Telecom Churn Case Study

- Group Case Study by

Abhishek, Rahul and Kiran

Problem Statement

This case study involves to predict from the telecom companies data, which customer are at high risk churn.

Task and objectives:

- Reduce customer churn and predict high risk of churn
- Build predict model and identify main reasons for churn
- List high profitable customer is the final goal of the case study

Business Problem Overview

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 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.

Understanding and Defining Churn

There are two main models of payment in the telecom industry - **postpaid (customers pay a monthly/annual bill after using the services)** and **prepaid (customers pay/recharge with a certain amount in advance and then use the services).**

In the postpaid model, when customers want to switch to another operator, they usually inform the existing operator to terminate the services, and you directly know that this is an instance of churn.

However, in the prepaid model, customers who want to switch to another network can simply stop using the services without any notice, and it is hard to know whether someone has actually churned or is simply not using the services temporarily (e.g. someone may be on a trip abroad for a month or two and then intend to resume using the services again).

Thus, churn prediction is usually more critical (and non-trivial) for prepaid customers, and the term ‘churn’ should be defined carefully. Also, prepaid is the most common model in India and southeast Asia, while postpaid is more common in Europe in North America.

This project is based on the Indian and Southeast Asian market.

Definitions of Churn

There are various ways to define churn, such as:

Revenue-based churn: Customers who have not utilised any revenue-generating facilities such as mobile internet, outgoing calls, SMS etc. over a given period of time. One could also use aggregate metrics such as ‘customers who have generated less than INR 4 per month in total/average/median revenue’.

The main shortcoming of this definition is that there are customers who only receive calls/SMSes from their wage-earning counterparts, i.e. they don’t generate revenue but use the services. For example, many users in rural areas only receive calls from their wage-earning siblings in urban areas.

Usage-based churn: Customers who have not done any usage, either incoming or outgoing - in terms of calls, internet etc. over a period of time.

A potential shortcoming of this definition is that when the customer has stopped using the services for a while, it may be too late to take any corrective actions to retain them. For e.g., if we define churn based on a ‘two-months zero usage’ period, predicting churn could be useless since by that time the customer would have already switched to another operator.

In this project, we will use the usage-based definition to define churn.

High-value Churn

In the Indian and the southeast Asian market, approximately 80% of revenue comes from the top 20% customers (called high-value customers). Thus, if we can reduce churn of the high-value customers, we will be able to reduce significant revenue leakage.

In this project, we will define high-value customers based on a certain metric (mentioned later below) and predict churn only on high-value customers.

Data Understanding

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.

Business 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. To do this task well, understanding the typical customer behaviour during churn will be helpful.

Understanding Customer Behaviour During Churn

Customers usually do not decide to switch to another competitor instantly, but rather over a period of time (this is especially applicable to high-value customers). In churn prediction, we assume that there are three phases of customer lifecycle :

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

The ‘action’ phase: The customer experience starts to sore in this phase, for e.g. he/she gets a compelling offer from a competitor, faces unjust charges, becomes unhappy with service quality etc. In this phase, the customer usually shows different behaviour than the ‘good’ months. Also, it is crucial to identify high-churn-risk customers in this phase, since some corrective actions can be taken at this point (such as matching the competitor’s offer/improving the service quality etc.)

The ‘churn’ phase: In this phase, the customer is said to have churned. We define churn based on this phase. Also, it is important to note that at the time of prediction (i.e. the action months), this data is not available to you for prediction. Thus, after tagging churn as 1/0 based on this phase, we discard all data corresponding to this phase.

In this case, since we are working over a four-month window, the first two months are the ‘good’ phase, the third month is the ‘action’ phase, while the fourth month is the ‘churn’ phase.

Model Building Approach

Build models to predict churn. The predictive model that we are going to build will serve two purposes:

1. It will be used to predict whether a high-value customer will churn or not, in near future (i.e. churn phase). By knowing this, the company can take action steps such as providing special plans, discounts on recharge etc.

2. It will be used to identify important variables that are strong predictors of churn. These variables may also indicate why customers choose to switch to other networks.

In some cases, both of the above-stated goals can be achieved by a single machine learning model. But here, you have a large number of attributes, and thus we should try using a dimensionality reduction technique such as PCA and then build a predictive model. After PCA, we can use any classification model.

Also, since the rate of churn is typically low (about 5-10%, this is called class-imbalance) - we will try using techniques to handle class imbalance.

We took the following suggestive steps to build the model:

- Preprocessed data (converted columns to appropriate formats, handle missing values, etc.)
- Derived new features.
- Conducted appropriate exploratory analysis to extract useful insights (whether directly useful for business or for eventual modelling/feature engineering).
- Reduced the number of variables using PCA.
- Train a variety of models, tune model hyperparameters, etc. (handled class imbalance using SMOTE(Synthetic Minority Oversampling Technique).
- Evaluate the models using appropriate evaluation metrics. Note that it is more important to identify churners than the non-churners accurately - choose an appropriate evaluation metric which reflects this business goal.
- Finally, choose a model based on some evaluation metric.

The above model will only be able to achieve one of the two goals - to predict customers who will churn. We can’t use the above model to identify the important features for churn. That’s because PCA usually creates components which are not easy to interpret.

Therefore, we will build another model with the main objective of identifying important predictor attributes which help the business understand indicators of churn. A good choice to identify important variables is a logistic regression model or a model from the tree family. In case of logistic regression, we will make sure to handle multi-collinearity.

Data Pre-Processsing and Preparation

Converted columns to appropriate formats, handled missing values and outliers.

