Telecom Churn Case Study

Submitted By:
Akshay Patil,
K M Sreeraj &
Rishabh Satija.

Problem Statement

To reduce customer churn, telecom companies need to predict which customers are at high risk of churn. In this project, we will analyse customer-level data of a leading telecom firm, build predictive models to identify customers at high risk of churn and identify the main indicators of churn.

Retaining high profitable customers is the main business goal here.

Step Involved:

1. Reading, understanding and visualising the data
2. Preparing the data for modelling
3. Building the model
4. Evaluate the model

EDA

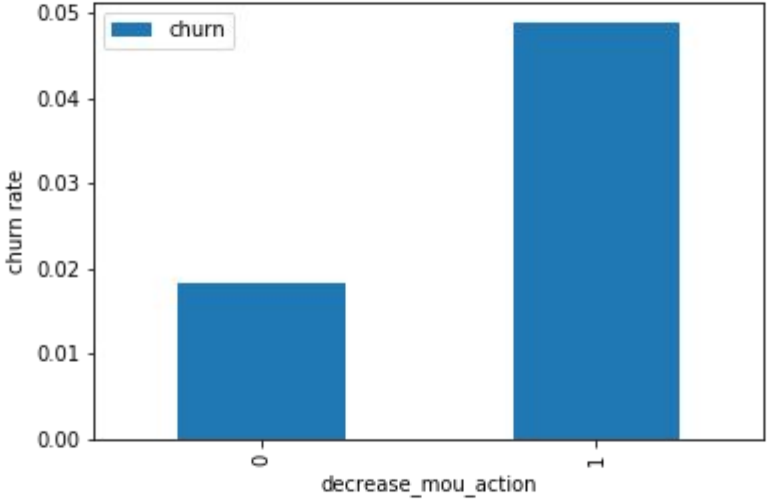
Univariate analysis

Churn rate on the basis whether the customer decreased her/his MOU in action month.

Analysis:

We can see that the churn rate is more for the customers, whose minutes of usage(mou) decreased in the action phase than the good phase.

Churn rate on the basis whether the customer decreased her/his number of recharge in action month

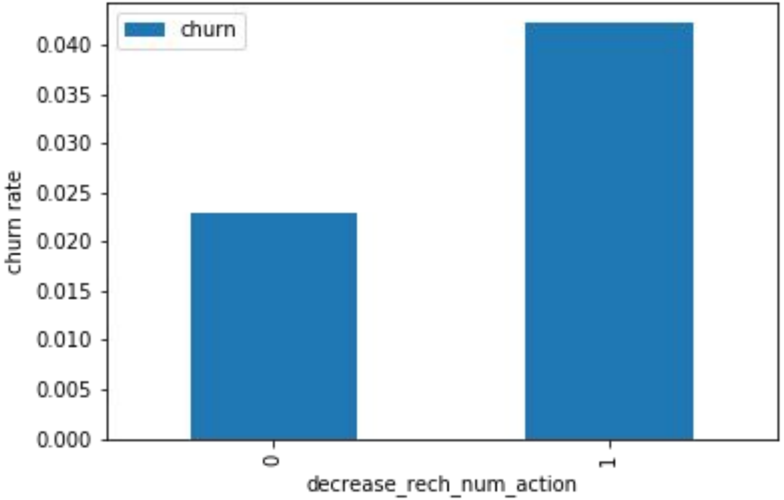


EDA

Analysis:

As expected, the churn rate is more for the customers, whose number of recharge in the action phase is lesser than the number in good phase.

Churn rate on the basis whether the customer decreased her/his amount of recharge in action month

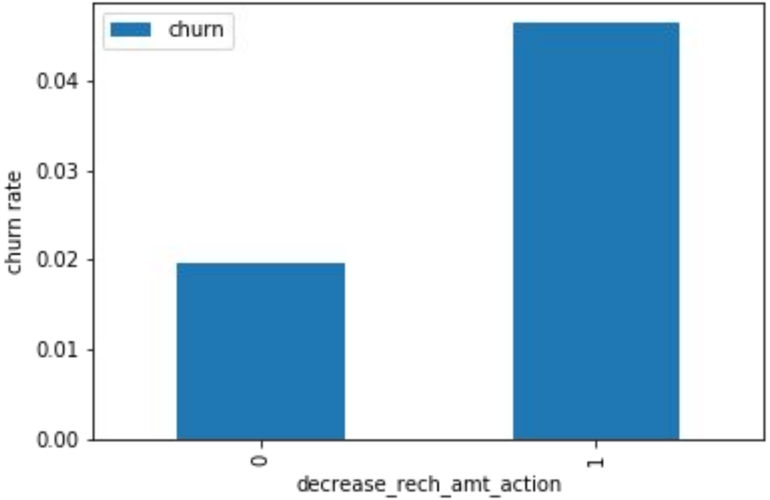


EDA

Analysis:

Here also we see the same behaviour. The churn rate is more for the customers, whose amount of recharge in the action phase is lesser than the amount in good phase.

