Telecom churn case study

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
- ❖ we will analyse customer-level data of a leading telecom firm, build predictive models to identify customers at high risk of churn on the conditions of
  - A. Prepaid Model
  - B. we will use the usage-based definition to define churn
  - C. we will define high-value customers based on 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) and predict churn only on high-value
- ❖ Identify the main indicators of churn.

Final Model results summary

1. **Train set**
   a. Accuracy = 0.797
   b. Precision_score = 0.793
   c. Recall_score = 0.807
2. **Test set**
   a. Accuracy = 0.793
   b. Precision_score = 0.783
   c. Recall_score = 0.805

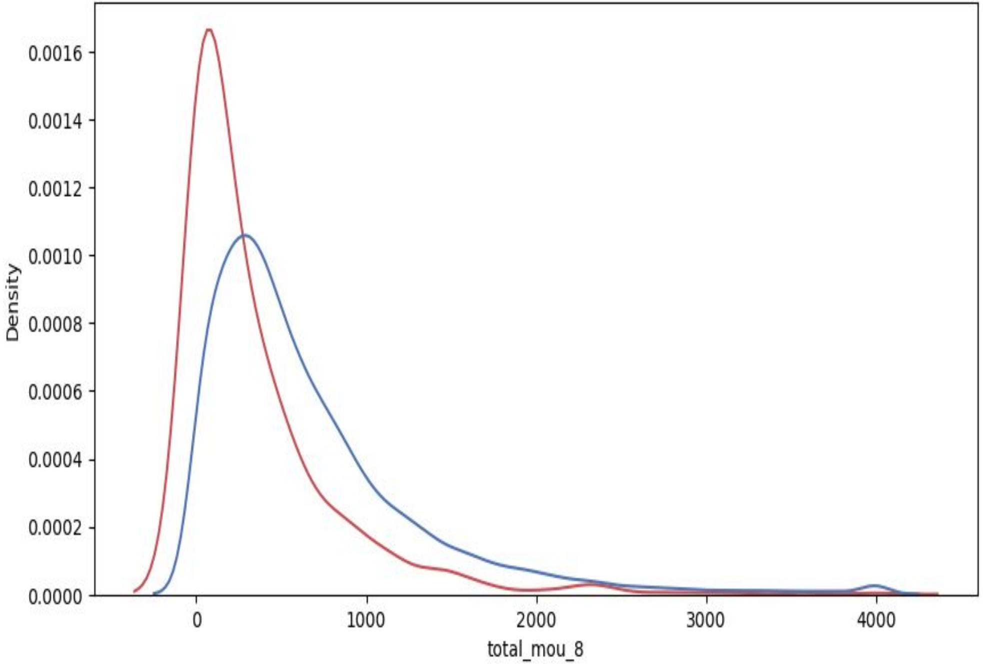
Overall, the model is performing well in the test set, what it had learnt from the train set.

Given our business problem, to retain their customers, we need higher recall. As giving an offer to an user not going to churn will cost less as compared to losing a customer and bring new customer, we need to have high rate of correctly identifying the true positives, hence recall.

