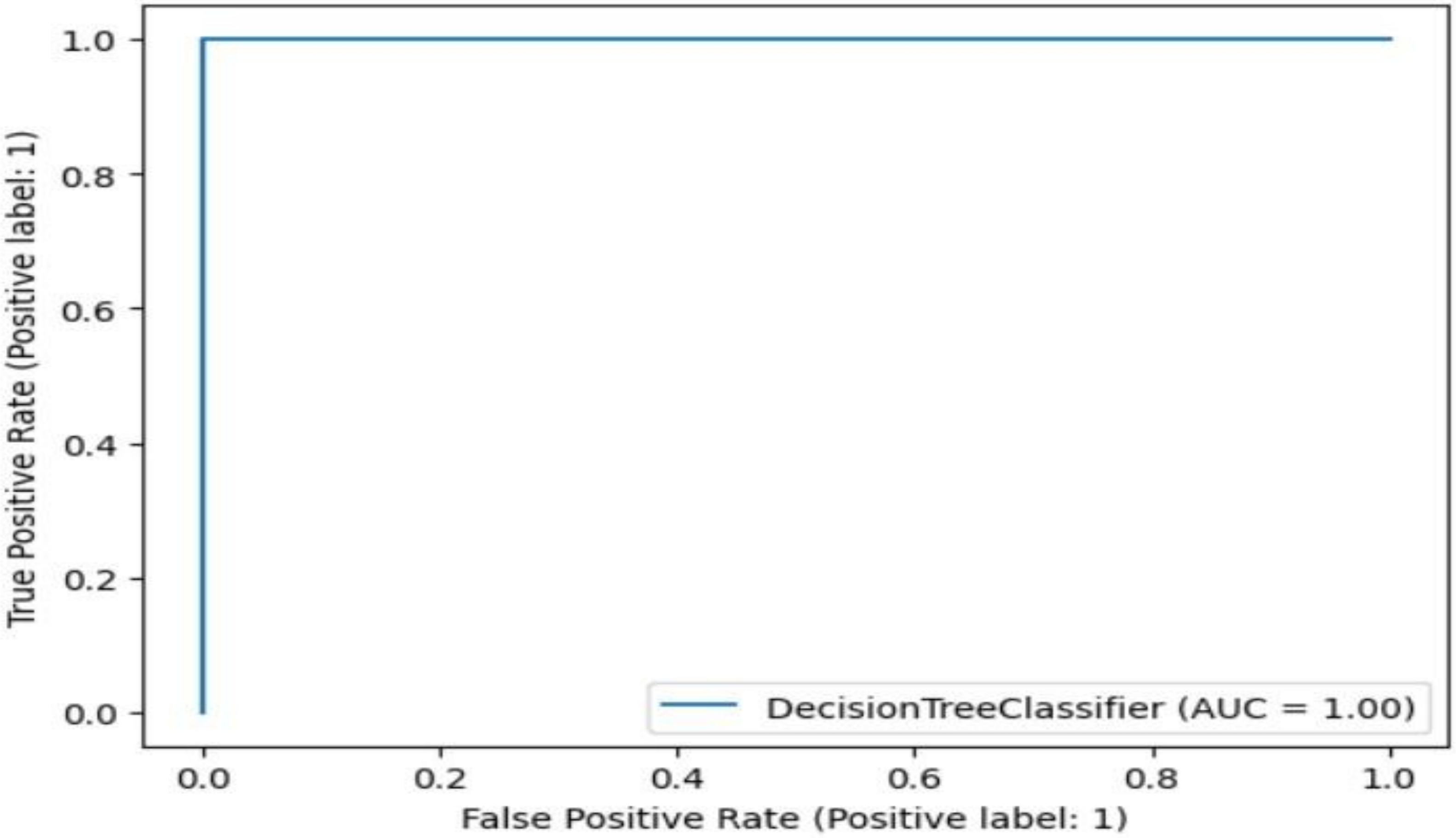


The class is now balanced, and the target variable is not skewed as well.

