Telecom Churn Case Study

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Predict which customers are at high risk of churn:

- 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.
- For many incumbent operators, retaining high profitable customers is the number one business goal.
- To reduce customer churn, telecom companies need to predict which customers are at high risk of churn.
- In this project, we will analyze 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.

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Objective:

- Understanding the business objective and the data
- The dataset contains customer-level information for a span of four consecutive months - June, July, August and September. The months are encoded as 6, 7, 8 and 9, respectively.
- The **business objective** is to predict the churn in the last month using the data from the first three months. To do this task well, understanding the typical customer behavior during churn will be helpful.

We assume that there are three phases of customer

- **The ‘good’ phase:** In this phase, the customer is happy with the service and behaves as usual.

- **The 'action' phase:** The customer experience starts changing in this phase, for example, when he or she receives a compelling offer from a competitor, experiences unfair charges, is dissatisfied with service quality, and so on.

- **The 'churn' phase:** The customer is considered to have churned during this phase. Based on this phase, we define churn. It is also important to remember that this data is not available for prediction during the period of forecast.

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Strategies to Manage Customer Churn

- 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).
- Target the customers, whose outgoing others charge in July and incoming others on August are less.
- 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.
- Customers, whose monthly 3G usage in August is less, are likely to be churned.
- 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 decreasing monthly 2g usage for August are most probable to churn.
- Customers having decreasing incoming minutes of usage for operators T to fixed lines of T for August are more likely to churn.
- roam_og_mou_8 variables have positive coefficients (0.8160). That means for the customers, whose roaming outgoing minutes of usage is increasing are more likely to churn.

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The data set includes information about:

- Customers who left within the last month – the column is called Churn
- Services that each customer has signed up for – phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies
- Customer account information – how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges
- Demographic info about customers – gender, age range, and if they have partners and dependents

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We can take the following suggestive steps to build the model:

- Preprocess data
- Conduct appropriate exploratory analysis to extract useful insights
- Derive new features.
- Reduce the number of variables using PCA.
- Train a variety of models, tune model hyper parameters, etc.
- Evaluate the models using appropriate evaluation metrics.
- Important to identify churners than the non-churners accurately
- Appropriate evaluation metric which reflects this business goal.
- Finally, choose a model based on some evaluation metric.

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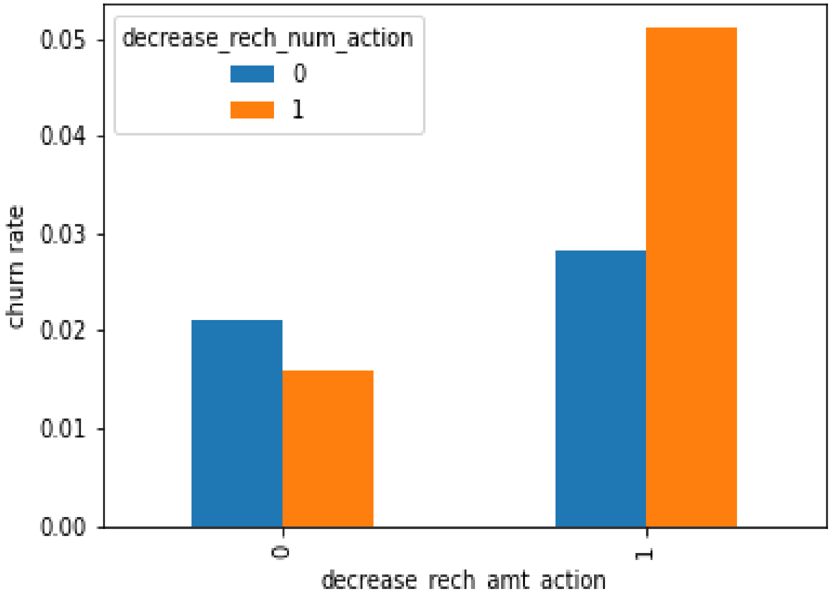
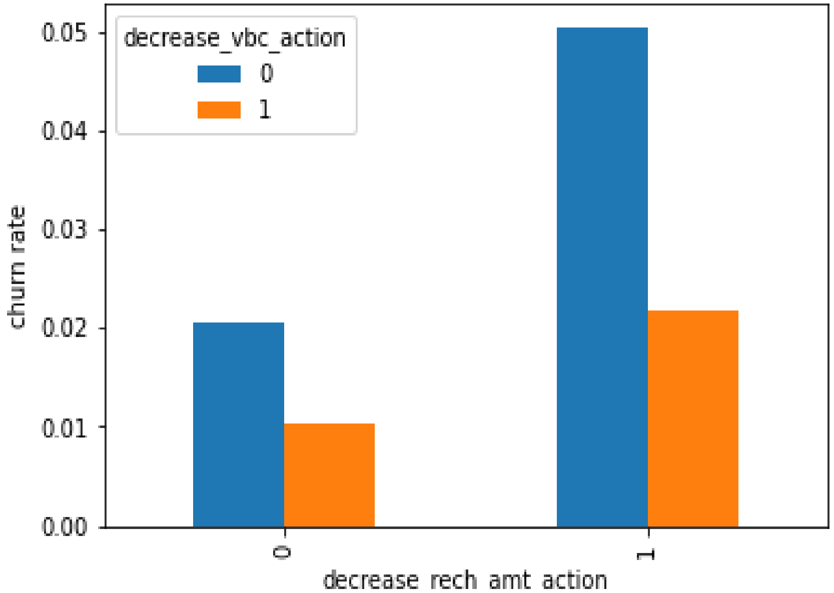
Bivariate Analysis