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

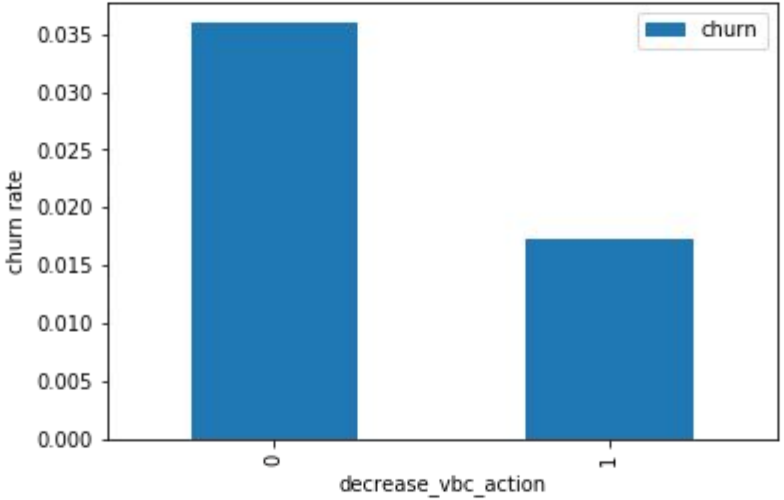


EDA

Analysis:

Here we see the expected result. The churn rate is more for the customers, whose volume based cost in action month is increased. That means the customers do not do the monthly recharge more when they are in the action phase.

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



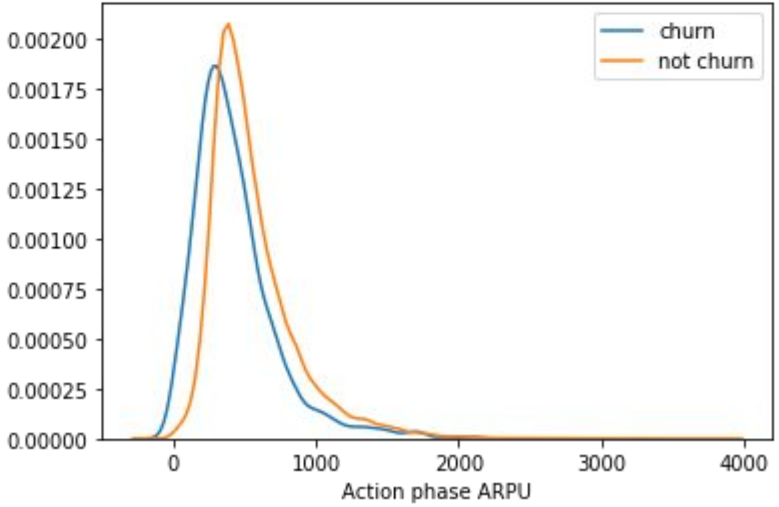
EDA

Analysis:

Average revenue per user (ARPU) for the churned customers is mostly densed on the 0 to 900. The higher ARPU customers are less likely to be churned.

ARPU for the not churned customers is mostly densed on the 0 to 1000.

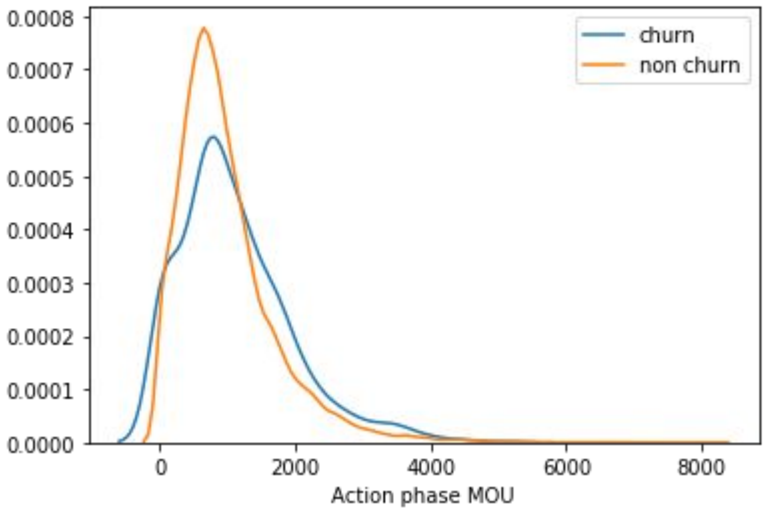
Analysis of the minutes of usage MOU (churn and not churn) in the action phase