Decision Tree ROC: Before Hyperparameter Tuning

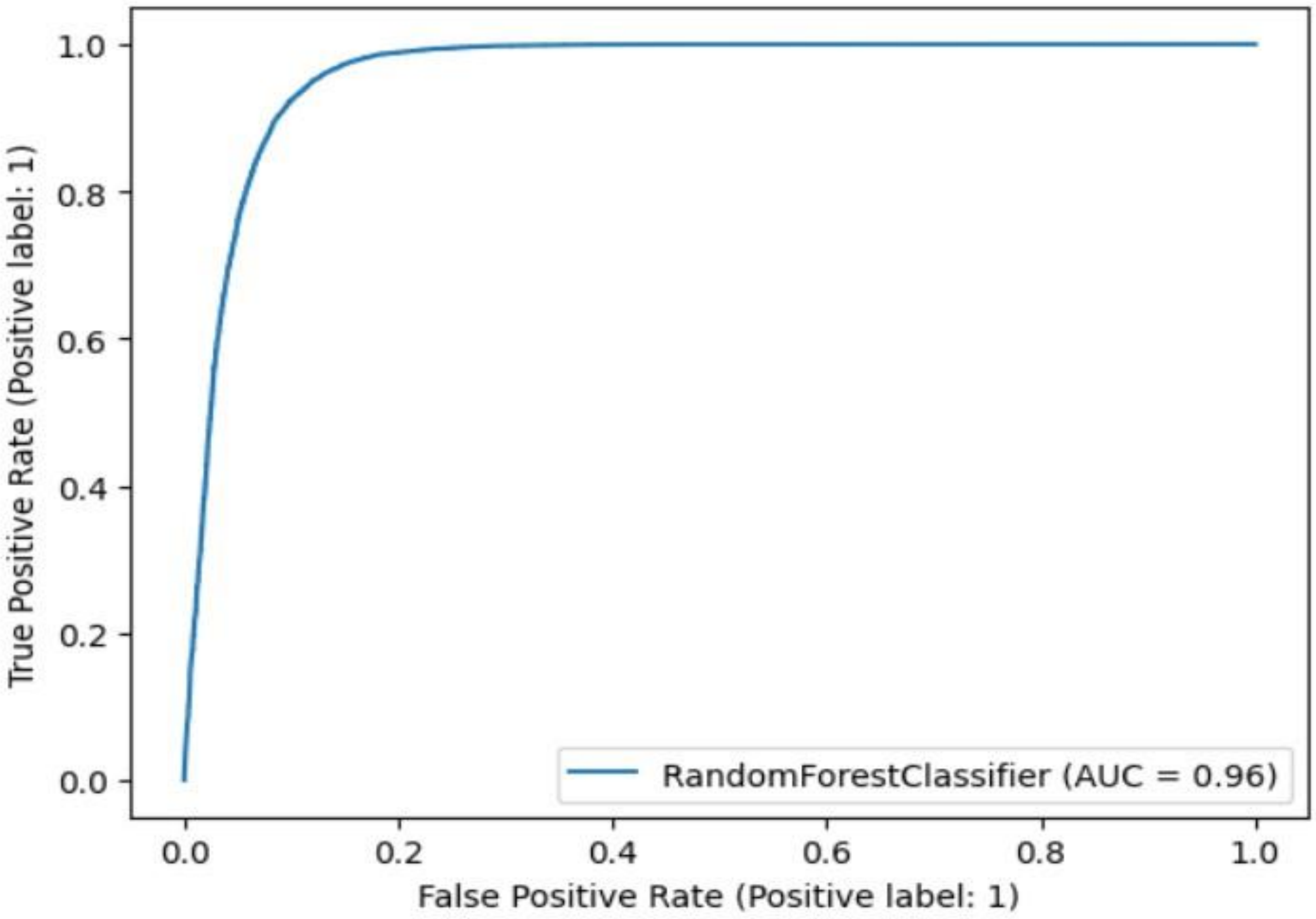


Decision Tree ROC: After Hyperparameter Tuning