The following data preparation steps were taken :

1. **Derived new features**

- **decrease_mou_action** - This feature indicates whether the minutes of usage of the customer has decreased in the action phase than the good phase.
- **decrease_rech_amt_action** - This column indicates whether the amount of recharge of the customer has decreased in the action phase than the good phase.
- **decrease_arpu_action** - This column indicates whether the average revenue per customer has decreased in the action phase than the good phase.
- **decrease_vbc_action** - This column indicates whether the volume based cost of the customer has decreased in the action phase than the good phase.

Based on our business understanding derived the above features that we think could be important indicators of churn.

2. **Filtered high-value customers** As mentioned above, we need to predict churn only for the high-value customers. Defined high-value customers as follows: 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).
3. **Tagged churners and removed attributes of the churn phase** Tagged the churned customers (churn=1, else 0) based on the fourth month as follows: Those who have not made any calls (either incoming or outgoing) AND have not used mobile internet even once in the churn phase. The attributes we need to use to tag churners are:

- total_ic_mou_9
- total_og_mou_9
- vol_2g_mb_9
- vol_3g_mb_9

After tagging churners, we removed all the attributes corresponding to the churn phase (all attributes having ‘ _9’, etc. in their names).

Inferences based on conducted EDA

- The churn rate is more for the customers, whose minutes of usage(mou) decreased in the action phase than the good phase.
- The churn rate is more for the customers, whose number of recharge in the action phase is lesser than the number in good phase.

- The churn rate is more for the customers, whose amount of recharge in the action phase is lesser than the amount in good phase.
- 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.
- 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.
- Minutes of usage(MOU) of the churn customers is mostly populated on the 0 to 2500 range. Higher the MOU, lesser the churn probability.
- 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.
- 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.
- The recharge number and the recharge amount are mostly propotional. More the number of recharge, more the amount of the recharge.

Model with PCA

Model performance metrics summary

- Using Logistic regression with PCA

- Train set
  - Accuracy = 0.86
  - Sensitivity = 0.89
  - Specificity = 0.83
- Test set
  - Accuracy = 0.83
  - Sensitivity = 0.81
  - Specificity = 0.83

- Using Support Vector Machine(SVM) with PCA

- Train set
  - Accuracy = 0.89
  - Sensitivity = 0.92
  - Specificity = 0.85
- Test set
  - Accuracy = 0.85
  - Sensitivity = 0.81

    - Specificity = 0.85

- Using Decision tree with PCA

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

- Using Random forest with PCA

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

Final conclusion with PCA

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

Model performance metrics summary using Logistic regression with No PCA

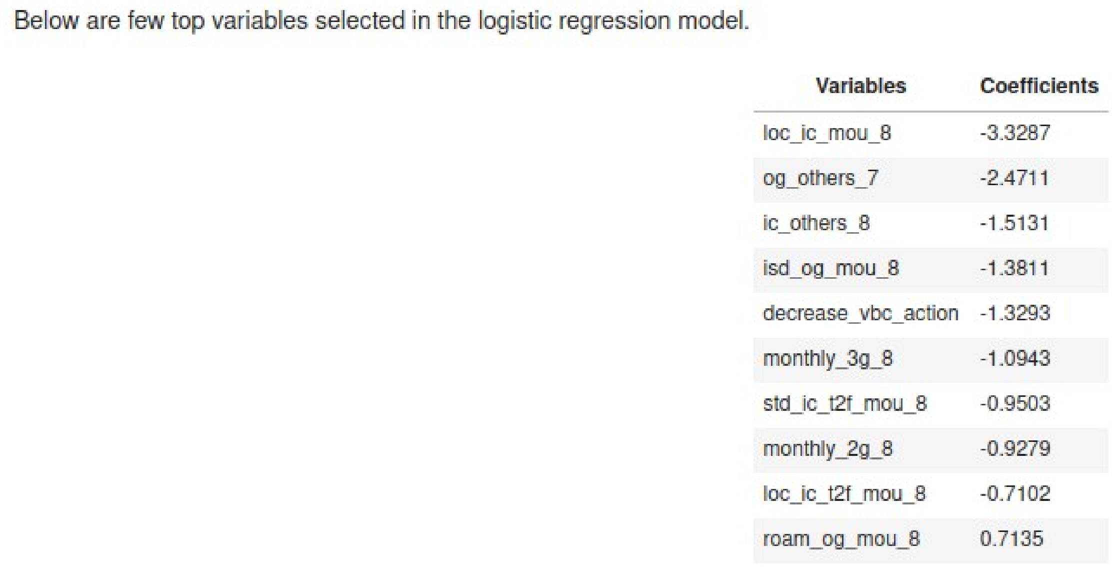
- Train set
    - Accuracy = 0.84
    - Sensitivity = 0.81
    - Specificity = 0.83
- Test set
    - Accuracy = 0.78
    - Sensitivity = 0.82
    - Specificity = 0.78

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 expliains 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

Top Predictors



Below are few top variables selected in the logistic regression model.

Variables	Coefficients
loc_ic_mou_8	-3.3287
og_others_7	-2.4711
ic_others_8	-1.5131
isd_og_mou_8	-1.3811
decrease_vbc_action	-1.3293
monthly_3g_8	-1.0943
std_ic_t2f_mou_8	-0.9503
monthly_2g_8	-0.9279
loc_ic_t2f_mou_8	-0.7102
roam_og_mou_8	0.7135

We can see most of the top variables have negative coefficients. That means, the variables are inversely correlated with the churn probablity.

Ex: If the local incoming minutes of usage (loc_ic_mou_8) is lesser in the month of August than any other month, then there is a higher chance that the customer is likely to churn.

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. Cutomers, 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. Cutomers 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.

Thank You !