Top 10 Predictors

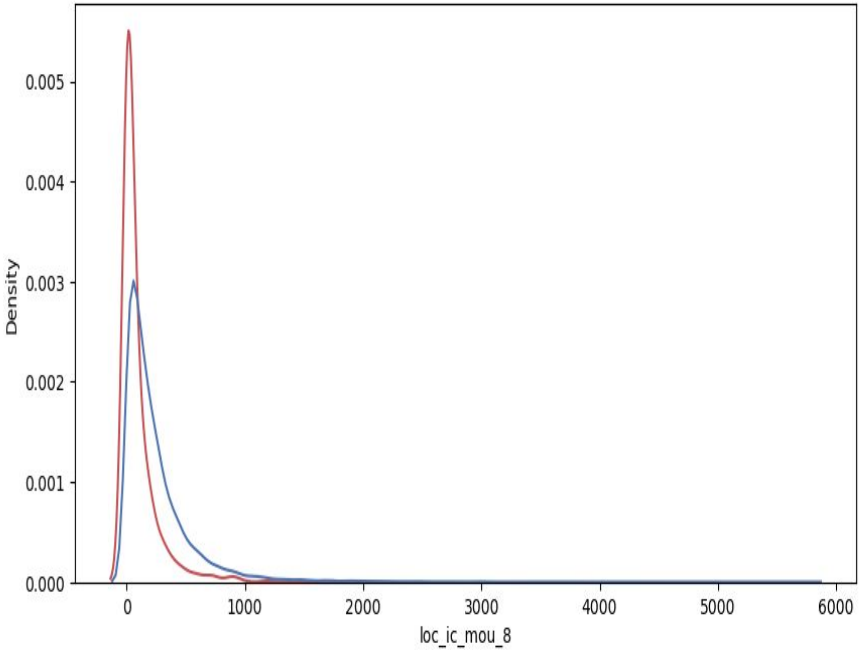
loc_ic_mou_8
const
total_mou_8
monthly_3g_8
gd_ph_loc_ic_mou
total_rech_num_8
arpu_8
monthly_2g_8
last_day_rch_amt_8
std_ic_t2t_mou_8
loc_og_mou_8

total_mou_8 (min of usage - voice calls) predictor for churn and not churn customers



We can see that for the churn customers the minutes of usage for the month of August is mostly populated on the lower side than the non churn customers

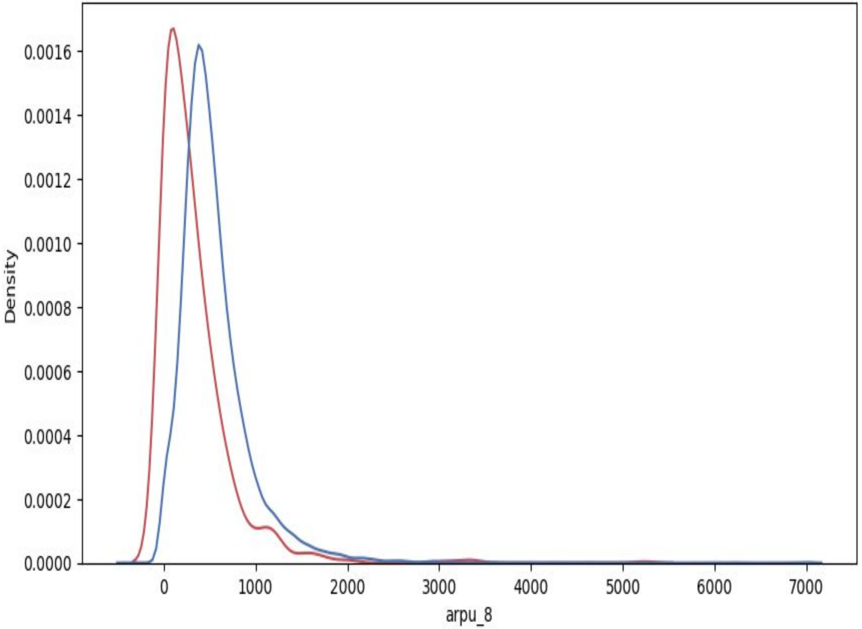
loc_ic_mou_8 (local incoming calls) predictor for churn and not churn customers



MOU is one of the major factors

Minutes of uses of local incoming calls reducing in churn as compared to non churn