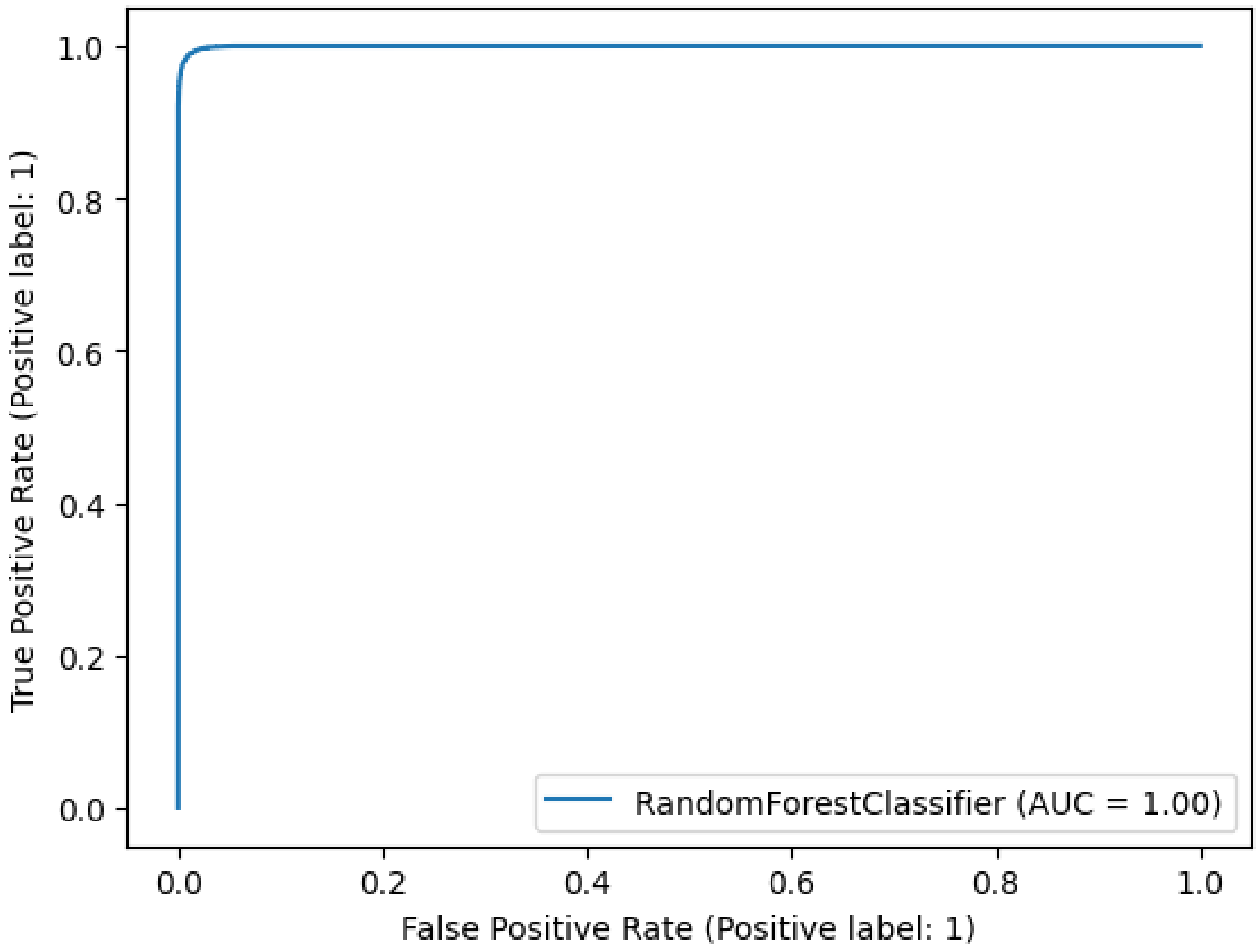


Using decision tree, we got us an accuracy of 90% on test data.