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



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



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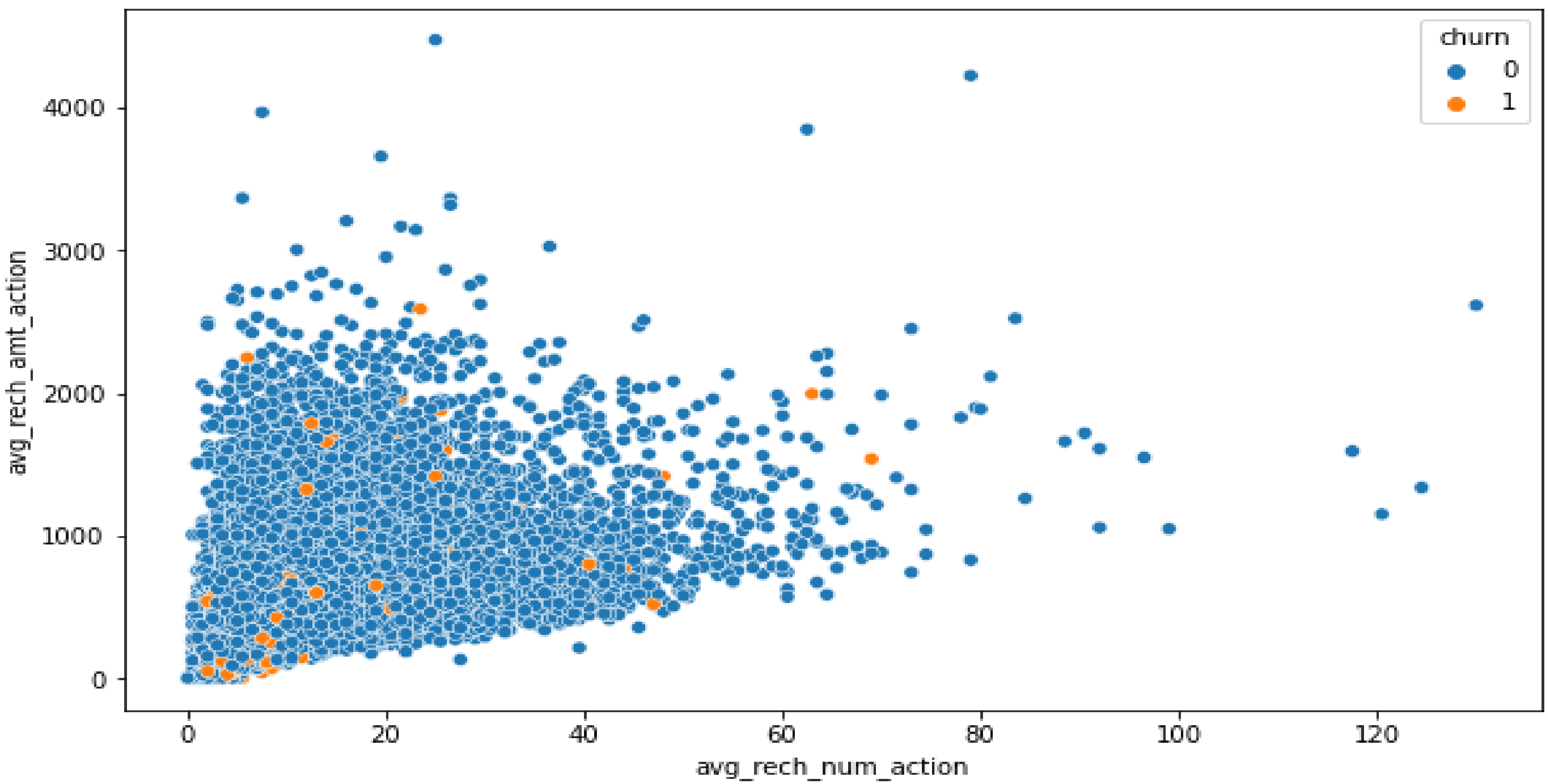
❖ Analysis of recharge amount and number of recharge in action month