EDA

Analysis:

Minutes of usage(MOU) of the churn customers is mostly populated on the 0 to 2500 range. Higher the MOU, lesser the churn probability.



EDA

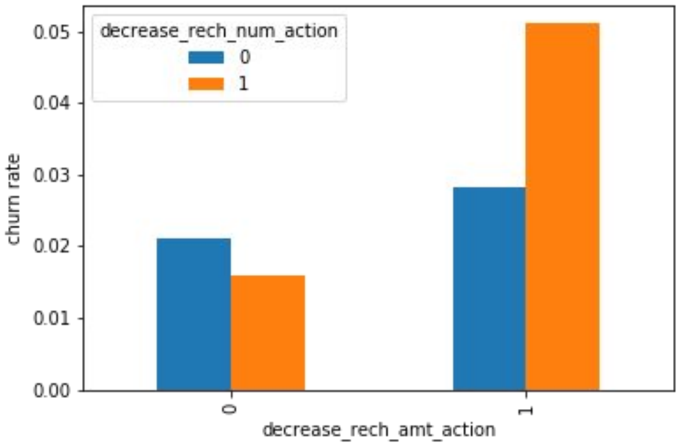
Bivariate analysis

Analysis of churn rate by the decreasing recharge amount and number of recharge in the action phase

Analysis:

We can see from the above plot, that the churn rate is more for the customers, whose recharge amount as well as number of recharge have decreased in the action phase than the good phase.

Analysis of churn rate by the decreasing recharge amount and volume based cost in the action phase

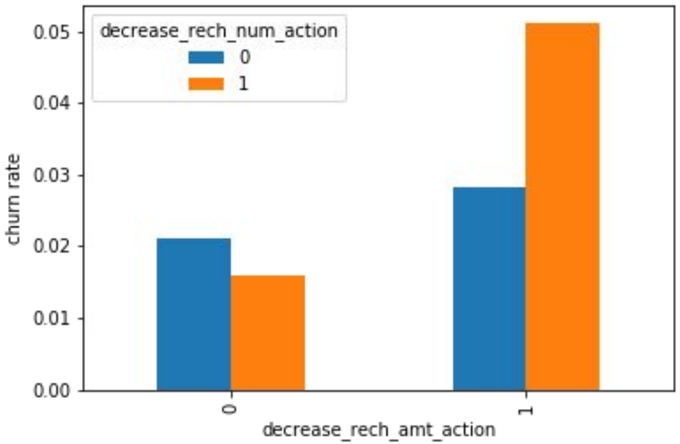


EDA

Analysis:

Here, also we can see that the churn rate is more for the customers, whose recharge amount is decreased along with the volume based cost is increased in the action month.