arpu_8 (average revenue per user) predictor for churn and not churn customers

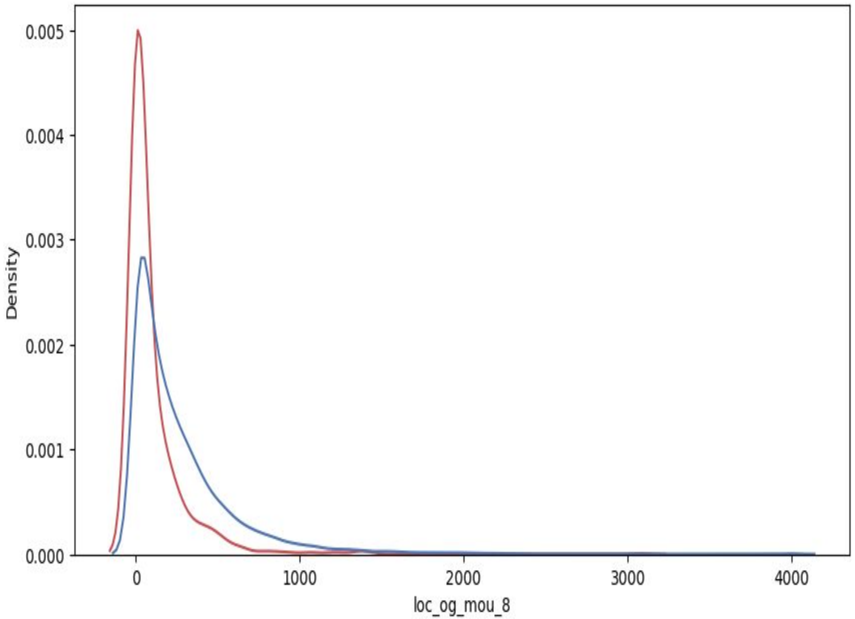


Average revenue per user is the most important factor in deciding churn and not churn customers

We are overbearing significant amount of reduce in the revenue in the action phase in the churn customers

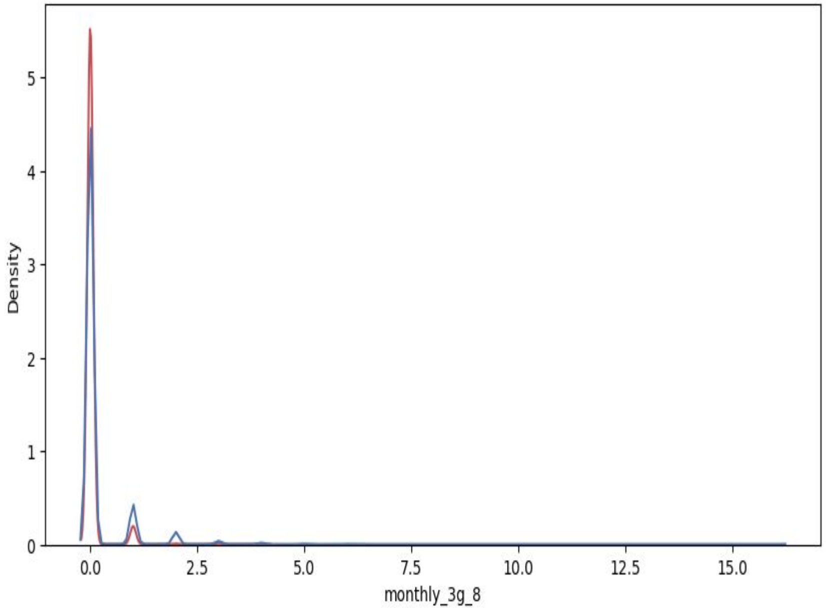
Users whose maximum recharge amount is less than 200 even in the good phase, should have a tag and re-evaluated time to time as they are more likely to churn

loc_og_mou_8 (og=outgoing call) predictor for churn and not churn customers



In the action phase , there is significant amount of reduction in the outgoing calls in the churn customers as compared to the non churn customers

monthly_3g_8 (3G network use) predictor for churn and not churn customers



The number of monthly 3g data for August for the churn customers are very much populated around 0, whereas of non churn customers it spreaded across various numbers.

Business Recommendations

- If total revenue form any customer is greater than Rs. 368.5 /- per month then consider it as high value customer.

- If the average revenue generating from the customer is dropping below Rs.321/- then there is higher chance of churn

- Also, the customers having value based cost in the action phase increased are more likely to churn than the other customers. Hence, these customers may be a good target to provide offer.

-Target the customers, whose average minutes of usage of the incoming local calls and outgoing ISD calls are less than 346 min in the action phase (mostly in the month of August).

- Customers having decreasing STD incoming minutes of usage for operators T to fixed lines of T for the month of August are more likely to churn.

- Customers having decreasing incoming minutes of usage for operators T to fixed lines of T for August are more likely to churn.

- Target the customers, whose outgoing others charge in July and incoming others on August are less.

- Customers decreasing monthly 2g usage for August are most probable to churn.