Random Forest ROC: Before Hyperparameter Tuning

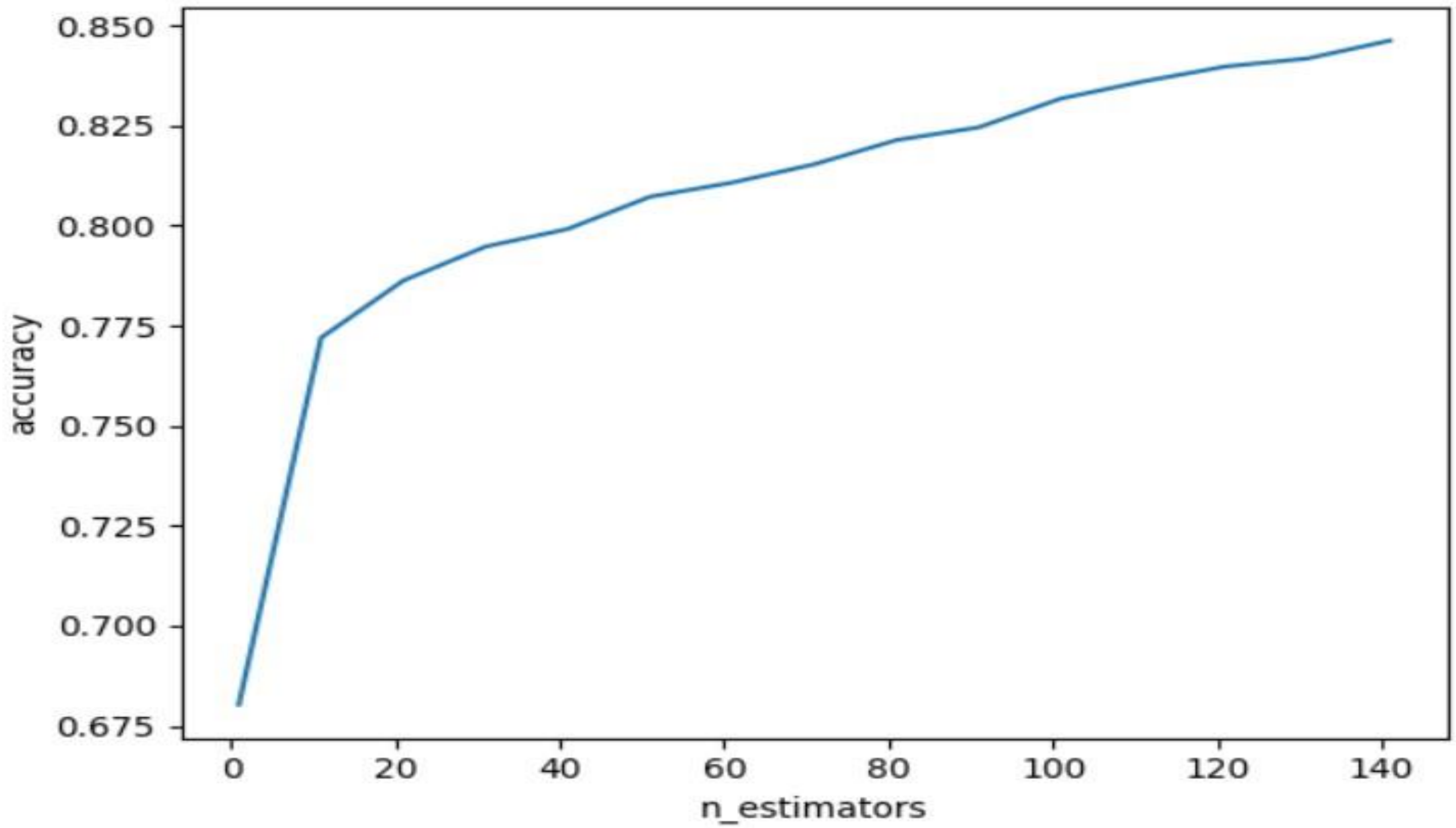


Random Forest ROC: After Hyperparameter Tuning



With Random forest, we got an accuracy of 95% on test data.

Adaptive Boosting: Plot



Conclusions

- Most of the top predictors are from the action phase, given that the drop in engagement is significant during that phase.
- During the Exploratory Data Analysis (EDA), we observed certain factors that can be combined with these insights:

a. Users whose maximum recharge amount remains below 200 even during the good phase should be tagged and re-evaluated periodically since they are more likely to churn.

b. Users who have been with the network for less than 4 years should be monitored regularly, as the data shows that users with less than 4 years of association tend to churn more.

c. While MOU (Minutes of Usage) is a major factor, it's also essential to consider data usage, especially VBC (Volume-based Charging), if the user is not using a data pack; this is another factor to watch out for.