Analysis of recharge amount and number of recharge in action month



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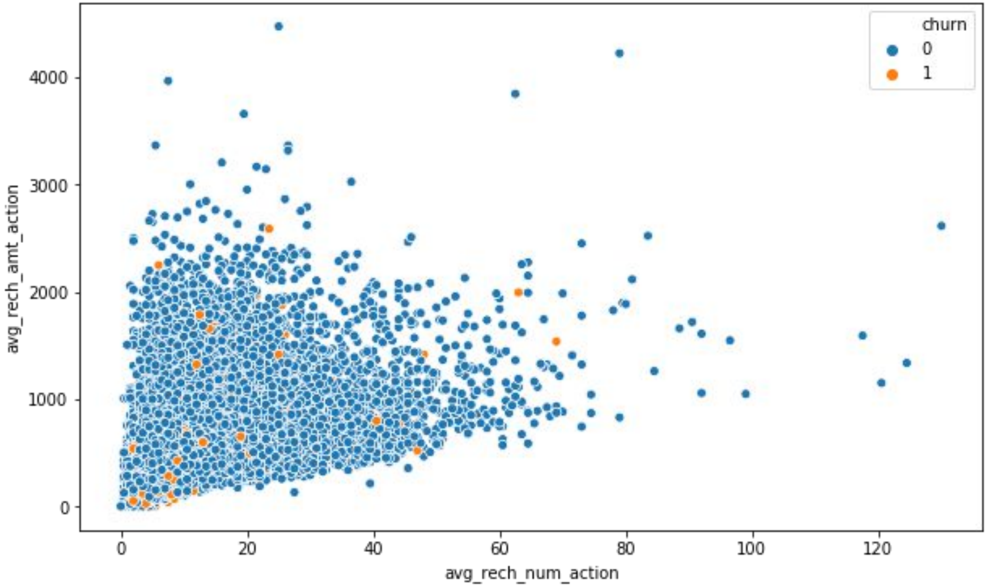
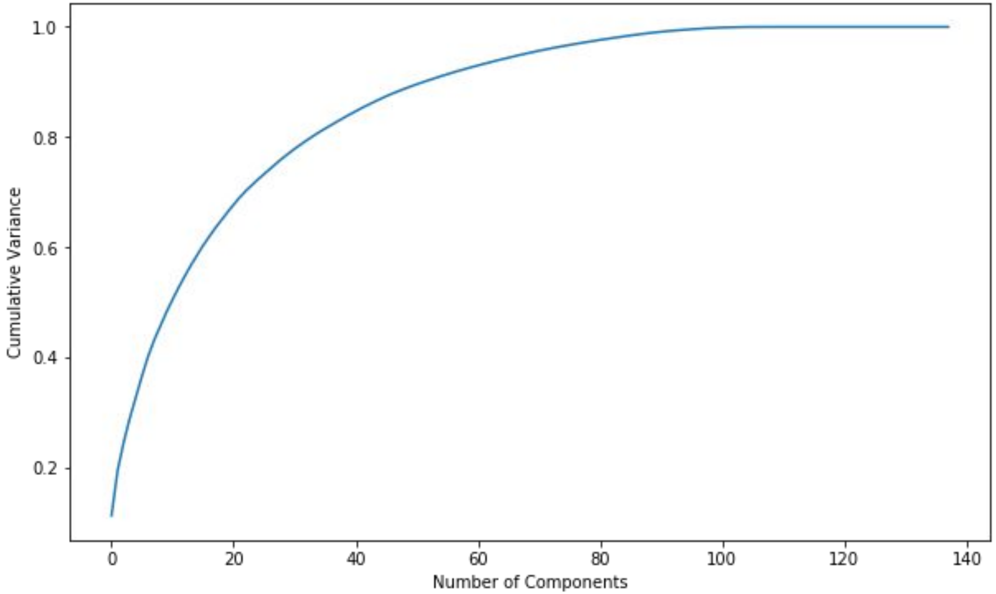
Analysis:

We can see from the above pattern that the recharge number and the recharge amount are mostly proportional. More the number of recharge, more the amount of the recharge.