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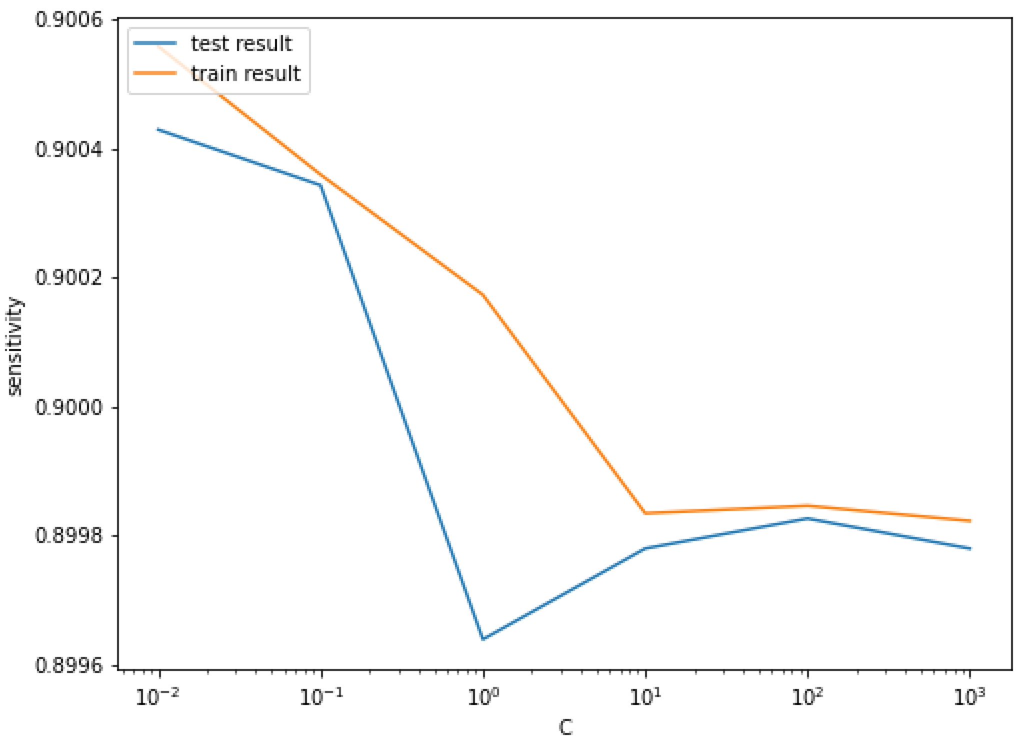
❖ Logistic Regression with PCA



❖ Top predictors

roam_og_mou_8	0.8160
std_og_t2m_mou_8	0.0703
isd_og_mou_8	-0.9899
og_others_7	-2.9093
loc_ic_t2f_mou_8	-0.9672
std_ic_t2f_mou_8	-0.5471
total_ic_mou_8	-2.7579
ic_others_8	-1.2314
total_rech_num_8	-0.5263
monthly_2g_8	-0.9787
monthly_3g_8	-1.1557
decrease_vbc_action	-1.3181

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Business Recommendation and Conclusion:

- We can see most of the top predictors are from the action phase, as the drop in engagement is prominent in that phase

Some of the factors we noticed while performing EDa which can be clubbed with these insights are:

- 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

- Users that have been with the network less than 4 years, should be monitored time to time, as from data we can see that users who have been associated with the network for less than 4 years tend to churn more

- MOU is one of the major factors, but data especially VBC if the user is not using a data pack if another factor to look out