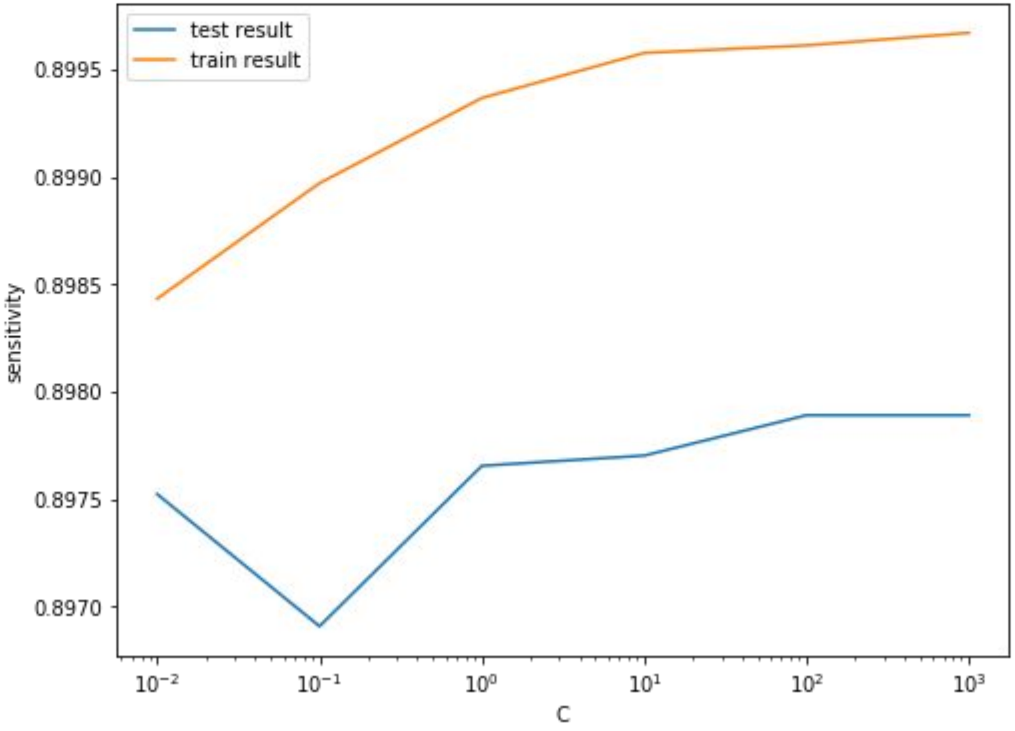


Model with PCA

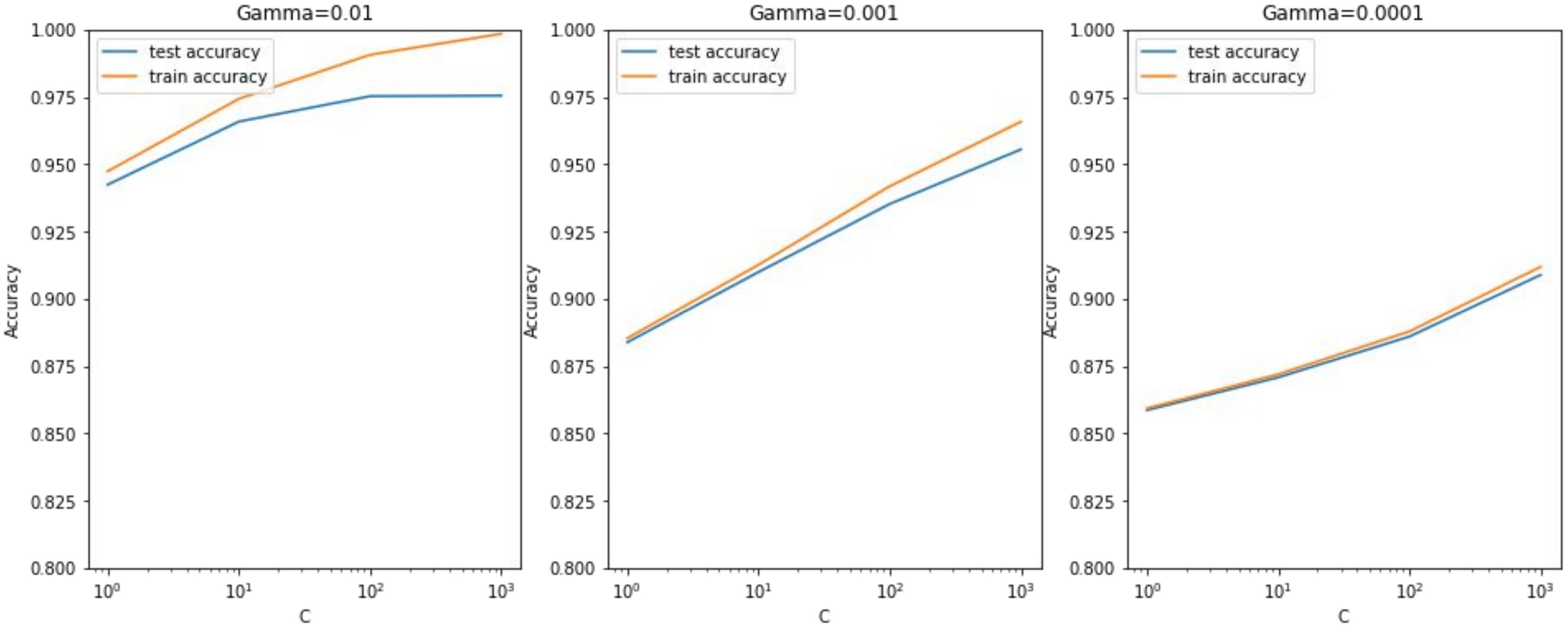
We can see that 60 components explain almost more than 90% variance of the data. So, we will perform PCA with 60 components.



Test Result vs Train Result



Plotting the accuracy with various C and gamma values



Plotting the accuracy with various C and gamma values

From the Graph ploted, we can see that higher value of gamma leads to overfitting the model. With the lowest value of gamma (0.0001) we have train and test accuracy almost same.

Also, at C=100 we have a good accuracy and the train and test scores are comparable.

Though sklearn suggests the optimal scores mentioned above (gamma=0.01, C=1000), one could argue that it is better to choose a simpler, more non-linear model with gamma=0.0001. This is because the optimal values mentioned here are calculated based on the average test accuracy (but not considering subjective parameters such as model complexity).

We can achieve comparable average test accuracy (~90%) with gamma=0.0001 as well, though we'll have to increase the cost C for that. So to achieve high accuracy, there's a tradeoff between:

- High gamma (i.e. high non-linearity) and average value of C
- Low gamma (i.e. less non-linearity) and high value of C

We argue that the model will be simpler if it has as less non-linearity as possible, so we choose gamma=0.0001 and a high C=100.

Decision Tree with PCA

Accuracy:- 0.8603140227395777

Sensitivity:- 0.6994818652849741

Specificity:- 0.8661181750186986

Model summary

- Train set
  - Accuracy = 0.90
  - Sensitivity = 0.91
  - Specificity = 0.88
- Test set
  - Accuracy = 0.86
  - Sensitivity = 0.70
  - Specificity = 0.87

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.

Random Forest with PCA

Model summary:

- Train set
  - Accuracy = 0.84
  - Sensitivity = 0.88
  - Specificity = 0.80
- Test set
  - Accuracy = 0.80
  - Sensitivity = 0.75
  - Specificity = 0.80

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.

Final conclusion with PCA

After trying several models we can see that for achieving the best sensitivity, which was our ultimate goal, the classic Logistic regression or the SVM models performs well. For both the models the sensitivity was approx 81%. Also we have good accuracy of approx 85%.

Logistic Regression with NO PCA

Model analysis:

1. We can see that there are few features have positive coefficients and few have negative.
2. Many features have higher p-values and hence became insignificant in the model.

Coarse tuning (Auto+Manual)

We'll first eliminate a few features using Recursive Feature Elimination (RFE), and once we have reached a small set of variables to work with, we can then use manual feature elimination (i.e. manually eliminating features based on observing the p-values and VIFs).

Model Performance on Train Set

We had concluded that **Model-3 log_no_pca_3 will be the final model**.

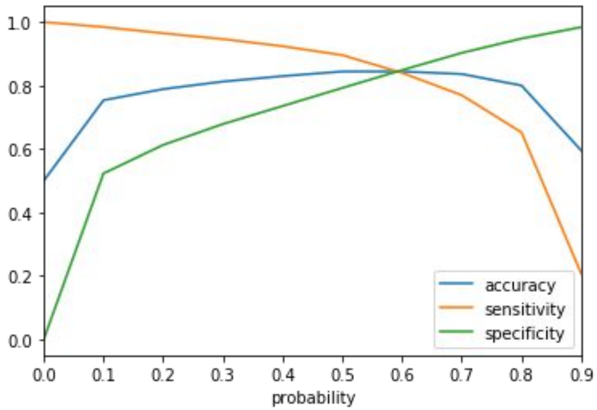
Accuracy - Becomes stable around 0.6

Sensitivity - Decreases with the increased probability.

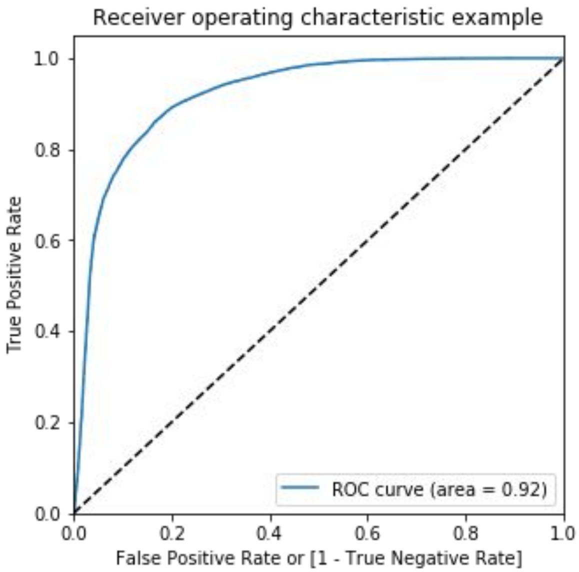
Specificity - Increases with the increasing probability.

At point 0.6 where the three parameters cut each other, we can see that there is a balance between sensitivity and specificity with a good accuracy.

Here we are intended to achieve better sensitivity than accuracy and specificity. Though as per the above curve, we should take 0.6 as the optimum probability cutoff, we are taking ***0.5*** for achieving higher sensitivity, which is our main goal.



Plotting the ROC Curve (Trade off between sensitivity & specificity)



We can see the area of the ROC curve is closer to 1, which is the Gini of the model.

Testing the Model on Test Data

Accuracy:- 0.7848763761053962

Sensitivity:- 0.8238341968911918

Specificity:- 0.7834704562453254

Model summary:

- Train set
  - Accuracy = 0.84
  - Sensitivity = 0.81
  - Specificity = 0.83
- Test set
  - Accuracy = 0.78
  - Sensitivity = 0.82
  - Specificity = 0.78

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

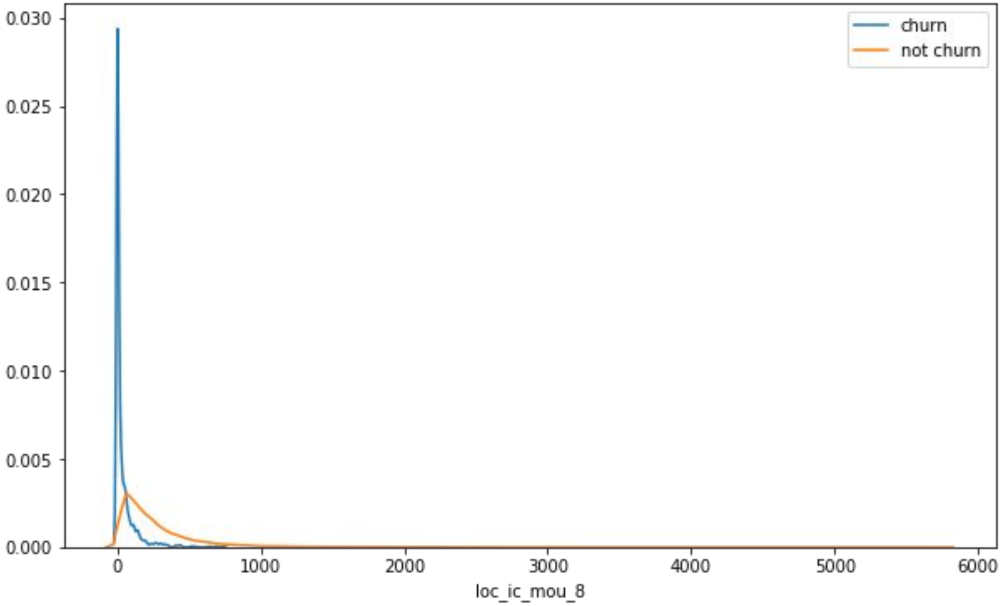
Final Conclusion with NO PCA

We can see that the logistic model with no PCA has good sensitivity and accuracy, which are comparable to the models with PCA. So, we can go for the more simplistic model such as logistic regression with PCA as it explains the important predictor variables as well as the significance of each variable. The model also helps us to identify the variables which should be act upon for making the decision of the to be churned customers. Hence, the model is more relevant in terms of explaining to the business.

Business Recommendations

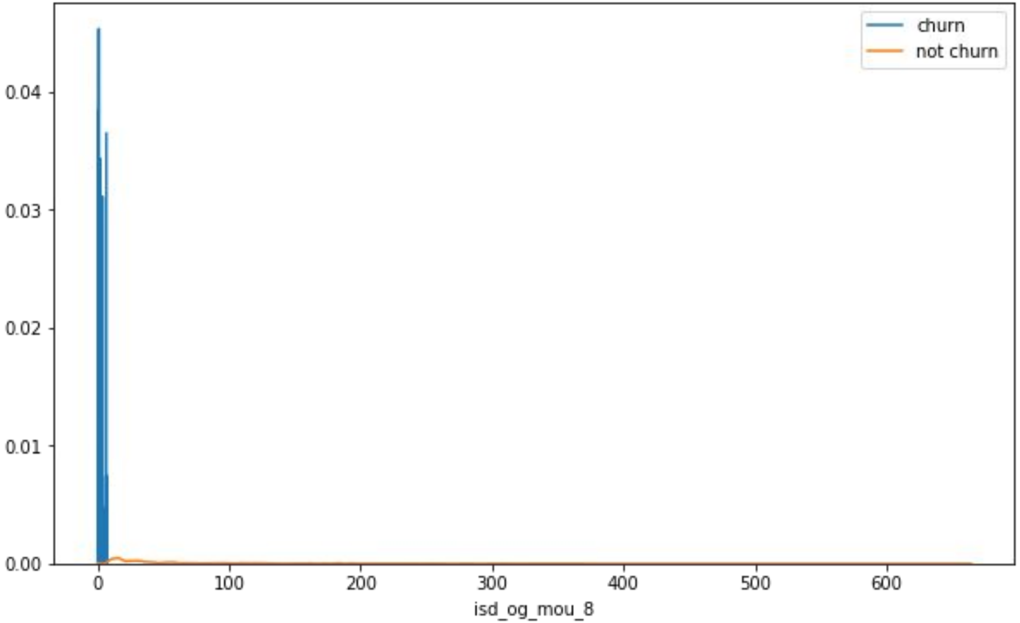
1. Target the customers, whose minutes of usage of the incoming local calls and outgoing ISD calls are less in the action phase (mostly in the month of August).
2. Target the customers, whose outgoing others charge in July and incoming others on August are less.
3. Also, the customers having value based 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.
4. Customers, whose monthly 3G recharge in August is more, are likely to be churned.
5. 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.
6. Customers decreasing monthly 2g usage for August are most probable to churn.
7. Customers having decreasing incoming minutes of usage for operators T to fixed lines of T for August are more likely to churn.
8. roam_og_mou_8 variables have positive coefficients (0.7135). That means for the customers, whose roaming outgoing minutes of usage is increasing are more likely to churn.

Plots of Important Predictors for Churn & Non Churn Customers



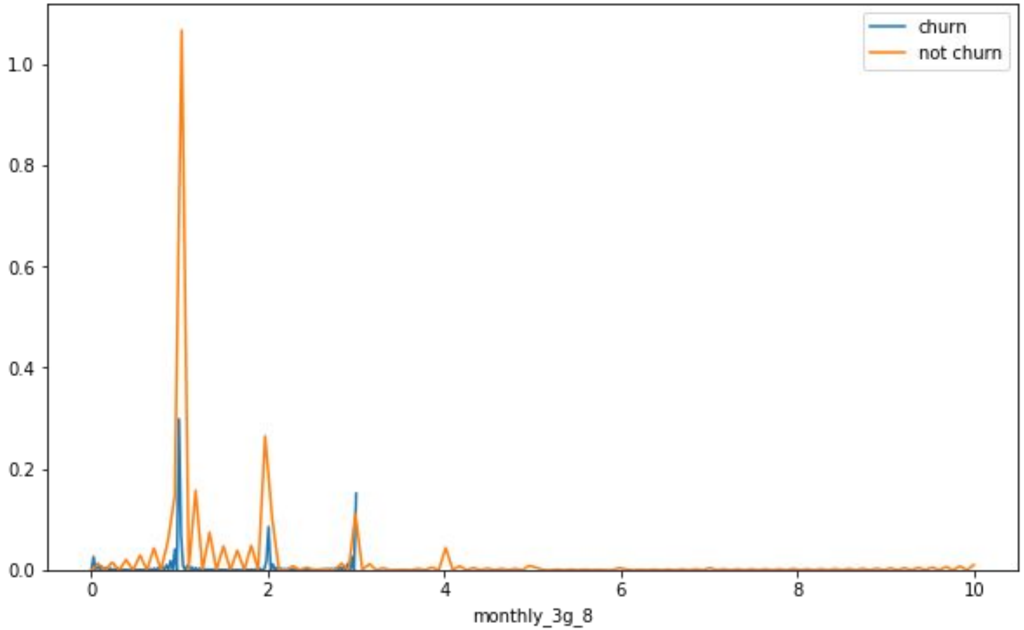
We can see that for the churn customers the minutes of usage for the month of August is mostly populated on the lower side than the non churn customers.

Plots of Important Predictors for Churn & Non Churn Customers



We can see that the ISD outgoing minutes of usage for the month of August for churn customers is densed approximately to zero. On the other hand for the non churn customers it is little more than the churn customers.

Plots of Important Predictors for Churn & Non Churn Customers



The number of monthly 3g data for August for the churn customers are very much populated around 1, whereas of non churn customers it spreaded across various numbers.

Similarly we can plot each variables, which have higher coefficients, churn distribution.

Thank You